Mind The Gap

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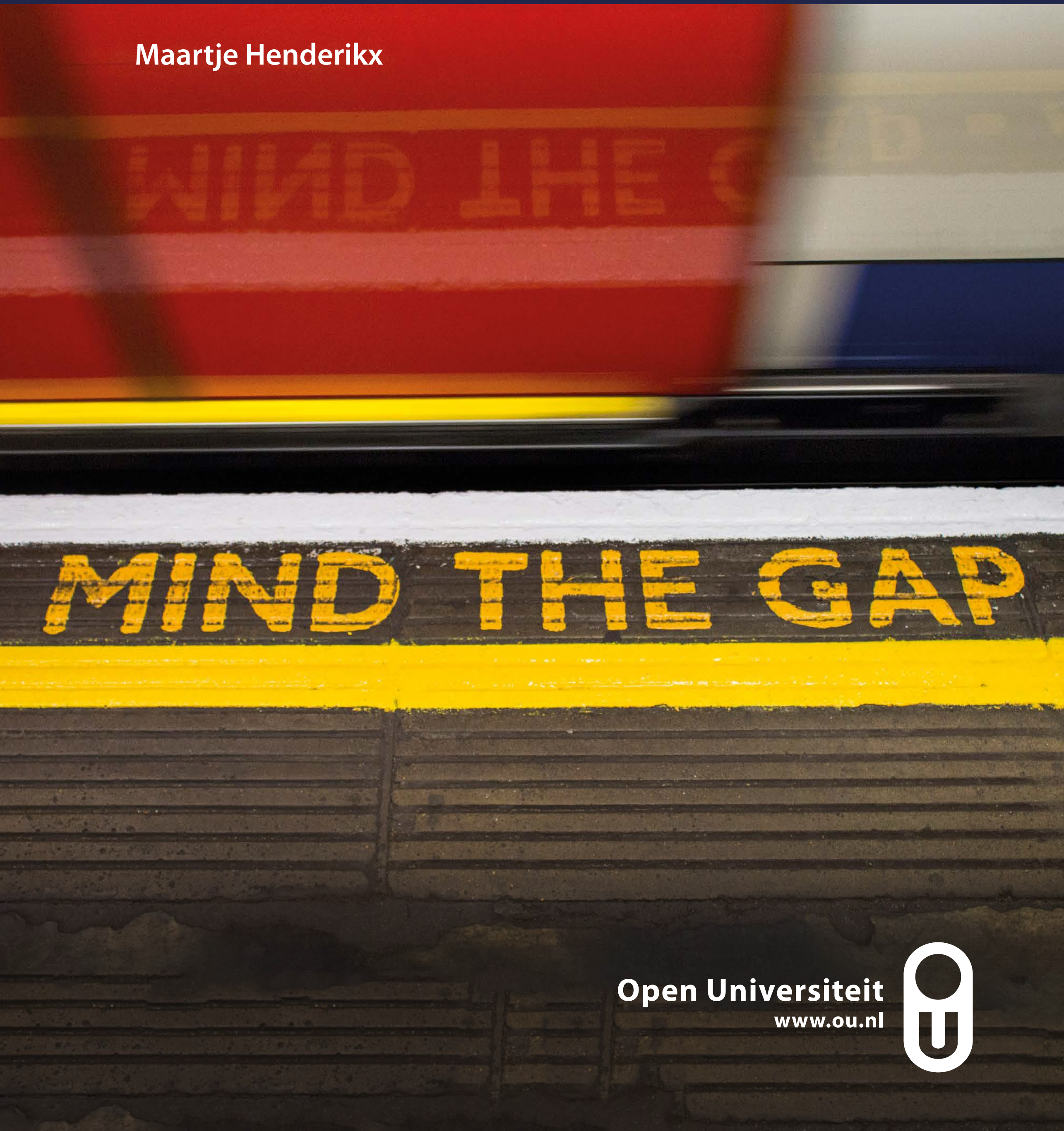
Unraveling learner success and behaviour in Massive Open Online Courses

Maartje Henderikx



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The research reported in this thesis was carried out at the Open Universiteit in the Netherlands at the Welten Institute – Research Centre for Learning, Teaching and Technology

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Prof. dr. ir. C.J. Kreijns, Open Universiteit

Overige leden van de beoordelingscommissie:
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It is never too soon or too late for learning

Irakli Gvaramadze (2007)

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Chapter 1

General introduction

Lifelong learning is the new paradigm in the educational landscape. Learning is not limited to traditional learning environments like school settings or the occasional corporate course or workshop environment anymore. Yet it is encouraged to be regarded as an ongoing process, relevant at all stages in life and should be accessible to everyone regardless of race, gender or beliefs (Sheehan, 2012). The European commission (2001) defined lifelong learning as "all learning activity undertaken throughout life, with the aim of improving knowledge, skills and competencies within a personal, civic, social and/or employment- related perspective" (p. 33). Following this definition, this includes learning activities undertaken in formal, informal and non-formal learning settings.

Formal learning refers to learning as a result of an organized and coordinated learning event provided by an education provider (Eraut, 2000). The goal of formal learning is to teach or share knowledge and the way the learning program is designed and delivered is crucial and generally leads to a recognized qualification (ISCED, 2011). Within the concept of formal learning a distinction can be made between traditional education and non-traditional education (Wedemeyer, 2010). Traditional education refers to the teacher centred, day-time face to face instruction (Dewey, 1986). Non-traditional education moves away from the place- and time-restricted classroom and is generally referred to as distance education or distance learning (Wedemeyer, 2010). Informal learning can be defined as learning from own experiences (Choi & Jacobs, 2011) as well as acquiring knowledge from others (Eraut, 2004). Learning from others often takes place unplanned when individuals observe and listen to each other, participate in discussions, interact with clients and colleagues or reflect on performance with peers (Billet, 2011; Doornbos, Simons & Denessen, 2008). Non-formal learning, according to the international standard classification of education (ISCED), typically adds to formal learning in the process of lifelong learning. These learning activities are similar to formal learning activities, organized by an education provider yet accessible for people of all ages and backgrounds. Non-formal learning takes place outside the traditional (formal) learning context, yet are planned and structured learning activities of a voluntary nature and often do not lead to generally recognised qualifications (Eaton, 2010; ISCED, 2011; Reddy, 2003). Recognition of skills and experiences acquired in informal or non-formal learning contexts is possible in some cases and involves a validation process of several stages during which an individual's acquired learning outcomes are assessed against a relevant standard (Council of the EU, 2012).

However, the most common and preferred model of learning is formal learning, also when it comes to professionalisation and professional development while active in the workforce (Banks & Meinert, 2016; Linardopoulos, 2012). Although this model of learning typically leads to official qualifications which are recognized by employers and other instances, learners also face barriers which make it difficult or even impossible for them in some cases to engage in this form of learning. Following several studies, which studied barriers to learning in formal adult learning contexts, Roosmaa and Saar (2017) referred to situational, institutional and dispositional barriers. Situational barriers are related to a learner's life stage especially with regard to family and work life. Institutional barriers are related to the educational institution and include practices or procedures that impede or hinder participation like for example high fees or entry requirements, lack of learning arrangements or opportunity, timing of the learning arrangements, general lack of flexibility. Dispositional barriers are related to the learner's personality, personal qualities and beliefs (Roosmaa & Saar, 2017).

Despite the increased importance of continuously updating knowledge and competences to enhance one's employability, a substantial group of individuals in the employable age of 18+ years did not engage in lifelong learning activities in the context of traditional education. As reported by EUROSTAT, the statistical office of the European Union, main reasons for this were the high costs and the lack of flexibility. Other reasons given were distance to an educational institution, family and work responsibilities and a lack of suitable education or training offer (EUROSTAT, 2019). When referring to the types of barriers as used by Roosmaa and Saar (2017) the majority of the aforementioned barriers are institutional and situational barriers. In addition to the traditional way of updating knowledge and competences, non-traditional education like distance education or distance learning (Wedemeyer, 2010), which has been established as an alternative to traditional education in the 1970s (Guri-Rosenblit, 2016) might be the answer to some of the major issues as experienced by the aforementioned group of individuals. Distance education typically provides more flexibility to learning and enables individuals to choose from a wide range of topics without the restriction of local educational institutions' offerings (Quayyam & Zawacki-Richter, 2018). Some of the institutional barriers like lack of flexibility, distance to an educational institution and lack of suitable education offer, are addressed by this form of education. Nevertheless, other institutional barriers like high costs in addition to situational barriers like work and family responsibilities prevail (Muilenburg & Berge, 2005). In addition, some new issues arise in the form of motivational, social context and IT-related barriers (Muilenburg & Berge, 2005). These findings indicate that quite a substantial group of individuals misses out on the opportunity to (continuously) develop themselves, which creates tension with the claim that lifelong learning opportunities should be accessible to everyone.

A possible solution for some of the issues might be found in the context of Massive Open Online Courses (MOOCs), which were a fairly new, promising phenomenon at the time of starting this research project. MOOCs are online-courses of various lengths, covering various topics, designed to be accessible to anyone, anywhere, at any time (Barnes, 2013). They embodied the promise to bring free education closer to the masses, with the ideological potential to reach countries without solid educational systems (Margaryan, Bianco & Littlejohn, 2015). MOOCs were a result of the open educational resources (OER) movement (Ozturk, 2015), which started in 2001 when the Massachusetts Institute of Technology (MIT) began to offer open access course materials on the web (Liyanagunawardena, Adams & Williams, 2013). At the beginning of the MOOC development, a clear distinction was made between cMOOCs (connectivist MOOCs), which built on user-generated content and connections between the participants (Siemens, 2014), and xMOOCs, which were MOOCs that followed the "traditional educational model of knowledge transfer from teachers to students" (Alario-Hoyos, Pérez-Sanagustín, Delgado-Kloos & Munoz-Organero, 2014). In the past few years the hybrid MOOC, a MOOC containing a combination of cMOOC and xMOOC teaching principles, made its entrance (Saadatoost, Sim, Jafarkarimi & Mei Hee, 2015), blurring the previously clear distinction between MOOCs. In the meantime, a rich diversity of educational approaches for MOOCs has emerged. MOOC-learners are primarily adults, with post-secondary degrees who seek learning opportunities, similar to distance education, yet even more flexible, less expensive and less committing (Loizzo, Ertmer, Watson & Watson, 2017).

During the first years of the appearance of MOOCs, they were completely open to everyone and learners could receive free certificates of participation if they completed the course or at least a minimum percentage of the course. These certificates were for the learners' own interest as they were not recognised by educational or professional organisations (Jobe, 2014). However, since the start of this research project in 2015, recognition of MOOCs including a shift from free access for all to paid programs has been an ongoing development. The yearly MOOC report by Class Central (Shah, 2015; 2016; 2017; 2018) pointed out that in 2015, Coursera was starting to put certificates behind paywalls and that several MOOC providers initially started creating their own credential programs in the form of specialisations, micro masters and nanodegrees. In addition, they also started initiatives to create ways to earn credits with MOOCs in participation with credit granting institutions. This development continued over the next three years resulting in an increase paid certificates and credential programs, MOOC-based degrees like master degrees, MBA's, corporate training programs and the expanding possibility for on-campus students to earn credits by completing (specific) MOOCs as part of their educational program (Shah, 2016; 2017; 2018). Generally, the focus changed from making education available to the masses to professional learners -paying users - who take courses for lifelong learning and professional development purposes.

Simultaneous to the evolvement of the MOOC, research into this topic was and is expanding. At the start of this research project most studies reported on were not empirically grounded exploratory and descriptive research at the macro and meso level and mainly focused on pedagogical, technological and dropout issues (Bozkurt, Agun-Ozbek & Zawacki-Richter, 2017; Raffaghelli, Cucchiara & Persico, 2015). Especially the dropout rates, which were estimated as high as 90%-98% (Jordan, 2014;2015; Koller, Gd, Do & Chen, 2013; Liyanagunawardena, Parslow & Williams, 2014; Reich, 2014; Reich & Ruipérez-Valiente, 2018) gained a lot of attention and made scholars question the potential and usefulness of MOOCs (Bozkurt, Agun-Ozbek & Zawacki-Richter, 2017). These reported dropout rates are based on the assumption that completion of the whole MOOC is the goal of every learner. However, the learning circumstances regarding MOOCs are exceptional (Koller, Gd, Do & Chen, 2013; Liyanagunawardena, Parslow & Williams, 2014; Huin, Bergheaud, Caron, Codina & Disson, 2016) and should not be compared with traditional learning contexts with respect to completion and dropout (Huin et al., 2016). Nevertheless, when evaluating success in MOOCs or running achievement analyses, completing the MOOC or, in other words, getting the certificate, is still equated to learner success. This approach to success assessment completely overlooks the viewpoint of the individual learners who, due to the design and set up of MOOCs, have the opportunity to model their learning according to their own needs in accordance with lifelong learning. Interestingly, this shortcoming of perspective was also regarded as an important drawback by Tinto (1975) many years ago regarding the interpretation and determination of dropout in the traditional educational context: “A […] more important limitation […] is the tendency to ignore the perspective of the individual […] Such definitions of dropout […] imply connotations of inferiority […] of the individual dropping out” (p. 5).

The aim of this research project was to advance research into open education and MOOCs by conducting empirically grounded studies on micro level, taking the viewpoint of the individual learner as a starting point. More specifically, our goal was to refine the definition of learner success and identify issues that hinder learners from being successful.

Theoretical foundation

In order to study learner success in MOOCs, the reasoned action approach (RAA; Fishbein & Ajzen, 2010), more specifically, the intention-behaviour gap as defined in the RAA (Figure 1) runs as a common thread through the studies as it takes the individual (i.e. the learner) as a starting point when assessing intention-behaviour patterns.

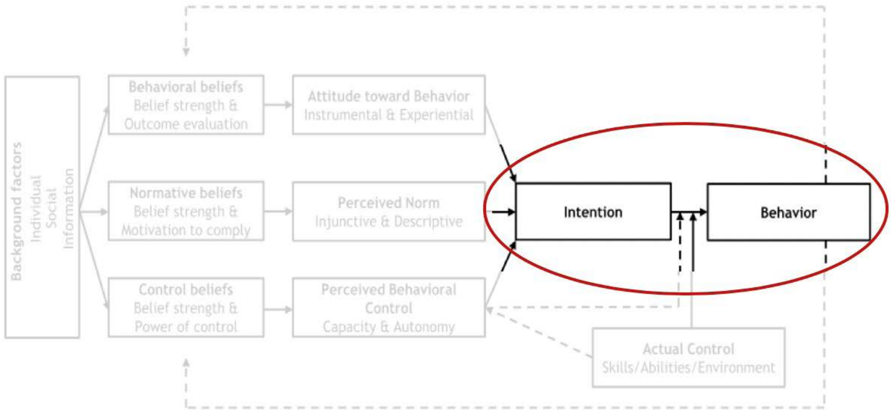

Figure 1. Reasoned action approach (Fishbein & Ajzen, 2010)

The RAA framework is centered around the formation of an intention and the translation of this intention into actual behaviour. As in practice, in the end, not all intentions are realized in actual behaviour, this translation of intentions into actual behaviours is referred to as the intention-behaviour gap (highlighted in Figure 1). In general, the RAA aims to understand an individual’s voluntary behaviour; therefore, the concept of intention can also referred to as behavioural intention and is defined as ‘an indication of a person’s readiness to perform a behaviour which will lead to a desired outcome’ (Fishbein & Ajzen, 2010). The concept of intention was also used by Gollwitzer (1990; 1999) who specified intention as ‘a certain end point that may be either a desired performance or an outcome’ (p. 494) and is referred to as goal intention. For the purpose of this research project intention will be referred to as goal intention and will be defined as "a person's readiness to perform a behaviour which will lead to a certain end point". This definition integrates both Fishbein & Ajzen's and Gollwitzer's definitions, since both of these theories are an important part of the theoretical foundation of this research project. In the context of MOOC-learning intention was operationalised as a learner's readiness to perform the behaviour which will lead to gaining the desired knowledge by completing some or all learning units in the MOOC. Behaviour represents the extent to which a learner completes the intended learning units. As said mentioned: in practice, in the end, not all intentions are realized in actual behaviour.

According to Gollwitzer (1990) the process of the formation of a goal intention until the evaluation of the actual behaviour is divided into 4 phases (see Figure 2).

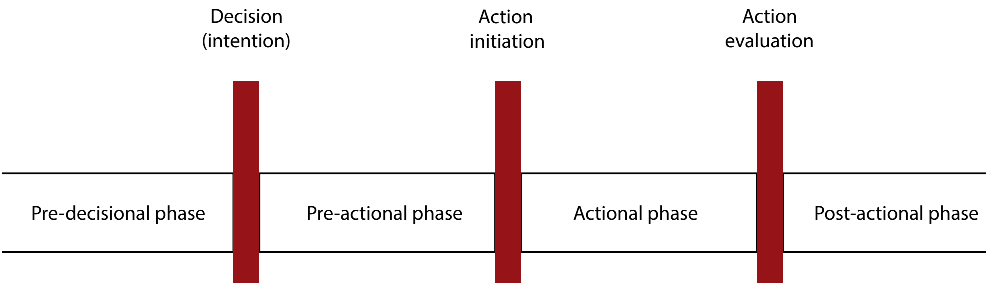

Figure 2. The Rubikon model of action phases (Gollwitzer, 1990)

In the pre-decisional phase, which is about deliberating and weighing the different options the individual might have (Gollwitzer, 1990), a specific goal intention is formed. The pre- actional phase is about planning concrete strategies for achieving the set goal intentions and in the actional phase the individual goal intention should be carried out according to plan. During this phase re-formulation of the goal intention can occur due to various reasons. In the post-actional phase an evaluation takes place of whether the individual goal intention which was formed in the pre-decisional phase was indeed translated to actual behaviour.

Intention-behaviour research, which originates from the field of Health sciences, often found that intention, especially intention to perform certain behaviour (as opposed to the intention to not perform a certain behaviour), did not equal actual behaviour (Sheeran, 2002; Sheeran & Orbell, 2000; Sutton, 1998). According to Fishbein & Ajzen (2010), a possible reason for not being able to translate intentions into actual behaviour, is the experience of unforeseen barriers. In the framework of this study, barriers can be defined as issues which hinder or prevent learners from acting out their individual learning intentions. Especially, if there is a longer time between the formation of an intention and the measurement of behaviour, which is often the case when learning in MOOCs, the possibility of experiencing one or more barriers increases and therefore the accuracy of intention as a predictor for behaviour decreases (Hassan, 2014).

Ultimately, according to a conceptual review about intention-behaviour relations by Sheeran (2002) four different intention-behaviour relations are possible:

1. *Inclined actors* - individuals who formed a certain intention and did act according to that intention

2. *Inclined abstainers* - individuals who formed a certain intention, but failed to act according to this intention

3. *Disinclined actors* - individuals who formed a certain intention but end up doing more than they intended to do

4. *Disinclined abstainers* - individuals who did not have any intentions and accordingly did not act

Figure 3 visualises how the different models and theories of intention-behaviour relate to each other in the overall framework of this research project.

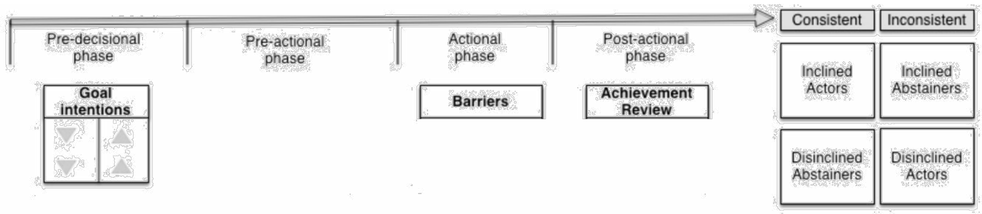

Figure 3. Visualisation of the theoretical foundation (based on Kalz, Henderikx & Kreijns, 2016)

Research questions

The main question underlying this dissertation is: How can the definition of success in open education and MOOCs be refined and what barriers impede individual learner success? In order to answer this main question the following research questions were investigated:

1. How can success and dropout assessment in MOOCs be refined?

2. How dynamical is the intention-behaviour process and what are reasons for this?

3. What individual goals do learners set and do they succeed in achieving these goals?

4. What type of barriers do learners face while learning in MOOCs?

5. Which barriers to learning in MOOCs can be identified and how can these barriers be classified?

6. How can we classify barriers into a diagnostic instrument to guide learner support and MOOC development?

7. Which determinants affect barriers faced by learners while learning in MOOCs?

Context of the research

The studies presented in this research project were part of the SOONER project, which was fully funded by the Netherlands Initiative for Education Research (NRO) (SOONER/http://sooner.nu). The main goals of this project, which focused on fundamental research about open online education in the Netherlands, were to enable systematic and long term research on open online education revolving around four research strands: 1) self- regulated learning, 2) scalable support solutions for feedback, 3) learner intention-behaviour and 4) organizational implications of open and online learning. The research conducted for this dissertation connects to the learner intention-behaviour strand.

Outline of the thesis

This dissertation consists of nine chapters. *Chapter 2* presents an alternative typology for refining success and dropout in MOOCs. As MOOCs provide an exceptional learning context that cannot be compared to traditional learning contexts, assessing their success should move away from the commonly used completion or certificate centric view and move towards a learner centric view. The proposed typology is builds on the intention-behaviour gap as defined in the reasoned action approach (Fishbein & Ajzen, 2010) and is based on the individual intentions of the learners and their subsequent behaviour. In addition to the introduction of the alternative typology, an explorative study was carried out to test the practical applicability of this learner centric view of assessing success and dropout in

MOOCs. The next two chapters focus on explorative studies aiming to advance our understanding of learner behaviour in MOOCs. *Chapter 3*, explores the dynamicity of the intention-behaviour process. A model to visualise and capture potential intention changes and the translation of these intentions into actual behaviour is introduced and validated. *Chapter 4*, gives additional insight into the goal achievement process by examining learner behaviour using Gollwitzer's Rubikon model of action phases (1990) as a guideline for interpreting a learner's path through a MOOC. Previous studies indicate that intention is not a perfect predictor for behaviour as not all learners achieve their individual learning goals. *Chapter 5* gives a first overview of literature about barriers to learning that hinder or prevent learners from reaching their personal learning goals and presents the results of data gathered in two MOOCs about the most experienced barriers by learners. *Chapter 6*, builds on chapter 5 by expanding the literature overview about barriers. Based on the identified barriers a questionnaire was developed to gather data about the extent to which learners experienced (certain) barriers while learning in MOOCs, which was then empirically classified by using a factor analytical approach. The next study, in *chapter 7*, reports on the validation of the empirical classification as found in chapter 6 with the aim to develop a self-report instrument to capture barriers to learning as experienced by learners in MOOCs. Additional data was collected and exploratory and confirmatory factor analyses were performed to examine the validity of the structure taking into account measurement indicators. *Chapter 8*, provides insight into whether the determinants age, gender, educational level and online learning experience affect the experience of barriers while learning in MOOCs. Considering the lack of literature concerning predictors of barriers to learning in MOOCs, the determinants were derived from research on predictors of academic achievement in online learning contexts and were then related to barriers. This way hypotheses could be formulated and tested by analyzing the data. The last chapter, *chapter 9*, provides an overview of the findings in each chapter and concludes with a discussion and conclusion of the complete research project and addresses limitations, suggestions for future research and implications for practice.

References

Alario-Hoyos, C., Perez-Sanagustin, M., Delgado-Kloos, C., & Munoz-Organero, M. (2014). Delving into participants' profiles and use of social tools in MOOCs. *IEEE Transactions on Learning Technologies*, 7(3), 260-266.

Banks, C., & Meinert, E. (2016). The Acceptability of MOOC Certificates in the Workplace. *International Association for Development of the Information Society*, pp 215-218. Retrieved from https:// files.eric.ed.gov/fulltext/ED571496.pdf.

Billett, S. *(2001).* Learning in the Workplace: Strategies for Effective Practice. Australia: Allen & Unwin.

Castaño-Muñoz, J., Kalz, M., Kreijns, K., & Punie, Y. (2018). Who is taking MOOCs for teachers' professional development on the use of ICT? A cross-sectional study from Spain. Technology, *Pedagogy and Education*, 1-18.

Choi, W., & Jacobs, R. L. (2011). Influences of formal learning, personal learning orientation, and supportive learning environment on informal learning. *Human Resource Development Quarterly*, 22(3), 239-257.

Dennen, V. P., & Bong, J. (2017). Reframing MOOCs in higher education: Exploring professional development options. In *Massive Open Online Courses and Higher Education* (pp. 151-167). Routledge.

Dewey, J. (1986, September). Experience and education. In *The Educational Forum*, Volume 50, No. 3, pp. 241-252. Taylor & Francis Group.

Doornbos, A. J., Simons, R. J., & Denessen, E. (2008). Relations between characteristics of workplace practices and types of informal work-related learning: A survey study among Dutch Police. *Human resource development quaterly*, 19(2), 129-151.

Eaton, S. E. (2010). *Formal, Non-Formal and Informal learning: The Case of Literacy, Essential Skills, and Language Learning in Canada*. Retrieved from http://www.infed.org/archives/e-texts/eaton_formal_nonformal_informal_ learning.htm

Eraut, M. (2000). Non-formal learning and tacit knowledge in professional work. *British Journal of Educational Psychology*, 70(1), 113-136.

Eraut, M. (2004). Informal learning in the workplace. *Studies in continuing educ*ation, 26(2), 247-273.

European Commission (2001). *Making a European area of lifelong learning a reality.* (COM (2001) 678 final). Retrieved from http://viaa.gov.lv/files/free/48/748/pol_10_com_en.pdf Brussels: Author, 2001.

Eurostat (2019). Obstacles to participation in education and training [data file]. Retrieved from https:// ec.europa.eu/eurostat/web/education-and-training/data/database

Guri-Rosenblit, S. (2016). Distance Higher Education in the Digital Era: Challenges and Prospects, *Distance Education in China*, 6, 16-25

Jobe, W. (2014, October). No university credit, no problem? Exploring recognition of non- formal learning. In 2014 IEEE *Frontiers in Education Conference* (FIE) Proceedings (pp. 1-7). IEEE.

Kalz, M., Henderikx, M., & Kreijns, K. (2016, 5 October). The determination of success in MOOCs and the role of participant's intentions. Presentation provided during the Learning with MOOCs Conference 2016: *Being and learning in a digital age*, Philadelphia, USA.

Laurillard, D. (2016). The educational problem that MOOCs could solve: professional development for teachers of disadvantaged students. *Research in Learning Technology*, 24. Retrieved from https://journal.alt.ac.uk/index.php/rlt/article/view/

Linardopoulos, N. (2012). Employers' perspectives of online education. *Campus-Wide* Information Systems, 29(3), 189-194. doi:10.4135/9781483318332.n131

Loizzo, J., Ertmer, P. A., Watson, W. R., & Watson, S. L. (2017). Adult MOOC Learners as Self-Directed: Perceptions of Motivation, Success, and Completion. *Online Learning*, 21(2), n2.

Olsson, U. (2016). Open courses and MOOCs as professional development–is the openness a hindrance?. *Education+Tra*ining, 58(2), 229-243.

Qayyum, A., & Zawacki-Richter, O. (Eds.). (2018). *Open and distance education in Australia, Europe and the Americas: National perspectives in a digital age*. Springer. doi: 10.1007/978-981-13-0298-5

Reddy, R. S. (Ed.). (2003). *Recent trends in non-formal education: Some forays*. Rajat Publications.

Reich, J., & Ruipérez-Valiente, J. A. (2019). The MOOC pivot. *Science*, 363(6423), 130- 131. oi: 10.1126/science.aav7958

Roosmaa, E. L., & Saar, E. (2017). Adults who do not want to participate in learning: A cross-national European analysis of their perceived barriers. International Journal of Lifelong Education, 36(3), 254-277.

Saadatdoost, R., Sim, A. T. H., Jafarkarimi, H., & Mei Hee, J. (2015). Exploring MOOC from education and Information Systems perspectives: a short literature review. *Educational Revi*ew, 67(4), 505-518.

Shah, D. (2015, December 30). Less experimentation, more iteration. A review of MOOC stats and trends in 2015. Retrieved from https://www.classcentral.com/report/ moocs-stats-and-trends-2015/

Shah, D. (2016, December 29). Monetization over massiveness. A review of MOOC stats and trends in 2016. Retrieved from https://www.classcentral.com/report/moocs- stats-and-trends-2016/

Shah, D. (2018, January 22). A product at every price. A review of MOOC stats and trends in 2017. Retrieved from https://www.classcentral.com/report/moocs-stats-and- trends-2017/

Shah, D. (2019, January 6). Year of the MOOC-based degrees. A review of MOOC stats and trends in 2018. Retrieved from https://www.class-central.com/report/tag/ mooc-roundup-2018/

Sheehan, P. (2012). Foreword. Aspin, D. N., Chapman, J., Hatton, M., & Sawano, Y. (Eds.). (2012). *International handbook of lifelong learning* (Vol. 6). Springer Science & Business Media.

Siemens, G. (2005). Connectivism - A learning theory for the digital age. *International Journal of Instructional Technology and Distance Learning*, 2(1), 3–10.

UNESCO Institute for Statistics. (2012). *International standard classification of education: ISCED 2011*. Montreal: UNESCO Institute for Statistics. http://uis.unesco.org/sites/default/files/documents/international-standard- classification-of-education-isced-2011-en.pdf

Veletsianos, G., & Shepherdson, P. (2016). A systematic analysis and synthesis of the empirical MOOC literature published in 2013–2015. *The International Review of Research in Open and Distributed Learning*, 17(2), 202-221.

Wedemeyer, C. A. (2010). *Learning at the back door: Reflections on nontraditional learning in the lifespan*. Charlotte, NC: Information Age Publishing.

2

Chapter 2

Refining success and dropout in massive open online courses based on the intention–behaviour gap

This chapter is based on:
Henderikx, M. A., Kreijns, K., & Kalz, M. (2017). Refining success and dropout in massive open online courses based on the intention–behaviour gap. *Distance Education, 38(3)*, 353–368. doi:10.1080/01587919.2017.1369006

Abstract

In this paper, we present an alternative typology for determining success and dropout in massive open online courses (MOOCs). This typology takes the perspectives of MOOC-learners into account and is based on their intentions and subsequent behaviour. An explorative study using two MOOCs was carried out to test the applicability of the typology. Following the traditional approach based on course completion to identify educational success, success rates were 6.5 and 5.6%. The success rates from the perspectives of the MOOC-learner were 59 and 70%. These findings demonstrate that merely looking at course completion as a measure for success does not suffice in the context of MOOCs. This change in addressing MOOC success and dropout provides an alternative view and demonstrates the importance of MOOC-learners' perspectives.

Introduction

Massive open online courses (MOOCs) as a novel form of open education were initially received with great enthusiasm. Hundreds of thousands of learners and even more enrolled in MOOCs (Jordan, 2014). However, after a short time, this first excitement was followed by frustration. Despite its popularity, the number of MOOC-learners who actually completed a MOOC after enrollment was reported to be very low with dropout rates between 98 and 90% (Jordan, 2014, 2015; Koller, Ng, Do, & Chen, 2013; Liyanagunawardena, Parslow, & Williams, 2014; Reich, 2014). Many researchers agreed that the learning circumstances in MOOCs are exceptional (Huin, Bergheaud, Caron, Codina, & Disson, 2016; Koller et al., 2013; Liyanagunawardena et al., 2014). In contrast to traditional face-to-face education and also distance education – where students often have to meet certain admission requirements and primarily follow full educational programmes – a MOOC is a relatively short course (generally 5–12 weeks) which is accessible to anyone, anywhere, at any time in disposal of an Internet connection. It is therefore recognized that it should not be compared to the traditional learning context with respect to completion and dropout (Huin et al., 2016; Walji, Deacon, Small, & Czerniewicz, 2016).

Academic research on dropout has a long tradition. Tinto (1975) differentiated between two levels of perspectives for defining dropout in his seminal work on college dropout: On the one hand, there is the level of the educational institution dealing with students who leave without receiving an end qualification; on the other hand, there is the state- or country- wide perspective of students who attend one or more educational institutions, but never receive an end qualification from any of these institutions. Tinto (1975) proposed a model for explaining student dropout that includes a combination of individual and organizational variables that influence dropout. Sweet (1986) used this theoretical model and applied it in a study situated in a distance education context. Results of this study partially confirm the relations as proposed by Tinto (1975). Motivation, measured in the form of locus of control, had a direct and indirect effect on persistence. Further, Garrison (1987) argued that research on dropout in distance education was too much focused on understanding and predicting without actually taking into account the nature of distance education. Garrison recommended focusing on the student's perspectives and developing situation-specific models and theories before trying to generalize. This is also in line with recommendations by Tinto (1975): 'A […] more important limitation […] is the tendency to ignore the perspective of the individual' (p. 5). In addition, Peters (1971) argued that new criteria for analyses are necessary when analysing different forms of education.

We assume that Tinto's (1975) model and the variables he described are important for the context of open education and MOOCs. Yet, due to the variety of possible goals in this context, we expect that individual differences in goal commitment will play a prominent part in the understanding of dropout in MOOCs compared to the distance education context. We expect that the non-formal nature of learning in open education requires a situation- specific approach to understand success and failure as signified by dropout. Framing success from a certificate- and completion-centric view will nurture a false understanding of success and dropout in MOOCs, which may subsequently lead to unnecessary interventions and unjustified negative reviews. The benefit of MOOCs is that they afford individuals the opportunity to follow their own learning paths. It seems, therefore, legitimate to take the intention of the individual MOOC-learner as a starting point for measuring and interpreting success and subsequently dropout. These intentions may vary from simply browsing through a MOOC to – indeed – getting a certificate.

In this paper, we present a typology based on the individual intentions of MOOC-learners. As the point of departure is the MOOC-learners' intention, it is necessary to consider theories about intention formation and how individuals comply with this intention and ultimately translate this intention into actual behaviour. In our study, we used Fishbein and Ajzen's (2010) reasoned action approach (RAA) as described in Kalz et al. (2015) and built on the intention–behaviour patterns as defined by Sheeran (2002) to reinterpret success and dropout in MOOCs.

The paper is structured as follows: First we discuss the theoretical background and related work. Via the integration of several socio-psychological perspectives on the connection between intention and behaviour we introduce the new typology. Next, data from two MOOCs is presented and analysed in line with the theory and new typology. Lastly, we discuss the results and implications for using the typology in empirical studies, and consider limitations of the approach.

Related work on dropout and success in MOOCs

In his extensive research on the process of dropping out in higher education, Tinto (1975) defined dropout as students who leave the educational institution at which they are registered without an end qualification. This dropout rate is fairly easy to calculate (i.e., the number of students without an end qualification divided by total number of registered students) and is widely used as a measurement for institutional success and quality of education (Eisenberg & Dowsett, 1990; Peters, 1992; Tinto, 1975).

When assessing success in MOOCs, this definition of dropout (i.e., dropout equals not receiving a certificate) is often used. A study by Breslow et al. (2013) determined the success rate by calculating the percentage of students who earned a certificate for completion. This resulted in a success rate of 5%, hence a dropout rate of 95%. Likewise, Belanger and Thornton (2013) analysed Duke University's first MOOC and found a success rate of 2% and a dropout rate of 98%. A study by Jordan (2014) further illustrated that success assessment of MOOCs was primarily directed at earning an end qualification in line with the approach discussed in the introduction. She found that on average 6.5% of the students who enrolled in a MOOC met the certificate-earning criteria of the course. In a later study she found that the success rate reached a mean value of 12.6%, which entailed an average dropout rate of 87.4% (Jordan, 2015).

This approach to success assessment of MOOCs resulted in very low success rates and, subsequently, extremely high dropout rates. It also ignored the viewpoint of the individual student. Following Tinto (1975), the perspectives of individual learners in the assessment of dropout brings a new point of view to the discussion. This new viewpoint adds the origin of the leaving behaviour to the discussion. Tinto (1982) classified academic dismissal and voluntary withdrawal as two distinct types of leaving behaviour. Academic dismissal, a type of dropout, which will not occur in the context of a MOOC, is initiated by the educational institution. A reason for this could be insufficient performance. Voluntary withdrawal, on the other hand, is initiated by the individual and can be caused by multiple factors in the dynamic between the individual, peers, and the institution (Eisenberg & Dowsett, 1990; Tinto, 1975).

Voluntary withdrawal could, however, also be retraced to the individual intentions of the student. Students entering education might have intentions other than receiving an end qualification; for example, they may intend to complete only some courses to develop specific skills and knowledge (Roberts, 1984; Tinto, 1982). Also, intentions may change over time. For example, the initial intention of a student may be to receive the end qualification, yet over time this intention may change and the student leaves the educational institution and/or system voluntarily completely satisfied with the accomplishment at hand (Tinto, 1982). As was pointed out in the introduction, MOOCs provide an exceptional learning context. The open and accessible character of MOOCs affords individuals to follow their own personal learning paths, which are likely to be based on a variety of individual intentions and not merely on receiving an end qualification.

Recent work on dropout in MOOCs has shifted from an outcome-related perspective to a more individual perspective. Liyanagunawardena et al. (2014) argue that the way dropout is measured fails to identify various forms of dropout such as academic failure and voluntary withdrawal. Categorizing participants who do not complete a course as dropouts leads to ambiguous conclusions regarding course success. The main conclusion of their study is that factors like start date and intentions should be considered when it comes to defining dropout.

Koller et al. (2013) have provided the first peer-reviewed article in which retention is considered in the context of student intent. They purport that 'observing how students participate in online classes can reveal student intent' (p. 2). By using log data to reveal behavioural patterns they distinguished four categories of learners: browsers, passive participants (limited course engagement), active participants (full course engagement), and community contributors (course engagement specifically aimed at generating new content). Yet, even though they acknowledged the fact that success measurements of MOOCs should be interpreted with individual intention in mind, they nevertheless focused on studying student intention to complete a MOOC. MOOC completion, therefore, still implied ultimate study success. Reich (2014) also explored the issue of MOOC completion and retention in the context of student intent. He found that students with the intention to complete were most likely to earn a certificate (22%). In contrast to the research by Koller et al. (2013), student intention was based on intentions reported by the students in a pre-course survey rather than derived from student log data. Their choice of intentions was limited to four options: unsure, browse, audit, complete. Similar to the research by Koller et al. (2013), Reich (2014) regarded solely the intention to complete as the preeminent success measurement. Neither research by Koller et al. (2013) nor by Reich (2014) took into account related theories and empirical research on intentions.

Huin et al. (2016) propose a learner-centered model for measuring completion and dropout in MOOCs. This model can be regarded as the first attempt to refine the view on learner success and failure in MOOCs. Their proposed typology is structured along three theoretical key concepts: intention, commitment, and behaviour. These concepts are based on related research on intention and motivation, namely the integrative model of motivation (Fenouillet, 2012), Fishbein and Ajzen's (1975) theory of reasoned action, and Deci and Ryan's (2002) self-determination theory. However, it remains unclear what precise aspects Huin et al. (2016) used from these theories and how they were reflected in their model. In their study learners could indicate whether they chose to follow the learning objectives provided by the instructional design or their personal learning objectives. This intention and subsequently the actual behaviour was then inferred from log data in the MOOC.

To summarize, studies to date illustrate the growing awareness that the individual intention of MOOC-learners should indeed be taken into account to avoid misinterpretations of success and dropout in MOOCs, as well as individual success and failure. These studies, however, merely based the intention of the MOOC-learners on log data, focused only on the intention to earn a certificate or did not reflect findings based on the theoretical model they used for research with regard to understanding success and dropout in the context of MOOCs.

Theoretical foundation

As indicated in the introduction, the RAA (Fishbein & Ajzen, 2010) serves as our theoretical framework. This framework contains two levels: the formation of an intention to reach certain goals and the translation of this intention into actual behaviour, which may or may not lead to an intention–behaviour gap. Our focus in this study is on the latter level. Even though the RAA was originally developed to explain and predict behaviour in the field of health science, it has been widely adopted by numerous other fields to gain insight into intention– behaviour relations (Kreijns, Vermeulen, Kirschner, Buuren, & Acker, 2013). According to Fishbein and Ajzen (2010), intention is determined by three main factors: an individual's attitude towards the behaviour, perceived norm (an individual's perceived social pressure to perform or not to perform the intended behaviour), and perceived behavioural control (an individual's perception of whether a person is capable or has control over the performance of the intended behaviour). Furthermore, intention is expected to be a predictor for behaviour.

A study by Sutton (1998) on how well intentions predict behaviour found an average correlation of .48 (equivalent to explaining 24% of the variance). Sheeran (2002) conducted a meta-analysis of ten meta-analyses on how well intentions actually predict behaviour and found an average correlation of .53 (equivalent to explaining 28% of the variance), which approximately matches Sutton's (1998) findings. According to Cohen's

(1992) power primer, these findings can be regarded as a large effect size (r = 0.10 is 'small', r = 0.30 is 'medium', and r = 0.50 is 'large'), yet these results are biased due to the fact that negative intentions (i.e., the intention to not engage in something) are more often translated into actual behaviour than positive intentions (i.e., the intention to engage in something) (Fishbein & Ajzen, 2010, p. 59). To illustrate this, a study by Sheeran and Orbell (2000) found that individuals who form a negative intention (i.e., they were not willing to exercise) indeed did not exercise (97%). Of the individuals who formed the positive intention (i.e., willing to exercise) only 46% actually did so. In general, most intention–behaviour studies supported this finding, which indicates that there is a substantial gap between (mainly) positive intentions and actual behaviour.

Fishbein and Ajzen (2010) describe two possible reasons why certain behaviour is not performed and thus the possibility of the intention–behaviour gap arises:

1. The intention to perform specific behaviour has not been formed.

2. The intention is formed, but cannot be performed due to certain barriers which impede the performance.

McBroom and Reed (1992) and Sheeran (2002) described four different intention–behaviour patterns which can be distinguished:

1. *Inclined actors:* individuals who formed a certain intention and did act according to this intention.

2. *Inclined abstainers:* individuals who formed a certain intention but fail to act according to this intention.

3. *Disinclined actors:* individuals who formed no intentions but acted anyway.

4. *Disinclined abstainers:* individuals who formed no intentions and accordingly did not act.

In the context of a MOOC many individual intentions are possible. We adapted the initial definitions of Sheeran (2002) and subsume in the group of disinclined actors also individuals who did form initial intentions and acted out behaviour that went beyond these initial intentions. The group of disinclined abstainers is included in the context of MOOCs, for the reason that this group will never start a MOOC in the first place.

Intentions in MOOCs may vary from the intention to finish only the first three modules or completing the course and getting the certificate, to expanding one's network (or any other intention an individual might have). Following the discussed theories, MOOC-learners who formed the intention to finish the first three modules of a MOOC and actually succeed in doing so achieved their respective goal and can be defined as inclined actors and are considered successful MOOC-learners. MOOC-learners who only planned to browse through the course or download some interesting materials and who eventually finish three modules are also considered successful. These 'disinclined actors' did more than intended, which can be regarded as a positive outcome. This reasoning does not (yet) take into account the weight of the effort of various intentions. For example, the intention to browse requires less effort to translate to actual behaviour than the intention to complete all modules. Consequentially, the effort to change the initial intention from browsing into a behaviour in which a MOOC- learner participates in a single learning activity is a smaller step compared to MOOC-learners who intended to participate in some learning activities and in the end finish the course with a certificate.

Thus, to refine the assessment of success and dropout in MOOCs, the individual intention should be taken as a starting point. The following subsection will explain the (theoretical) scope of intentions when considering a MOOC environment and present a typology based on the translation of individual intention into actual behaviour.

The MOOC-learner typology

Taking individual intention as a starting point for the discussion about dropout and success in MOOCs leads to various intention–behaviour patterns that can be identified. The composition of these intention–behaviour patterns, contrasted by the goals set by the MOOC provider, lead to the identification of different types of MOOC-learners. We use Venn diagrams (Figure 1) to visually illustrate the variety of intention–behaviour patterns with respect to goal achievement. In these diagrams the black dots represent all possible goals that can be formulated as an intention, when following a MOOC. Generally, a MOOC provider defines a certain set of goals that must be achieved in order to obtain a certificate; in Figure 1 the grey ellipse with the dotted outline represents this MOOC provider's set of goals (i.e., the minimal set of requirements that must be satisfied in order to earn a certificate). However, a MOOC- learner may formulate a different set of goals; this individual set of intended goals is represented in the Venn diagrams by a circle with a solid outline. As can be seen from Figure 1(a), the individual set of intended goals is, in this case, a subset of the MOOC provider's set of goals; apparently, the MOOC-learner is not planning to obtain a certificate. But any other individual set of intended goals is possible. Individual sets of intended goals generally may or may not overlap, match, or even encompass the MOOC provider's set of goals. The circle with the dotted outline represents the set of intended goals that a MOOC-learner actually has achieved (i.e., actual behaviour). The difference between the set of intended goals and the set of achieved goals identifies the type of MOOC-learner. From the Venn diagrams we can see that the MOOC-learner may have achieved more, less, or other goals than initially intended. Three types of MOOC-learners were identified:

1. *Inclined actors:* These MOOC-learners fully achieved their individual set of intended goals and are considered successful according to our perspective. (Figure 1(a)).

2. *Inclined abstainers:* These MOOC-learners achieved none or less than their individual set of intended goals or decided to quit the MOOC, and are considered not successful according to our perspective (dropouts; Figure 1(b)).

3. *Disinclined actors:* These MOOC-learners achieved more than their individual set of intended goals and are considered successful according to our perspective. (Figure 1(c)).

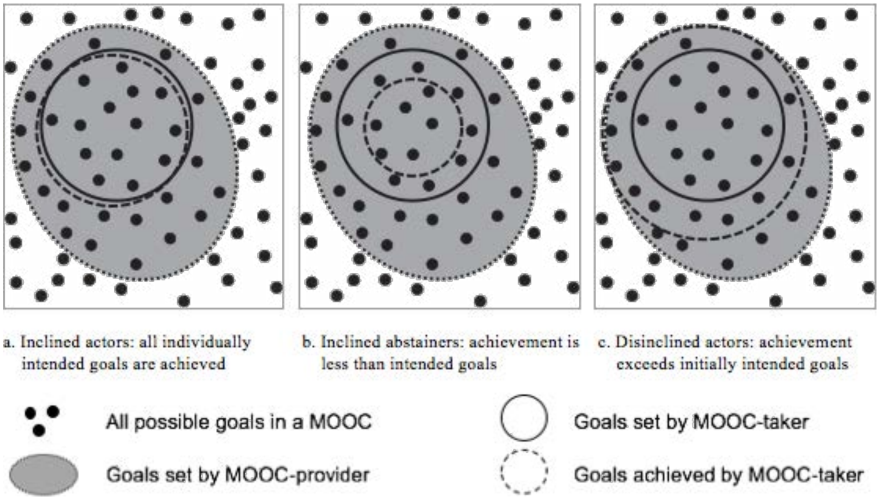

Figure 1. Venn diagrams illustrating intention-behaviour relations that identify MOOC- learners

For each of these types if their achieved set of goals encompasses the MOOC provider's set of goals, the MOOC-learners may obtain a certificate. Only then they will be considered successful according to the traditional success perspective.

This set of Venn diagrams, as depicted in Figure 1, is a non-exhaustive overview of possible intention–behaviour combinations. For instance, an inclined actor's individual set of intended goals may also equal the MOOC provider's set of goals. MOOC-learners then merely follow the pre-defined set of goals of the MOOC provider to obtain a certificate. Or this MOOC-learner's individual set of intended goals may not overlap the pre-defined set of goals by the MOOC provider at all, as is depicted in Figure 1(a). If MOOC-learners achieve their individual sets of goals, they are considered successful according to our perspective. Thus, in every possible scenario, the MOOC-learner's individual intention is the starting point for measuring success or failure. To explore the applicability of the typology for assessing MOOC success and drop- out, we have conducted an explorative study which is described in the next section.

Method

Participants

Participants took part in two MOOCs. Both MOOCs were designed by respective teams at the Open University of the Netherlands in cooperation with external parties. None of the authors was involved in the design of the courses; one of the authors supported the technical implementation of the courses.

The first MOOC (MOOC-I) was a MOOC about marine litter which ran from October until December 2015, covering eight modules for 8 weeks. MOOC-learners who completed all study tasks, including the final assignment, obtained a certificate of participation free of cost. The study load was estimated at 4 h per week. A pre-course questionnaire was completed by 689 MOOC-learners (487 women, 202 men, M_{age} = 35.6, age range: 17–73 years). The post- course questionnaire was completed by 163 MOOC-learners (109 women, 54 men, M_{age} = 38.9, age range: 17– 71 years). In total 65 MOOC-learners completed both questionnaires (49 women, 16 men, M_{age} = 40.3, age range: 21–66 years).

The second MOOC (MOOC-II), 'The Adolescent Brain,' was in Dutch, and ran from April until June 2016, covering seven modules for 7 weeks. MOOC-learners who participated in all learning activities could request a certificate free of charge. The weekly study load was estimated at 3 to 5 h per week. The pre-course questionnaire was completed by 821 MOOC- learners (664 women, 157 men, M_{age} = 45.1, age range: 18–74 years). The post-course questionnaire was completed by 126 MOOC-learners (unfortunately, participant demographics were not available). In total 101 MOOC-learners completed both questionnaires (90 women, 11 men, M_{age} = 37 age range: 18–54 years).

Materials

To measure the initial intention of the individual MOOC-learners a self-constructed set of items was used which were aligned with the design of the respective MOOCs. Items covered increasing intentions from browsing, partial participation in one or more modules, up to participating in all learning activities and receiving a certificate (see Appendix A). These items were included in the pre- and post-course questionnaires of both MOOCs. In the post- course questionnaire MOOC-learners were asked to indicate their actual behaviour on the same set of items used in the pre-course questionnaire taking into account the methodological issues of scale correspondence (Sutton, 1998) and the principle of compatibility (Fishbein & Ajzen, 2010). Scale correspondence refers to using corresponding magnitudes, frequencies, or response formats when measuring intention and behaviour. The principle of compatibility requires that when measuring intention–behaviour relations, both intention and behaviour should be measured at the same level of specificity or generality. If even one is defined on another level, it will not be possible to find a reliable correlation between intention and behaviour.

Procedure

In the first week of both MOOCs, all the registered MOOC-learners received an invitation to participate in the pre-course questionnaire. At the end of the last week of the MOOCs all the registered MOOC-learners received an invitation to participate in the post-course questionnaire. Participation was voluntary, and informed consent was obtained from participants following ethical guidelines of the providing institution.

Results

Traditional success and dropout measurement of MOOCs

The analyses focused on the success and dropout rates of the two MOOCs following the traditional dropout calculation (Peters, 1992; Tinto, 1975): number of certificates earned by the MOOC-learners divided by the total number of registered MOOC-learners (Figure 2).

MOOC-I had 6452 registered MOOC-learners, of whom 422 earned a certificate. This results in a success rate of 6.5%and consequently a dropout rate of 93.5% (Figure 2(a)). MOOC-II had 1763 registered MOOC-learners of whom 98 earned a certificate. This results in a success rate of 5.6% and a dropout rate of 94.4% (Figure 2(b)).

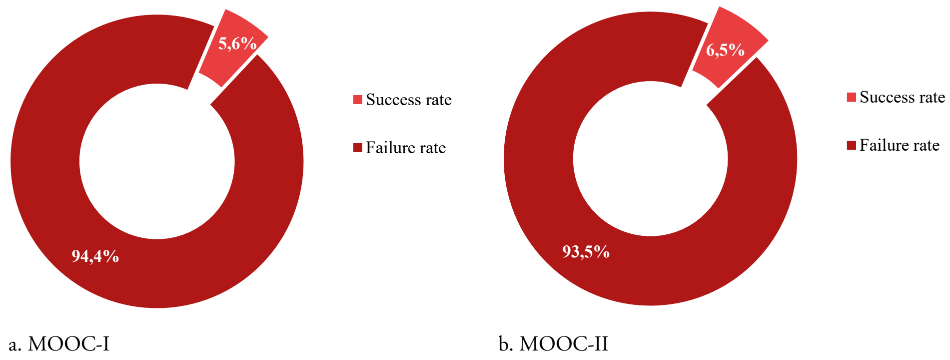

Figure 2. Certificate oriented success measurement of MOOC-I and MOOC-II

Intention–oriented success and dropout measurement of MOOCs

The second analysis focused on identifying success and dropout rates taking the intention of the MOOC-learner as a starting point. In this analysis the data allowed us to identify the three types of our proposed typology. In MOOC-I, 65 participants completed both the pre- course and post-course questionnaires (Figure 3(a)).

Of these 65 MOOC-learners, 42% can be regarded as inclined actors, their actual behaviour being equal to their intention. A further 17% can be regarded as disinclined actors, their actual behaviour exceeding their intention, and 41% of the MOOC-learners are inclined abstainers since their intention exceeded their actual behaviour. This results in an overall success rate of 59% and a dropout rate of 41%.

In MOOC-II, a total of 101 participants completed both the pre- and the post-course questionnaires (Figure 3(b)). Of these 101 MOOC-learners, 49% are inclined actors as their behaviour equaled their intention. Disinclined actors represent 21% of the MOOC-learners as their actual behaviour exceeded their intention, and 30% of the

MOOC-learners can be regarded as inclined abstainers as their intention exceeded their actual behaviour. This results in an overall success rate of 70% and a dropout rate of 30%.

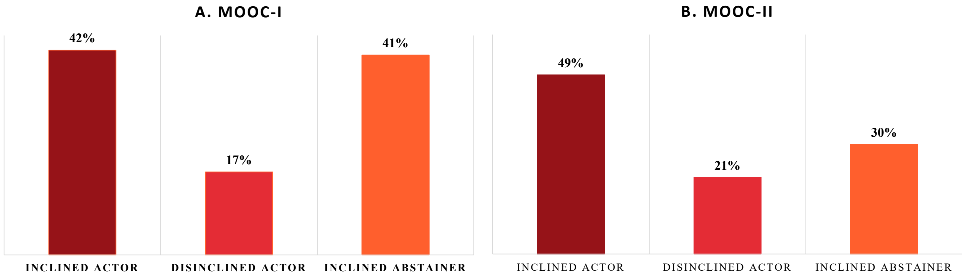

Figure 3. Intention–behaviour relations in MOOC-I and MOOC-II.

Discussion

In this paper, we have presented an alternative typology to refine the measurement of suc- cess and dropout in MOOCs. This typology is based on the initial intentions of individual MOOC-learners and their subsequent behaviour, which in the end results in a number of achieved goals. The RAA by Fishbein and Ajzen (2010), which centres around the formation of an intention to achieve certain goals and the translation of this intention into actual behaviour, as well as the intention–behaviour patterns as defined by Sheeran (2002), served as a theoretical framework for our typology. Furthermore, a first explorative study was carried out to test the applicability of the typology for assessing success and dropout in MOOCs and to compare it to the currently used approach to identify educational success.

One of the implications of our proposed typology is that all MOOC-learners who actually do as they intended (inclined actors) or do more than they intended (disinclined actors) are considered successful. Only MOOC-learners who quit during the runtime of the MOOC or who end up doing less than they intended are regarded as dropouts (inclined abstainers). This way of calculating success and dropout in MOOCs leads to a completely different picture. To illustrate this, we used data of two MOOCs; following the currently used approach to identify educational success, success rates of the MOOCs were between 5.6 and 6.5%. The success rates from the perspectives of the MOOC-learners were between 59 and 70%. These findings demonstrate that merely looking at course completion as a measure for MOOC and individual success does not suffice. This small change in the way we look at assessing MOOC success and dropout may have a large impact on future research on MOOCs. This approach represents a situation-specific approach that should build the foundation for future studies on dropout in the context of MOOCs.

In both MOOCs, most MOOC-learners were identified as inclined actors (42 and 49%). This group did what they intended to do in the MOOC, whether it was completing only some modules, just watch all the videos, or earning a certificate. It can therefore be expected that these MOOC-learners are content with their achievement. However, this does not necessarily imply that they were satisfied with issues such as MOOC content, design, or learning experience. Future research should aim to analyse their learner profile and their activities in more detail.

A substantial group in both MOOCs was classified as disinclined actors (17 and 21%). At some point during the runtime of the MOOC they found themselves exceeding their intentions. Reasons for this could be that they might have set low targets for themselves (just browse or do some learning activities), or the course content might have unexpectedly interested them more than they anticipated. Further research is necessary to understand reasons behind this behaviour.

The last group comprised the inclined abstainers (41 and 30%). In both MOOCs, this was the second largest group. These MOOC-learners formed certain goal intentions but were not able to or did not transform these intentions into actual behaviour. Did they set the highest targets? Were they first time MOOC-users and therefore not familiar with this learning environment? Were they dissatisfied with the course design or content? Future research should aim to map the complex and dynamic process of intention–behaviour and provide some insight into possible reasons that can cause the intention–behaviour gap.

The typology, based on individual intentions versus actual behaviour of the MOOC-learners, provides a more nuanced insight into individual learner success, hence MOOC success. It gives an indication of which group of participants is responsible for the intention–behaviour gap. Sheeran (2002) found, in the context of health science, that it was mainly the group of inclined abstainers who were responsible for the intention–behaviour gap. However, according to his theory the group of disinclined actors can also add to the intention–behaviour gap, as their intention does not reflect their actual behaviour either (Sheeran, 2002). Future studies should explore whether this is indeed the case in the context of MOOCs and consider dividing the intention–behaviour gap into a positive gap – caused by disinclined actors – and a negative gap – caused by inclined abstainers – as these respective groups have a very different impact on establishing MOOC success or dropout and subsequently MOOC (re)design. Furthermore, the impact of variables defined in the model by Tinto (1975) and confirmed in a distance education context need to be evaluated with regard to their impact on the three different types of MOOC learners we have proposed in this paper.

A limitation which needs to be taken into consideration is the weight or effort of the intention in comparison to the actual behaviour. A MOOC-learner who intended to download materials but ends up finishing one module is regarded as a disinclined actor. A MOOC-learner who intended to download materials but ends up completing the course is also regarded as a disinclined actor. Yet, the weight of the difference in behaviour is substantial; the step from downloading to finishing one module requires less effort than the step from down- loading to completing the course. Future research should take this into account by, for instance, applying weighted factors to intention–behaviour data.

Furthermore, several methodological issues regarding the measurement of intention–behaviour should be taken into account (Fishbein & Ajzen, 2010; Hassan, Shiu, & Shaw, 2014; Sutton, 1998). For our follow-up studies we regard these methodological issues as guidelines for the development of our intention–behaviour scales. One of the issues concerns when to measure intention and behaviour, because the timing can be of great influence on the correlation between intention and subsequent behaviour as intentions may change due to various reasons (Sutton, 1998; Tinto, 1982). Consequently, 'the more distal the behaviour is when intention is measured, the less likely the intention will provide an accurate prediction of the then intended behavioural enactment' (Hassan et al., 2014, p. 7). This indicates that the longer the time between measuring the formed intention and measuring the subsequent behaviour, the more likely it is that they don't match. Also, scale correspondence (Sutton, 1998, p. 1328) and the principle of compatibility (Fishbein & Ajzen, 2010, p. 44) should be considered, as described in the Method section.

Lastly, some general issues should be noted. The MOOC-learners who participated in both questionnaires are likely to belong to the group of MOOC-learners with higher intentions. This leads to survival bias (mostly MOOC-learners who 'survive' until the end of the MOOC participate in both questionnaires), a form of selection bias that can occur in MOOCs (Reich, 2014) and should be taken into consideration when interpreting the results. Also, the samples are relatively small, especially the matched intention–behaviour data from the pre- and post- course questionnaires. Future studies should strive to increase the number of MOOC-learners who complete both pre- and post-course questionnaires. Yet when interpreting results, using self-reporting for measuring intention and behaviour might not be as accurate as independent observation. In the context of MOOCs, however, independent observation will not suffice for establishing individual intentions and possible re-formulation of intentions.

In conclusion, with our proposed MOOC-learner typology we aim to underline the importance of individual perspectives when assessing MOOC success and dropout, thus taking into consideration that individual goal achievement does not necessarily matches goal achievement from the institutional perspective. This does not mean that it should replace the institutional perspective, but rather complement it. For MOOC-learners who want to gain institutional credit in the form of a certificate and thus need to demonstrate performance in line with certain institutional criteria that were set, the institutional perspective is valuable and necessary. Although further research needs to validate the practical applicability of the typology, it is a first step towards more profound and theoretically grounded research into dropout in MOOCs.

References

Belanger, Y., & Thornton, J. (2013, February 5). *Bioelectricity: A quantitative approach: Duke University's rst MOOC*. Durham, NC: Duke University. Retrieved from http://dukespace.lib.duke.edu/dspace/bitstream/handle/10161/6216/ Duke_Bioelectricity_MOOC_Fall2012.pdf?sequence=1

Breslow, L., Pritchard, D. E., DeBoer, J., Stump, G. S., Ho, A. D., & Seaton, D. T. (2013). Studying learning in the worldwide classroom: Research into edX's rst MOOC. *Research & Practice in Assessment, 8*, 15–25. Retrieved from http://www.rpajournal.com

Cohen, J. (1992). A power primer. *Psychological Bulletin, 112*, 155–159. doi:10.1037/0033-2909.112.1.155

Deci, E., & Ryan, R. (2002). *Handbook of self-determination research*. Rochester, NY: University Rochester Press.

Eisenberg, E., & Dowsett, T. (1990). Student drop-out from a distance education project course: A new method of analysis. *Distance Education, 11*, 231–253. doi:10.1080/0158791900110205

Fenouillet, F. (2012). *Les theories de la motivation* [Theories of motivation]. Paris: Dunod.

Fishbein, M., & Ajzen, I. (1975). *Belief, attitude, intention, and behaviour: An introduction to theory and research*. Reading, MA: Addison-Wesley. doi:10.2307/2065853

Fishbein, M., & Ajzen, I. (2010). *Predicting and changing behaviour: The reasoned action approach*. New York, NY: Taylor & Francis. doi:10.4324/9780203838020

Garrison, D. R. (1987). Researching dropout in distance education. *Distance Education, 8*, 95–101. doi:10.1080/0158791870080107

Hassan, L. M., Shiu, E., & Shaw, D. (2014). Who says there is an intention–behaviour gap?Assessing the empirical evidence of an intention–behaviour gap in ethical consumption. *Journal of Business Ethics, 136*(2), 1–18. doi:10.1007/s10551-014- 2440-0

Huin, L., Bergheaud, Y., Caron, P. A., Codina, A., & Disson, E. (2016). Measuring completion and dropout in MOOCs: A learner-centered model. In M. Khalil, M. Ebner, M. Koop, A. Lorenz, & M. Kalz (Eds.), *Proceedings of the European MOOC Stakeholder Summit 2016* (pp. 55–68). Norderstedt: Books on Demand GmbH.

Jordan, K. (2014). Initial trends in enrolment and completion of massive open online courses. *The International Review of Research in Open and Distributed Learning, 15*, 133–160. doi:10.19173/irrodl. v15i1.1651

Jordan, K. (2015). Massive open online course completion rates revisited: Assessment, length and attrition. *The International Review of Research in Open and Distributed Learning, 16*, 341–358. doi:10.19173/irrodl.v16i3.2112

Kalz, M., Kreijns, K., Walhout, J., Castaño-Munoz, J., Espasa, A., & Tovar, E. (2015). Establishing a European cross-provider data collection about open online courses. *The International Review of Research in Open and Distributed Learning, 16*, 62– 77. doi:10.19173/irrodl.v16i6.2150

Koller, D., Ng, A., Do, C., & Chen, Z. (2013, June 3). Retention and intention in massive open online courses: In depth. *Educause Review Online*. Retrieved from https://er.educause.edu/articles/2013/6/retention-and-intention-in-massive-open- online-courses-in-depth

Kreijns, K., Vermeulen, M., Kirschner, P. A., Buuren, H., & Acker, F. (2013). Adopting the Integrative Model of Behaviour Prediction to explain teachers' willingness to use ICT: A perspective for research on teachers' ICT usage in pedagogical practices. *Technology, Pedagogy and Education, 22*, 55–71. doi:1 0.1080/1475939X.2012.754371

Liyanagunawardena, T. R., Parslow, P., & Williams, S. A. (2014). Dropout: MOOC participants' perspective. In U. Kress, & C. Delgado Kloos (Eds.), *Proceedings of the European MOOC Stakeholder Summit 2014* (pp. 95–100). Lausanne: eLearning Papers.

McBroom, W. H., & Reed, F. W. (1992). Toward a reconceptualization of attitude- behaviour consistency. *Social Psychology Quarterly, 55*, 205–216. Retrieved from http://www.jstor.org/stable/2786946

Peters, O. (1971). Theoretical aspects of correspondence instruction. In O. MacKenzie, & E. L. Christensen (Eds.), *The changing world of correspondence study: International readings* (pp. 223–228). University Park: Pennsylvania State University Press.

Peters, O. (1992). Some observations on dropping out in distance education. *Distance Education, 13*, 234–269. doi:10.1080/0158791920130206

Reich, J. (2014, December 8). MOOC completion and retention in the context of student intent. *Educause Review Online*. Retrieved from http://er.educause.edu/articles/2014/12/mooc-completion-and-retention-in-the- context-of-student-intent

Roberts, D. (1984). Ways and means of reducing early student drop-out rates. *Distance Education, 5*, 50–71. doi:10.1080/0158791840050104

Sheeran, P. (2002). Intention–behaviour relations: A conceptual and empirical review. *European Review of Social Psychology, 12*(1), 1–36. doi:10.1080/14792772143000003

Sheeran, P., & Orbell, S. (2000). Self-schemas and the theory of planned behaviour. *European Journal of Social Psychology, 30*, 533–550. doi:10.1002/1099- 0992(200007/08)30: 4<533::AID-EJSP6>3.0.CO;2-F

Sutton, S. (1998). Predicting and explaining intentions and behaviour: How well are we doing? *Journal of Applied Social Psychology, 28*, 1317–1338. doi:10.1111/j.1559- 1816.1998.tb01679.x

Sweet, R. (1986). Student dropout in distance education: An application of Tinto's model. *Distance Education, 7*, 201–213. doi:10.1080/0158791860070204

Tinto, V. (1975). Dropout from higher education: A theoretical synthesis of recent research. *Review of Educational Research, 45*, 89–125. doi:10.2307/1170024

Tinto, V. (1982). De ning dropout: A matter of perspective. *New Directions for Institutional Research, 1982*, 3–15. doi:10.1002/ir.37019823603

Walji, S., Deacon, A., Small, J., & Czerniewicz, L. (2016). Learning through engagement: MOOCs as an emergent form of provision. *Distance Education, 37*, 208–223. doi:10.1080/01587919.2016.1184400

3

Chapter 3

Intention-behaviour dynamics in MOOC Learning; What happens to good intentions along the way?

This chapter is based on:
Henderikx, M., Kreijns, K., & Kalz, M. (2018, September). Intention-behaviour dynamics in MOOCs Learning; What happens to good intentions along the way? In 2018 Learning With MOOCS (LWMOOCS) (pp. 110-112). IEEE. doi:10.1109/LWMOOCS.2018.8534595

Abstract

In this study, we introduce a model that captures and visualises the dynamical process of individual intention forming and the translation of this intention into actual behaviour when learning in MOOCs. To validate the model and further our understanding of learning in MOOCs, we constructed a short survey based on this theoretically grounded intention- behaviour dynamics model. This survey was sent to MOOC learners who at the time of their respective MOOCs indicated that we could contact them for further research purposes. The combination of open and closed questions referred to the most recent MOOC they took and was answered by 84 learners. The results revealed that most learners start a MOOC with a specific intention in mind, but that nearly one third of these learners reformulates this initial intention, once or more often, at some point due to barriers they face which hinder or prevent them from reaching their individual intentions. These barriers are mainly non- MOOC related, which may be valuable input for future research as well as guide the development of interventions for supporting learners to reach their personal learning intentions.

Introduction

Initially MOOCs were received with great enthusiasm. Yet, after a short time it appeared that only few learners completed their courses; dropout rates as high as 95% were (and still are) often reported (Jordan, 2014). The initial excitement was followed by disappointment. The focus on these rates has its origin in traditional education, where not finishing an educational program and thus not getting the diploma equals failure (Tinto, 1975). MOOCs however, provide an exceptional learning environment which should not be compared to traditional education (Huin, Bergheaud, Caron, Codina, & Disson, 2016; Walji, Deacon & Czerniewicz, 2016). Henderikx, Kreijns and Kalz (2017a), proposed an alternative approach which takes the intention of the individual learner as a starting point for measuring learning success. These intentions may cover a broad spectrum from just browsing the course to finishing it and earning the certificate. This approach, despite some limitations, provides a more authentic view on learner success.

However, intention is not a perfect predictor for actual behaviour as there are many factors that may influence the process of acting out these intentions (Fishbein & Ajzen, 2011). These factors that possibly hinder or prevent learners from reaching their individual intentions can be either MOOC- or non-MOOC related barriers (Henderiks, Kreijns &Kalz, 2017b; 2018). With this study, we aim to further our understanding of success in MOOCs and take the next step in untangling the process of intention formulation and potential reformulation in the case of barriers. The results may serve as input for supporting learners in reaching their individual learning intentions.

Theoretical framework

In this study, we wanted to develop an understanding of the process underlying individual intention-forming and the translation of these intentions into actual behaviour as we expect this to be a dynamical process. The reasoned action approach [RAA; Fishbein & Ajzen, 2011], served as a theoretical guideline in developing a model that could capture and visualise this dynamical process of learning in MOOCs. To describe these dynamics, we use a state diagram to depict the different states in which learners can find themselves as shown in Figure 1. Important assumptions are that (1) learners can only find themselves in one state at a time, (2) a triggering event is needed to transit to another state, (3) learners start the process in the state 'formulating of goal intention' and (4) learners end the process by leaving the MOOC.

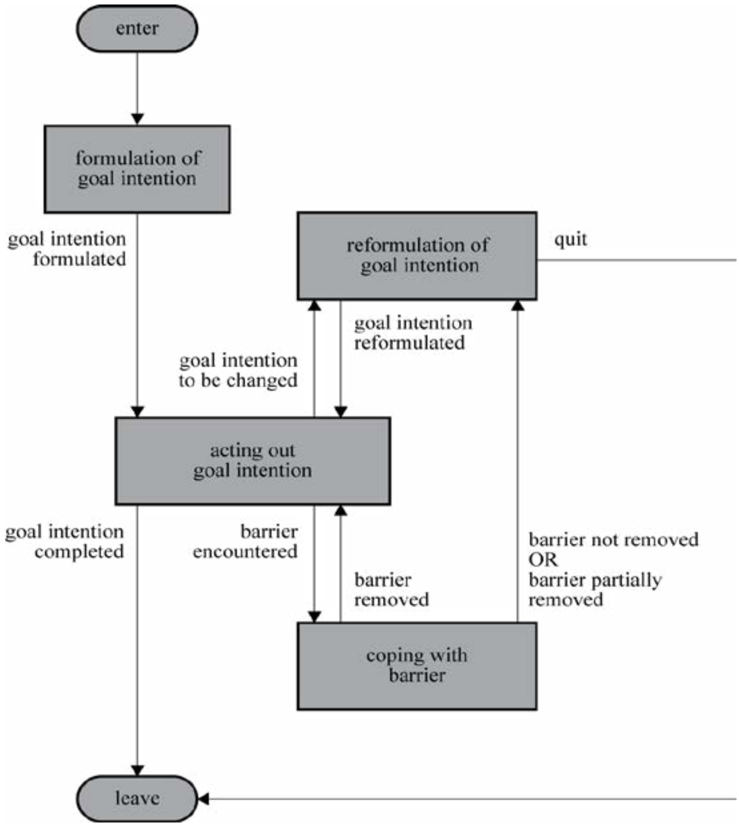

Figure 1. Intention-behaviour dynamics state diagram

In the first state 'formulation of intention', the individual set of intended goals is defined. This state is all about deliberating and weighing the different options an individual might have and the triggering event 'intention formulated' is needed to transit to the state 'acting out intentions'. In this state learners are actively engaged with achieving their individual goals until all goals are achieved. If their individual goals are indeed achieved, the triggering event is 'intention completed'.

However, a barrier may be experienced which interrupts learners' active engagement in the MOOC and transits them to the state 'coping with barrier'. In this state learners are occupied with resolving the barrier. They may fully, partially, or not succeed in resolving the barrier, which may correspondently, lead to the respective triggering events 'barrier removed,' 'barrier partially removed,' and 'barrier not removed.' If the barrier is fully removed, learners can continue with achieving their individual set of goals. If the barrier is partially removed or not removed, learners may want to redefine their individual set of intended goals, which transits them to the state 'reformulation of intended goals'. In this state, it is decided to add new goals, to remove 'old' goals or to quit.

Method

Participants

Participants of this study were learners who participated in a MOOC on Marine Litter in 2015 and in 2017 and at that time indicated that we could contact them for future research purposes. A total of 423 learners were invited to participate in this study; 84 learners actually completed the questionnaire (56 women, 28 men, Mage = 40,9, age range = 21-90 years).

Materials

To gain insight in the possible intention-behaviour dynamics of the learners, a self–constructed set of open and closed questions was formulated which were based on the theoretically grounded intention-behaviour dynamics model. The questions referred to the most recent MOOC these learners participated in in the last two years (thus did not refer to the Marine Litter MOOC they participated in unless that MOOC was their most recent MOOC). Example questions are: 'Did you have a specific intention in mind when you started the MOOC?', 'Did your initial intention change?', and 'Can you explain why it changed?'.

Procedure

Between February and June 2018 learners, who at the time of their participation in the respective Marine litter MOOCs indicated that we could contact them for future research, received an invitation via the open source online survey tool Limesurvey (visit http://www.limesurvey.org) to complete the survey on a voluntary basis. The survey was open for several weeks.

Results

The first five questions referred to the states "formulation of goal intention" and "reformulation of goal intention". Figure 2. shows that most learners (85%) had a specific intention in mind at the start of the most recent MOOC they participated in. Nearly one third of the learners (30%) indicated that their intentions changed in this MOOC. Of these learners 40% answered that their intention changed more often than once. One third of the learners (32%) participated in more MOOCs in the last two years and a further 33% indicated that their intention did change while learning in these MOOCs.

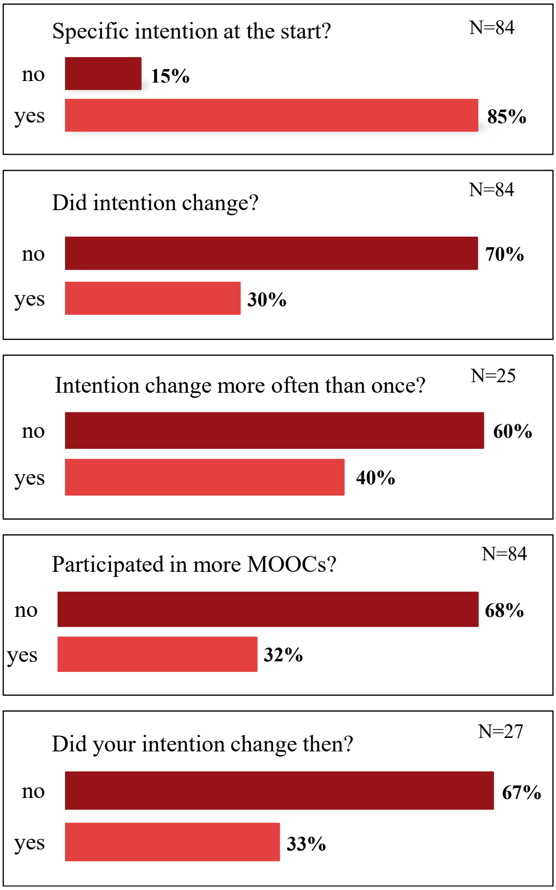

Figure 2. Overview of answers to closed questions

In the last question, the respondents who indicated that their intention changed once or more often, were asked to specify what the reason(s) was (were) for this change. The main reasons mentioned by the respondents for reformulation of their intention were:

- "My ability to complete the MOOC changed as I got busy with other things"
- "Other commitments became higher priorities"
- "Changes in life or work demands were the biggest reason for changes of intention"
- "I did not have enough time to finish the MOOC"
- "The interaction with the instructors was deceiving"
- "The intention change was due to poor internet"
- "I underestimated the amount of time"
- "In the end, I couldn't complete due to time constraints and commitments"

Discussion

This explorative study, is a next step towards understanding success in MOOCs. We tried to disentangle the intention-behaviour process of MOOC learners to get insight into its possible dynamics. These results confirm that learning in MOOCs can be a changeable and thus dynamical process for learners as nearly one third of the respondents indicated that their intention indeed changed once or more often while progressing through the MOOC. These changes of intention can be ascribed to the experience of barriers to learning in MOOCs.

Reasons for reformulation of intention mentioned were predominantly barriers which were related to the individual learner like lack of time, work issues and family issues. This is consistent with earlier studies, which found that most barriers MOOC-learners experienced were non-MOOC related [Henderikx et al., 2017b; 2018). Future studies should expand research on learner behaviour in MOOCs and specifically investigate whether learners who reformulate their intentions are equally successful in reaching their personal learning intentions as learners who indicate that they don't reformulate their intentions.

Some limitations that need to be taken into account are that we had no knowledge of the design of the MOOCs the respondents were referring to when answering the survey questions. It might be for instance, that learners who participate in paid MOOCs are less prone to reformulation of intentions than learners who participate in MOOCs which are free of charge. Also, a specific design or topic of a MOOC might, to a certain extent, also have an influence on reformulation of intentions. In addition, this is a first study with a relatively small sample. More extensive research, as well in terms of sample size as in terms of survey questions covering more contextual information, is necessary to further disentangle the dynamics of intention and behaviour. Lastly, There is also a qualitative component that should be taken into account. On the one hand, learners who start with higher (stronger) intentions might be more inclined to change their intentions and also cope with barriers than learners with lower (weaker) intentions. On the other hand, we need to realize that a change of intentions is not necessarily only a negative process, but that it can also mean that a learner experiences a so called drop-in effect (the opposite of the drop-out effect) in which learners with lower (weaker) intentions actually set themselves higher (stronger) intentions during the course compared to their initial intentions.

In conclusion, the results of this exploratory study indicate that intention formation and the adaptation of intentions is a dynamical process that needs to be studied more into detail before erroneous conclusions are drawn or unnecessary interventions are designed. A reason for these dynamics is the experience of barriers which hinder or prevent learners from reaching their individual intentions. These barriers are found to be predominantly non- MOOC related. The results of current and future studies may guide MOOC designers and providers in supporting learners to achieve their personal learning intentions.

References

Fishbein, M., & Ajzen, I. (2010). *Predicting and changing behaviour: The reasoned action approach.* New York: Taylor & Francis. doi:10.4324/9780203838020

Jordan, K. (2014). Initial trends in enrolment and completion of massive open online courses. *The International Review of Research in Open and Distributed Learning*, *15*(1), 133-160. doi:10.19173/irrodl.v15i1.1651

Henderikx, M. A., Kreijns, K., & Kalz, M. (2017a). Refining success and dropout in massive open online courses based on the intention–behaviour gap. *Distance Education, 38(3)*, 353–368. doi:10.1080/01587919.2017.1369006

Henderikx, M., Kreijns, K., & Kalz, M. (2017b). To change or not to change? That's the question..., On MOOC-success, barriers and their implications. In C. Delgado Kloos, P. Jermann, M. Pérez-Sanagustin, D.T. Seaton, and S. White (Eds.), *Lecture Notes in Computer Science: Vol. 10254. Digital Education: Out to the World and Back to the Campus*, (pp. 210-216). doi 10.1007/978-3-319-59044- 8_25

Henderikx M., Kreijns K., & Kalz M. (2018). A classification of barriers that influence intention achievement in MOOCs. In Pammer-Schindler V., Pérez-Sanagustín M., Drachsler H., Elferink R.,& Scheffel M. (Eds.) *Lifelong Technology-Enhanced Learning. EC-TEL 2018*. LNCS, vol 11082 (pp. 3 – 15). doi 10.1007/978-3-319- 98572-5_1

Huin, L., Bergheaud, Y., Caron, P. A., Codina, A., & Disson, E. (2016). Measuring completion and dropout in MOOCs: A learner-centered model. In M.Khalil, M. Ebner, M. Koop, A. Lorenz & M. Kalz (Eds.), *Proceedings of the European MOOC Stakeholder Summit 2016* (pp. 55-68). Norderstedt: Books on Demand GmbH.

Tinto, V. (1975). Dropout from higher education: A theoretical synthesis of recent research. *Review of educational research*, *45*(1), 89-125. doi:10.2307/1170024

Walji, S., Deacon, A., Small, J., & Czerniewicz, L. (2016). Learning through engagement: MOOCs as an emergent form of provision. *Distance Education*, 37(2), 208-223. doi:10.1080/01587919.2016.1184400

4

Chapter 4

Goal Setting and Striving in MOOCs A Peek inside the Black Box of Learner Behaviour

This chapter is based on:
Henderikx, M., & M. Kalz (2019). Goal setting and striving in MOOCs; A peek inside the black box of learner behaviour. In M. Calise, C. Delgado-Kloos & M. Wiesing (Eds.), *Lecture Notes in Computer Science: Vol.11475. Digital Education: At the MOOC Crossroads Where the Interests of Academia and Business Converge.* Cham, Switzerland: Springer. doi:10.1007/978-3-030-19875-6_8

Abstract

Reaching goals, especially if they are not in the near future like with learning in MOOCs, can be challenging. The aim of this explorative study was to get insight in this goal achievement process, which can help to understand learner behaviour. Two research questions were examined namely 1) what goals do learners set, and do they succeed in reaching these goals? and 2) How does the course of action of several learners look taking Gollwitzer's Rubikon model of action phases as a guideline? We found that even though learners did not achieve the goals they set, they were still generally satisfied with the knowledge they gained. In addition, learners went more or less intuitively through the theorised action phases, yet typically did not take the time to deliberately plan (before the start) and evaluate (after finishing) their learning process. This insight can serve as starting point for developing learner supporting tools and personalised dashboards, which can offer the tools at the appropriate times in a learner's course of action.

Introduction

Reaching goals can be challenging, especially if a goal is not in the near future (Gollwitzer, 1990) like with learning in MOOCs. Since the appearance of the MOOC, many studies focused on learner retention and behaviour as a way to unravel the success or failure of MOOCs (Veletsianos & Shepherdson, 2016). In these studies completion of the course, thus getting the certificate predominates as the main goal of learners. Gradually scholars agreed that due to the exceptional learning circumstances learners can have alternative learning goals in MOOCs and that earning the certificate is often not the ultimate goal (Henderikx, Kreijns & Kalz, 2017; Koller, Ng, Do & Chen, 2013; Reich, 2014).

Yet, despite the vast and increasing amount of research about MOOC-learning covering many different topics (Zawacki-Richter, Bozkurt, Alturki & Aldraiweesh, 2018), there are still important issues which need to be addressed in order to further our understanding of MOOC-learning. One of these issues concerns the course of action learners undertake after they decide they want to gain certain knowledge. This starts with a learner's wish for (certain) knowledge and ends with the evaluation of the outcome (Gollwitzer, 1990). Gollwitzer (1990) proposes the Rubikon model of action phases for getting insight into the processes involved in achieving goals. This 4-phase model addresses questions like how individuals choose their goals (goal setting), how they plan and enact on the execution of these goals (goal striving) and how they evaluate their efforts.

Insight in the complete goal setting and goal striving process will help to understand learner behaviour in MOOCs and subsequently to develop useful interventions to support learners in this process. This paper presents an overview of a first explorative study explaining learner behaviour in MOOCs taking the Rubikon model of action phases as a theoretical guideline. The research questions that will be answered are: 1) what goals do learners set, and do they succeed in reaching these goals? And 2) How does the course of action of several learners look?

The Rubicon model of action phases

According to Gollwitzer (1990, 2018) a course of action (i.e. the process of forming an intention to evaluating actual behaviour) is a "temporal and horizontal path" (p. 6), that can be divided into 4 phases: 1) the predecisional phase, 2) the preactional phase, 3) the actional phase and finally the 4) postactional phase (see Figure 1). Each phase is marked by a transition point; the end of the pre-decisional phase is marked by setting a goal, the end of the preactional phase is marked by planning on how to reach this goal and the initiation of actions and the end of the actional phase is marked by evaluating the achieved outcomes (see Figure. 1).

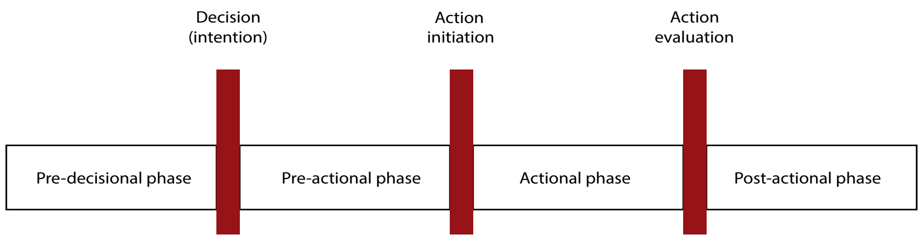

Figure. 1. The Rubikon model of action phases (Gollwitzer, 1990)

In the pre-decisional phase, which is about deliberating and weighing the different options an individual might have (Gollwitzer, 1990, 2018), a specific goal is set or in other words a goal intention is formed. Translated to learning in MOOCs this means that a potential MOOC-learner might contemplate whether a MOOC best fits his needs and wishes for gaining certain knowledge and subsequently decide to enroll. Furthermore, based on the available information about the content of the MOOC, the learner will make a (first) decision about what he intends do in the MOOC. This may vary from the intention to browse to finish one or more modules to completing the course and getting the certificate. Due to the open accessible nature of MOOCs, a learner can formulate his own individual intention.

The preactional phase is about planning concrete strategies for achieving the set goal. Ideally a MOOC-learner should address issues like when, where and how learning will take place to strengthen the attainment of the specified goal intention and what action to take if something interferes with this initial planning (Gollwitzer, 1990, 2018). This is particularly important if multiple steps are needed to achieve the desired goal, or if a set goal cannot be reached in the near future (Gollwitzer, 1990). The formulation of when, where, how plans is generally referred to as forming implementation intentions (Gollwitzer, 1999). Implementation intentions have the purpose to shield a learner from getting distracted from unwanted and/or anticipated disturbances. The rationale is that by formulating if…then questions, anticipating issues that could hinder goal attainment, the chance of reaching the goal will increase. For example, if X happens, then I will perform goal directed response Z (Gollwitzer, 1990, 2018). Also, the strength of the goal intention (how determined is someone to reach the intended goal) and the perceived behavioural control (someone's perception of the degree of control (s)he has over performing a behaviour) will have an effect on goal attainment (Gollwitzer, 1999, Fishbein & Ajzen, 2010).

The actional phase revolves around enacting the strategies which were planned in the preactional phase in pursuit of goal achievement (Gollwitzer, 1990, 2018). During this phase, various disturbances may be experienced that can delay or even prevent individuals from reaching their goals. In MOOCs these disturbances, or barriers as they are generally referred to, can be either MOOC-related like or non-MOOC related (Henderikx, Kreijns & Kalz, 2018a; 2018b). Typical MOOC-related barriers often mentioned by learners are lack of interaction, lack of instructor presence and bad course content. Examples of Non-MOOC related barriers are insufficient academic knowledge, lack of time and technical issues like bad internet or lack of digital skills. Depending on the strength of the goal commitment and whether the individual was sufficiently shielded from these barriers, the intended outcome will be achieved to a greater or lesser extent.

In the final phase, the postactional phase, an evaluation takes place of whether the goal striving has succeeded (Gollwitzer, 1990, 2018). This success depends on two criteria. The first criterion is whether the individual goal intentions, which were formed in the predecisional phase are achieved. Did the MOOC-learner achieve the goal that (s)he intended to achieve? According to Henderikx, Kreijns and Kalz (2017) this can result into three different (goal) intention –behaviour (achievement) patterns: 1) the learner achieved the intended goal (inclined actor), 2) the learner did more than intended (disinclined actor), 3) the learner did not achieve the intended goal (inclined abstainer). The second criterion which must be addressed when evaluating the achieved outcome is whether the achievement matches the expectation. In other words, is the result of the goal striving in sync with the expected value. After finishing learning in the MOOC, a learner will assess whether the learning gains met expectations and satisfied all the learning needs. A proper postactional evaluation will benefit future deliberation and planning needs.

According to Gollwitzer (1990, 2018), there are some issues regarding the goal setting and goal striving process, as visualised in the Rubikon model of action phases, that need to be taken into consideration. Firstly, not every initiation of action is preceded by careful deliberation, and goal setting (forming a goal intention). Secondly, formation of a goal intention is not always followed by concrete planning i.e. forming implementation intentions. Thirdly, overlap between action phases is possible. In some cases, a course of action can be an iterative process. Fourthly, the decision points in the model, which mark the end of the phases do not represent points of no return, yet points of putting deliberation to rest and commitment to pursue a set goal.

Method

Participants

Participants took part in a MOOC about 'Governing climate change; Polycentricity in action'. The MOOC was designed by respective teams at the Open University of the Netherlands in cooperation with external parties. None of the authors was involved in the design of the course. The MOOC ran from September 2018 until the end of October 2018, covering 10 units in 8 weeks and the estimated study load was 4-5 hours per week. A total of 49 learners enrolled in this MOOC of which 22 learners completed the pre-course survey (16 females, 6 males, M_{age}=35,9 years, age range: 22 - 62 years). The post-course questionnaire was completed by 13 learners (11 females, 2 males, M_{age}=36,4 years, age range: 22 - 62 years). In addition, 5 learners, 4 females and 1 male (M_{age}=28,8 years, age range: 24 - 33 years) were recruited using convenience sampling, to provide additional in- depth information in the form of interviews.

Materials
To measure individual goal setting and goal striving a self-constructed set of items was used which were aligned with the design of the respective MOOCs. Items covered increasing goal intentions from browsing, participation in one or more units, up to participating in all learning activities and requesting a certificate. These items were included in both pre- and post-course surveys of the MOOC. In the post-course survey learners were asked to indicate their actual goal achievement on the same set of items used in the pre-course survey taking into account the methodological issues of scale correspondence (Sutton, 1998). In addition, the pre-course survey included several general questions on gender, age, educational background, employment status and online learning experience and the post-course survey included additional questions about the perceived value of the learning and course satisfaction.

To gain deeper insight in the goal setting and goal striving process of the learners, a self– constructed set of open questions was formulated based on the Rubikon model of four action phases (Gollwitzer, 1990, 1999, 2018) for the purpose of face-to-face or email interviews. Example questions are: 'Were you looking for a MOOC specifically about this subject?' and 'Were you able to learn in the MOOC according to your plan?'. Questions regarding (perceived) control were derived from Fishbein and Ajzen (2010). An example question is: 'Were you confident that you would reach your learning goals?".

Procedure
In the first week of the MOOC, all the registered learners received an invitation via the open source online survey tool Limesurvey (visit http://www.limesurvey.org), to participate in the pre-course questionnaire. At the end of the last week, again, all registered learners received an invitation via Limesurvey, to participate in the post-course questionnaire. Participation was on a voluntary basis and filling out the questionnaire took approximately 5 minutes.

Two weeks after the runtime of the MOOC all registered learners received an invitation via email to provide more in depth information about their goal setting ands goal striving process in the MOOC in the form of an interview, either face-2-face, via email or via a videoconferencing application. It was emphasised that it was not necessary to have finished the course or completed any of the surveys.

Results

Goal setting
In the first phase, the predecisional phase the goal is set. Figure 2 shows that most learners in the MOOC indicated that they set the goal to complete the MOOC (23%) and request the certificate (45%).

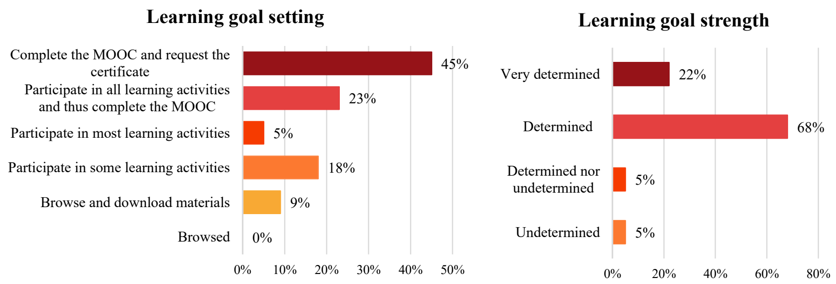

Figure 2. Goal setting (N=22) and goal strength (N=22, 5-point Likert scale)

They also indicated that they were generally determined (68%) or very determined (22%) to reach this goal (see Fig. 2). Additionally, besides the content-oriented goals which were set, learners indicated alternative goals which were important for them. Seeking connection with other learners on the topic of climate change (39%) and finding collaboration possibilities with other organisations on climate change issues (36%) were mentioned most (see Figure 3).

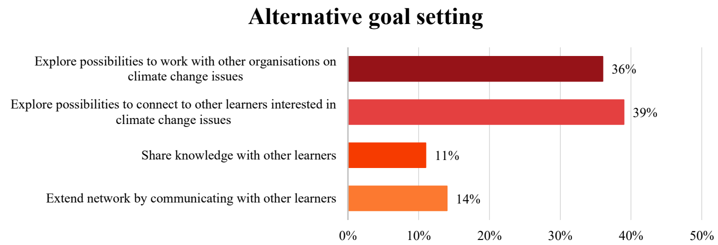

Figure 3. Alternative goal setting (N=22)

Goal achievement

In the postactional phase an evaluation takes place of whether the goal striving actions were successful. At first, it was evaluated if the content-oriented goal of the learners, which was set in the predecisional phase was achieved. Figure 4 shows that 23% of the learners completed the MOOC and that the majority of the learners merely participated in some (46%) or most learning activities (15%).

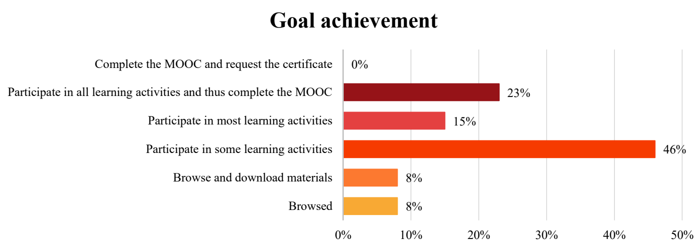

Figure 4. Goal achievement (N=13)

Yet, achievement reaches further than the mere quantitative measurement of the content- oriented goals. Therefore, it was additionally evaluated if the achieved outcome matched the expectation, which can be characterised as a form of subjective evaluation of achievement. The majority of the learners indicated that they achieved their personal goals to some extend (46%) or a great extend (15%), that their expectations were met to a great extend (46%) or completely (7%) and that they were satisfied (54%) or very satisfied (7%) with the course (see Figure 5).

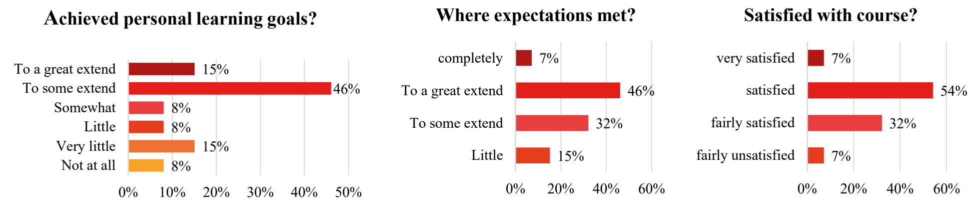

Figure 5. Subjective evaluation of achievement, expectations and satisfaction (N=13, 7-point Likert scale)

In-depth interviews were conducted to give additional insight into the courses of action these learners followed, how they progressed through the goal setting and goal striving process and how their subjective value judgements are substantiated.

Qualitative results

The post-interviews were analysed using deductive thematic analysis (Braun & Clarke, 2006) and were coded for themes derived from the theoretical framework of the Rubikon model of action phases (Gollwitzer, 1990).

The interviewees rated their English proficiency as good to very good and all of them had a master degree. In addition, each of them had previous experience with learning in MOOCs yet most of them indicated that they learn best face-to-face. All but one set the goal to complete the MOOC and all of them indicated that they were determined to very determined to reach their set goals. In addition to their set learning goals they also specified that they wanted to share knowledge with other interviewees, explore possibilities to connect to other people who are interested in climate change issues and explore possibilities to work with other organisations on climate change issues.

Predecisional phase

In this phase, different options are deliberated and weighed and a specific goal is set (Gollwitzer, 1990, 2018). All five of the interviewees indicated that they were not specifically looking for a MOOC, but merely for information and learning possibilities regarding the topic of climate governance and polycentricity: "…I stumbled across it when I was looking for information on polycentric governance" (P2) and "…In fact, I was not actively searching for a MOOC" (P5).

In addition, neither of them knew whether there were more MOOCs available on this specific topic. As soon as they came across this specific MOOC, they did not search any further for alternative learning options. Before making the decision to enroll, all of them evaluated the specified weekly workload of the MOOC, yet only one interviewee stated that the workload actually influenced his decision to sign up, as he wanted to make sure that he would able to follow the MOOC next to his normal daily workload. The other four interviewees did think about their available time for learning in the MOOC, but did not let this influence their decision: "…I knew that I would not be able to complete it, because I was on field research that time, but I still enrolled to look at it" (P2) and "…When I enrolled in the course I was not yet sure whether I would have time to participate in the MOOC" (P3).

All interviewees but one signed up for the MOOC immediately after they found the MOOC and read the available information. One interviewee first send an email to the MOOC organisers to ask for any formal requirements and signed up after receiving an answer.

Preactional phase

This phase is about planning concrete strategies for achieving the goal set in the predecisional phase (Gollwitzer, 1990, 2018). Three of the interviewees specifically spend time thinking about planning their learning and indicated that they would generally learn at home after work and during weekends. However, most of the interviewees did not think about issues that could hinder their learning and thus did not make alternative (shielding) plans in advance. Only one interviewee indicated that he specifically thought about issues in his personal environment that could hinder him successfully reach his set goal intention: "I Figured that if I would not be able to study on a certain day, or would not have sufficient time, instead of working smarter or harder, I would just have to work longer" (P5).

Three of the interviewees were confident that they would reach their learning goals and two of them were not sure about it. One of the interviewees stated that a previous experience with a MOOC made her uncertain: "… I had done another MOOC in the spring, one that even cost money, but I could not motivate myself to finish. So, I was unsure if I would be able to hold on [in this MOOC]" (P4).

The opinions of the interviewees are divided regarding their own responsibility for reaching their goal intentions. Some of them are very determined that it is totally up to the learner, some are not sure and one of them feels that it also depends on the course design and the feedback of the instructors.

Actional phase

Enacting the strategies which were planned in the preactional phase in pursuit of goal achievement is what this phase is about (Gollwitzer, 1990, 2018). Two interviewees indicated that they learned according to their plan. Another two interviewees were not able to study as planned due to circumstances and one interviewee stated that she kind of learned as planned: "…as I did not have a real plan, but I did have time… to look into it once in a while" (P2).

While acting in this phase in pursuit of their set goals, two of the interviewees deliberately changed their set goal intention because their interest changed and they did not like the method of learning (online as opposed to face-to-face) which made them lose motivation and ultimately quit the MOOC after several weeks. Yet, one of the interviewees specifically indicated that: "…the quality (content) and quantity (workload) were not the reasons why I dropped out" (P3).

Postactional phase

In this final phase, the achievement of the individual goal intentions is evaluated (Gollwitzer, 1990, 2018). None of the interviewees consciously took the time to evaluate their achievement. Yet, when specifically asked about it, four interviewees stated that they did not reach their initially set goals, yet at the same time all five of the interviewees were mostly satisfied with the knowledge they gained: "… Even if I didn't reach the goal completely, there was a lot of learning involved" (P1). One of the interviewees added that although she gained the knowledge she aimed for, she was not happy with the amount of time she had to spend on it: "…but [I] do not feel satisfied with the knowledge I gained versus the time I invested" (P4).

Further evaluation whether the achieved outcome was in line with the expected value was also very positive. One source of some dissatisfaction was the lack of interaction in the course" "… the instructors had little participation. At some point, it seemed like the course was "abandoned" (P1) and "…too little discussion took place in the discussion forum. … I had hoped to learn much more from others' experiences and thoughts on the course" (P5). Overall, all interviewees indicated that the MOOC met their expectations. Most important aspects for this value judgement were content, theoretical deepening, usefulness for practice and flexibility of the MOOC.

Discussion

The aim of this explorative study was to get a deeper understanding of learner behaviour. We examined two research questions namely 1) what goals do learners set, and do they succeed in reaching these goals? and 2) How does the course of action of several learners look? Regarding the first research question we found that the majority of the participants (90%) wanted to finish the MOOC, with or without requesting a certificate. They also indicated that they were determined or very determined to do so. In addition, besides the content orientated goal they set, most of them had some alternative goals which were mainly to connect with other participants in the course and to explore possibilities to work with other organisations. The goal achievement results showed that only 23% of the participants did reach their initially set goals, yet 61% indicated that they achieved their personal learning goals and over 50% indicated that their expectations were met and that they were satisfied with the course. This was confirmed by the interviewees who all but one did not achieve their set goals, yet who were overall satisfied with the knowledge they gained. The apparent discrepancy might be explained by the broad learning opportunities MOOCs provide. The individual learning can go beyond course content related learning and also include alternative goals participants set for themselves at the start of the course or somewhere along the way. Another explanation can be the dynamicity of the intention-behaviour process (Henderikx et al., 2018b). Learners may change their intention (set goal) while learning in the MOOC due to various circumstances (Henderikx et al., 2018b). As this happens after they start learning in the MOOC, changes of goal setting are very difficult to determine, but should still be taken into consideration when evaluating learner and MOOC-success.

In answer to the second research question, we found that the interviewed learners more or less intuitively went through the action phases as theorized by Gollwitzer (1990, 2018), touching upon the transition points (setting the goal, planning how to reach the goal and initiate action and evaluating the achievement) to a greater or lesser extent. All of the interviewees set their goals before the start of the MOOC, yet neither of them weighted or deliberated different options or let the indicated workload and their individual available time influence their decision. Once they came across the MOOC, they basically immediately sign up. Some of the interviewees did spend time thinking about the planning of their learning, however they did not anticipate issues that could hinder their learning. While learning in the MOOC some of the interviewees changed their initial set goal or quit the MOOC and after finishing the MOOC neither of them consciously took the time to evaluate the process. This is somewhat surprising, especially as one interviewee stated that a negative experience with a previous MOOC made her feel unsure about reaching her learning goal this time.

These transition points might be the key to supporting a successful learning experience. A well-thought-out planning, also anticipating issues which could hinder the learning process can contribute to achieving the set goals (Gollwitzer, 1999). Evaluation of the learning process after finishing learning in the MOOC in the sense of reflecting on the process and determining why negative as well as positive outcomes happened will benefit future deliberation and planning needs (Gollwitzer, 1990, 2018) and take away unnecessary uncertainties.

This study has several limitations. One important issue is that the current sample is very small. Another limitation is that the topic of the MOOC is very specific, thus the findings are context-specific. Also, due to convenience sampling, the interviewees were moderately representative for the participant population. Needless to say, that more research is necessary to establish learner behaviour patterns in courses of action in various MOOCs, which can then serve as starting point for developing learner supporting tools and personalised dashboards, which can offer the tools at the appropriate moments in a learner's course of action.

References

Braun, V., & Clarke, V. (2006). Using thematic analysis in psychology. *Qualitative research in psychology*, 3(2), 77-101. doi:10.1191/1478088706qp063oa

Fishbein, M., & Ajzen, I. (2010). *Predicting and changing behaviour: The reasoned action approach.* New York, NY: Taylor & Francis. doi:10.4324/9780203838020

Gollwitzer, P. M. (1990). Action phases and mind-sets. *Handbook of motivation and cognition: Foundations of social behavior*, 2, 53-92. doi:10.2307/2072281

Gollwitzer, P. M. (1999). Implementation intentions: Strong effects of simple plans. American psychologist, 54(7), 493-503. doi:10.1037/0003-066x.54.7.493

Gollwitzer, P. M. (2018). The goal concept: A helpful tool for theory development and testing in motivation science. *Motivation Science*, 4(3), 185-205.

Henderikx, M. A., Kreijns, K., & Kalz, M. (2017). Refining success and dropout in massive open online courses based on the intention–behaviour gap. *Distance Education*, 38(3), 353–368. doi:10.1080/01587919.2017.1369006

Henderikx M., Kreijns K., & Kalz M. (2018a). A classification of barriers that influence intention achievement in MOOCs. In V. Pammer-Schindler, M. Pérez-Sanagustín, H. Drachsler, R. Elferink, & M. Scheffel (Eds.), *Lifelong technology-enhanced learning.* EC-TEL 2018. LNCS, vol. 11082 (pp. 3–15). doi:10.1007/978-3-319- 98572-5_1

Henderikx, M., Kreijns, K., & Kalz, M. (2018b). Intention-behaviour dynamics in MOOCs Learning; What happens to good intentions along the way? In 2018 *Learning With MOOCS (LWMOOCS)* (pp. 110-112). IEEE. doi:10.1109/LWMOOCS.2018.8534595

Koller, D., Ng, A., Do, C., & Chen, Z. (2013, June 3). Retention and intention in massive open online courses: In depth. *Educause Review Online*. Retrieved from https://er.educause.edu/articles/2013/6/retention-and-intention-in-massive-open- online-courses-in-depth mooc-completion-and-retention-in-the-context-of- student-intent

Reich, J. (2014, December 8). MOOC completion and retention in the context of student intent. *Educause Review Online*. Retrieved from http://er.educause.edu/articles/2014/12/

Sutton, S. (1998). Predicting and explaining intentions and behavior: How well are we doing? *Journal of Applied Social Psychology*, 28, 1317–1338. doi:10.1111/j.1559- 1816.1998.tb01679.x

Veletsianos, G., & Shepherdson, P. (2016). A systematic analysis and synthesis of the empirical MOOC literature published in 2013–2015. The International Review of Research in Open and Distributed Learning, 17(2), 198-221. doi:10.19173/irrodl.v17i2.2448

Zawacki-Richter, O., Bozkurt, A., Alturki, U., & Aldraiweesh, A. (2018). What research says about MOOCs–An explorative content analysis. The International Review of Research in Open and Distributed Learning, 19(1), 242-259. doi:10.19173/irrodl.v19i1.3356

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Chapter 5

To Change or not to Change? That's the Question… On MOOC-Success, Barriers and their Implications

This chapter is based on:
Henderikx, M., Kreijns, K., & Kalz, M. (2017). To change or not to change? That's the question… On MOOC-success, barriers and their implications. In Delgado Kloos, C., Jermann, P., Pérez-Sanagustin, M., Seaton, D.T., & White, S. (Eds.), Lecture Notes in Computer Science: Vol.10254. *Digital Education: Out to the World and Back to the Campus (pp. 210-216)*. Cham, Switzerland: Springer. doi:10.1007/978-3-319-59044-8_25

Abstract

This explorative study aimed to get an understanding of MOOC-success as seen from the perspective of the MOOC-learner and the types of barriers which might stand in the way of this success. Data of two MOOCs was used to illustrate MOOC-success from two perspectives and which barriers were experienced by learners. Following the currently used approach to identify educational success, the success rate of MOOC-II was 5,6%. The success rates from the perspective of the MOOC-learner was 70%. In addition, data of MOOC-I and II showed that the experienced barriers were mainly non-MOOC- related. Workplace issues and lack of time were most frequently indicated. For MOOC-designers' decision making regarding redesign of a MOOC after evaluation, it is valuable to have insight in these matters to prevent unnecessary design interventions.

Introduction

When learners start a MOOC their intentions are very diverse; some of them want to complete the MOOC and earn a certificate, others just want to freshen up on some specific knowledge or only browse to see what it is all about (Koller, 2013). For this reason, it does not suffice to only look at the number of certificates earned by the MOOC-learners for determining success, even though this method is often transferred from the formal education context to the MOOC and is the most widely-used method of identifying educational success. As an alternative approach, we take the initial intention of the individual as a starting point for measuring success taking into account that MOOCs allow individuals to follow their own learning paths (Henderikx, Kreijns & Kalz, 2017). These intentions may vary from simply browsing through a MOOC to—indeed—getting a certificate. Studies on behavioural and cognitive psychology, however, showed that in general intention is not a perfect predictor for actual behaviour as there are many factors that can influence the process of acting out intentions (Fishbein & Ajzen, 2010). Therefore, insight into the issues which hinder or prevent individuals from translating their intentions into actual behaviour is of great value when it comes to deciding whether course (re)design interventions are necessary. This paper is structured as follows: First we discuss the theoretical background. Next data from three MOOCs is analysed in line with the theoretical framework. Lastly, results of these analyses are discussed as well as implications for future research and limitations.

Theoretical Framework

The reasoned action approach (RAA; Fishbein & Ajzen, 2010) serves as a theoretical framework to our study, as it pays attention to the intention-behaviour gap. The framework is centred around the formation of an intention and the translation of this specific intention to actual behaviour. Sheeran (2002) described four different intention-behaviour patterns that can be distinguished: 1) *Inclined actors*; individuals who formed a certain intention and did act according to those intentions, 2) *Inclined abstainers*; individuals who formed a certain intention but fail to act according to this intention, 3) *Disinclined actors*; individuals who formed a certain intention but end up doing more than they intended to do and finally, 4) *Disinclined abstainers*; individuals who do not have any intentions and accordingly do not act. This latter group shall not be included in the context of MOOCs, for the reason that this group will never start a MOOC in the first place.

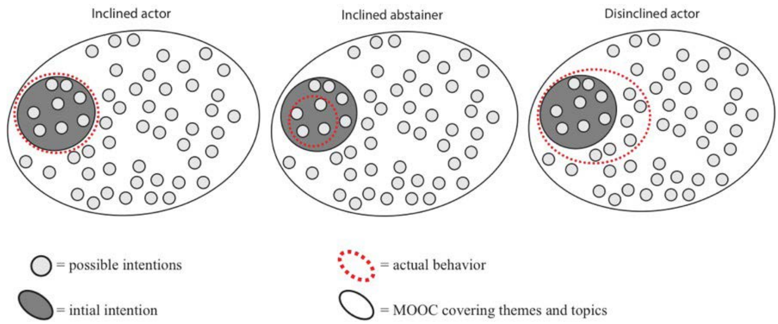

Figure 1. Intention-behaviour patterns

Figure 1 visually illustrates the three possible intention-behaviour patterns in a MOOC. As can be seen, many individual intentions are possible which may vary from only finishing the first three modules to completing the full course and getting the certificate. Following the intention-behaviour patterns, MOOC-learners who formed the intention to finish the first three modules of a MOOC and actually succeed in doing so, are identified as inclined actors and are considered successful MOOC-learners. MOOC-learners who only planned to browse through the course or download some interesting materials and who eventually finish three modules are also considered as successful.

However, an intention which is formed at the start of a MOOC does not always equal the actual behaviour (Fishbein & Ajzen, 2010). This gap between intention and behaviour can be caused by barriers; these barriers can be either MOOC-related (i.e. lack of interaction) or non MOOC-related (i.e. workplace issues) and may cause MOOC-learners to change their individual intention or even stop. An explorative, non-exhaustive, literature review on barriers experienced by students in MOOCs and online learning in general showed that lack of interaction (Khalil & Ebner, 2013; Levy & Schrire, 2012; McAuley, Stewart, Siemens & Cormier, 2010), lack of time (Belanger & Thornton, 2013; Khalil & Ebner, 2014; Onah, Sinclair & Boyatt, 2014) and insufficient academic background (Belanger & Thornton, 2013; Onah et al., 2014) are barriers students frequently experience. Other barriers experienced by students were: family issues and lack of support family and friends (Onah et al., 2014), workplace commitments and lack of support from the workplace (Onah et al., 2014) and insufficient technology background (Khalil & Ebner, 2014). Only a sub-set of these barriers can be addressed by redesign of the MOOC.

Thus, insufficient insight into the reasons behind success and failure rates in MOOCs could lead to negative evaluations and unnecessary interventions. To address this problem, the following two research questions will be addressed in this study:

1. What are implications of an intention-centric success measurement in MOOCs compared to a certificate-oriented success measurement?

2. What type of barriers do MOOC-learners face while learning in a MOOC?

Method

Participants

Participants were MOOC-learners of two MOOCs. The first MOOC (MOOC-I) was a Spanish MOOC about Business Intelligence and Big Data and was offered from February until April 2016, covering five modules for five weeks. The pre-questionnaire was unfortunately not distributed due technical problems with the platform but the post- questionnaire was completed by 143 MOOC-learners (37 women, 106 men, M_{age}= 41,6, age range: 25-64 years).

The second MOOC (MOOC-II) was a Dutch MOOC about The Adolescent Brain and ran from April until June 2016 in Dutch, covering seven modules for seven weeks. The pre- questionnaire was completed by 821 MOOC-learners (664 women, 157 men, M_{age}= 45,1, age range: 18-74 years). The post-questionnaire was completed by 126 MOOC-learners (unfortunately participant information was not available). In total 101 MOOC-learners completed both questionnaires (90 women, 11 men, M_{age}= 37, age range: 18-54 years).

Materials

To measure the intention of the individual MOOC-learners a self-constructed set of items was used aligned with the design of the respective MOOCs. Items covered increasing intentions from browsing, partial participation in one or more modules, up to participating in all learning activities and receiving a certificate. These items were included in the pre- and post-questionnaire of MOOC-II. In the post-questionnaire MOOC-learners were asked to indicate their actual behaviour on the same set of items as was used in the pre-questionnaire.

The post-questionnaire of MOOC-I and II included several questions on specific barriers MOOC-learners experienced. These barriers were derived from an explorative, non- exhaustive, literature review on barriers in MOOCs and online learning in general, including articles from 2008 until present. Figure 2 displays these barriers categorized into MOOC- related and MOOC. MOOC-learners could indicate multiple barriers.

MOOC-related		Non-MOOC related	
Design		General	
Problems with the site	Lack of support	Workplace issues	Lack of information literacy
Lack of interaction	Content was not appropriate	Lack of time	Insufficient academic background
Lack of instant feedback	Expectations management	Family issues	Lack of motivation
Lack of instructor presence	Course was too easy	Lack of workplace support	Lack of personal commitment
Lack of useful feedback	Course did not meet expectations	Lack of family support	Technical
	Course was too difficult	Personal	Technological problems pc
		Lack of technological skills	Bad internet connection

Figure 2. Overview barriers arranged by type

Procedure
In the first week of MOOC-II, all the registered MOOC-learners received an invitation to participate in the pre-questionnaire. Due to technical difficulties, MOOC-learners of MOOC- I did not receive an invitation for the pre-questionnaire and therefore were not able to complete the pre-questionnaire. At the end of the last week of both MOOCs all the registered MOOC-learners received an invitation to participate in the post-questionnaire.

Results

Intention-oriented vs certificate-oriented success measurement
Part one of this analysis focused on success measurement from the MOOC-learner perspective. We mapped the intention-behaviour on an individual level which follows the theory as discussed in the theoretical framework. In MOOC-II, 101 participants completed both the pre-questionnaire and the post-questionnaire.

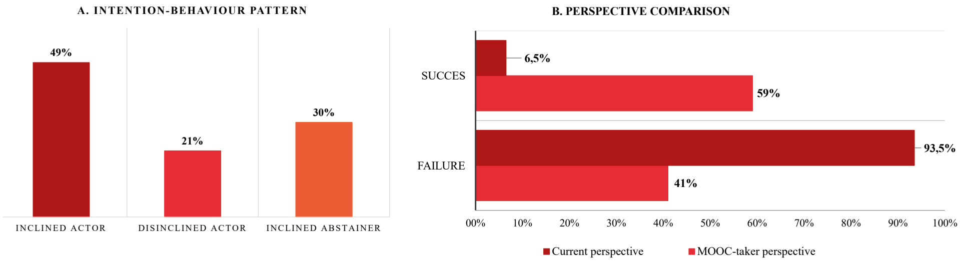

Figure 3a+b. Intention-behaviour patterns MOOC-II (a) and perspective comparison MOOC-II (b)

In this MOOC, 49% of the MOOC-learners who completed both the pre-questionnaire and the post-questionnaire, can be regarded as inclined actors, 21% as disinclined actors, and 30% of the MOOC-learners as inclined abstainers (Figure 3a).

Part two of the analysis focussed on comparing the intention-oriented with the certificate-oriented measurement of success. The certificate-oriented rates were calculated by taking the number of certificates earned by the MOOC-learners divided by the total number of registered MOOC-learners (Figure 3b). MOOC-II had 1763 registered MOOC-learners, of whom 98 earned a certificate. which results in a success rate of 5,4%[1]. The intention-oriented rates result in a success rate of 70% and a failure rate of 30%.

Barriers

The question which type of barriers learners experienced during the runtime of MOOCs I and II was answered by 50 MOOC-learners of MOOC-I and 76 MOOC-learners of MOOC-II who completed both questionnaires. Figure 4a shows that in MOOC-I 75% and in MOOC- II 66% of the barriers were non MOOC-related. Figure 4b displays that 25% of the indicated barriers of MOOC-I are MOOC-related and 34% of the

1 Calculation: (422/6452) x 100%

barriers of MOOC-II. Of the non MOOC-related barriers MOOC-learners mostly indicated general barriers; 50% in MOOC-I and 55% in MOOC-II.

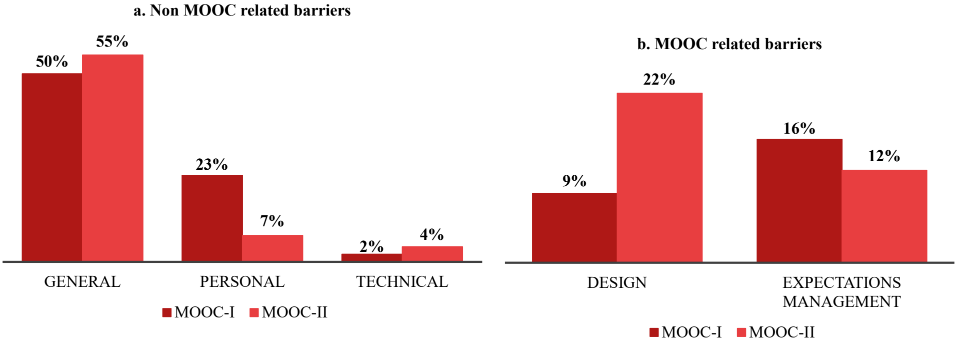

Figure 4a+b. Overview MOOC-related (a) vs non MOOC-related barriers (b)

Furthermore, Table 2 gives an overview of the top-5 barriers participants experienced during the runtime of the MOOC. In MOOC-I, lack of time and workplace issues are the most indicated barriers, followed by insufficient academic background, easy course content and family issues. In MOOC-II, lack of time and workplace issues are also the most indicated barriers, followed by family issues, problems with the site and course content too easy.

Table 2. Overview top-5 barriers MOOC I and II

	MOOC-I	MOOC-II
MOOC-related		
Design		
Problems with the site	4%	10%
Expectations management		
Course was too easy	10%	7%
Non MOOC-related		
General		
Workplace issues	20%	22%
Lack of time	23%	22%
Family issues	7%	10%
Personal		
Insufficient academic background	10%	1%

Note: Participants were able to indicate multiple barriers

Chapter 5

Discussion

This explorative study aimed to get an understanding of MOOC-success as seen from the perspective of the MOOC learner and the types of barriers which might stand in the way of transferring intentions into actual behaviour. Insight in these matters is valuable for MOOC- makers as the success measurement is often used as an indicator for the necessity of design interventions (Henderikx et al., 2017).

Data of MOOC-II was used to compare currently used certificate-oriented success measurement with our proposed intention-oriented success measurement. The results show that there is a big difference between success rates, which are respectively 5,4% and 70%. This finding demonstrates that merely looking at course completion as a measure for MOOC and individual success might not suffice. A small change in the way we look at determining MOOC-success might have a large impact on MOOC (re)design and strategic choices of the MOOC providers.

Furthermore, three intention-behaviour patterns were determined: inclined actors, disinclined actors and inclined abstainers (Sheeran, 2002). After matching the intention-behaviour data from the pre- and post-questionnaire of MOOC-II, most MOOC-learners (49%) were identified as inclined actors. It can be expected that these MOOC-learners are content with their achievement. However, this does not necessarily imply that they were satisfied with issues like MOOC-content, design or learning experience. Quite a substantial group of 21% of the MOOC-learners were distinguished as disinclined actors. Reasons for this could be that they might have set low targets for themselves (just browse, or do some learning activities), or the course content might have unexpectedly interested them more than they anticipated. Further research is necessary to understand the reasons behind this behaviour. A third group of 30% was identified as inclined abstainers. These participants formed certain goal intentions but were not able to transform these intentions to actual behaviour. Did this group meet the most barriers? Did they set the highest targets? Future research should open this proverbial black box.

The five most frequent barriers of MOOC-I, in descending order, were lack of time, workplace issues, insufficient academic background, course too easy and family issues. In MOOC-II the top-5 consisted of workplace issues, lack of time, family issues, problems with the site and too easy course content. As our explorative - non-exhaustive – literature review indicated lack of time (Belanger & Thornton, 2013; Khalil & Ebner, 2014; Onah, Sinclair & Boyatt, 2014)and insufficient academic background (Belanger & Thornton, 2013; Onah et al., 2014) as one of the main barriers, this result is partially consistent with literature. However, another main barrier found in literature, lack of interaction (Khalil & Ebner, 2013; Levy & Schrire, 2012; McAuley, Stewart, Siemens & Cormier, 2010), was not present in either top-5. An analysis of whether barriers experienced by MOOC-learners were MOOC- related or non-MOOC-related showed that most of the barriers can be considered as non MOOC-related barriers. In MOOC-II and III 75% and 66% of the barriers were not related to the course itself. This indicates that it is important for MOOC-makers to be well informed about the reasons behind success and failure rates. Furthermore, future research should make a connection between type of MOOC-learners (inclined actor, disinclined actor and inclined abstainer) and barriers experienced per type to study the relationship between certain groups and types of barriers.

This study had several limitations. First of all, the MOOC-learners who participated in the questionnaires are likely to belong to the group with higher intentions due to the survival bias that can occur in MOOCs. In addition, the samples are relatively small, especially to compare the intention-behaviour gap based on data from the pre-and-post questionnaire. Also, the way the respective MOOCs were designed might have had an impact on the type of barriers MOOC-learners experienced.

In conclusion, insight into individual intentions of MOOC-learners and types of barriers they experienced provides a richer knowledge base for MOOC-makers as it comes to deciding whether redesign is necessary. This explorative study is a first step into providing these insights and a first step towards further research into these matters to support MOOC-makers in their decision-making processes.

References

Belanger, Y., & Thornton, J. (2013). *Bioelectricity: A quantitative approach*. Durham, NC. Retrieved from http://dukespace.lib.duke.edu/dspace/bitstream/handle/10161/6216/Duke_ Bioelectricity_ MOOC_Fall2012.pdf?sequence=1.

Fishbein, M., & Ajzen, I. (2010). *Predicting and changing behaviour: The reasoned action approach*. New York, NY: Taylor & Francis. doi:10.4324/9780203838020

Henderikx, M. A., Kreijns, K., & Kalz, M. (2017). Refining success and dropout in massive open online courses based on the intention–behaviour gap. *Distance Education*, 38(3), 353–368. doi:10.1080/01587919.2017.1369006

Khalil, H. & Ebner, M. (2013). Interaction Possibilities in MOOCs – How Do They Actually Happen?. *International Conference on Higher Education Development* (pp. 1-24). Mansoura University, Egypt.

Khalil, H., & Ebner, M. (2014). MOOCs Completion Rates and Possible Methods to Improve Retention - A Literature Review. *In World Conference on Educational Multimedia, Hypermedia and Telecommunications* (pp. 1236–1244). Chesapeake, VA: AACE.

Koller, D., Ng, A., Do, C., & Chen, Z. (2013, June 3). Retention and intention in massive open online courses: In depth. *Educause Review Online*. Retrieved from https://er.educause.edu/articles/2013/6/retention-and-intention-in-massive-open- online-courses-in-depth

Levy, D., & Schrire, S. (2012). *The case of a massive open online course at a college of education*. Retrieved from http://conference.nmc.org/files/smkbMOOC.pdf

McAuley, A., Stewart, B., Siemens, G., & Cormier, D. (2010). *The MOOC model for digital practice.* Retrieved from https://oerknowledgecloud.org/sites/ oerknowledgecloud.org/files/MOOC_Final.pdf

Onah, D. F., Sinclair, J., & Boyatt, R. (2014). Dropout rates of massive open online courses: behavioural patterns. *In International conference on education and new learning technologies*. EDULEARN14 proceedings, 1, (pp. 5825-5834). Barcelona

Sheeran, P. (2002). Intention–behaviour relations: A conceptual and empirical review. *European Review of Social Psychology, 12*(1), 1–36. doi:10.1080/14792772143000003

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Chapter 6

A Classification of Barriers that Influence Intention Achievement in MOOCs

This chapter is based on:
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Abstract.

MOOC-learning can be challenging as barriers which prevent or hinder acting out MOOC- learners' individual learning intentions may be experienced. The aim of this research was to elicit and to empirically classify barriers that influence this intention achievement in MOOCs. The best fit model of our factor-analytical approach resulted in 4 distinctive components; 1. Technical and online-learning related skills, 2. Social context, 3. Course design/ expectations management, 4. Time, support and motivation. The main finding of our study is that the experienced barriers by MOOC-learners are predominantly non-MOOC related. This knowledge can be of value for MOOC-designers and providers. It may guide them in finding suitable re-design solutions or interventions to support MOOC-learners in their learning, even if it concerns non-MOOC related issues. Furthermore, it makes a valuable contribution to the expanding empirical research on MOOCs.

Introduction

An often-heard concern regarding MOOCs is their high dropout rate (Jordan, 2014). These dropout rates—generally used to assess MOOC-success—are misleading, as often success measurements from traditional education are used Henderikx, Kreijns & Kalz, 2017a, 2017b; Huin, Bergheaud, Caron, Codina & Disson, 2017; Walji, Deacon, Small & Czerniewicz, 2016). Kalz, Kreijns, Walhout, Castaño-Munoz, Espasa, and Tovar (2015) introduced a theoretical framework that com- bines distal and proximal variables and which takes into account individual intentions and barriers. Since different educational contexts deserve different educational measures (De Boer, HO, Stump & Breslow, 2014). Henderikx et al. (2017b) further specified this theoretical framework into a model to take into account individual intentions of MOOC-learners as a starting point for measuring educational success in MOOCs. But, even when taking the individual intentions as a starting point, a study by Henderikx et al. (2017a) showed that there is still a substantial group of MOOC-learners who do not achieve what they intended to do. It seems that they experience barriers preventing or hindering them from acting out their individual learning intentions.

These barriers can be either MOOC related or non-MOOC related and may cause MOOC- learners to change their individual intentions or even to stop (Henderikx et al., 2017a). While there are related studies dealing with the empirical analysis of the effects of barriers to online learning and distance education using various statistical techniques (Eom, Wen & Ashill, 2006; Galusha, 1998; Muilenburg & Berge, 2005; Park & Choi, 2009; Peltier, Drago & Schibrowski, 2003; Song, Singleton, Hill & Koh, 2004) for the context of massive open online learning such analyses are limited. Current studies on barriers in MOOCs mainly focus on a restricted number of barriers in case studies, qualitative research setups, literature reviews and descriptive studies (Belanger & Thornton, 2013; Khalil & Ebner, 2014; Onah, Sinclair & Boyatt, 2014; Shapiro, Lee, Roth, Li, Çetinkaya-Rundel & Canelas, 2017). There are some studies which empirically investigate barriers to student retention, however these studies merely focus on the effect of specifically selected barriers (Adamapoulos, 2013; Hone & El Said, 2016). Furthermore, some studies in online learning or distance education context grouped types of barriers (Galusha, 1998) or aimed to empirically identify barrier components (Muilenburg & Berge, 2005). But, apart from an exploratory study on barriers in MOOCs by Henderikx et al. (2017a), there is no synthesized overview of MOOC-specific barriers available.

In this study, an exploratory factor analysis was used to categorize these potential barriers and present a MOOC-specific barrier classification, that could contribute to purposefully improve MOOCs and enhance MOOC-learner experiences and intention achievement. First, a literature review will give a brief overview of the most relevant literature on barriers to online learning and MOOCs specifically. Second, the methodology of the study will be reported, followed by the results of the factor analysis. Lastly, the results will be discussed as well as the limitations, implications for practice and recommendations for future research.

Literature Review

Many different issues are perceived as possible barriers to online learning and distance education. An extensive literature review on barriers in distance education by Galusha (1998) showed that students in a distance learning environment regard financial costs, disruption of family life, lack of support from the employer, lack of feedback, lack of instructor presence, lack of technical assistance, lack of planning assistance, lack of social contact, unfamiliarity with distance learning, lack of computer or writing skills as disablers to their learning. She grouped these barriers into five categories (1) costs and motivators, (2) feedback and teacher contact, (3) student support and services, (4) alienation and isolation and (5) lack of experience and training.

Peltier et al. (2003) chose to investigate which role six specific dimensions, drawn from literature, played in perceived effectiveness of online education. These dimensions were (1) instructor support and mentoring, (2) course content, (3) course structure, (4) student-to- student interaction, (5) information technology and (6) instructor-student. Their regression results showed that course content, instructor support and mentoring played a substantial role and can be regarded as the most important barriers - or success factors if positively experienced - to students' learning experiences. Other reported challenging characteristics as perceived by students in online learning context are technical problems, perceived lack of community, time constraints and unclear course objectives as found by Song et al. (2004) in their mixed-methods study.

Eom et al. (2006) examined the determinants of students' satisfaction in the context of university online courses. They included the variables course structure, instructor feedback, self-motivation, learning style, interaction, and instructor facilitation, quite similar to the study undertaken by Peltier et al. (2003). Results of the structural equation modelling analysis revealed that instructor feedback and learning style were significant predictors for student success, indicating that these issues are important for learning and could become barriers if students are not satisfied with these specific issues.

Qualitative research by Aragon and Johnson (2008) uncovered that self-reported reasons for non-completion of community college online courses were time constraints, lack of instructor interaction, bad course content, lack of communication and techno- logical issues Furthermore, Park and Choi (2009) found that lack of family- and work support are positively related to non-completion and can thus be regarded as barriers to online learning.

Research that sought to integrate perceived barriers students (expected to) face in an online distance education context was conducted by Muilenburg and Berge (2005). Their factor analytical study which used the principal component extraction method, revealed that these barriers could be assigned to eight distinctive components: (1) administrative/instructor issues, (2) social interactions, (3) academic skills, (4) technical skills, (5) learner motivation, (6) time and support for studies, (7) cost and access to the internet, (8) technical problems. A composite scores calculation per component identified social interactions as the most important barrier for students' online-learning. Academic skills have been identified as the least important barrier.

These studies, reporting on aforementioned barriers were all conducted in a general online learning or distance education context. Yet, with the still relatively new online learning environment of MOOCs, research on barriers in MOOC-specific context has caught on and is increasing. In a study on student retention in MOOCs, Adamopoulos (2013) used various text mining and predictive modelling techniques to analyse online student reviews and online available course characteristics. The analysis showed that the negative sentiment for the discussion forum, length of the course and workload had a significant negative effect on student retention. Belanger and Thornton (2013) evaluated a MOOC on Bioelectricity by analysing pre- and post-questionnaires and log-data. The main barriers that were mentioned by students as reason for non-completion were time constraints and insufficient background knowledge. A literature review by Khalil and Ebner (2014) found, in addition to the barriers mentioned in Belanger and Thornton's (2013) study, that student motivation, feelings of isolation and hidden costs are also considered barriers to MOOC-learning. Further, a descriptive analysis of MOOC data to uncover reasons for dropout by Onah et al. (2014) showed that difficulty of the MOOC, timing, lack of digital skills and lack of in-MOOC support were often experienced barriers by MOOC-learners. In addition, Hone and El Said (2016) explored factors which affect MOOC retention. Their factor analytic study focused on student experiences with the course instructor, experiences with other learners and experiences with the design features of the course and found that especially instructor interaction and course content are important features for students. If these features are not perceived positively by students, they have the potential to become barriers to their learning and ultimately retention.

Also, a very recent study by Shapiro at al. (2017) on barriers to retention in MOOCs, sought to identify which antecedents, both inside and outside the course setting, had an impact on MOOC-learning. Their qualitative approach of conducting 36 online interviews identified, in order of severity, lack of time, bad previous experiences, online format and inadequate background as barriers to MOOC-learning.

Previous studies confirmed that research on barriers to learning in MOOCs is developing and has strong parallels with the research findings in online learning and distance education context. Still, a shortcoming of prior studies is that they merely examine several specific potential barriers to MOOC-learning and are limited in their empirical analysis. As it is important to continue to explore potential barriers to MOOC-learning to gain a richer understanding of these issues (Hew, 2016; Shapiro et al. 2017), a next step is to generate a composite overview of potential MOOC-specific barriers or groupings of barriers based on literature and related studies as already available in online learning or distance education context (Galusha, 1998; Muilenburg & Berge, 2005).

Henderikx et al. (2017a), composed an overview of potential barriers based on a limited literature review and made a first effort to categorize these barriers (see Figure 1).

MOOC-related		Non-MOOC related	
Design		General	
Problems with the site	Lack of support	Workplace issues	Lack of information literacy
Lack of interaction	Content was not appropriate	Lack of time	Insufficient academic background
Lack of instant feedback	Expectations management	Family issues	Lack of motivation
Lack of instructor presence	Course was too easy	Lack of workplace support	Lack of personal commitment
Lack of useful feedback	Course did not meet expectations	Lack of family support	Technical
	Course was too difficult	Personal	Technological problems pc
		Lack of technological skills	Bad internet connection

Figure 1. Overview of barriers arranged by type (Henderikx et al. 2017a)

The choice for categorization was based on the rationale: which classification would be most useful to MOOC-designers and/or providers and MOOC-learners. The current study took this initial typology of barriers in MOOCs as a starting point. In addition, this overview was expanded by the (potential) barrier items based on findings in the previously discussed literature. An exploratory factor analysis was conducted to empirically summarize the data set and to categorize the barriers.

Method

Participants

The participants were individuals who took part in one or more MOOCs in the Spanish language from different MOOC providers in the last 2 years and who indicated that we could contact them for further research, regardless of whether or not they successfully achieved their personal goals in these MOOCs. 1618 Potential respondents received an invitation to participate in the survey of whom 317 actually completed the survey (163 women, 154 men, M_{age} = 47, age range: 20–83 years). Most of the participants hold a master (26.1%) or bachelor (32.9%) degree. 8.1% of the participants have a doctorate degree, while 24.8% have an associate or secondary education degree. The remaining 8.1% of the participants finished middle school or below. 66.1% Of the participants are employed for wages, while 13.9% are self-employed. A further 8.5% is currently looking for work and 1.7% is not looking for work. 3.4% of the participants are students, 0.3 military and 6.1% indicated that were retired or other. A majority of the participants participated in up to 5 MOOCs (45.2%). 27.9% participated in 6 to 10 MOOCs, 17% between 11 and 20 MOOCs and 9.9% between 21 and 100 MOOCs. Furthermore, 58.3% of the participants actually finished between 1 and 5 MOOCs, 23.7% finished between 6 and 10 MOOCs, 10.2% between 11 and 20 MOOCs and 7.8% indicated that they finished between 21 and 80 MOOCs. Lastly, 24.4% of the participants prefer the traditional face-to-face way of learning, 39.3% indicates that it makes no difference to them whether they learn face-to-face or online and 36.3% prefers to learn online. Overall, the sample is similar to samples reported in other research on MOOCs (Ho et al., 2015).

Materials

A ‘Barriers to MOOC-learning’ survey was developed, which contained items drawn from general online learning, distance education and MOOC-specific context literature on barriers and enablers to learning, as discussed in previous section. After answering several general questions on gender, age, educational background, employment status, MOOC-learning experience and preferred learning context, respondents were asked to indicate to what extent they considered the 44 listed items as barriers to learning in a MOOC on a 5-point Likert scale ranging from ‘to a very large extent’ to ‘not at all’. Examples of items are ‘lack of decent feedback’, ‘family issues’, ‘technical problems with the computer’ and ‘lack of instructor presence’.

Procedure
Over the course of several weeks potential respondents were invited via email batches using the open source online survey tool Limesurvey (visit http://www.limesurvey.org). Filling out the questionnaire took 5–10 min. After four and six weeks, a reminder was sent to those who did not yet completed the survey.

Data Screening
The Mahalanobis distance was calculated to identify possible outliers. Based on these calculations, 22 outliers were determined and removed, which resulted in a final sample of 295 cases, which is within the generally accepted item ratio to conduct a factor analysis of 5 to 10 respondents per item (Comrey & Lee, 1992).

Analysis
The suitability of the data for factor analysis was assessed by first examining the correlation between items. It was observed that all items correlated with at least .3 with one other item, which is a positive indication of factorability. Additionally, the Kaiser- Meyer-Olkin measure showed a value of .95 which exceeded the recommended minimum value of .6 (Kaiser, 1970, 1974) and the Bartlett’s Test of Sphericity was statistically significant ($p < .05$), which further supports the factorability of the data. Lastly, the communalities all exceeded .3 (see Figure 2). Given these indicators, the factorability of the data could be considered positive.

Principal component analysis was selected as extraction method because this method allows for reducing the observed variables to a smaller set of independent composite variables. A cut-off of 0.4 was used for statistical significance of the component loadings and the component structure was examined using both Varimax and Oblimin rotation. After initial analysis, the Oblimin rotation was selected as this rotation method produced the simplest component structure. The Kaiser criterion (Kaiser, 1960), which retains components with an eigenvalue above 1, and inspection of the scree plot were used to determine the number of components. Yet, as these methods are not considered very accurate (Velicer & Jackson, 1990), parallel analysis was also performed. The first analysis showed the presence of 6 components with eigenvalues above 1, explaining respectively 48,2%, 9,2%, 5,8%, 4,5%, 2,6% and 2,3% of the variance, yet with very few or no loadings in the last two components.

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The screen plot indicated a break after the 4th component. This was further supported by the results of parallel analysis, which produced 4 random eigenvalues smaller than the first 4 eigenvalues of the PCA. Solutions for 4 and 5 components were then examined, also using Oblimin rotation. The 4-component solution, which explained 67,7% of the variability was preferred because of (a) the combined results of the scree plot and the parallel analyses and (b) the reasonably clear interpretable components.

A total of nine items were removed because they did not meet the criteria of no cross-loading of .4 and failed to have a primary component loading of more than .4, thus not contributing to a simple component structure. The items 'Procrastinate (delay), cannot get started', 'Lack of instructor presence', 'Insufficient training/experience to use the delivery system', 'Lack of adequate internet access', 'Lack of technical assistance', 'Technical problems with the site' and 'Lack of language skills' had cross- loadings of more than .4 on multiple components. The items 'Course content was too easy' and 'Course content was too hard' did not load above .4 on any component. Furthermore, two items which seem very similar: 'workplace issues' and 'workplace commitments' were not removed as their mutual correlation was low to medium.

For the final stage, a factor analysis of the remaining 35 items, using the principal component extraction method and oblimin rotation was conducted, forcing four components explaining 70,4% of the variance (see Table 1). All items in this analysis had primary loadings over .4 on one single component. The component loading matrix for this final solution is presented in Figure 2.

Table 1. Total variance explained

Initial Eigenvalues	Component Total	% of Variance	Cumulative %
1	16.72	47.76	47.76
2	3.63	10.37	58.13
3	2.43	6.93	65.06
4	1.86	5.32	70.38

Results

The data analysis indicated that four distinct components summarized the experienced barriers in MOOCs. Component labels were defined that fitted the extracted component/ item-combinations. This resulted in the following labels:

Component 1: Technical and online-learning related skills. MOOC-learners perceived lack of skills like information literacy, insufficient knowledge of the delivery systems, insufficient academic back ground as barrier to MOOC- learning

Component 2: Social context. These issues are typically related to learning individually. In other words, not learning in a classical and/or physical learning environment. Issues like the impersonal feel of learning, lack of interaction, no collaboration, no interaction and feelings of isolation are included.

Component 3: Course design/expectations management. This component concerns barriers related to the design and expectations management of the course like the low quality of the course materials, bad course instruction, no instructor interaction, bad course content and lack of feedback

Component 4: Time, support and motivation. MOOC-learners experience time constraints due to workplace, family and general issues as well as support issues due to lack of family, peer and work support. Further, motivational issues like being responsible for your own learning and motivation are included in this component

Items	Pattern Matrix Component 1	2	3	4	Communalities
1. Lack of skills for using the delivery system	.883				.865
2. Lack of software skills	.882				.849
3. Shy or lack of confidence	.762				.661
4. Unfamiliar with online learning technical tools	.759				.751
5. Lack of information literacy skills	.758				.786
6. Lack of typing skills	.744				.821
7. Lack of reading skills	.661				.791
8. Lack of writing skills	.630				.734
9. Insufficient academic background (prior knowledge)	.610				.678
10. Technical problems with the computer	.505				.668
11. Feeling of isolation		.837			.742
12. Lack of social context cues		.818			.771
13. Learning feels impersonal		.792			.702
14. Lack of student collaboration		.760			.686
15. Lack of interaction/communication among students		.592			.573
16. Prefer to learn in person/face-to-face		.581			.398
17. Lack of clear expectations/instructions			-.840		.793
18. Low quality materials/instruction			-.808		.802
19. Unavailability of course materials			-.732		.560
20. Lack of in-course support			-.732		.698
21. Instructors do not know how to teach online			-.718		.666
22. Lack of interaction with instructor			-.715		.678
23. Lack of timely feedback from instructor			-.700		.699
24. Lack of decent feedback			-.674		.715
25. Course content was bad			-.619		.693
26. Workplace issues				.849	.797
27. Lack of support from employer				.828	.750
28. Too many interruptions during study time				.822	.657
29. Lack of time in general				.796	.650
30. Family issues				.753	.715
31. Lack of support from family, friends				.746	.699
32. Workplace commitments				.617	.570
33. The learning environment is not very motivating				.532	.697
34. Lack of personal motivation				.430	.713
35. Own responsibility for learning				.428	.609

Figure 2. Component loadings and communalities based on a factor analysis with principal component extraction method and oblimin rotation for 35 items (N = 295)

As can be seen in Figure 2, the majority of the commonalities are reasonably high, which indicates that the extracted components represent the variables well. The internal consistency for each of the components was tested by calculating the Cronbach's alpha. The alphas were strong: .96 for component 1 (10 items), .882 for component 2 (6 items), .94 for component 3 (9 items) and .94 for component 4 (10 items). Removal of the item 'prefer to learn in person/face-to-face' in factor 2, would slightly improve that Cronbach alpha score to .90, yet as the initial score was already strong it was decided not to eliminate this item.

Furthermore, composite scores were calculated for each of the four components (see Table 2), based on the mean of the items that had their primary loadings on each component. Lower scores indicated that this component represented a more severe barrier to the respective MOOC-learners who completed the survey.

Table 2. Means and standard deviations per barrier component and the barrier perceived as

Barrier components	Mean	SD
Technical and online learning skills	3.40	1.19
Technical problems with the computer	3.07	1.41
Social interactions	3.54	0.90
Lack of interaction/communication among students	3.35	1.09
Course design	2.93	1.09
Course content was bad	2.69	1.56
Time, support and motivation	2.95	1.09
Lack of time in general	2.45	1.32

Note: answers were rated on a 5-point Likert scale with 1 = too a very large extent and 5 = not at all

Discussion

This study has implemented a factor-analytical approach to identify the components that represent the barriers to intention achievement in MOOCs. The iterative process of determining the best fit model, resulted in 4 distinctive components; 1. Technical and online- learning related skills, 2. Social context, 3. Course design/expectations management, 4. Time, support and motivation. This result partly overlaps with a comparable study by Muilenburg and Berge (2005), who combined barriers students (expected to) face in an online distance education context into a collective overview for factor analysis. Their analysis found eight components of which administrative issues and costs and access to the internet were not present in our analysis. The lack of barriers concerning administrative issues can be explained by the fact that we did not include administration related barriers in our questionnaire as the administrative issues in MOOCs as a non-formal learning context are not comparable to administrative issues in formal education. An explanation regarding internet issues can most likely be explained by the fact that the Muilenburg and Berge (2005) study collected data in 2003. Internet was less available and affordable then compared to present time where access to the internet is inexpensive and available at practically all places and time using various devices.

Also, our study identified one component with technical related issues and online-learning related skill barriers whereas Muilenburg and Berge (2005) found three separate components containing technical and academic skills and technical problems. Further, both studies found a social interactions/social context component but time, support and motivation barriers are part of one component in our study, while the Muilenburg and Berge (2005) study found two components to cover these barriers. Lastly, our study found one distinct component containing MOOC-design related barriers, which is the largest difference compared to Muilenburg and Berge's (2005) study that found instructor related issues combined with administrative issues in one component. However, this difference could be explained by the fact that, as stated before, we did not include any administrative related barriers in the questionnaire.

The composite scores per barrier component (see Table 2) indicate that course design and time, support and motivation are near enough equally considered as most severe barrier components by the respondents of the barriers to MOOC learning questionnaire. Social context was rated as least severe barrier. In contrast, Muilenburg and Berge's (2005) study found that the social interactions component was perceived as most severe. This is quite a big difference in perception, which might also be explained by the moment in time of the study. As online presence is part of everyday life nowadays, people are increasingly used to this phenomenon; in 2003, this was merely emerging.

Further, when looking at the course design barrier component, bad course content is rated as most severe barrier. Studies by Peltier et al. (2003), and Aragon and Johnson (2008), in online learning context, found similar results. In the MOOC-learning context, the study by Hone and El Said (2013) also identified course content as an important feature for course retention. Additionally, the most severe barrier included in the time, support and motivation barrier component was lack of time. This is consistent with the findings of Song et al. (2004) in online learning context and Belanger and Thornton (2013) and Shapiro et al. (2017) in MOOC-learning context.

When further assessing the literature review, it stands out that instructor related issues are consistently perceived as important for retention in online learning (Aragon & Johnson, 2008; Eom et al. 2006; Peltier et al., 2003). Yet, in MOOC-learning context this issue is only found by Hone and El Said (2016) and in current study this issue was also not perceived as a severe barrier. This is an interesting observation, even though, with the exception of current study, all of these aforementioned studies merely focused on several specifically selected, mainly course related barriers in their research setup. Possibly, learners have higher expectations, or attach more value to, instructor related issues in a formal education context. As MOOCs are easily accessible and do not have a formal education status (yet), instructor issues, might not be perceived as important for a satisfying learning experience.

Table 3. Classification of barrier components

Component	Label	Type	Coping level
1	Technical and online related skills	Non-MOOC related	Can be dealt with on a personal level
2	Social context	Partly MOOC and partly non-MOOC related	Can be dealt with on a personal and MOOC level
3	Course design	MOOC related	Can be dealt with on MOOC level
4	Time, support and motivation	Non-MOOC related	Can be dealt with on a personal level

An assessment of the barrier components in light of the study by Henderikx et al. (2017a) resulted in Table 3. From Table 3, it can be inferred that the barrier components and thus the experienced barriers by MOOC-learners are predominantly non-MOOC related. This knowledge can be of value for MOOC-designers and providers. It may guide them in finding suitable re-design solutions or interventions to support MOOC-learners in their learning, even if it concerns non-MOOC related issues. For instance, to support MOOC-learners regarding technical and online-learning related skills, it would be possible to, prior to the start of a MOOC, specifically draw attention to the minimum requirements regarding technical and online learning skills needed to be able to finish the MOOC. The barriers related to social context, that are considered MOOC-related like lack of interaction and lack of collaboration could be addressed in the design of the MOOC by for instance integrating assignments which demand or support interaction and collaboration with fellow MOOC- learners. Course design related barriers are addressable by re-design interventions depending on the specific issues at hand. More- over, barriers concerning time, support and motivation could, even though not MOOC- related, be supported by MOOC providers and/or designers by for instance providing information on how to handle and cope with these kinds of barriers, as well as by providing supporting interventions.

There are some limitations that should be taken into account. Firstly, the sample is limited in the sense that it only considers MOOC-learners who took part in one or more MOOCs in the Spanish language. Future research should replicate this study finding respondents in other MOOC-learner populations. Also, we do not know to what extent the respondents who completed the survey were successful in achieving their personal goals when participating in their respective MOOCs. It would be interesting and potentially valuable to differentiate between these two groups to investigate if either group experiences different barriers. Furthermore, even though the item ratio of 6:1 is within the generally accepted limits for factor analysis (Comrey and Lee, 1992), a bigger sample will add to the reliability of the analysis. Further research should be conducted using bigger samples to either confirm or contradict our results. Lastly, as this is the first study examining components influencing intention achievement in MOOCs, further refinement of the barrier overview is necessary. A possible next step is to expand this composed barrier overview into an assessment tool for MOOC-providers and/or designers that can support them in their effort to enhance the MOOC-learning experience, in identifying areas for improvement either MOOC related or not.

To conclude, the aim of this research was to empirically analyse barriers that influence intention achievement in MOOCs and translate this for practical purposes into MOOC or non-MOOC related barrier components. The findings identified 4 barrier components of which the majority contained non-MOOC related barriers, which is useful information for MOOC providers and designers and makes a valuable contribution to the expanding empirical MOOC-research.

References

Adamopoulos, P. (2013). What Makes a Great MOOC? An Interdisciplinary Analysis of Student Retention in Online Courses. *In 34th International Conference on Information Systems: ICIS 2013*. United States: Association for Information Systems.

Aragon, S.R., & Johnson, E.S. (2008). Factors influencing completion and noncompletion of community college online courses. *The American Journal of Distance Education, 22*(3), 146-158. doi:10.1080/08923640802239962

Belanger, Y., & Thornton, J. (2013). *Bioelectricity: A quantitative approach: Duke University's first MOOC*. Retrieved from http://dukespace.lib.duke.edu/dspace/bitstream/handle/10161/6216/Duke_Bioelect ricity_MOOC_Fall2012.pdf?sequence=1

Comrey, A. L., & Lee, H. B. (1992). *A First Course in Factor Analysis* (2nd ed.). Hillsdale, NJ: Lawrence Erlbaum.

DeBoer, J., Ho, A. D., Stump, G. S., & Breslow, L. (2014). Changing "course" reconceptualizing educational variables for massive open online courses. \ *Educational Researcher*, 43(2), 74-84. doi:10.3102/0013189X14523038

Eom, S. B., Wen, H. J., & Ashill, N. (2006). The determinants of students' perceived learning outcomes and satisfaction in university online education: An empirical investigation. *Decision Sciences Journal of Innovative Education*, 4(2), 215-235. doi: 10.1111/j.1540-4609.2006.00114.x

Galusha, J. M. (1998). Barriers to learning in distance education. *Interpersonal Computing and Technology. An electronic journal for the 21st century*. 5(3), 6-14. Retrieved from https://eric.ed.gov/?id=ED416377

Henderikx, M. A., Kreijns, K., & Kalz, M. (2017a). Refining success and dropout in massive open online courses based on the intention–behavior gap. *Distance Education, 38*(3), 353–368. doi:10.1080/01587919.2017.1369006

Henderikx, M., Kreijns, K., & Kalz, M. (2017b). To change or not to change? That's the question..., On MOOC-success, barriers and their implications. In C. Delgado Kloos, P. Jermann, M. Pérez-Sanagustin, D. T. Seaton, and S. White (Eds.), *Lecture notes in computer science: Vol. 10254. Digital education: Out to the world and back to the campus* (pp. 210–216). doi 10.1007/978-3-319-59044-8_25

Hew, K. F. (2016). Promoting engagement in online courses: What strategies can we learn from three highly rated MOOCS. *British Journal of Educational Technology*, 47(2), 320-341.

Ho, A. D., Reich, J., Nesterko, S., Seaton, D. T., Mullaney, T., Waldo, J., & Chuang, I. (2014). HarvardX and MITx: The first year of open online courses. HarvardX Working Paper No. 1. Retrieved from http://harvardx.harvard.edu/multiple-course- report

Hone, K. S., & El Said, G. R. (2016). Exploring the factors affecting MOOC retention: A survey study. *Computers & Education*, 98, 157-168.

Huin, L., Bergheaud, Y., Caron, P. A., Codina, A., & Disson, E. (2016). Measuring completion and dropout in MOOCs: A learner-centered model. In M.Khalil, M. Ebner, M. Koop, A. Lorenz & M. Kalz (Eds.), *Proceedings of the European MOOC Stakeholder Summit 2016* (pp. 55-68). Norderstedt: Books on Demand GmbH.

Jordan, K. (2014). Initial trends in enrolment and completion of massive open online courses. *The International Review of Research in Open and Distributed Learning*, *15*(1), 133-160. doi:10.19173/irrodl.v15i1.1651

Kaiser, H.F. (1970). A second-generation little jiffy. *Psychometrika* ,35(4), 401–415. Kaiser, H.F.(1974). An index of factorial simplicity. *Psychometrika*, 39(1), 31–36.

Kaiser, H.F. (1960). The application of electronic computers to factor analysis. *Educational Psychology Measurements*, 20(1), 141–151.

Kalz, M., Kreijns, K., Walhout, J., Castaño-Munoz, J., Espasa, A., & Tovar, E. (2015). Setting-up a European cross-provider data collection on open online courses. *The International Review of Research in Open and Distributed Learning*, *16*(6). 62– 77.

Khalil, H., & Ebner, M. (2014). MOOCs Completion Rates and Possible Methods to Improve Retention - A Literature Review. *In World Conference on Educational Multimedia, Hypermedia and Telecommunications* (pp. 1236–1244). Chesapeak, VA: AACE. from https://www.learntechlib.org/primary/p/147656/

Muilenburg, L. Y., & Berge, Z. L. (2005). Student barriers to online learning: A factor analytic study. *Distance Education*, *26*(1), 29–48. doi:10.1080/01587910500081269

Onah, D. F., Sinclair, J., & Boyatt, R. (2014). Dropout rates of massive open online courses: Behavioural patterns. *EDULEARN14 Proceedings*, Barcelona, 5825– 5834. Retrieved from http://wrap.warwick.ac.uk/65543/

Park, J. H., & Choi, H. J. (2009). Factors influencing adult learners' decision to drop out or persist in online learning. *Journal of Educational Technology & Society*, 12(4), 207–2017. Retrieved from https://pdfs.semanticscholar.org/3b3c/47a09120bcd232369e29ea383593e251b220.pdf

Peltier, J. W., Drago, W., & Schibrowsky, J. A. (2003). Virtual communities and the assessment of online marketing education. Journal of Marketing Education, 25(3), 260-276. doi: 10.1177/0273475303257762

Shapiro, H. B., Lee, C. H., Roth, N. E. W., Li, K., Çetinkaya-Rundel, M., & Canelas, D. A. (2017). Understanding the massive open online course (MOOC) student experience:An examination of attitudes, motivations, and barriers. *Computers & Education*, 110, 35-50.

Song, L., Singleton, E. S., Hill, J. R., & Koh, M. H. (2004). Improving online learning: Student perceptions of useful and challenging characteristics. *The internet and higher education, 7*(1), 59–70. doi: 10.1016/j.iheduc.2003.11.003

Velicer, W. F., & Jackson, D. N. (1990). Component analysis versus common factor analysis: Some issues in selecting an appropriate procedure. *Multivariate behavioral research,* 25(1), 1-28. doi: 10.1207/s15327906mbr2501_1

Walji, S., Deacon, A., Small, J., & Czerniewicz, L. (2016). Learning through engagement: MOOCs as an emergent form of provision. *Distance Education*, *37*(2), 208-223.

7

Chapter 7

The Development and Validation of an Instrument to Assess Barriers to Learning in MassiveOpen Online Courses

This chapter is based on:
Henderikx, M., Xu, K, Kreijns, K., & Kalz, M. (2019). The Development and Validation of an Instrument to Assess Barriers to Learning in Massive Open Online Courses. (submitted)

Abstract

The openness and less supported form of learning in MOOCs can elicit considerable challenges for learners. Some of these challenges can be identified as barriers to learning which may negatively influence individual learner's achievement. This study aimed to develop a self-report instrument to capture barriers to learning as experienced by learners in MOOCs. Factor analyses were performed and showed promising results. The strength of the standardized factor loadings, which indicated good measurement quality in combination with the coherent diagnostic categories that correspond to the Theoretical propositions that steered the construction of the instrument pointed towards a good construct validity. Even though further research is recommended, the instrument can very well be utilized in its current form, as a diagnostic tool by MOOC-providers and designers to gather information that will benefit further development of MOOCs and subsequently, support learners in achieving their personal learning goals.

Introduction

Massive open online courses (MOOCs) provide a fairly novel non-formal learning opportunity to gain knowledge on a wide variety of topics (Greene, Oswald & Pomerantz, 2015; Misopoulos, Argyropoulou & Tzavara, 2018). Although there are similarities with distance education, there are also some important differences; MOOCs are free of charge (though often certificates are charged), there are no educational entry level requirements, in- course support is not always available and most MOOCS do only provide limited acknowledged credentials or academic credits (Reich & Ruipérez-Valiente, 2019). In addition, learners can individually form their own goal intentions of what they want to achieve in the MOOC, which may deviate from completing the course in order to get the certificate (Henderikx, Kreijns & Kalz, 2017).

Yet, due to its open, accessible and less supported form of learning, learners face quite a number of challenges (Gamage, Fernando & Perera, 2015). Some of these challenges can be identified as barriers to attaining learning goals. Barriers to learning can be described as obstacles that hinder or prevent learners from reaching their individual goals (Henderikx, Kreijns & Kalz, 2018). These barriers can be either MOOC related or non-MOOC related and cause MOOC-learners to change their individual intentions or to stop (Henderikx et al., 2018). Typical MOOC-related barriers often mentioned by learners are lack of interaction, lack of instructor presence and bad course content (e.g. Hone & Said, 2016; Onah, Sinclair & Boyatt, 2014). Examples of Non-MOOC related barriers are insufficient academic knowledge, lack of time and technical issues like bad internet or lack of digital skills (e.g. Conole, 2016; Khalil & Ebner, 2014).

Several studies revealed that barriers negatively influence individual achievement (Adamopoulos, 2013; Belanger & Thornton, 2013; Hone & El Said, 2016). Yet, some barriers may be solved by (minor) adjustments in the MOOC-design if a barrier is MOOC- related or some may be solved by supporting and informing the learner if a barrier is not MOOC related. Therefore, an instrument for the identification of barriers learners' faced while learning in a MOOC will be beneficial for making informed decisions about potential redesign and learner support interventions and subsequently optimize learner success.

However, to our knowledge, such an instrument is not available yet. As such, the purpose of this article is to fill that research gap by 1) developing a self-report instrument to assess the barriers as experienced by learners in MOOCs and 2) examine the validity of this new instrument. The current article builds upon a previous study which reported on a classification of barriers to learning in MOOCs using principal component analysis (see Henderikx et al. 2018). The article is structured as follows: First, a literature review will give an overview of the most relevant literature on barriers to online learning and MOOCs specifically. Second, the methodology of the study is presented, followed by the results of the factor analyses. Lastly, the results will be discussed as well as the limitations and recommendations for future research.

Barriers to learning online

Research about issues that can potentially impede successful learning in MOOCs is growing and holds similarities with research findings that pertain to online learning and distance education contexts. Often reported barriers learners experience while learning in distance education and other online learning contexts are lack of interaction (Algarni & Burd, 2015; Bocchi, Eastman & Swift, 2004; Carnevale, 2000; Croft, Dalton & Grant, 2010; Ivankova & Stick, 2007; Nash, 2005; Pigliapoco & Bogliolo, 2008; Tello, 2007; Wojciechowski & Palmer, 2005), time constraints (Aragon & Johnson, 2008; Dabaj & Yetkin, 2011; Musingafi, Mapuranga, Chiwanza & Zebron, 2015; Osborn, 2001) and insufficient academic background knowledge (Castles, 2004; Dabaj & Yetkin, 2011; Heung & Kan, 2002; Morris, Wu & Finnegan, 2005; Musingafi et al., 2015; Osborn, 2001; Park & Choi, 2009; Poellhuber, Chomienne & Karsenti, 2008). Furthermore, learners also experience family and work issues (Castles, 2004; Kemp, 2002; Martinez, 2003; Packham, Jones, Miller & Thomas, 2004; Park & Choi, 2009; Perry, Boman, Care, Edwards & Park, 2008; Pierrakeas, Xenos, Panagiotakopoulos & Vergidis, 2004; Tello, 2007), motivation (Chyung, 2001; Hartnett, George & Dron, 2011; Ivankova & Stick, 2007; Osborn, 2001; Parker, 2003), poorly designed course content (Angelino, Williams & Natvig, 2007; Ivankova & Stick, 2007; Perry et al., 2008), feelings of isolation (Algarni & Burd, 2015; Croft et al., 2010; Hara & Kling, 2001) and lack of technical skills (Dabaj & Yetkin, 2011; Dupin-Bryant, 2004; Moody, 2004; Musingafi et al., 2015; Osborn, 2001) as barriers that hinder or prevent academic achievement.

Research about barriers pertaining to learning in MOOCs is for obvious reasons not yet as extensive as in distance learning and other online learning contexts. Nevertheless, as MOOCs develop over time, more studies focus on issues that stand in the way of learner achievement. One of the main barriers experienced by learners in MOOCs is lack of interaction (Hone & Said, 2016; Khalil & Ebner, 2013; Levy & Schrire, 2012; Mcauley, Stewart, Siemens & Cormier, 2010) and connected to that lack of instructor presence and in-MOOC support (Mackness, Mak & Williams, 2010; Onah, et al., 2014). Other barriers mentioned by learners in MOOCs are: lack of time (Belanger & Thornton, 2013; Boyatt, Joy, Rocks & Sinclair, 2013; Conole, 2016; Khalil & Ebner, 2014; Onah, et al., 2014; Shapiro, Lee, Roth, Li, Çetinkaya-Rundel, & Canelas, 2017), lack of decent and/or instant feedback (Balfour, 2013; Grover, Franz, Schneider & Pea, 2013), insufficient academic background (Belanger & Thornton, 2013; Shapiro et al., 2017), the content of the MOOC (Hone & Said, 2016; Onah, et al., 2014) and lack of technical skills (Conole, 2016; Khalil & Ebner, 2014; Onah et al., 2014).

The aforementioned studies generally explored one or some specific issues that may impede successful learning in MOOCs. Yet, there are two exceptions to this. First, a study in distance education context presented a compiled overview of potential barriers students (expected to) face while learning online (Muilenburg & Berge, 2005). Their principal component analysis revealed eight barrier categories: (1) administrative/ instructor issues, (2) social interactions, academic skills, (4) technical skills, (5) learner motivation, (6) time and support for studies, (7) cost and access to the internet, (8) technical problems. Second, based on the previous study by Muilenburg and Berge (2005), Henderikx et al. (2018), expanded barrier research in MOOCs by composing a synthesized overview of barriers experienced by learners in MOOCs which were drawn from literature about online learning in general, distance education and MOOCs. Four different barriers categories were distinguished and they interestingly found that most barriers could be classified as non-MOOC related (see Figure 1).

This finding has implications for the interpretation of success assessment of MOOCs and, therefore, for redesign decisions (Henderikx et al., 2018). As MOOCs are generally short courses, running once or several times per year, they have a fast turn over time which is beneficial when it comes to adjusting and further developing the course. However, to make the necessary adjustments information is needed from the learners. An instrument for determining barriers to learning in MOOCs can provide this information and give insight into which particular barriers hinder learners in reaching their individual goals and whether these barriers are MOOC or non-MOOC related.

Component 1	Lack of technical and online learning skills	α = .96
	Lack of software skills	
Non-MOOC related barriers	Lack of skills using the delivery system	
	Unfamiliair with online learning tools	
	Lack of writing skills	
	Lack of reading skills	
	Lack of typing skills	
	Lack of information literacy skills	
	Technical problems with the computer	
	Insufficient academic background (prior knowledge)	
	Lack of confidence	
Component 2	**Social interaction**	**α = .89**
	Learning feels impersonal	
Partly MOOC and partly non-MOOC related barriers	Feeling of isolation	
	Lack of social context	
	Lack student collaboration	
	Prefer to learn face to face	
	Lack of interaction/communication among students	
Component 3	**Course design**	**α = .94**
	Lack of clear expectations/instructions	
MOOC-related barriers	Low quality materials	
	Unavailable course materials	
	Instructors dont know how to teach online	
	Lack of in-course support	
	Lack of interaction with the instructor	
	Lack of timely feedback from the instructor	
	Lack of decent feedback	
	Course content was bad	
Component 4	**Time, support and motivation**	**α = .94**
	Familiy Issues	
Non-MOOC related barriers	Lack of support family and friends	
	Workplace Issues	
	Lack support employer	
	Lack of time	
	Too many interruptions during study	
	Lack of time in general	
	Lack of motivation	
	Own responsibility for learning	
	The learning environment is not motivating	

Figure 1. Classification of barriers to learning in MOOCs (Henderikx et al. 2018)

Development of a barriers to learning in MOOCs instrument

The previously discussed barrier classification by Henderikx et al. (2018) provided a basis for developing an instrument to measure barriers for MOOC learners, however, this study did not formally validate such a scale using a psychometric method. In this study, we aimed to further develop the previous classification into a valid diagnostic instrument. The barriers were selected based on their prevalence in existing literature about distance education, online learning in general and MOOC-learning specifically as discussed before, as well as their possible relevance to learning in MOOCs.

The extent to which learners experience something as a barrier is generally of a subjective nature. Therefore, self-reported measures, which rely on individual's experiences (Duffy, Lajoie, Pekrun & Lachapelle, 2018), are well suited for measuring barriers to learning. Based on the list of barriers as presented in previous literature overview, we expect that the factor analysis will result in distinguishable categories based on item clusters that will at least represent learning impeding issues concerning course content, social interactions, skills, motivation and time related issues.

Method

Participants

Participants were randomly selected from a list of 50,000+ potential respondents. These potential respondents, participated at some point in time in a MOOC from Delft University in the English language, offered on the EdX platform, during which they agreed to be contacted for future research purposes. A total of 6000 requests for participation in the survey were send out in 3 batches (1000, 3000, 2000), 540 respondents completed the survey, resulting in a response rate of 9%, which is not unusual for online administrations (Saleh & Bista, 2017). The majority of the participants were European (27%), North-American (20%) and South-American nationality (21%). Participants of Asia comprised 15% of the sample, while the remaining 17% were participants from other countries. Most of the participants held a master (49%) or bachelor (33%) degree. 7% of the participants had a doctorate degree, while 11% had an associate degree or secondary or primary education. 57% Of the participants were employed for wages, while 12% was self-employed. A further 7% is currently looking for work and 3% is not looking for work. 13% Of the participants are students, 8% indicated that they were retired or other. Most participants rated their English proficiency good to very good (88%). 10% indicated that their command of the English language was average, while the remaining 2% of the participants rated their level as fair to poor. Overall, the sample is similar in terms of demographics to samples reported in other research on MOOCs (Ho et al., 2015).

Material

A survey was developed containing the list of barriers derived from literature about issues that hindered or impeded learning in distance education, online learning in general and MOOC-learning contexts. The survey contained several demographic questions about educational background and employment status as well as questions about barriers. Respondents were asked to what extend the presented barriers negatively influenced or hindered their progression while learning in a MOOC. A five-point Likert scale gave the opportunity to indicate their experienced hindrance from 'to a very large extent' to 'not at all'. Examples of items are 'lack of motivation, 'workplace issues', 'technical problems with the site' and 'lack of timely feedback' (see Appendix B, for mean scores and standard deviation per barrier item).

Procedure
Over the course of several weeks from December 2017 until January 2018, potential respondents were invited to participate in the study via email batches using Qualtrics. Participation was voluntary and the minimum age requirement was set to 17 years. Before being able to proceed to the survey, participants had to confirm their age and voluntary participation by giving electronic consent. The survey took about 5-10 minutes to complete. Per batch, one reminder was sent.

Data screening

Outliers were removed as they affect the estimation of the correlation coefficient, which can cause misleading results especially with statistical methods like factor analysis or structural equation models (Treiblmaier & Filzmoser, 2011). Due to the likert-scale data, it is not possible to identify potential outliers by using the often applied interquartile range technique, therefor the Mahalanobis distance was calculated. Based on these calculations, 96 outliers were determined and removed, which resulted in a final sample of 445 cases, which is well within the generally accepted item ratio of 5 to 10 respondents per item (Comrey & Lee, 2013).

Analysis
All analyses were performed in Mplus v.7.3. (Muthén and Muthén, 1998-2014) using Exploratory Factor Analysis (EFA) and Confirmatory Factor Analysis (CFA; Byrne, 2012). Although the data was ordered-categorical (Likert scales) we treated it as continuous data and thus used Maximum Likelihood as estimation approach, as this is the recommended approach when the number of categories is 5 or more and the distribution and skewness/kurtosis of the data was approximately normal (Rhemtulla, Brosseau-Liard & Savalei, 2012).

Firstly the data was assessed and reassessed using EFA to determine the number of factors emerging from the item pool. The factors are expected to match the barrier classification previously found by Henderikx, Kreijns & Kalz (2018). EFA approach is recommended in cases where there is sparse theory available as it will provide the best understanding of the factor structure (Schmitt, 2011; Schmitt, Sass, Chapelle & Thompson, 2018). For determining the number of factors we did not rely solely on the fit indices provided by MPlus, but combined this with item interpretation and common sense (Schmitt et al., 2018). Preacher, Zhang, Kim and Mels (2013) alerted that merely searching for good fit indices i.e. models that best fit the data, often leads to overly complex and overfitted models (Hayduk, 2014), which will not benefit the exploratory power of the model (Preacher, 2006). Therefore, our main goal was to explain and describe the factor structure consistent with the theoretical framework and potential for generalizability (Hastie, Tibshirani & Friedman 2013; Preacher et al., 2013). Furthermore, it has also been suggested that when a factor structure is expected to be complex, an EFA approach is preferred (Schmitt et al., 2018). The review of the barrier literature suggested a high number of potential barriers which implied a possible complex factor structure meaning that the barriers are difficult to classify into completely distinct categories, thus indicating EFA might be preferable to a CFA approach. Nevertheless, we still performed a CFA to verify the best analytical approach in this case.

Thus, subsequently a CFA was performed assuming a more restrictive factor structure based on the EFA. We did not split the sample to run separate analysis as it has been suggested that using the same sample improves the understanding of the data generating process and factor structure (Schmitt et al., 2018).

Model goodness of fit was evaluated using the commonly applied fit indices. Since the chi- square is known to be highly sensitive to sample size (Marsh, Balla, & McDonald, 1988; Marsh, Hau, & Grayson, 2005), a variety of sample-size independent goodness of fit indices was also examined to assess the fit of the alternative models: The Root Mean Square Error of Approximation (RMSEA), the Tucker-Lewis Index (TLI), and the Comparative Fit Index (CFI; Fan, Thompson, & Wang, 1999; Hu & Bentler, 1999; Kenny, Kaniskan, & McCoach, 2015). Marsh, Hau, & Wen, 2004; Yu, 2002). The TLI and CFI vary along a 0-to-1 continuum and values greater than 0.90 and 0.95 typically reflect an acceptable and excellent fit to the data. RMSEA values of less than 0.06, 0,08 and 0.10 indicate a close fit, acceptable fit and mediocre fit to the data respectively.

Results

Exploratory Factor Analyses

EFA analysis with oblique rotation was performed on the pool of 44 barrier items. Taking the 4-component classification of barriers by Henderikx, Kreijns and Kalz (2018) into account, we focused on examining factor structures of EFA models with 3 to 8-factors. the fit indices in combination with the maximum allocation of items indicated that the 6, 7 and 8-factor models adequately to best represented the data (see table 1 for fit indices).

Table 1. Model Goodness of Fit values for respectively the 6, 7 and 8-factor solutions (n = 445)

		Fit indices			criteria
Test		**6-factor solution**	**7-factor solution**	**8-factor solution**	
Chi-Square Test of Model Fit					
	Value	1506.457	1295.389	1108.325	
	degrees of freedom	697	659	622	
	p-value	.000	.000	.000	
RMSEA					
	Estimate	0.051	0.047	0.042	[.00, .06) =
	90% C.I.	0.048-0.055	0.043-.0.50	0.038-0.046	good fit [.06, .08) = acceptable fit [.08, .10) = mediocre fit
	probability RMSEA <= .05	0.302	0.933	1.00	
CFI/TLI					
	CFI	0.929	0.944	0.957	> 0.90 for acceptable fit
	TLI	0.904	0.920	0.935	> .90 for acceptable fit
Standardized/weighted Root Mean Square Residual					
	Value	0.028	0.025	0.022	should be <.08 for good fit

As underlined by Schmitt et al. (2018) fit indices should be assessed in combination with item interpretation and common sense, which resulted in the 8-factor model providing the best overall solution. (see Table 2). In terms of goodness of fit indices, the 8-factor model fitted the data best. Furthermore, the pattern of factor loadings also matched the theoretical descriptions of the barriers. In order to further refine the instrument, nine items were removed from the analysis if their loadings were < .40 (Comrey & Lee, 2013; Tabachnick & Fidell, 2007) or had cross loadings on more than one factors. These were items presenting barriers 'lack interaction students', 'course content too hard'. 'lack support family and friends', 'insufficient academic knowledge', 'course content too easy', 'course content bad', 'lack of language skills', 'lack support employer' and 'workplace commitments'. The factor loadings of this revised EFA model are presented in Table 2.

Table 2. Loadings of the barriers (i.e. items) on their target categories (i.e. factors) in the 8-factor solution.

	8-factor solution							
Item description	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**
LackInstructorPresence	**0.688***	*0.171**	*0.358**	*0.007*	*-0.142**	*0.077*	*-0.035*	*0.082*
LackInCourseSupport	**0.770***	*0.229**	*-0.010*	*0.022*	*0.178**	*-0.011*	*0.040*	*0.047*
LackTimelyFeedback	**0.773***	*0.189*	*0.053*	*0.015*	*0.126*	*0.001*	*-0.024*	*0.034*
LackDecentFeedback	**0.815***	*0.335**	*0.091*	*-0.055*	*0.019*	*0.059*	*0.009*	*-0.002*
LackInteractionInstructor	**0.732***	*0.010*	*0.356**	*-0.024*	*-0.107*	*0.055*	*-0.011*	*-0.060*
UnavailableCourseMaterials	*0.244**	**0.724***	*-0.107**	*0.187**	*0.092*	*-0.005*	*0.014*	*0.142**
InstructorsDontKnowHowTo Teach Online	*0.163*	**0.835***	*-0.034*	*0.038*	*0.021*	*0.028*	*-0.034*	*0.015*
LackClearExpectationsInstructions	*0.283**	**0.764***	*0.056*	*0.110**	*0.045*	*0.075*	*0.035*	*0.028*
LowQualityMaterials	*0.102*	**0.859***	*-0.061*	*0.067*	*0.008*	*0.010*	*-0.011*	*0.008*
LearningImpersonal	*0.255**	*0.025*	**0.645***	*0.045*	*-0.051*	*0.089*	*0.002*	*0.036*
FeelingOfIsolation	*-0.003*	*0.094*	**0.650***	*0.084*	*0.025*	*0.044*	*0.050*	*0.055*
LackSocialContext	*0.011*	*0.051*	**0.665***	*0.194**	*0.155**	*-0.074*	*-0.005*	*0.005*
LackStudentCollaboration	*0.281**	*-0.120**	**0.725***	*0.146**	*0.098*	*-0.089*	*0.008*	*-0.016*
PreferFaceToFaceLearning	*0.238**	*-0.065*	**0.544***	*0.149**	*-0.066*	*0.188**	*-0.014*	*0.033*
LearningEnvironmentNotMotivating	*0.055*	*0.312**	**0.682***	*-0.150**	*0.082*	*0.308**	*0.005*	*-0.025*
LackWritingSkills	*0.081*	*-0.066*	*0.062*	**0.786***	*0.004*	*-0.021*	*0.023*	*-0.136*
LackReadingSkills	*0.030*	*0.156**	*-0.009*	**0.759***	*0.119**	*0.053*	*-0.024*	*0.126*
LackTypingSkills	*-0.056*	*-0.025*	*0.128**	**0.734***	*0.243**	*-0.039*	*0.014*	*-0.002*
LackInformationLiteracySkills	*-0.028*	*0.068*	*0.099**	**0.820***	*0.301**	*0.018*	*-0.023*	*0.120*
LackOfConfidence	*-0.054*	*0.026*	*0.318**	**0.688***	*-0.036*	*0.025*	*0.090*	*-0.042*
LackSoftwareSkills	*-0.028*	*0.041*	*0.023*	*0.010*	**0.674***	*0.047*	*-0.039*	*0.221*
LackSkillsUsingDeliverySystem	*-0.009*	*-0.087**	*0.021*	*0.042*	**0.847***	*0.118*	*0.021*	*0.123*
UnfamiliairWithOnlineLearningTools	*-0.018*	*-0.050*	*0.031*	*-0.020*	**0.513***	*0.186**	*-0,027*	*0.090*
InsuffTrainingTooUseDeliverySystem	*0.169**	*0.119*	*0.012*	*-0.002*	**0.723***	*0.030*	*0.050*	*0.134*
Procratinate	*0.064*	*0.080*	*0.017*	*0.040*	*-0.041*	**0.676***	*0.110**	*0.017*
LackMotivation	*-0.005*	*0.146**	*-0.047*	*0.127*	*0.068*	**0.512***	*0.005*	*0.080*
OwnResponsibilityLearning	*0.034*	*0.039*	*0.057*	*0.030*	*0.100*	**0.490***	*0.048*	*-0.062*
FamiliyIssues	*-0.189**	*0.130**	*0.064*	*0.050*	*0.178**	*-0.008*	**0.651***	*0.044*
WorkplaceIssues	*-0.076*	*0.011*	*0.028*	*-0.010*	*0.166**	*0.026*	**0.770***	*-0.014*
LackTime	*0.064*	*-0.051*	*-0.141**	*0.000*	*0.007*	*0.320**	**0.567***	*-0.090*
TooManyInterruptionsDuringStudy	*-0.018*	*0.061*	*0.084*	*-0.014*	*-0.072*	*0.140**	**0.614***	*0.171**
LackAdequateInternet	*-0.035*	*0.004*	*0.020*	*0.105*	*0.021*	*0.037*	*0.075*	**0.555***
LackTechnicalAssitance	*0.227**	*0.115*	*0.022*	*0.083*	*0.092*	*-0.98**	*0.128**	**0.695***
TechProblemsPC	*0.042*	*-0.052*	*-0.058*	*-0,009*	*0.084*	*0.044*	*0.006*	**0.567***
TechProblemsSite	*0.006*	*0.263**	*0.045*	*-0.017*	*0.044*	*-0.073*	*0.012*	**0.614***

*statistically significant at 5% level
Note 1: Grey italic numbers represent items with factor loadings < .40.
Note 2: Bold numbers represent items with factor loadings > .40 onto their target factor.

In addition to a well fitted factor structure, we also assessed the internal consistency of these factors. It is suggested that when developing a research instrument a Cronbach's alpha of >.70 is perceived as acceptable, >.80 is good and > .90 is excellent (Taber, 2018). The Cronbach's alpha coefficients presented in Table 3 indicates that the internal consistency of the majority of the factors is good when taking the aforementioned indicators into account. Furthermore, as the main goal was to develop an instrument to measure barriers to learning in MOOCs, the model should make practical sense in addition to a good scientific fit. Therefore, the items per category were assessed for their descriptiveness and representation of a particular category of MOOC barriers and labelled accordingly (see Table 3).

Table 3. Factor labels and internal consistency value per factor

	# items	Label	α
Factor 1	5	Instructor related barriers	.87
Factor 2	4	Content related barriers	.87
Factor 3	6	Social context barriers	.82
Factor 4	5	General skills related barriers	.87
Factor 5	4	Technical skills related barriers	.87
Factor 6	3	Motivation related barriers	.77
Factor 7	4	Situational barriers	.80
Factor 8	4	IT related barriers	.86

Confirmatory Factor Analyses

As the EFA analysis resulted in a well fitted model with 8 factors, a next step was to test if this model would hold in the more restrictive form of factor structure based on a CFA. In the CFA, items will only load on their target factors (i.e., categories), thus all cross-loadings are fixed to zero. The CFA was performed allocating the 35 remaining barriers (i.e., items) to the respective factors to confirm the 8-factor solution. Table 4 displays the fit indices values for this model.

The absolute fit indices Chi-square test of model fit (X2), RMSEA and the SRMR, indicate how well a proposed model fits the data and generally provide the best indication of model fit (Hooper, Coughlan & Mullen, 2008). Table 4 reveals that, based on these indices, the model did not achieve a good fit. The X2 and the SRMR both show poor fits, while the RMSEA merely indicates a mediocre fit (Hu & Bentler, 1999). In addition, the incremental fit indices, CFI and TLI also indicate a poor model fit as their values are well below the minimum of .90 for good fit (Hu & Bentler, 1999). The lack of goodness of fit of the CFA model indicates that it is an overly restrictive model and that EFA is the more appropriate analytic approach to model the barrier items. This is in line with the expected complex structure corresponding to the categories of barriers.

Table 4. Fit values for the 8-factor model (n = 445)

		Fit indices	criteria
Test			
Chi-Square Test of Model Fit			
	Value	3455.496	
	degrees of freedom	717	
	p-value	.000	
RMSEA			
	Estimate	0.090	[.00, .06) = good fit
	90% C.I.	0.090-0.096	[.06, .08) = acceptable fit [.08, .10) = mediocre fit
	probability RMSEA <= .05	.000	
CFI/TLI			
	CFI		
	TLI		
Standardized/weighted Root Mean Square Residual			
	Value	0.141	should be <.08 for good fit

Discussion

The aim of this study was to develop a self-report instrument to capture barriers to learning as experienced by learners in MOOCs and to examine the validity of this new instrument. Firstly, a list of barrier overview was created in order to develop an instrument with diagnostic categories. Assessment and reassessment of the data using EFA analysis provided a very good model fit for the 8-factor structure. In addition, the interpretation of the items per factor revealed that the internal coherence per category was very large. This was confirmed by the high Cronbach's alpha values for the majority of the factors. Comparing the 8 factor structure to the earlier found 4-component classification (Henderikx, Kreijns & Kalz, 2018), revealed great content similarity between the two structures. Yet, the 8-factor presents finer specified diagnostic categories and can thus be regarded as an improved model. Previous category 1, which contained technical and online learning related skill barriers is roughly represented by the new categories 4 (general skills related barriers) and 5 (technical skills related barriers). Previous category 2, which consisted of barriers related to social context is represented by the new category 3 (social context) of the new model. These two categories are similar for the most part, indicating that specifically this set of items is very coherent. Previous category 3, which included course related barriers is represented by the new categories 1 (instructor related barriers) and 2 (content related barriers). Lastly, previous category 4, which contained time, support and motivation related barriers is represented by the new categories 6 (motivation related barriers) and 7 (situational barriers) of the new model. The new category 8, which consists of IT related barriers is not reflected in the previous categories, as three of the four items in this new category were dropped from the component analysis due to loading issues. Overall, the measuring structure of the instrument seems of good quality and corresponds well with the expectations that guided the construction of the instrument.

The considerable similarities between the structures of the two separate studies using different methodologies which were each conducted using completely different samples seemed a promising indication that a more rigid test, like CFA, would present a good model fit. This was however not the case as the fit values were predominantly in favour of rejecting the model. One could argue that the significant X^2, which indicates that the model should be rejected, can be attributed to the larger sample size (>200) (Hooper et al., 2008), yet the sample size independent fit indices also showed poor fit, which indicates that the model should be improved. A generally applied method to improve fit is to interpret the modification indices and make justifications accordingly. Though, this is not recommended when developing a new instrument which is tested for validation the first time (Prudon, 2014) and is thus not an option in this case. Based on this information it should thus be concluded that, although the self-report instrument we developed showed strong consistent diagnostic categories, we were not able to validate it as yet.

Nevertheless, there are some developments regarding the reliability of the commonly reported goodness of fit indices (RMSEA, SRMR, CFI and TLI) and its corresponding cut off values that should be taken into consideration (Jackson, Gillaspy & Purc-Stephenson, 2009; McNeish, An & Hancock, 2018; Prudon, 2014). Especially since the instrument has a good measuring structure that corresponds to the ideas that steered the construction which is typically regarded as clear support for the construct validity of the instrument (Prudon, 2014).

A majority of studies in which latent variable models are evaluated use cut off values as recommended by Hu and Bentler (1999) - current study included - despite the advice by Hu and Bentler themselves to be careful for overgeneralizing their findings outside the simulated context (Jackson et al., 2009). Over the last decade multiple studies demonstrated that the commonly applied fit indices are very sensitive to measurement quality (Cole & Preacher, 2014; Kang, McNeish & Hancock, 2016); measurement quality refers to 'the strength of the standardized factor loadings, which is highly related to reliability' (McNeish et al., 2018, p 44). This is the result of a lack of multiple measurement quality conditions in the simulation study by Hu & Bentler (1999) who's cut off values are widely applied. As a result, models with poor measurement quality (i.e. many standardized factor loadings of .4) seem to fit better when assessing the cut off values for the commonly used fit indices, than models with excellent measurement quality (i.e. many standardized factor loadings of .9) (McNeish et al., 2018). Hancock and Mueller (2011) referred to this as the reliability paradox. In addition, it has been suggested that instruments that have a complex structure such as a high number of factors often struggle with CFA analysis (Schmitt et al, 2018). Less restrictive analysis methods, like EFA are therefore the recommended approach for analysing complex data. When examining the standardized factor loadings of the current study, which are mainly between .6 and .8 and can be regarded as good quality loadings (McNeish et al., 2018), in combination with the descriptiveness and coherence of the factors, and the excellent fit indices of the EFA analysis, it seems reasonable to question the reliability of the goodness of fit results of the CFA and thus the earlier dismissal of the model.

There are some limitations that should be taken into account. Firstly, although the sample size is generally considered as good to very good and the item ratio of 1:10 is considered acceptable (Comrey & Lee, 1992), an item ratio of 1:20 generally provides the most stable results (Osborne& Costello, 2008). Future studies are recommended to increase sample size and thus increase item ratio to further refine and validate the instrument. In addition, we did not take age or gender into consideration when analysing the results. It might be interesting to investigate whether gender and age affect the structure of the instrument as it is known that gender as well as age can influence factor structures (Barnett, Hickling & Sheppard, 2018; Drake & Egan, 2017; Idrees Hafeez & Kim, 2017; Urushihata, Kinugasa, Soma & Miyoshi, 2010). Also, the moment of targeting the potential respondents, namely at a random point in time opposed to immediately after finishing a MOOC, might have influenced the reliability of their responses. We had no knowledge of how recent they participated in a MOOC at the moment of the survey and thus how far back they had to go in their memory to recollect their experience with barriers. Further studies should attempt to collect barrier data immediately at the end of a MOOC when barriers experiences are still fresh. Lastly, the majority of the participants came from a western culture, as a result future cross-cultural studies are needed to address the lack of cultural diversity in the current sample.

In conclusion, this newly developed self-report instrument for measuring barriers to learning in MOOCs showed promising results. The categories (factor structure) were further refined, with very acceptable factor loadings and a high internal consistency per factor, which points towards a good construct validity. Depending on how much value is attributed to the cut off values of the commonly used fit indices, the instrument can, in its current form, very well be utilized as a diagnostic tool by MOOC-providers and designers to gather information that will benefit further development of MOOCs and subsequently, support learners in achieving their personal learning goals.

References

Adamopoulos, P. (2013). What Makes a Great MOOC? An Interdisciplinary Analysis of Student Retention in Online Courses. *In 34th International Conference on Information Systems: ICIS 2013*. United States: Association for Information Systems.

Algarni, A., & Burd, L. (2015, October). Perceptions of students and instructors toward the role of CommEasy in tackling communication and interaction barriers in distance- learning classrooms. *In Frontiers in Education Conference (FIE), 2015 IEEE* (pp. 1-7). doi 10.1109/FIE.2015.7344130

Angelino, L. M., Williams, F. K., & Natvig, D. (2007). Strategies to engage online students and reduce attrition rates. *Journal of Educators Online*, 4(2), n2.

Aragon, S. R., & Johnson, E. S. (2008). Factors influencing completion and noncompletion of community college online courses. *The American. Journal of Distance Education,* 22(3), 146-158.

Balfour, S. P. (2013). Assessing Writing in MOOCs: Automated Essay Scoring and Calibrated Peer Review. *Research & Practice in Assessment*, 8, 40-48.

Barnett, S. D., Hickling, E. J., & Sheppard, S. (2018). The impact of gender on the factor structure of PTSD symptoms among active duty United States military personnel. *European Journal of Trauma & Dissociation*, 2(3), 117-124.

Belanger, Y., & Thornton, J. (2013). Bioelectricity: A quantitative approach. Durham, NC. Retrieved from http://dukespace.lib.duke.edu/dspace/bitstream/handle/10161/6216/Duke_ Bioelectricity_ MOOC_Fall2012.pdf?sequence=1.

Bocchi, J., Eastman, J. K., & Swift, C. O. (2004). Retaining the online learner: Profile of students in an online MBA program and implications for teaching them. *Journal of Education for Business,* 79(4), 245–253.

Boyatt, R., Joy, M., Rocks, C., and Sinclair, J. (2013). What (Use) is a MOOC? In L.Uden, Y. Tao, H. Yang & I. Ting (Eds.)*, Springer proceedings in complexity: 2nd International Workshop on Learning Technology for Education in Cloud (pp 133- 145)*. doi: 10.1007/978-94-007-7308-0_15

Byrne, B. M. (2012). *Structural equation modeling with Mplus: Basic concepts applications,and programming*. New York: Routledge.

Carnevale, D. (2000). 'Boot camp' helps new online students at Boise State U. *The Chronicle of Higher Education*, 46(24), p. A48

Castles, J. (2004). Persistence and the adult learner: Factors affecting persistence in Open University students. *Active Learning in Higher Education*, 5(2), 166–179

Chyung, S. Y. (2001). Systematic and systemic approaches to reducing attrition rates in Online higher education. *American Journal of Distance Education*, 15(3), 36–49

Cole, D. A., & Preacher, K. J. (2014). Manifest variable path analysis: Potentially serious and misleading consequences due to uncorrected measurement error. *Psychological Methods*, 19, pp. 300- 315.

Comrey, A. L., & Lee, H. B. (2013). *A first course in factor analysis (2nd ed.).* Psychology Press

Conole, G. (2016). MOOCs as disruptive technologies: strategies for enhancing the learner experience and quality of MOOCs. *RED: Revista de Educacion a Distancia*, (50), 1-18.

Croft, N., Dalton, A., & Grant, M. (2010). Overcoming isolation in distance learning: Building a learning community through time and space. *Journal for Education in the Built Environment*, 5(1), 27-64.

Dabaj, F. & Yetkin, A. (2011). Analysis of communication barriers to distance education: review study. *Online Journal of Communication and Media Technologies*, 1(1), pp. 1-15

Drake, K. E., & Egan, V. (2017). Investigating gender differences in the factor structure of the Gudjonsson Compliance Scale. *Legal and Criminological Psychology*, 22(1), 88-98.

Duffy, M. C., Lajoie, S. P., Pekrun, R., & Lachapelle, K. (2018). Emotions in medical education: Examining the validity of the Medical Emotion Scale (MES) across authentic medical learning environments. *Learning and Instruction*. doi 10.1016/j.learninstruc.2018.07.001

Dupin-Bryant, P. (2004). Pre-entry variables related to retention in online distance education. *American Journal of Distance Education*, 18(4), 199–206

Fan, X., Thompson, B., & Wang, L. (1999). Effects of sample size, estimation methods, and model specification on structural equation modeling fit indexes. *Structural Equation Modeling: A Multidisciplinary Journal*, 6(1), 56-83.

Gamage, D., Fernando, S., & Perera, I. (2015, August). Quality of MOOCs: A review of literature on effectiveness and quality aspects. *In Ubi-Media Computing (UMEDIA), 2015 8th International Conference* (pp. 224-229). IEEE.

Greene, J. A., Oswald, C. A., & Pomerantz, J. (2015). Predictors of Retention and Achievement in a Massive Open Online Course. *American Educational Research Journal*, 52(5), 925–955. doi:10.3102/0002831215584621

Grover, S., Franz, P., Schneider, E., & Pea, R. (2013, June). The MOOC as distributed intelligence: Dimensions of a framework & evaluation of MOOCs. *In Proceedings CSCL*, Vol. 2, pp. 42-5.

Hancock, G. R., & Mueller, R. O. (2001). Rethinking construct reliability within latent variable systems. In R. Cudeck, S. du Toit, & D. Sörbom (Eds.), *Structural equation modeling: Present and future—A festschrift in honor of Karl Jöreskog* (pp. 195–216). Lincolnwood, IL: Scientific Software International.

Hara, N., & Kling, R. (2001). Student distress in web-based distance education. *Educause Quarterly*, 3, 68-69

Hartnett, M., George, A. S., & Dron, J. (2011). Examining motivation in online distance learning environments: Complex, multifaceted and situation-dependent. *The International Review of Research in Open and Distributed Learning*, 12(6), 20-38.

Hastie, T., Tibshirani, R., & Friedman, J. (2009). *The elements of statistical learning: Data mining, inference, and prediction*. New York, NY: Springer

Hayduk, L. A. (2014b). Shame for disrespecting evidence: The personal consequences of insufficient respect for structural equation model testing. *BMC Medical Research Methodology,* 14, 124. doi:10.1186/1471- 2288-14-124

Henderikx, M. A., Kreijns, K., & Kalz, M. (2017). Refining success and dropout in Massive open online courses based on the intention–behaviour gap. *Distance Education*, 38(3), 353–368. doi:10.1080/ 01587919.2017.1369006

Henderikx M., Kreijns K., & Kalz M. (2018). A classification of barriers that influence intention achievement in MOOCs. In V. Pammer-Schindler, M. Pérez-Sanagustín, H. Drachsler, R. Elferink, & M. Scheffel (Eds.), *Lifelong technology-enhanced learning. EC-TEL 2018. LNCS*, vol. 11082 (pp. 3–15). doi:10.1007/978-3-319- 98572-5_1

Heung, L. L. W., & Kan, A. C. N. (2002). Evaluation of factors related to student performance in a distance-learning business communication course. *Journal of Education for Business*, 77(5), 257.

Hew, K. F. (2016). Promoting engagement in online courses: What strategies can we learn from three highly rated MOOCS. *British Journal of Educational Technology*, 47(2), 320-341.

Ho, A. D., Reich, J., Nesterko, S., Seaton, D. T., Mullaney, T., Waldo, J., & Chuang, I. (2014). HarvardX and MITx: The first year of open online courses. HarvardX Working Paper No. 1. Retrieved from http://harvardx.harvard.edu/multiple-course- report

Hone, K. S., & El Said, G. R. (2016). Exploring the factors affecting MOOC retention: A survey study. *Computers & Education*, 98, 157-168.

Hooper, D., Coughlan, J., & Mullen, M. (2008). Structural equation modelling: Guidelines For determining model fit. *Articles*, 2.

Hu, L., & Bentler, P. M. (1999). Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. *Structural Equation Modeling: A Multidisciplinary Journal*, 6(1), 1-55.

Idrees, M., Hafeez, M., & Kim, J. Y. (2017). Workers' age and the impact of psychological factors on the perception of safety at construction sites. *Sustainability*, 9(5), 745.

Ivankova, N. V., & Stick, S. L. (2007). Students' persistence in a distributed doctoral Program in educational leadership in higher education: A mixed methods study. *Research in Higher Education*, 48(1), 93–135.

Jackson, D. L., Gillaspy Jr, J. A., & Purc-Stephenson, R. (2009). Reporting practices in confirmatory factor analysis: An overview and some recommendations. *Psychological methods,* 14(1), 6.

Kang, Y., McNeish, D.M., & Hancock, G. R. (2016). The role of measurement quality on practical guidelines for assessing measurement and structural invariance. *Educational and Psychological Measurement*, 76, 533-561.

Kemp, W. C. (2002). Persistence of adult learners in distance education. *American Journal Of Distance Education,* 16(2), 65.

Kenny, D. A., Kaniskan, B., & McCoach, D. B. (2015). The performance of RMSEA in models with small degrees of freedom. *Sociological Methods & Research*, 44(3), 486-507.

Khalil, H. & Ebner, M. (2013). Interaction Possibilities in MOOCs – How Do They Actually Happen?. *International Conference on Higher Education Development* (pp. 1-24). Mansoura University, Egypt.

Khalil, H., & Ebner, M. (2014). MOOCs Completion Rates and Possible Methods to Improve Retention - A Literature Review. *In World Conference on Educational Multimedia, Hypermedia and Telecommunications* (pp. 1236–1244). Chesapeak, VA: AACE.

Levy, D., & Schrire, S. (2012). The case of a massive open online course at a college of education. Retrieved from http://conference.nmc.org/files/smkbMOOC.pdf

Mackness, J., Mak, S., Williams, R. (2010). The Ideas and Reality of Participating in a MOOC, Networked Learning Conference

Marsh, H. W., Balla, J. R., & McDonald, R. P. (1988). Goodness-of-fit indexes in confirmatory factor analysis: The effect of sample size. *Psychological Bulletin*, 103(3), 391-410.

Marsh, H. W., Hau, K. T., & Grayson, D. A. (2005). Goodness of fit evaluation in structural equation modeling. In A. Maydeu-Olivares & J. J. McArdle (Eds.), *Contemporary psychometrics. A festschrift to Roderick P. McDonald* (pp. 225- 340). Mahwah, NJ: Lawrence Erlbaum Associates, Inc.

Marsh, H. W., Hau, K. T., & Wen, Z. (2004). In search of golden rules: Comment on hypothesis-testing approaches to setting cutoff values for fit indexes and dangers in overgeneralizing Hu and Bentler's (1999) Findings. *Structural Equation Modeling: A Multidisciplinary Journal,* 11(3), 320-341.

Martinez, M. (2003, July 14). High attrition rate in e-learning: Challenges, predictors, and solutions. *The eLearning Developers Journal*, 1-7

McAuley, A., Stewart, B., Siemens, G., & Cormier, D. (2010). The MOOC model for Digital practice. Retrieved from https://oerknowledgecloud.org/sites/oerknow ledgecloud.org/files/MOOC_Final.pdf

McNeish, D., An, J., & Hancock, G. R. (2018). The thorny relation between measurement quality and fit index cutoffs in latent variable models. *Journal of personality assessment*, 100(1), 43-52.

Missopoulos, F., Argyropoulou, M., & Tzavara, D. (2018). Exploring the factors affecting student academic performance in online programs: a literature review. In A. Khare & D. Hurst (Eds.), *On the line* (pp. 235-249). doi 10.1007/978-3-319-62776-2_18

Moody, J. (2004). Distance education: Why are the attrition rates so high? *The Quarterly Review of Distance Education*, 5(3)

Morris, L. V., Wu, S., & Finnegan, C. L. (2005). Predicting retention in online general education courses. *American Journal of Distance Education*, 19(1), 23–36

Muilenburg, L. Y., & Berge, Z. L. (2005). Student barriers to online learning: A factor analytic study. *Distance Education*, 26(1), 29–48. doi:10.1080/01587910500081269

Musingafi, M. C., Mapuranga, B., Chiwanza, K., & Zebron, S. (2015). Challenges for Open and Distance Learning (ODL) Students: Experiences from Students of the Zimbabwe Open University. *Journal of Education and Practice*, 6(18), 59-66.

Muthén, L.K. & Muthén, B.O. (1998-2014). *MPlus user's guide (8th ed.).* Los Angeles, CA: Muthén & Muthén.

Nash, R. (2005, Winter). Course completion rates among distance learners: Identifying possible methods to improve retention. *Online Journal of Distance Learning Administration*, 8(4)

Osborn, V. (2001). Identifying at-risk students in videoconferencing and web-based distance education. *American Journal of Distance Education*, 15(1), 41–54.

Osborne, J. W., Costello, A. B., & Kellow, J. T. (2008). Best practices in exploratory factor analysis. *Best practices in quantitative methods*, 86-99.

Packham, G., Jones, P., Miller, C., & Thomas, B. (2004). E-learning and retention: Key factors influencing student withdrawal. *Education Training*, 46(6/7), 335–342.

Parker, A. (2003). Identifying predictors of academic persistence in distance education. *United States Distance Learning Association Journal*, 17(1), 55–61.

Perry, B., Boman, J., Care, W. D., Edwards, M., & Park, C. (2008). Why do students withdraw from online graduate nursing and health studies education? *Journal of Educators Online*, 5(1), 1–17.

Pierrakeas, C., Xenos, M., Panagiotakopoulos, C., & Vergidis, D. (2004). A comparative study of dropout rates and causes for two different distance education courses. *International Review of Research in Open and Distance Learning*, 5(2), 1–13.

Pigliapoco, E., & Bogliolo, A. (2008). The effects of psychological sense of community in online and face-to-face academic courses. *International Journal of Emerging Technologies in Learning*, 3 (4), 60–69.

Poellhuber, B., Chomienne, M., & Karsenti, T. (2008). The effect of peer collaboration and collaborative learning on self-efficacy and persistence in a learner-paced continuous intake model. *Journal of Distance Education*, 22(3), 41–62

Preacher, K. J., Zhang, G., Kim, C., & Mels, G. (2013). Choosing the optimal number of factors in exploratory factor analysis: A model selection perspective. *Multivariate Behavioural Research*, 48, 28–56. doi:10.1080/ 00273171.2012.710386

Prudon, P. (2014). Confirmatory factor analysis: a brief introduction and critique.Tilgængelig på.

Reich, J., Nesterko, S., Seaton, DT, Mullaney, T., Waldo, J., & Chuang, I.(2014). HarvardX and MITx: The first year of open online courses (HarvardX and MITx Working Paper No. 1).

Reich, J., & Ruipérez-Valiente, J. A. (2019). The MOOC pivot. *Science*, 363(6423), 130- 131. doi: 10.1126/science.aav7958

Rhemtulla, M., Brosseau-Liard, P. E., & Savalei, V. (2012). When can categorical variables be treated as continuous? A comparison of robust continuous and categorical SEM estimation methods under suboptimal conditions. *Psychological methods*, 17(3), 354-373. doi 10.1037/a0029315

Saleh, A., & Bista, K. (2017). Examining factors impacting online survey response rates in educational research: Perceptions of graduate students. *Journal of MultiDisciplinary Evaluation*, 13(29), 63-74.

Shapiro, H. B., Lee, C. H., Roth, N. E. W., Li, K., Çetinkaya-Rundel, M., & Canelas, D. A. (2017). Understanding the massive open online course (MOOC) student experience: An examination of attitudes, motivations, and barriers. *Computers & Education*, 110, 35-50.

Schmitt, T. A. (2011). Current methodological considerations in exploratory and confirmatory factor analysis. *Journal of Psychoeducational Assessment*, 29, 304– 321. doi:10.1177/0734282911406653

Schmitt, T. A., Sass, D. A., Chappelle, W., & Thompson, W. (2018). Selecting the best factor structure and moving measurement validation forward: An illustration. *Journal of personality assessment*, 100(4), 345-362. doi 10.1080/00223891.2018.1449116

Taber, K. S. (2018). The use of Cronbach's alpha when developing and reporting research instruments in science education. *Research in Science Education*, 48(6), 1273- 1296.

Tello, S. F. (2007). An analysis of student persistence in online education. International *Journal of Information and Communication Technology Education*, 3(3), 47–62.

Treiblmaier, H., & Filzmoser, P. (2011). Benefits from using continuous rating scales in online survey research. DOI: 10.13140/RG.2.1.2899.6643

Truong, Y., & McColl, R. (2011). Intrinsic motivations, self-esteem, and luxury goods consumption. *Journal of Retailing and Consumer Services*, 18(6), 555-561.

Urushihata, T., Kinugasa, T., Soma, Y., & Miyoshi, H. (2010). Aging effects on the structure underlying balance abilities tests. *Journal of the Japanese Physical Therapy Association*, 13(1), 1-8.

Wojciechowski, A., & Palmer, L. B. (2005). Individual student characteristics: Can any be predictors of success in online classes? *Online Journal of Distance Learning Administration*, 8(2)

Yu, C.-Y. (2002). Evaluating cutoff criteria of model fit indices for latent variable models with binary and continuous outcomes. University of California: Los Angeles,

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Chapter 8

Factors influencing the pursuit of personal learning goals in MOOCs

This chapter is based on:
Henderikx, M., Kreijns, K., Castaño Muñoz, J., & Kalz, M. (2019). Factors influencing the pursuit of personal learning goals in MOOCs. *Distance Education*, 40(2). doi 10.1080/01587919.2019.1600364

Abstract

MOOCs are promising opportunities for lifelong learning, as they are accessible to everyone and cover an ever-expanding range of topics and interests. But as promising as these learning opportunities seem, many learners do not succeed in pursuing their personal learning goals. Barriers to learning are the main reason for not finishing the intended (parts of the) MOOCs. The research question addressed in this paper is whether factors can be identified that affect barriers faced while learning in MOOCs. In particular, age, gender, educational level, and online learning experience were the factors investigated. The results show that it is challenging to combine work and family life with lifelong (online) learning activities, especially for learners in their early adulthood (20–35 years) and mid-life (36–50 years). However, more experience with online learning positively affects individuals' ability to cope with these challenges. Also, learners with a lower educational level more often experience a lack of knowledge or difficulties with the course content in comparison with learners who are more academically educated. These findings may serve as input to inform potentially vulnerable learners about these issues and support them in successfully achieving their personal learning goals.

Introduction

The possibility of learning online adds flexibility to opportunities for lifelong learning. MOOCs are particularly suitable for this purpose, as they are accessible to everyone and cover an ever-expanding range of topics and interests (Greene, Oswald, & Pomerantz, 2015; Misopoulos, Argyropoulou, & Tzavara, 2018). But as promising as these learning opportunities seem, many learners do not succeed in pursuing their personal learning goals (Henderikx, Kreijns, & Kalz, 2017a) and do not finish the intended (parts of the) MOOC they started. These learners are considered unsuccessful learners or dropouts and generally determine the overall assessment of course success.

As student achievement is often used as an evaluation measurement for online course success or even quality (Lim, Yoon, & Morris, 2006), research investigated which factors predict course outcomes. Scholars have studied whether factors like learner characteristics, learning skills, and learning experience influence academic achievement (Hattie, 2008). Yet, while progressing through a course, learners may come across barriers that hinder, or even prevent, them from reaching their personal learning goals. These goals do not necessarily equal achievement in the traditional sense of finishing the course, but may comprise any individual goal a learner may have, e.g. finishing the first three modules, following the whole course without taking the tests, or getting a certificate (Henderikx, Kreijns, & Kalz, 2017a). Research on barriers to MOOC learning illustrates that most learners face barriers to a greater or lesser extent (Henderikx, Kreijns, & Kalz, 2018; Khalil & Ebner, 2014), and that some of them are easier to overcome or are less interruptive to the learning process than others (Henderikx, Kreijns, & Kalz, 2017b). Besides the fact that these barriers may affect personal achievement, they may also affect the general learning experience or satisfaction, as well as the perceived difficulty of achieving personal goals and may, therefore, influence future decisions about participation in MOOCs. In this study, we thus focus on barriers to MOOC- based learning as an outcome variable. More specifically, we focus on age, gender, educational level and previous online learning experience and their predictive power for the experience of (specific) barriers (Figure 1). Consequently, the research question posed in the current study is: Do learner characteristics (age, gender, educational level, and online learning experience) affect the experience of (specific) barriers in Massive Open Online Courses?

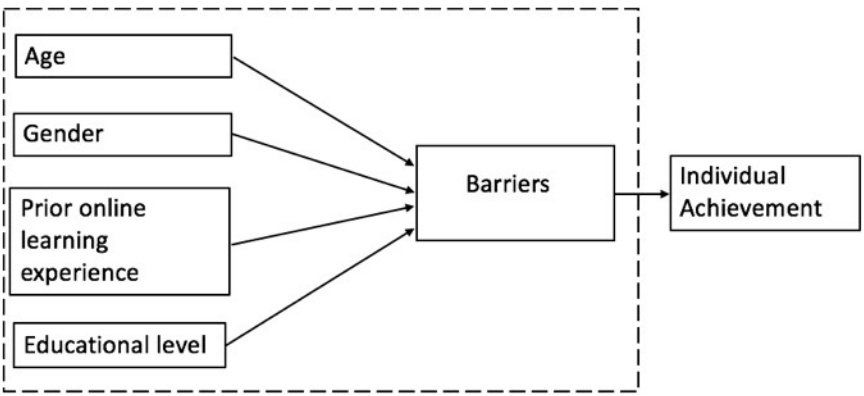

Figure 1. Research model illustrating the focus of the study.

Chapter 8

As no prior research can be found that investigates possible determinants that predict coming across barriers when learning in MOOCs or, more generally, barriers to online learning, the aim of this paper is to further untangle the online learning process by exploring whether certain variables do indeed affect the experience of barriers while learning in MOOCs. First a short overview of literature on barriers to MOOC-learning is given, as well as our hypotheses, which introduce barriers to learning as an independent variable opposed to academic achievement. Next, we introduce variables extracted from the literature as potential determinants, such as age, gender, educational level and prior online learning experience in combination with academic achievement. This is followed by an overview of the methodology and the results. Lastly, the results are discussed, as well as limitations and avenues for future research.

Barriers to MOOC-Learning

Online learning with MOOCs is not without challenges (Misopoulos et al., 2018). Learners do not always succeed in pursuing their personal learning goals due to various reasons, which we summarise under the construct of barriers. Barriers can be defined as obstacles that prevent or hinder learners from reaching their personal learning goals and can be either MOOC-related or non-MOOC related (Henderikx et al., 2017b; 2018). A non-exhaustive literature search, inspired by PRISMA (Moher, Liberati, Tetzlaff, & Altman, 2009), on barriers to online learning identified many different obstacles including 'lack of reading', 'typing and writing skills' (Muilenburg & Berge, 2005), 'technical problems with the computer' (Song, Singleton, Hill, & Koh, 2004), 'feelings of isolation' (Khalil & Ebner, 2014) and 'family issues' (Park & Choi, 2009). The barriers mentioned most often in the literature were 'lack of interaction' (Khalil & Ebner, 2013; Levy & Schrire, 2012; McAuley, Stewart, Siemens, & Cormier, 2010;), 'lack of time' (Aragon & Johnson, 2008; Belanger & Thornton, 2013; Khalil & Ebner, 2014; Onah, Sinclair, & Boyatt, 2014) and 'insufficient academic background' (Belanger & Thornton, 2013; Mackness, Mak, & Williams, 2010; Park & Choi, 2009). Other barriers experienced by students are: 'family and workplace issues' and 'lack of support from family and friends or the workplace' (Park & Choi, 2009), 'insufficient technology background' (Khalil & Ebner, 2014), 'computer and/or internet issues' (Aragon & Johnson, 2008; Song et al., 2004) and 'lack of instructor presence' (Onah, et al., 2014; Aragon & Johnson, 2008) are also often reported as obstacles to online learning. Furthermore, a recent empirical study on barriers to learning in MOOCs by Henderikx et al. (2018) found that 'own responsibility for learning', 'lack of time', 'bad course content', 'lack of motivation', 'low quality of instruction and/or materials' and 'family issues' were most often considered as barriers in this type of course. In the current study, we focussed on the number of barriers learners faced while learning in MOOCs in general, as well as on several specific barriers.

Empirical Research on Predictors of Academic Achievement in Online Learning Contexts

Age.

The relationship between various learner characteristics and online course outcomes has often been studied. A study by Breslow, Pritchard, DeBoer, Stump, Ho, and Seaton (2013) on gaining insight into predictors of student achievement in EdX's first MOOC found no significant relationship between age and student success. Greene et al. (2015) investigated which factors were likelihood predictors of student achievement and retention in MOOCs. Similar to the study by Breslow et al. (2013), age proved not to be a significant predictor of student success. In addition, Park and Choi (2009), who studied factors influencing online learning success, also found that age was not significantly predictive of achievement. These findings all indicate that age is not related to online student achievement or satisfaction.

However, because we do not look at achievement but concentrate on barriers that hinder or prevent personal achievement, we expect that age does make a difference with regards to certain barriers—especially related to barriers that belong to a specific age range. Life stages theory identifies various stages in which individuals can generally be categorised. These stages are: late adolescence (16–20 years), early adulthood (20–35 years), mid-life (36–50 years) and mature adulthood (50–80 years) (Armstrong, 2007; Stoffelsen & Diehl, 2007). The theory argues that at each stage in life, different demands are made on individuals regarding education, work, family and personal development, which makes certain age groups more prone to facing barriers then other age groups. Even though it is true that individuals of the same chronological age do not necessarily find themselves in the same life stage (Kooij, De Lange, Jansen, Kanfer, & Dikkers, 2011), it is most likely that individuals in the ages between 20–35 and 36–50 years (adulthood and mid-life) will experience the highest demands regarding career development and starting and running a family (Armstrong, 2007; Stoffelsen & Diehl, 2007). Therefore, we hypothesise that MOOC learners in these age categories are most likely to face a greater number of barriers in general and are also most likely to experience barriers specifically related to work and family, such as 'family issues' and 'workplace issues'.

Hypothesis 1a: Learners in the age categories of 20–35 and 36–50 years face a greater number of barriers while learning in MOOCs than learners in other age categories.

Hypothesis 1b: Learners in the age categories of 20–35 and 36–50 years more often experience barriers related to work and family than learners in other age categories.

Gender.

Research on gender as a predictor of online course success showed similar results as research on age as a predictor. The aforementioned studies by Breslow et al. (2013), Greene et al. (2015) and Park and Choi (2009) established that there is no significant difference between male or female learners with regards to study success. Furthermore, Marks, Sibley, and Arbaugh's (2005) empirical evaluation of potential predictors of effective online learning found no relation between gender and perceived effectiveness of learning. These findings indicate that gender is not a predictor of online course success.

Nevertheless, our aim is to investigate a possible relation between gender and barriers to MOOC learning, as opposed to individual achievement. Generally, women spend more time doing household work and daily child care than men, despite an increase in these women's paid working hours (Bitmann, England, Sayer, Folbre, & Matheson, 2003; Sayer, 2005; Yavorksi, Kamp Dush, & Schoppe-Sullivan, 2015). For this reason, we hypothesise that gender is related to experiencing barriers. More specifically, we expect that female MOOC- learners experience a greater number of barriers than male MOOC-learners. Also, we expect that female MOOC-learners more often face barriers related to work-life balance dimensions like 'family issues', workplace issues' and 'lack of time'.

Hypothesis 2a: Female learners experience a greater number of barriers while learning in MOOCs than men.

Hypothesis 2b: Female learners more often face barriers related to work and family than men.

Educational level.
A further characteristic frequently studied in relation to course outcome is educational level. Yukselturk and Bulut (2007) empirically evaluated predictors of student success in an online course and found no relation between prior education and student success. Further studies by Wang, Shannon and Ross (2013) and Park and Choi (2009) that examined the relationship between student characteristics and online course success did not find educational levels to be a significant predictor of course outcomes. Likewise, the study about predictors of achievement in MOOCs by Greene et al. (2015) and the study on the relationship between educational level and student success in a MOOC by Goldberg et al. (2015) established once again that level of education was not predictive of student achievement. However, a contradicting result was found by Breslow et al. (2013), whose findings showed a 'marginal relationship between highest degree earned and achievement' (p. 20).

The previously-discussed research, for the most part, found no significant relation between educational level and course outcome. However, 'insufficient academic background' is one of the barriers most often experienced by learners (Belanger & Thornton, 2013; Mackness, Mak, & Williams, 2010; Park & Choi, 2009). Academic background knowledge is generally acquired at educational institutions, and we can expect that higher educational levels indicate more academic knowledge. Therefore, we hypothesise that learners with a higher educational level are less likely to experience the barrier 'insufficient academic knowledge'. In addition, we expect that learners with lower educational levels are more likely to experience the barrier 'course content too hard'.

Hypothesis 3a: Learners who have a higher educational level less often experience the barrier ‘insufficient academic knowledge’ than learners who have a medium or low educational level.

Hypothesis 3b: Learners who have a lower educational level more often experience the barrier ‘course content too hard’ than learners who have a medium or high educational level.

Prior online learning experience.
Lastly, various studies on the relation between prior online learning experience and student performance showed uniform results. Marks et al. (2005) and Yukselturk and Bulut (2007) found no statistical significance for prior online learning experience as a predictor of student achievement in an online learning environment. In addition, Green et al. (2015), who studied predictors of achievement MOOC-learning context, determined that prior online learning experience was not predictive of study success in MOOCs. However, Wang et al. (2013) examined which student characteristics and skills were significantly related to course outcomes in online learning. Their findings indicated that previous online learning experience was positively and significantly related to learning strategies, which meant that students with more online learning experience used more effective learning strategies. Furthermore, the use of learning strategies was also positively and significantly related to time management. Time management, in turn, was found to be a crucial element of successful online learning (Morris, Finnigan, & Wu, 2005; Song et al., 2004).

Thus, taking these findings into account, we reason that learners with more previous MOOC learning experience are more skilled at managing their time. We therefore expect that prior online learning experience is negatively related to experiencing the barrier ‘lack of time’.

Hypothesis 4: Learners who have more prior online learning experience are less likely to face the barrier ‘lack of time’.

Overview of this study.

The focus of this study was to explore several determinants and their relation to experiencing barriers while learning in MOOCs. These determinants were derived from research on predictors of academic achievement in online learning contexts and were then related to barriers. The literature overview generally revealed no significant predictive relation between the variables age, gender, educational level and previous online learning experience, and academic achievement. However, our aim was not to investigate the relation between these variables and achievement as it is traditionally the case, but to study a possible relation to the experience of (specific) barriers while learning in MOOCs. This is the first study to explore these determinants in relation to experiencing barriers that impede learning. As we consider MOOC-learning to be a valuable addition to the learning and development possibilities for individuals, we wanted to expand and deepen the current knowledge base by establishing the extent to which certain variables impact achievement in MOOCs. Our specific hypotheses regarding the predictive power of these determinants are outlined in Table 1.

Table 1. Overview of hypothesis

	Predictor for	
Variable	**Number of barriers**	**Specific barrier(s)**
Age	yes	yes
Gender	yes	yes
Educational level	-	yes
Previous online learning experience	-	yes

Method

Participants

Participants were individuals who took part in 18 MOOCs offered by the National Institute for Educational Technology and Teacher Education (INTEF) INTEF, a centre from the Spanish Ministry of Education. Participants were mainly teachers and educational professionals (see Castaño-Muñoz, Kalz, Kreijns, & Punie, 2018 for a full characterisation of the participants).

Sample 1, post survey data.

Hypotheses 1, 2 and 3 were tested using solely data from the post-course questionnaire which was completed by 1349 participants (858 women, 491 men, Mage = 42.8, age range: 18–82 years). A majority of 83.4% were of Spanish nationality. Participants from other European countries comprised 3% of the sample, while the remaining 13.6% of participants were from countries outside Europe. Most participants (73.1%) were employed for wages (mainly teachers) and 5.2% were self-employed. In addition, 7.5% of the participants were unemployed, of which 3.3% were not currently looking for work, 3.6% were students, 1% retired and the remaining 9.6% of participants indicated that they were homemakers or other.

Sample 2, matched pre-post survey data.

Data about past MOOC experience was only collected in the pre-course questionnaire. Thus, to test Hypothesis 4, pre- and post data was matched, resulting in a total of 96 participants (405 women, 191 men, M_{age} = 42,8, age range: 20–72 years). These participants showed a similar distribution regarding nationality and employment as the post-questionnaire data. The majority of the participants of the matched data were of Spanish nationality (81%). A further 6.1% of participants were from other European countries and the remaining 12.9% represented participants from non-European countries. The majority (70.8%) of the participants were employed for wages, while 5.4% were self-employed. A further 4.4% were currently looking for work and 3.4%

were not looking for work. Of the remaining participants, 4.5% were students, 1.2% were retired and 10.3% indicated that they were homemakers or other.

Materials and Procedure
Within the framework of the MOOC Knowledge project, a pre- and post-course survey was constructed, including several general questions on gender, age, educational background, employment status and online learning experience (Kalz, Kreijns, Walhout, Castaño-Munoz, Espasa, & Tovar, 2015). To indicate their online learning experience (OLE), participants were asked in the pre-survey to indicate how many MOOCs they had taken in the past. The post-survey contained a list of 19 barriers and the option to indicate that no barriers were experienced. The respondents were asked to indicate which barriers (if any) they experienced during their MOOC learning. They had the option to indicate multiple barriers.

These barriers were derived from a non-exhaustive, literature review on barriers to online learning in general and in MOOCs specific if available, including articles from 2004 until the present. Examples of the barriers listed include 'lack of decent feedback', 'family issues', lack of motivation' and 'technical problems with the computer'. All the individuals registered in a MOOC received an invitation in the first week to participate in the pre-questionnaire. At the end of the last week of the MOOCs, all registered MOOC-learners received an invitation to participate in the post-questionnaire. Participation was voluntary and informed consent was collected from participants.

Data Analysis
First of all, some variables were recoded into groups. Age was recoded into three groups—20–35 years, 36–50 years and 50+ years—to fit the life stages theory (Armstrong, 2007; Stoffelsen & Diehl, 2007). After matching the pre- and post-survey, there were no learners in the age group between 16–19 years to represent the late adolescence life stage. Educational level was recoded into the groups non-academic (low), bachelor's (medium) and master's+ (high).

Furthermore, we performed descriptive statistics and, depending on the type of data (nominal, ordinal, continuous and number of groups) and the hypothesis, we performed Kruskall-Wallis tests, chi-square tests of independence and a binary logistic regression to test the various hypotheses. As the data was predominantly nominal and ordinal, not normally distributed and included some small samples, non-parametric tests were conducted to test the hypotheses. The assumptions of random samples and independent observations were met. Furthermore, as we were performing multiple tests using the same data, we also included (where applicable) the Bonferroni corrected significance level (Rice, 1989) to prevent unnecessary Type I errors. Since there are no hard rules concerning the employment of the Bonferroni correction (Cabin & Mitchell, 2000), and to prevent discussion about the interpretability of the analysis, we report both the corrected and uncorrected Bonferroni significance level.

Results

Descriptive Statistics

An overview of the descriptive statistics can be found in Table 2. The average number of barriers experienced by MOOC-learners was 1.75. Lack of time, family issues and workplace issues were more often experienced barriers in comparison to insufficient academic knowledge and course content being too hard. Furthermore, the majority of the MOOC- learners were women between the ages of 26 and 50 years old. The educational level was, in most cases, medium to high, which represented bachelor's to doctorate level education. Lastly, the average number of MOOCs taken in the past, which represented the prior online learning experience, was 3.00. The educational level was, in most cases, medium to high, which represented bachelor's to doctorate level education. Lastly, the average number of MOOCs taken in the past, which represented the prior online learning experience, was 3.00.

Table 2. Descriptive statistics of the variables

Variable	n	M	*SD*
Number of barriers		1.75	1.507
Barrier – Workplace issues	516		
Barrier – Family issues	386		
Barrier – Lack of time	593		
Barrier – Insufficient academic knowledge	45		
Barrier – Course content too hard	43		
Age			
20-35 years	295	29.61	4.103
36-50 years	751	43.1	4.125
51+ years	303	54.96	4.078
Gender			
Male	491		
Female	858		
Educational level			
Low	217		
Medium	635		
High	497		
Prior online learning experience (nr of past MOOCs)		3.00	5.248

Note: learners were able to indicate multiple barriers

The first two hypotheses concerned the independent variable age. We hypothesised that learners between the age of 20–35 and 35–50 years experienced a greater number of barriers in general (H1a), and were also more likely to face barriers specifically related to work and family (H1b).

To test hypothesis 1a, a Kruskal-Wallis Test was conducted. This test did not reveal a statistically significant difference in the number of barriers experienced across the three different age groups, χ^2 (2, n = 1349) = 3.442, p = .179. However, the mean ranks in Table 3 show that learners in their early adulthood (20–35 years) faced most barriers, followed by learners in their mid-life (36–50 years) stage.

Table 3. Difference in the number of barriers experienced per age group

Age groups	n	Mean Rank
20-35 years	295	694.74
36-50 years	751	681.05
51+ years	303	640.79

Hypothesis 1b was tested by using two chi-square tests of independence (Bonferroni corrected significance level p < .025, uncorrected significance level p < .05). The first test indicated that there was a significant relationship between age groups and the experience of the barrier 'family issues' (see Table 4), χ^2(2, n = 1349) = 18.071, p = .000. As can be seen in Table 4, learners in their mid-life stage (35–50 years) struggle most often with family issues. The second test showed no significant relationship between age groups and the barrier 'workplace issues' (see Table 5), χ^2(2, N = 1349) = .789, p = .674. Despite the fact that the result is not significant, it is interesting that again learners in their mid-life (35–50 years) most often indicated that they were hindered by workplace issues.

Table 4. The percentage of learners who did or did not face the barrier 'family issues' per age group

Age Groups	Family issues - No (n = 963)	Family issues - Yes (n = 386)	Total
20-35 years	75.3%	24.7%	n = 295
36-50 years	66.8%	33.2%	n = 751
51+ years	78.9%	21.1%	n = 303

Table 5. The percentage of learners who did or did not face the barrier 'workplace issues' per age group

Age Groups	Workplace issues - No (n = 833)	Workplace issues - Yes (n = 516)	Total
20-35 years	62.7%	37.3%	n = 295
36-50 years	60.7%	39.3%	n = 751
51+ years	61.7%	38.3%	n = 303

The next two hypotheses, regarding gender, indicated that female learners face more barriers in general than men (H2a), and that female learners more often come across barriers related to work-life balance than men (H2b). A Kruskal-Wallis Test was conducted to test Hypothesis 2a, and revealed no statistically significant difference in number of barriers experienced across gender, X^2(1, N = 1349) = 1.814, p = .178. However, the mean ranks in Table 6 show that women do indeed experience more barriers than men.

Table 6. Difference between males and females in the number of barriers experienced

Gender	*N*	Mean Rank
Male	491	656.58
Female	858	685.54

To test Hypothesis 2b, three chi-square tests of independence were conducted (Bonferroni corrected significance level $p < .025$, uncorrected significance level $p < .05$). The tests regarding 'family and workplace issues' were not found significant. The results for gender and the experience of the barrier 'family issues' (see Table 7) were $\chi^2(1, n = 1349) = 1.134$, $p = .287$, and the result for gender and the 'barrier workplace' issues were $\chi^2(1, n = 1349) = 2.014$, $p = .156$ (see Table 8). In contrast to the direction we were expecting—that women face barriers related to work and family more often than men—the results in Tables 7 and 8 actually indicate the opposite. In both cases, men more often indicated experiencing family and workplace issues.

Table 7. The percentage of male and female learners who did or did not face the barrier 'family issues'

Gender	Family issues - No (n = 963)	Family issues - Yes (n = 386)	Total
Male	69.7%	30.3%	n = 491
Female	72.4%	27.6%	n = 858

Table 8. The percentage of male and female learners who did or did not face the barrier 'workplace issues'

Gender	Workplace issues - No (n = 833)	Workplace issues - Yes (n = 516)	Total
Male	59.3%	40.7%	n = 491
Female	63.2%	36.8%	n = 858

The last chi-square test of independence indicated that there was indeed a significant relationship between gender and coming across the barrier 'lack of time' (see Table 9), $\chi^2(1, n = 1349) = 5.115$, $p = .024$. As shown in Table 9, women indicated more often that they experienced the barrier 'lack of time' than men did.

Table 9. The percentage of male and female who did or did not face the barrier 'lack of time'

Gender	Lack of time - No (n = 756)	Lack of time - Yes (n = 593)	Total
Male	60.1%	39.9%	n = 491
Female	53.7%	46.3%	n = 858

The next hypotheses predicted that, respectively, learners with a higher educational level experienced the barrier 'insufficient academic knowledge' less frequently (H3a), and that learners with a lower educational level more often indicated that they found the course content too hard (H3b). Again, the chi-square test of independence was used to test both hypotheses. The first test indicated that there was no significant relationship between the educational level groups and experiencing the barrier 'insufficient academic knowledge', $\chi^2(2, n = 1349) = 4.550$, $p = .103$. However, Table 10 shows that with the increase of educational level, the experience of this specific barrier decreases.

Table 10. The percentage of learners who did or did not experience the barrier 'insufficient academic knowledge' per educational level

Educational level	Insuff. Academic knowledge - No	Insuff. Academic knowledge - Yes	Total
	(n = 1304)	(n = 45)	
Low	94.5%	5.5%	n = 217
Medium	96.7%	3.3%	n = 635
High	97.6%	2.4%	n = 497

The second analysis, which tested the relationship between educational level and experiencing the barrier 'course content too hard', did reveal a significant relationship, $\chi^2(2, n = 1349) = 7.133$, $p = .028$. As can be seen in Table 11, with an increase of educational level, the experience of this specific barrier decreases.

Table 11. The percentage of learners who did or did not experience the barrier 'course content too hard' per educational level

Educational level	Course content too hard - No	Course content too hard - Yes	Total
	(n = 1306)	(n = 43)	
Low	94%	6%	n = 217
Medium	97%	3%	n = 635
High	97.8%	2.2%	n = 497

The last hypothesis predicted that learners with more online learning experience were less likely to face the barrier 'lack of time' (H4). To test this hypothesis, a binary logistic regression was performed. The model was found statistically significant $\chi^2(1, n = 596) = 6.581$, $p = .0.16$ (see Table 12), and showed that for every additional MOOC taken, a learner was 4.4% less likely to face the barrier 'lack of time'.

Table 12. Logistic regression result for determining the relationship between prior online learning experience and the experience of the barrier 'lack of time'.

Variable	B	S.E.	Wald	df	Sig.	Exp(B)
Prior learning experience	-.044	.018	5.797	1	.016*	.956

Discussion

The purpose of this study was to further untangle the online learning process in MOOCs by exploring whether the variables age, gender, educational level and prior online learning experience affect the experience of (specific) barriers. Based on the literature review, multiple hypotheses were formulated. Our analyses showed that these hypotheses were partially confirmed. Figure 2 and Table 13 give an overview of the results.

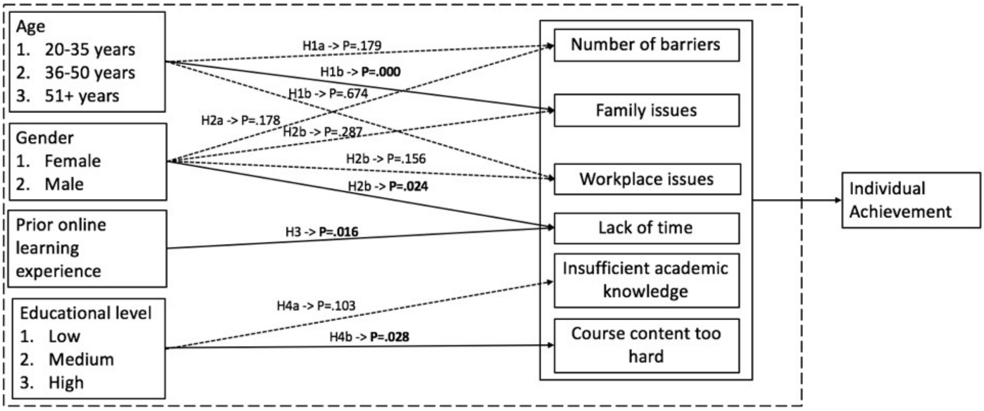

Figure 2. Overview of analyses results. All tested relationships are depicted in this model. Non-significant relationships are represented by dotted lines and significant relationships are represented by solid lines.

Table 13. Overview of hypotheses testing results

	Variables			
Predictor for	**Age**	**Gender**	**Educational level**	**Previous online learning experience**
Number of barriers	Not supported	Not supported	-	-
Specific barrier	Partially supported	Partially supported	Partially supported	Supported

Age

Our study hypothesised that, based on life stages theory (Armstrong, 2007; Stoffelsen & Diehl, 2007), learners in their early adulthood (20–35 years) and mid-life (36–50) stage experienced the most barriers, and that they also faced barriers related to work and family more often. The analysis indicated that learners in the age groups between 20–35 and 36–50 years did indeed experience more barriers than the 50+ group; however, the result did not confirm a significant difference between age groups. The association between facing the barrier 'workplace issues' and learners in the age groups between 20–35 and 36–50 years was also found not significant. Yet, learners in the age groups between 20–35 and 36–50 years did most often face the barrier 'family issues'. This association was found significant, also after Bonferroni correction, with learners in their mid-life (36–50 years) stage being the largest group to indicate that they were hindered by 'family issues'. These results are predominantly consistent with the life stages theory (Armstrong, 2007; Stoffelsen & Diehl, 2007), which suggests that different demands are made on individuals in different life stages and seems to confirm that specifically running a family can put extra strain on learners in their early adulthood (20–35 years) and mid-life (36–50 years) stage who combine work and family with learning (in MOOCs).

Gender
Based on research stating that women generally spend more time taking care of the children and doing housework than men do (Bitmann, England, Sayer, Folbre, & Matheson, 2003; Sayer, 2005; Yavorksi, Kamp Dush, & Schoppe-Sullivan, 2015), we hypothesised that women experience more barriers in general and also face barriers regarding work-life balance more often. Similar to the result we found for age, the analysis did display the hypothesised direction—women did experience more barriers than men—but this association was not significant. Further, both 'workplace and family issues' showed no significant association with gender. One interesting aspect of these findings is that men indicated that they experienced family or workplace issues more often than women did. This is the opposite of what we expected based on the literature. A possible explanation for this could be that even though women still spend more time on doing housework related activities and childcare than men do, men increasingly take responsibility for these care tasks as well and might have more difficulties combining work and care tasks than women do. Lastly, as was hypothesised, women faced the barrier 'lack of time' more often than men did. This difference was also found to be significant after Bonferroni correction.

Educational Level
We hypothesised that learners with a higher educational level would experience the barrier 'insufficient academic knowledge' least frequently, and that learners with a lower educational level would most often experience the barrier 'course content too hard'. The results showed that learners with a low educational level, compared to learners with a high educational level, twice as often indicated that they experienced the barrier 'insufficient academic knowledge'; however, this association was not significant. As hypothesised, we did find a significant association between educational level and the experience of the barrier 'course content too hard'. Learners with a low educational level more often indicted that they were hindered by this barrier.

Prior Online Learning Experience
Lastly, we hypothesised that more prior online learning experience would be negatively related to the likelihood of facing the barrier 'lack of time'. Our reasoning was that learners with more prior online learning experience use more effective learning strategies (Morris, Finnigan & Wu, 2005; Song et al., 2004). Learners who use more effective learning strategies were found more skilled in time management; thus, if learners are more skilled in time management, they are expected to be less likely to experience the barrier 'lack of time'. The analysis confirmed this hypothesis, and the significant result indicated that for every additional MOOC taken, a learner is 4.4% less likely to face the barrier 'lack of time'.

Limitations and Future Research

Some limitations to this study need to be acknowledged. The participants were Spanish-speaking learners who work in education, educational management or support positions. As this is a very specific population, the findings need to be interpreted with caution. Further research should establish whether these results also hold for differently composed populations. Furthermore, we analysed data of 18 MOOCs in the aggregate. Thus, we had no knowledge of whether learners experienced more or other barriers in certain MOOCs due to design issues or specific topics. It might be, for instance, that learners who participated in a MOOC which they experienced as learning-intensive indicated more often that they faced the barrier 'lack of time'. We also did not know whether the populations in the various MOOCs are comparable. It is possible, for example, that certain MOOCs are more interesting for females than males, or more suitable for more advanced (and thus likely older) educators than for beginners. To provide a more accurate overview of barriers to online learning in MOOCs and their potential predictors, future research should aim to take these issues into account by performing analyses on a MOOC specific level.

Conclusion

How can these results help to support, advise and prepare potential MOOC-learners embarking on new learning journeys? Some main issues MOOC-learners struggle with are once again confirmed here. It is challenging to combine work and family life with lifelong (online) learning activities, especially for certain age groups. However, more experience with online learning has a positive effect on coping with these challenges. Also, learners with a lower educational level more often experience a lack of knowledge or experience difficulties with the course content than learners who are more academically educated. Interestingly, these findings deviate from the presented literature overview, which generally revealed no predictive relation between the variables age, gender, educational level, and previous online learning experience and academic achievement. This might indicate that, although learners come across barriers that hinder them in reaching their personal learning goals, this does not necessarily mean that these barriers prevent them from reaching these goals.

Gollwitzer and Sheeran (2006) have pointed to the different phases of the intention-realisation process. While barriers are pervasive for lifelong learners, the way these barriers are tackled depends on the individual and environmental characteristics of each learner. While some learners will be able to cope with barriers easily, others will struggle and stop learning due to the same barriers. The perceived difficulty of overcoming these barriers may influence the learning experience and satisfaction and consequently affect future decisions to participate in further MOOCs. Studies should be designed to investigate the whole research model as depicted in Figure 1, thus including the possible relation between (specific) barriers and academic achievement, as this would close the circle of the intention-behaviour cycle (Henderikx et al., 2017a) and provide useful knowledge about the extent to which (certain) barriers are or are not related to the achievement of personal goals.

For MOOC-designers, the source of the barrier has important implications. Barriers can be related to the MOOC-design (e.g. 'lack of interaction with the instructor', 'lack of decent feedback' or 'low quality of course material') or related to the individual (Henderikx et al., 2018). The investigated barriers in this study—'family issues', 'work issues', 'lack of time', 'insufficient academic knowledge' and 'course content too hard'—are typically barriers which are related to the individual, and thus hard to address by changing the design of a MOOC. However, even though these issues are not addressable by mere redesign of a MOOC, MOOC educators, should be aware that barriers experienced by learners do have the potential to hinder the learning process and possibly influence individual achievement and learning experience. Despite the fact that MOOC designers and providers are only able to directly deal with course-related barriers, they are in the best position to inform potentially vulnerable learners about these issues. They could make learners aware of certain challenges that go with the territory of learning online and provide effective supportive tools where possible. For instance, they could start a MOOC with a short 'risk assessment' survey. Learners are asked several questions that refer to their personal (learning) circumstances. Based on these answers, an overview of personalised awareness messages and supporting tools can be suggested to the learner, which can subsequently increase the chance of personal learning success. This way learners can embark on new learning adventures well informed and anticipate possible barriers they might face along the way.

References

Aragon, S.R., & Johnson, E.S. (2008). Factors influencing completion and noncompletion of community college online courses. *The American Journal of Distance Education, 22*(3), 146-158. doi:10.1080/08923640802239962

Armstrong, T. (2007). *The human odyssey: Navigating the twelve stages of life*. New York, NY: Sterling Publishing Company.

Belanger, Y., & Thornton, J. (2013). *Bioelectricity: A quantitative approach: Duke University's first MOOC*. Retrieved from http://dukespace.lib.duke.edu/dspace/bitstream/handle/10161/6216/Duke_Bioelect ricity_MOOC_Fall2012.pdf?sequence=1

Bittman, M., England, P., Sayer, L., Folbre, N., & Matheson, G. (2003). When does gender trump money? Bargaining and time in household work. *American Journal of Sociology, 109*(1), 186–214. doi:10.1086/378341

Breslow, L., Pritchard, D. E., DeBoer, J., Stump, G. S., Ho, A. D., & Seaton, D. T. (2013). Studying learning in the worldwide classroom: Research into edX's first MOOC. *Research & Practice in Assessment*, 8, 13–25. Retrieved from https://www.rpajournal.com/dev/wp-content/uploads/2013/05/SF2.pdf

Cabin, R. J., & Mitchell, R. J. (2000). To Bonferroni or not to Bonferroni: When and how are the questions. *Bulletin of the Ecological Society of America*, 81(3), 246–248. Retrieved from https://www.jstor.org/stable/20168454?seq=1#page_scan_tab_Contents

Castaño-Muñoz, J., Kalz, M., Kreijns, K., & Punie, Y. (2018). Who is taking MOOCs for teachers' professional development on the use of ICT? A cross sectional study from Spain. *Technology, Pedagogy and Education*. doi: 10.1080/1475939X.2018.1528997

Goldberg, L. R., Bell, E., King, C., O'Mara, C., McInerney, F., Robinson, A., & Vickers, J. (2015). Relationship between participants' level of education and engagement in their completion of the Understanding Dementia Massive Open Online Course. *BMC Medical Education, 15*(1). doi:10.1186/s12909-015-0344-z.

Gollwitzer, P. M., & Sheeran, P. (2006). Implementation intentions and goal achievement: a meta-analysis of effects and processes. *Advances in Experimental Social Psychology* 38, 69–119. doi:10.1016/s0065-2601(06)38002-1

Greene, J. A., Oswald, C. A., & Pomerantz, J. (2015). Predictors of retention and achievement in a massive open online course. *American Educational Research Journal, 52*(5), 925–955. doi:10.3102/0002831215584621

Hattie, J. (2008). *Visible learning: A synthesis of over 800 meta-analyses relating to achievement*. Abingdon, England: Taylor & Francis Ltd. doi:10.4324/9780203887332

Henderikx, M. A., Kreijns, K., & Kalz, M. (2017). Refining success and dropout in massive open online courses based on the intention–behaviour gap. *Distance Education, 38*(3), 353–368. doi:10.1080/01587919.2017.1369006

Henderikx, M., Kreijns, K., & Kalz, M. (2017b). To change or not to change? That's the question..., On MOOC-success, barriers and their implications. In C. Delgado Kloos, P. Jermann, M. Pérez-Sanagustin, D. T. Seaton, and S. White (Eds.), *Lecture notes in computer science: Vol. 10254. Digital education: Out to the world and back to the campus* (pp. 210–216). doi 10.1007/978-3-319-59044-8_25

Henderikx M., Kreijns K., & Kalz M. (2018). A classification of barriers that influence intention achievement in MOOCs. In V. Pammer-Schindler, M. Pérez-Sanagustín, H. Drachsler, R. Elferink, & M. Scheffel (Eds.), *Lifelong technology-enhanced learning. EC-TEL 2018*. LNCS, vol. 11082 (pp. 3–15). doi:10.1007/978-3-319- 98572-5_1

Kalz, M., Kreijns, K., Walhout, J., Castaño-Munoz, J., Espasa, A., & Tovar, E. (2015). Setting-up a European cross-provider data collection on open online courses. *The International Review of Research in Open and Distributed Learning*, *16*(6). 62– 77.

Khalil, H., & Ebner, M. (2013, March). *Interaction possibilities in MOOCs—How do they actually happen?* Paper presented at the International Conference on Higher Education Development, Mansoura University, Egypt.

Khalil, H. & Ebner, M. (2014). MOOCs completion rates and possible methods to improve retention—A literature review. In J. Viteli & M. Leikomaa (Eds.), *Proceedings of EdMedia 2014—World Conference on Educational Media and Technology* (pp. 1305–1313). Retrieved from https://www.learntechlib.org/primary/p/147656/

Kooij, D. T. A. M., De Lange, A. H., Jansen, P. G. W., Kanfer, R., & Dikkers, J. S. E. (2011). Age and work-related motives: Results of a meta-analysis. *Journal of Organizational Behaviour, 32*(2), 197–225. doi:10.1002/job.665

Levy, D., & Schrire, S. (2012). *The case of a massive open online course at a college of education.* Retrieved from http://conference.nmc.org/files/smkbMOOC.pdf

Lim, D. H., Morris, M. L., & Yoon, S. W. (2006). Combined effect of instructional and learner variables on course outcomes within an online learning environment. *Journal of Interactive Online Learning*, *5*(3), 255–269. Retrieved from https://www.ncolr.org/jiol/issues/pdf/5.3.3.pdf

Mackness, J., Fai, S., Mak, J., Williams, R., & Mak, S. (2010). The ideals and reality of participating in a MOOC. *Proceedings of the Seventh International Conference on Networked Learning,* Denmark. Retrieved from http://eprints.port.ac.uk/5605/1/The_Ideals_and_Realilty_of_Participating_in_a_MOOC.pdf

Marks, R. B., Sibley, S. D., & Arbaugh, J. B. (2005). A structural equation model of predictors for effective online learning. *Journal of Management Education, 29*(4), 531–563. doi:10.1177/1052562904271199

McAuley, A., Stewart, B., Siemens, G., & Cormier, D. (2010). *Massive open online courses: Digital ways of knowing and learning.* University of Prince Edward Island, Charlottetown, Canada.

Missopoulos, F., Argyropoulou, M., & Tzavara, D. (2018). Exploring the factors affecting student academic performance in online programs: A literature review. In A. Khare & D. Hurst (Eds.), *On the line* (pp. 235–249). doi 10.1007/978-3-319- 62776-2_18

Moher, D., Liberati, A., Tetzlaff, J., & Altman, D. G. (2009). Preferred reporting items for systematic reviews and meta-analyses: The PRISMA statement. *BMJ, 339*(jul21 1), b2535–b2535. doi:10.1136/bmj.b2535

Morris, L. V., Finnegan, C., & Wu, S.-S. (2005). Tracking student behaviour, persistence, and achievement in online courses. *The Internet and Higher Education*, *8*(3), 221– 231. doi:10.1016/j.iheduc.2005.06.009

Muilenburg, L. Y., & Berge, Z. L. (2005). Student barriers to online learning: A factor analytic study. *Distance Education*, *26*(1), 29–48. doi:10.1080/01587910500081269

Onah, D. F., Sinclair, J., & Boyatt, R. (2014). Dropout rates of massive open online courses: Behavioural patterns. *EDULEARN14 Proceedings*, Barcelona, 5825– 5834. Retrieved from http://wrap.warwick.ac.uk/65543/

Park, J. H., & Choi, H. J. (2009). Factors influencing adult learners' decision to drop out or persist in online learning. *Journal of Educational Technology & Society*, 12(4), 207–2017. Retrieved from https://pdfs.semanticscholar.org/3b3c/47a09120bcd232369e29ea383593e251b220.pdf

Rice, W. R. (1989). Analyzing tables of statistical tests. *Evolution, 43*(1*)*, 223–225. doi:10.2307/2409177

Sayer, L. C. (2005). Gender, time and inequality: Trends in women's and men's paid work, unpaid work and free time. *Social Forces*, 84(1), 285–303. doi: 10.1353/sof.2005.0126

Song, L., Singleton, E. S., Hill, J. R., & Koh, M. H. (2004). Improving online learning: Student perceptions of useful and challenging characteristics. *The internet and higher education, 7*(1), 59–70. doi: 10.1016/j.iheduc.2003.11.003

Stoffelsen, J., & Diehl, P. (2007). *Handboek levensfasebewust personeelsbeleid*. Alphen aan den Rijn: Kluwer.

Wang, C.-H., Shannon, D. M., & Ross, M. E. (2013). Students' characteristics, self- regulated learning, technology self-efficacy, and course outcomes in online learning. *Distance Education, 34*(3), 302–323. doi:10.1080/01587919.2013.835779

Yavorsky, J. E., Kamp Dush, C. M., & Schoppe-Sullivan, S. J. (2015). The production of inequality: The gender division of labor across the transition to parenthood. *Journal of Marriage and Family, 77*(3), 662–679. doi:10.1111/jomf.12189

Yukselturk, E., & Bulut, S. (2007). Predictors for student success in an online course. *Journal of Educational Technology & Society*, 10(2), 71–83. Retrieved from http://anitacrawley.net/Resources/Articles/Yukselturk.pdf

9

Chapter 9

General Discussion

The main question underlying this dissertation was: How can the definition of success in open education and MOOCs be refined and what barriers impede individual learner success? Answering these questions is valuable as MOOCs seem to be a realistic alternative for the generally expensive, inflexible traditional professional development programs (Mabuan, Ramos, Matala, Navarra & Ebron, 2018; Donitsa-Schmidt & Topaz, 2018; Castaño-Muñoz, Kalz, Kreijns & Punie, 2018; Dennen & Bong, 2017; Laurillard, 2016; Olsson, 2016), particularly for groups of learners who are hindered by institutional and to some extent situational barriers (Roosmaa & Saar, 2017). To guide the research project, multiple research questions were formulated and investigated. The first study focused on refinement of the success definition in MOOCs in order to get a more realistic view on learner success taking into account the open and accessible learning context of MOOCs and the individual perspective of learners. The two subsequent studies aimed to get insight into the individual intention-behaviour processes while progressing through a MOOC. The next three studies were specifically directed at getting insight into what type of barriers learners face while learning in MOOCs and at empirically investigating barriers to learning in MOOCs, while the last study focused on identifying determinants which affect the experience of barriers to learning in MOOCs. Besides the goal to advance MOOC research with theoretically grounded studies, we hope that the findings of the studies will guide further MOOC development and learner support.

Main findings

The first study set out to answer the first research question: How can success and dropout assessment in MOOCs be refined? To answer this question, a theoretically grounded success assessment approach to refine measurement of success and dropout in MOOCs was developed and investigated (see Chapter 2). This resulted in a proposed learner typology, which takes the individual learner as a starting point, and is based on the intention-behaviour gap as visualised in the reasoned action approach by Fishbein and Ajzen (2010) in combination with the intention-behaviour patterns as distinguished by McBroom and Reed (1992) and Sheeran (2002). Following this typology three types of learners can be identified (see Figure 1 on page 31):

1. Learners who learn what they intended to learn when they started the MOOC. These learners are considered succesful learners.

2. Learners who learn more than they intented to learn when they started the MOOC. These learners are considered succesful learners.

3. Learners who learn less than they intended to learn at the start of the MOOC. These learners are not considered succesful learners (dropouts).

Furthermore, data from two different MOOCs was analysed to assess the initial usefulness of the typology to provide a refined measurement of learner success in MOOCs. The results showed that when following the institutional more traditional approach to measuring educational success which is based on course completion, the success rates were 6,5% and 5,6% respectively. The success rates measured from the perspective of the learner, following the proposed learner typology, were 59% and 70%. This indicates that there is a discrepancy between success from the perspective of the learner and success from the perspective of the institution which underlines the importance of taking into account that individual goal achievement does not necessarily match institutional goal achievement.

The findings of the first study provided new insights into learner success but also raised new questions regarding learner behaviour after starting a MOOC. These questions were reformulated into two research questions 1) How dynamical is the intention-behaviour process and what are reasons for this? And 2) What individual goals do learners set and do they succeed in reaching these goals? Chapter 3 and 4 of this dissertation explored these questions by conducting two studies. Both studies confirmed that learning in MOOCs can be a changeable and dynamical process (see Figure 1. on page 44) and that a considerable group of learners (about 30%) changes their initial intention once or more often while learning in a MOOC. Reasons indicated by the learners for these intention changes often pointed towards time issues and changes of priority. Even though these changes of intentions are difficult to determine, they should be taken into consideration when evaluating learner success in MOOCs. In addition, the second study (Chapter 4) showed that learners progress through a MOOC following the action phases as theorized by Gollwitzer (1990, 2018; see Figure 1 on page 54) more or less intuitively. This finding provides valuable clues for targeting interventions which can support learners in reaching their individual learning goals.

Previous studies provided interesting and useful information about learner intention-behaviour and how intentions are susceptible for change while in the process of translating intentions into behaviour. Yet, these studies merely touched upon the variety of reasons for these changes in intentions. Chapter 5 describes a first explorative study into these reasons for changing intentions; that is, barriers which impede learners in achieving their personal learning goals, or in other words, prevent or hinder learners from translating their intentions into actual behaviour. The objective was to get insight into what type of barriers learners face while learning in MOOCs. An explorative literature review resulted in a non-exhaustive list of barriers which were categorized, based on the rationale: which classification would be most useful to MOOC-designers and/or providers and learners, into MOOC-related and non- MOOC related barriers including sub groups (see Figure 2 on page 69). Data analyses of two separate MOOCs showed that lack of time and workplace issues were the barriers learners experienced the most, followed by family issues, insufficient academic background and issues with the site. Further analysis of whether the experienced barriers were MOOC-related or non-MOOC-related showed that most of the barriers can be considered as non MOOC-related barriers. This indicates that it is important for MOOC-providers and designers to be well informed about the reasons behind success and failure rates.

Chapter 6 further builds on results of chapter 5 and aimed to find an empirically grounded answer to the fifth research question which revolved around identifying and categorising barriers to learning. A literature review focused on issues which impeded academic achievement in the context of online learning, distance learning and MOOC specific learning identified 44 barriers to learning. The data was inspected using principal component analysis as this method allows for categorizing data. After several analyses iterations, during which 9 barrier items were dropped, the principal component analysis indicated that 4 distinct components or categories summarized the barriers as experienced by learners, namely 1) Technical and online related skills, 2) Social context, 3) Course design and 4) Time, support and motivation with high internal coherence (see Figure 2 on page 86). Further investigation of these categories revealed that most barriers experienced by learners are non-MOOC related (see Table 3 on page 89), which means that these barriers are not related to the design of the MOOC and thus primarily need to be addressed on the level of the learner.

The results of the previous study in which barriers to learning in MOOCs were identified and categorized instigated the following study which examined the next research question: Can barriers be classified into a diagnostic instrument to guide learner support and MOOC development? Chapter 7 reports on how an online self-report instrument was constructed and tested for identifying barriers to learning in MOOCs. Via this instrument, MOOC learners could indicate to what extent they experienced any of the 44 barrier items as hindering their MOOC learning. Ultimately, 35 barrier items were categorised using several exploratory factor analyses iterations. The final analysis provided a very good model fit for an 8-factor structure with a high internal coherence per category (see Table 2 on page 104). The identified categories are 1) Instructor related barriers, 2) Content related barriers, 3) Social context, 4) General skills related barriers, 5) Technical skills related barriers, 6) Motivation related barriers, 7) Situational barriers and 8) IT related barriers. This classification revealed great similarity with and seems a further refinement of the earlier found 4 component classification. Based on the good construct validity, the self-report instrument can, in its current form, be utilized as a diagnostic tool by MOOC-providers and designers to gather information that will benefit further development of MOOCs and the support of learners in achieving their personal learning goals.

The previous two chapters focused on gaining insight into experienced barriers to learning in MOOCs and into the potential for developing a self-report instrument to identify these barriers. The purpose of Chapter 8 was to further untangle the online learning process in MOOCs by exploring whether several learner related variables affect the experience of (specific) barriers. In this chapter we therefore answered the last research question: Which determinants affect the occurrence of barriers faced by learners while learning in MOOCs? More specifically, the study explored whether the variables age, gender, educational level and prior online learning experience were related to the occurrence of (specific) barriers. The results showed (see Figure 2 on page 130) that learners in their early adulthood (20-35) and mid-life (36-50) stage experienced most barriers in general as well as barriers specifically related to work and family. In addition, women more often faced the barrier ‘lack of time’ than men did and learners with a low educational level more often indicated that they struggled with the content of the MOOC than learners with a high educational level. Lastly, learners with more prior online learning experience less often faced the barrier ‘lack of time’.

Limitations and directions for future research

When interpreting the studies reported and discussed in this dissertation, several limitations should be taken into consideration that inform directions of future research. Some of the limitations specifically apply to the first four studies (Chapter 2-5). First, the samples in the studies are relatively small. This can be attributed to the setup of the studies, which collected pre- and post-data on intention-behaviour of individual learners. The pre-survey at the start of the MOOC generally had a high response rate whereas the post survey showed very low response rates. The pre- and post-data was then matched on learner level using unique identifiers which mostly resulted in a low number of matches. Due to the relatively small sample sizes, the generalisability of these studies is limited and calls for further research preferably with bigger sample sizes. Previous shortcoming connects to the next limitation, which concerns the issue of survival bias, which is a form of selection bias that is common in MOOCs due to its openness and flexibility (Reich, 2014). It means that learners who 'survive' until the end of the MOOC, which is probably the group of learners who had the intention to complete the MOOC, are generally the learners who fill in the post questionnaire. This is likely to lead to over positive and less representative results. Future studies should invite all learners who initially enrolled for the MOOC for participation in the post-survey (e.g. via email) as opposed to solely targeting learners who are still in the course at the end of the MOOC by sharing a link to the survey in the course. Another possible option is to match pre-survey data with learner analytic data about behaviour. Although this approach is more complicated than targeting all enrolled learners via email, it has the benefit that all learners who started the MOOC can be included. As such, it will lead to bigger sample sizes and will also solve the subjectiveness of self-report. However, independent observation, in the form of learner analytics, or even collecting pre- and post-data in a MOOC, does not account for any changes of learner intentions which might take place after starting a MOOC. This issue should always be taken into account when interpreting the intention-behaviour findings and ultimately learner achievement in MOOCs. Also, when it comes to measuring intention and behaviour it is not only possible to identify learners who dropout but also learners who drop-in i.e. learners who ultimately do more than they initially intended to do in the MOOC. It would be very interesting to study which design traits of MOOCs motivate learners to go beyond their initially lower intention. Lastly, extending aforementioned, we did not address any difference in weight or effort of the initial intention in comparison to actual behaviour. In other words, we did not differentiate between a learner who intended to download materials in the MOOC vs a learner who intended to finish the MOOC in relation to behaviour. The first intention takes far less effort and is easier to translate to actual behaviour than the intention to finish a MOOC. Further research focused on assessing success form the viewpoint of the learner, could for instance apply weighted factors to intentions based on effort to get achieve more realistic results.

Furthermore, two limitations particularly affected the interpretation and generalisability of the 5th and 6th study on the topic of barriers to learning as reported in Chapter 6 and 7. Firstly, the survey about barriers to learning in MOOCs was on both occasions send to learners who had taken part in a MOOC in the near past. Therefore, we had no knowledge of how recent these learners participated in a MOOC at the moment of the survey and thus how accurate their memory was when answering the questions in the survey. Future studies should attempt to collect data about barriers to learning immediately at the end of the MOOC, targeting all the learners who initially enrolled to prevent survival bias. Some of these learners might not have finished the MOOC, which means that for these learners the experience of barriers might also be in the past, but it will still be in the recent past and thus probably more accurate. Secondly, we were not aware of to what extent learners who completed the survey were successful in achieving their personal learning goals when participating in their respective MOOCs nor were we aware of the design of the respective MOOCs. It would be very interesting if future research could include learner achievement as well as several context specific questions in the survey that supports the possibility for making certain distinctions based on learner success or MOOC design regarding the experience of barriers to learning in MOOCs.

Finally, there are some limitations that should be taken into account in general. The majority of the data was collected using online surveys in which learners were requested to answer factual as well as experience related questions. Although this method is widely used and well suited for determining individual perceptions and experiences (Duffy, Lajoie, Pekrun & Lachapelle, 2018; Spector, 2006), self-report bias should still be taken into account when interpreting the results of the studies. As mentioned before, in some cases it might worth exploring the possibility of using learning analytics to identify (or verify) certain issues as this will objectify the outcome and thus benefit the overall validity of the findings. Further, the majority of the respondents came from western cultures and were in some cases (chapter 1, 4 and 7) very specific with respect to nationality and even occupation. Due to this limitation the study results should be interpreted with caution within the appropriate context. It is recommended that future cross-cultural and cross occupational studies are performed to address the lack of cultural and occupational diversity in (some of) these studies. Different cultural backgrounds might also lead to different approaches for goal achievement (King, McInerney, & Nasser, 2017) and even coping with barriers. Another general shortcoming is the fact that the design of the MOOC was not included as an explaining variable in any of the studies. Including specific features of the design of the MOOC, like for instance instructor supported vs self-paced, paid vs free of charge or part of a curriculum vs stand-alone etc. in the analyses may lead to different outcomes. Further research is needed, using a broader range of explaining variables to enhance the current findings and possibly refine them. Also, individual achievement in the context of this research project was approached in a fairly quantitative way as it refers to actions learners intent to perform such as browsing and downloading materials or parts of a MOOC learners intent to finish. This way of approaching achievement fails to measure whether actual learning took place or whether learners were satisfied with learner content or quality. In this respect it could be possible that learners did indeed finish what they intended to finish and are therefore considered successful learners from our perspective, but at the same time it may be that no or only little actual learning took place or that they were not at all satisfied with the content or quality.

Finally, a shortcoming with regard to the addressed methodologies of the various studies is that we failed to include an intervention study focused on supporting the learners in reaching their personal learning goals. We did design and execute an intervention study, involving a control and treatment group, to investigate whether students who formulated implementation intentions (concrete when, where & how plans that anticipate barriers (to learning in our case; Gollwitzer, 1999) at the start of a MOOC, would be more successful when it comes to reaching their personal learning goals, than students who would not formulate implementation intentions. Unfortunately, we were not able to collect sufficient data to report any results on this study. Considering the positive findings in the field of health science and education (Achtziger, Gollwitzer & Sheeran, 2008; Brandstätter, Heimbeck, Malzacher, & Frese, 2003; Friedman & Ronen, 2015; Gollwitzer & Sheeran, 2006; Hagger et al., 2016; Rise, Thompson & Verplanken, 2003; Sheeran, Webb & Gollwitzer, 2005) it seems worth it for future studies, to explore its usefulness for supporting MOOC-learners in reaching their personal learning goals.

Implications for practice

The findings regarding success and dropout presented in Chapter 2 in combination with the findings concerning the dynamicity of learner intention as presented in Chapter 3 and 4 underline the importance of taking the viewpoint of the learner into account when assessing MOOC-success. Learners who did not complete the course may very well have reached their personal learning goals and can thus be considered as successful learners. This information should make MOOC-providers and designers aware that a mere certificate and completion centric approach only tells one side of the story. That approach should ideally be complemented with the perspective of the individual learners to provide the most complete picture of success and to prevent unjustified negative reviews and unnecessary (re) design interventions of the MOOC.

Chapter 3, although reporting an explorative study, provides interesting leads for supporting learners in reaching their individual learning goals. The learners proceeded largely intuitively through the action phases touching upon the transition points as theorized by Gollwitzer (1990, 2018). These transition points, or more precisely what they represent (i.e. setting the goal, planning how to reach the goal, initiate action and evaluate the achievement), can serve as guiding points for offering supporting tools to learners. These tools can then be tailored to the needs of the learners based on their indicated goal intention and offered via personalized dashboards at the appropriate moments during their progress through the MOOC.

The findings of Chapter 5, 6 and 7 gave insight into barriers learners face while learning in MOOCs and showed evidence that they can be empirically categorized in comprehensive and useful categories and that many barriers learners experienced were not directly related to the MOOC. MOOC-providers and designers could benefit from having insight into barriers learners experience while learning in a MOOC, as different types of barriers have a different impact on improvement and further development of a MOOCs. The refined categories as found in Chapter 7, can be converted into a diagnostic instrument (dashboard) which is powered by learner self-report of barriers after finishing learning in the MOOC. Such a dashboard can also provide insight into specific issues learners face during their learning in the MOOC, which can be valuable information for developing learner supporting tools and interventions even if it concerns non-MOOC related issues. For instance, to support learners regarding technical and online-learning related skills, it would be possible to, prior to the start of a MOOC, specifically draw attention to the minimum requirements regarding technical and online learning skills needed to be able to successfully learn in the MOOC. Or, learners who struggle with barriers related to time or motivation can be supported by providing information on how to handle and cope with these kinds of barriers, as well as by providing supporting interventions. Ultimately, being able to make informed decisions about possible re-design and development of supporting tools, is likely to benefit learner success and overall quality of the MOOC.

Chapter 8, in which variables were identified that affect the experience of predominantly non-MOOC related barriers also provides interesting and useful information for practice which can be used to support, advise and prepare learners who want to develop their knowledge by taking a MOOC. As discussed above, it is important to know the source of the barrier in order to being able to take the most appropriate actions. The results showed that age, gender, educational level and prior online learning experience can affect the experience of several non-MOOC related barriers. MOOC providers and designers could use this knowledge to inform potentially vulnerable learners about these issues and make them aware of certain challenges they might face and provide supportive tools where possible. A reasonably easy way to inform and support learners is by starting a MOOC with a short 'risk assessment' survey. Learners are asked several questions that refer to their personal (learning) circumstances. Based on these answers, an overview of personalised awareness messages and supporting tools can be suggested to the learner, with the aim to increase individual learner success and experience.

Conclusion

At the time of starting this research project, MOOC research was taking off but mainly comprised of exploratory and descriptive studies on macro and meso level which mainly focused on pedagogical, technological and dropout issues which mostly lacked empirical grounding (Bozkurt, Agun-Ozbek & Zawacki-Richter, 2017; Raffaghelli, Cucchiara & Persico, 2015). Especially the high dropout rates that were reported fuelled many discussions about the value of MOOCs (Bozkurt et al., 2017). What was missing in this discussion was the micro level or in other words the perspective of the learner. Although scholars were gradually starting to realise that all stakeholders should be taken into account, thus also the learner, when studying and assessing the MOOC phenomenon (Liyanagunawardena, Adams & Williams, 2013), this was still in its infancy, as was also the case with empirical studies. The goal of this project was to contribute to MOOC-research by conducting studies taking the viewpoint of the learner as a starting point, and at the same time address the call and the necessity for theoretically grounded research. This goal was reached by proposing an empirically grounded alternative view on learner success which can make MOOC educators aware of the importance of the learner perspective and learner behaviour and can complement the institutional perspective when assessing MOOC success. In addition, we zoomed in on reasons why learners were not successful or less successful than they intended to be. This resulted in empirical studies about barriers to learning in MOOCs and about which determinants possibly affected the experience of certain barriers. Although, further research into these topics is necessary to increase the generalisability of the studies, the outcomes of this dissertation provide opportunities and insights for both MOOC educators as well as MOOC-learners (via MOOC educators) that can support them in their strive for the best possible learning results.

Leaves us with the question whether MOOCs are indeed a possible solution for learners who struggle with some issues related to formal learning contexts in their pursuit of lifelong learning as discussed in the introduction of this dissertation. Their main reasons for not engaging in lifelong learning activities were high costs, lack of flexibility, distance to an educational institution, family and work responsibilities and a lack of suitable education or training offer (EUROSTAT, 2019). These barriers are mainly of situational and institutional nature (Roosmaa & Saar, 2017). When looking at the findings of this dissertation, it can be inferred that MOOCs, due to their non-formal extraordinary learning context, can indeed alleviate some of these barriers. Especially the institutional barriers like the high costs, lack of flexibility and distance to educational institutions no longer apply due to its online accessible format. However, the challenges involving situational barriers remain, as well as new challenges arise. These new challenges concern for instance course content and instructor related issues and issues regarding social context. Furthermore, the flexibility of MOOCs proves to be a blessing as well as a curse in some cases, as it asks a lot of self- regulatory and self-motivational skills of learners (Jansen, Van Leeuwen, Janssen, Kester, & Kalz, 2017; Littlejohn, Hood, Milligan & Mustain, 2016; Martin, Kelly & Terry, 2018; Weinhardt & Sitzmann, 2019). Also, at this point in time MOOCs only provide limited acknowledged credentials or academic credits (Reich & Ruipérez-Valiente, 2019), which may keep learners from considering MOOCs as a way to advance knowledge for professional purposes as many employers attach great value to acknowledged certificates and diplomas. However, considering the development of MOOCs over the past years (Shah, 2017, 2018) official acknowledgements are likely to increase and therefore cater for more learning needs.

For now, however, MOOCs provide interesting and challenging learning opportunities for whoever is interested in learning whether or not for professional reasons. Thus keep in mind:

It is never too soon or too late for learning

Irakli Gvaramadze (2007)

References

Achtziger, A., Gollwitzer, P. M., & Sheeran, P. (2008). Implementation intentions and shielding goal striving from unwanted thoughts and feelings. *Personality and* Social Psychology Bulletin, 34(3), 381-393. doi:10.1177/0146167207311201

Bozkurt, A., Akgün-Özbek, E., & Zawacki-Richter, O. (2017). Trends and patterns in massive open online courses: Review and content analysis of research on MOOCs (2008-2015). *The International Review of Research in Open and Distributed Learning*, 18(5), 118-147. doi: 10.19173/irrodl.v18i5.3080

Brandstätter, V., Heimbeck, D., Malzacher, J., & Frese, M. (2003). Goals need implementation intentions: The model of action phases tested in the applied setting of continuing education. *European Journal of work and organizational psychology*, 12(1), 37-59. doi: 10.1080/13594320344000011

Castaño-Muñoz, J., Kalz, M., Kreijns, K., & Punie, Y. (2018). Who is taking MOOCs for teachers' professional development on the use of ICT? A cross sectional study from Spain. *Technology, Pedagogy and Education*. doi: 10.1080/1475939X.2018.1528997

Dennen, V. P., & Bong, J. (2017). Reframing MOOCs in higher education: Exploring professional development options. In *Massive Open Online Courses and Higher Education* (pp. 151-167). Routledge. doi: 10.4324/9781315594248-11

Donitsa-Schmidt, S., & Topaz, B. (2018). Massive open online courses as a knowledge base for teachers. *Journal of Education for Teaching*, 44(5), pp 608-620. doi: 10.1080/02607476.2018.1516350

Duffy, M. C., Lajoie, S. P., Pekrun, R., & Lachapelle, K. (2018). Emotions in medical education: Examining the validity of the Medical Emotion Scale (MES) across authentic medical learning environments. *Learning and Instruction*. doi 10.1016/j.learninstruc.2018.07.001

Fishbein, M., & Ajzen, I. (2010). *Predicting and changing behaviour: The reasoned action approach*. New York, NY: Taylor & Francis. doi:10.4324/9780203838020

Friedman, S., & Ronen, S. (2015). The effect of implementation intentions on transfer of training. *European Journal of Social Psychology*, 45(4), 409-416. doi: 10.1002/ejsp.2114

Gollwitzer, P. M. (1990). Action phases and mind-sets. *Handbook of motivation and cognition: Foundations of social behavior*, 2, 53-92. doi:10.2307/2072281

Gollwitzer, P. M. (1999). Implementation intentions: Strong effects of simple plans. *American psychologist*, 54(7), 493-503. doi:10.1037/0003-066x.54.7.493

Gollwitzer, P. M. (2018). The goal concept: A helpful tool for theory development and testing in motivation science. *Motivation Science*, 4(3), 185-205. doi:10.1037/mot0000115

Gollwitzer, P. M., & Sheeran, P. (2006). Implementation intentions and goal achievement: A meta-analysis of effects and processes. *Advances in experimental social psychology*, 38, 69-119. doi: 10.1016/S0065-2601(06)38002-1

Hagger, M. S., Luszczynska, A., de Wit, J., Benyamini, Y., Burkert, S., Chamberland, P. E., ... & Gauchet, A. (2016). Implementation intention and planning interventions in Health Psychology: Recommendations from the Synergy Expert Group for research and practice. *Psychology & health*, 31(7), 814-839. doi: 10.1080/08870446.2016.1146719

Jansen, R. S., Van Leeuwen, A., Janssen, J., Kester, L., & Kalz, M. (2017). Validation of the self-regulated online learning questionnaire. *Journal of computing in higher education*, 29(1), 6-27. doi: 10.1007/s12528-016-9125-x

King, R. B., McInerney, D. M., & Nasser, R. (2017). Different goals for different folks: a cross-cultural study of achievement goals across nine cultures. *Social Psychology of Education*, 20(3), 619-642. doi: 10.1007/s11218-017-9381-2

Laurillard, D. (2016). The educational problem that MOOCs could solve: professional development for teachers of disadvantaged students. *Research in Learning Technology*, 24. Retrieved from https://journal.alt.ac.uk/index.php/rlt/article/view/ 1738/pdf_30

Liyanagunawardena, T. R., Adams, A. A., & Williams, S. A. (2013). MOOCs: A systematic study of the published literature 2008-2012. *The International Review of Research in Open and Distributed Learning*, 14(3), 202-227. Retrieved from http://centaur.reading.ac.uk/33109/

Littlejohn, A., Hood, N., Milligan, C., & Mustain, P. (2016). Learning in MOOCs: Motivations and self-regulated learning in MOOCs. *The Internet and Higher Education*, 29, 40-48. doi: 10.1016/j.iheduc.2015.12.003

Mabuan, R.A., Ramos, A., Matala, C., Navarra, A., & Ebron, G. (2018). MOOCs for teacher professional development: The Philippine experience. *Asian EFL Journal*, 20 (12.3), pp 194-214. Retrieved from https://www.researchgate.net/publication/329735512_MOOC_Camps_for_Teache r_Professional_Development_The_Philippine_Experience

Martin, N., Kelly, N., & Terry, P. C. (2018). A framework for self-determination in massive open online courses: Design for autonomy, competence, and relatedness. *Australasian Journal of Educational Technology*, 34(2), 35-55. doi: doi.org/10.14742/ajet.3722

McBroom, W. H., & Reed, F. W. (1992). Toward a reconceptualization of attitude- behaviour consistency. *Social Psychology Quarterly, 55*, 205–216. Retrieved from http://www.jstor.org/stable/2786946

Olsson, U. (2016). Open courses and MOOCs as professional development–is the openness a hindrance?. *Education+Tra*ining, 58(2), 229-243. doi: 10.1108/ET-01-2015- 0006

Raffaghelli, J. E., Cucchiara, S., & Persico, D. (2015). Methodological approaches in MOOC research: Retracing the myth of Proteus. *British Journal of Educational Technology*, 46(3), 488-509. doi: 10.1111/bjet.12279

Reich, J. (2014, December 8). MOOC completion and retention in the context of student intent. *Educause Review Online*. Retrieved from http://er.educause.edu/articles/2014/12/

Reich, J., & Ruipérez-Valiente, J. A. (2019). The MOOC pivot. *Science*, 363(6423), 130-131. doi: 10.1126/science.aav7958

Rise, J., Thompson, M., & Verplanken, B. (2003). Measuring implementation intentions in the context of the theory of planned behavior. *Scandinavian Journal of Psychology*, 44(2), 87-95. Retrieved from https://www.ncbi.nlm.nih.gov/pubmed/12778976

Roosmaa, E. L., & Saar, E. (2017). Adults who do not want to participate in learning: A cross-national European analysis of their perceived barriers. *International Journal of Lifelong Education*, 36(3), 254-277. Doi: 10.1080/02601370.2016.1246485

Sheeran, P. (2002). Intention–behaviour relations: A conceptual and empirical review. *European Review of Social Psychology, 12*(1), 1–36. doi:10.1080/14792772143000003

Sheeran, P., Webb, T. L., & Gollwitzer, P. M. (2005). The interplay between goal intentions and implementation intentions. *Personality and Social Psychology Bulletin*, 31(1), 87-98. Doi: 10.1177/0146167204271308

Weinhardt, J. M., & Sitzmann, T. (2019). Revolutionizing training and education? Three questions regarding massive open online courses (MOOCs). *Human Resource Management Review*, 29(2), 218-225. doi: 10.1016/j.hrmr.2018.06.004

Appendices

Appendix A

These are the general standard questions, which will be aligned with the design of the respective MOOC before use.

Pre-questionnaire

In this MOOC I intend to….	
○ Browse ○ Browse and download learning materials ○ Participate in some learning activities of …?... modules and optionally browse and download learning materials* ○ Participate in most learning activities of …?... modules and optionally browse and download learning materials* ○ Participate in all learning activities of …?… modules and optionally browse and download learning materials* ○ Participate in all learning activities and strive for a certificate of participation (pass at least 75% of the course) ○ Participate in all learning activities and strive for a certificate of accomplishment (pass 100% of the course)	* ○ Only one module ○ Two modules ○ Three modules ○ Four modules ○ All modules

Note. Single response.

Post-questionnaire

In this MOOC I have…	
○ Browsed ○ Browsed and downloaded learning materials ○ Participated in some learning activities of …?….. modules and optionally browsed and downloaded learning materials* ○ Participated in most learning activities of ….?... modules and optionally browsed and downloaded learning materials* ○ Participated in all learning activities of …?….. modules and optionally browsed and downloaded learning materials* ○ Participated in all learning activities and earned a certificate of participation (pass at least 75% of the course) ○ Participated in all learning activities and earned a certificate of accomplishment (pass 100% of the course)	* ○ Only one module ○ Two modules ○ Three modules ○ Four modules ○ All modules

Note. Single response.

Appendix B

Sample information N=445

Item number	Item description	M	SD
Bar_1	LackInstructorPresence	-.91	1.011
Bar_2	UnavailableCourseMaterials	-.82	1.218
Bar_3	InstructorsDontKnowHowToTeachOnline	-.95	1.214
Bar_4	LackClearExpectationsInstructions	-.83	1.107
Bar_5	LackInCourseSupport	-.92	.997
Bar_6	LackTimelyFeedback	-.86	1.053
Bar_7	LackDecentFeedback	-.73	1.072
Bar_8	LackInteractionInstructor	-.58	1.105
Bar_9	LowQualityMaterials	-.84	1.270
Bar_10	InsuffTrainingTooUseDeliverySystem	-1.26	.946
Bar_11	LackInteractionStudents	-.82	1.048
Bar_12	LearningImpersonal	-1.10	1.021
Bar_13	FeelingOfIsolation	-1.20	.988
Bar_14	LackSocialContext	-1.16	.961
Bar_15	LackStudentCollaboration	-.90	1.075
Bar_16	PreferFaceToFaceLearning	-.62	1.212
Bar_17	LackLanguageSkills	-1.31	1.076
Bar_18	LackWritingSkills	-1.28	.973
Bar_19	LackReadingSkills	-1.39	1.020
Bar_20	LackTypingSkills	-1.51	.810
Bar_21	LackInformationLiteracySkills	-1.33	.976
Bar_22	LackOfConfidence	-1.21	1.003
Bar_23	LackSoftwareSkills	-1.37	.958
Bar_24	LackSkillsUsingDeliverySystem	-1.36	.916
Bar_25	UnfamiliairWithOnlineLearningTools	-1.36	.980
Bar_26	Procratinate	-.06	1.269
Bar_27	LackMotivation	-.38	1.279
Bar_28	OwnResponsibilityLearning	-.35	1.286
Bar_29	LearningEnvironmentNotMotivating	-.71	1.120
Bar_30	FamiliyIssues	-.90	1.152
Bar_31	WorkplaceIssues	-.69	1.173
Bar_32	LackTime	.31	1.240
Bar_33	LackSupportFamilyFriends	-1.28	.924
Bar_34	LackSupportEnmployer	-.92	1.242
Bar_35	TooMayInterruptionsDuringStudy	-.43	1.159

Item number	Item description	M	SD
Bar_36	LackAdequateInternet	-.98	1.294
Bar_37	LackTechnicalAssitance	-1.16	.950
Bar_38	CourseContentTooEasy	-.88	1.069
Bar_39	CourseContentTooHard	-.90	1.010
Bar_40	CourseContentBad	-.95	1.211
Bar_41	TechProblemsPC	-1.24	1.053
Bar_42	TechProblemsSite	-1.23	1.021
Bar_43	WorkplaceCommittments	-.21	1.311
Bar_44	InsufficientAcademicKnowledge	-1.03	1.033

Note: items were measured on a 5-point Likert scale (-2 = not at all, 2 = to a very large extend

Summary

Lifelong learning is the new paradigm in the educational landscape. Learning is not limited to traditional face-2-face learning environments anymore, yet it is encouraged to be regarded as an ongoing process which is relevant at all stages in life. Even though learning opportunities are expanding, learning in traditional face-2-face context is still most common. However, many learners experience barriers which make it difficult or even impossible for them to engage in this form of learning. Open education in the form of Massive Open Online Courses (MOOCs), which are openly accessible to anyone, anywhere at any time, may be a viable alternative for this group of (lifelong) learners. At the same time, reported dropout rates are very high and the open, flexible and less supported form of learning in MOOCs can elicit considerable challenges for learners.

The aim of this research project was to advance research into open education and MOOCs specifically by conducting empirically grounded studies to answer the main question underlying this dissertation: How can the definition of success in open education and MOOCs be refined and what barriers impede individual learner success?

The first study in *Chapter 2* presents an alternative typology for determining success and failure (dropout) in MOOCs. This typology takes the perspectives of learners into account and is based on their intentions and subsequent behaviour. An explorative study using two MOOCs was carried out to test the applicability of the typology. Following the traditional approach based on course completion to identify educational success, success rates were 6.5 and 5.6%. The success rates from the perspectives of the learner were 59 and 70%. These results demonstrated that merely looking at course completion as a measure for success does not suffice in the context of MOOCs. These findings also hinted towards dynamicity in the intention-behaviour process. The next two studies, presented in Chapter 3 and 4 further explore this. In *chapter 3*, a model is introduced that captures and visualizes the possible dynamical process of individual intention forming and the translation of this intention into actual behaviour. To validate the model and further our understanding of learning in MOOCs, we constructed a short survey, containing open and closed questions, based on this theoretically grounded intention-behaviour model. The results revealed that most learners start a MOOC with a specific intention in mind, but that nearly one third of these learners reformulates this initial intention, once or more often, at some point due to barriers they have to face during their learning in a MOOC. The study in *Chapter 4*, further examines goal achievement because reaching goals can be challenging, especially if they are not in the near future like with learning in MOOCs. The aim of this study was to get insight in the goal achievement process, to increase our understanding of learner behaviour. Two research questions were examined namely: 1) what goals do learners set, and do they succeed in reaching these goals? and 2) how does the course of action of several learners look taking Gollwitzer's Rubikon model of action phases as a guideline? We found that even though learners did not achieve the goals they set, they were still generally satisfied with the knowledge they gained. In addition, learners went more or less intuitively through the theorised action phases, yet typically did not take the time to deliberately plan (before the start) and evaluate (after finishing) their learning process. This insight can serve as starting point for developing supporting tools for learners and personalised dashboards, which can offer the tools at appropriate times in a learner's course of action.

Previous studies indicate that intention is not a perfect predictor for behaviour as not all learners translate their intention into actual behaviour. It seems that learners face barriers which prevent or hinder them from acting out their individual learning intentions and achieving their goals. *Chapter 5* presents an explorative study about types of barriers that stand in the way of learner success. Data of two MOOCs was used to illustrate MOOC- success from two perspectives and to identify barriers learners faced in the MOOCs. Descriptive data of both MOOCs showed that the non-MOOC related barriers workplace issues and lack of time were the most frequently experienced barriers. The aim of our next study, which is presented in Chapter 6, was to elicit and to empirically classify barriers that influence intention achievement in MOOCs. The best fit model of our factor-analytical approach resulted in 4 distinctive components; 1. Technical and online-learning related skills, 2. Social context, 3. Course design/ expectations management, 4. Time, support and motivation. The main finding of our study was that the experienced barriers by learners are predominantly non-MOOC related, which is in line with our results of previous study. This insight is particularly interesting and valuable for MOOC-designers because knowledge about the type of barriers learners face can prevent unnecessary design interventions of the MOOC. The next study, in *chapter 7*, further builds on previous study and aimed to develop a self-report instrument which can be used, as a diagnostic tool by MOOC-providers and designers to gather information that will benefit further development of MOOCs and subsequently, support learners in achieving their personal learning goals. Factor analyses were performed and showed promising results. The strength of the standardized factor loadings, which indicated good measurement quality in combination with the coherent diagnostic categories that correspond to the ideas that steered the construction of the instrument pointed towards a good construct validity and therefor usability of the instrument.

The last study, presented in *chapter 8*, addresses the question whether age, gender, educational level, and online learning experience affect barriers faced while learning in MOOCs. The results show that it is challenging to combine work and family life with lifelong (online) learning activities, especially for learners in their early adulthood (20-35 years) and mid-life (36-50 years). However, more experience with online learning positively affects learners' ability to cope with these challenges. Also, learners with a lower educational level may experience a lack of knowledge or difficulties with the course content.

The goal of this research project was to contribute to open education and MOOC-research specifically by conducting empirical studies to answer the main question underlying this dissertation: How can the definition of success in open education and MOOCs be refined and what barriers impede individual learner success?

This goal was reached by proposing an empirically grounded alternative view on learner success which can make MOOC educators aware of the importance of the learner perspective and learner behaviour and can complement the institutional perspective when assessing MOOC success. In addition, the studies zoomed in on reasons why learners were not successful or less successful than they intended to be. This resulted in empirical studies about barriers to learning in MOOCs and about which determinants possibly affected the experience of certain barriers. Although there are several limitations and further research into these topics is necessary to increase the generalisability of the studies, the outcomes of this dissertation provide opportunities and insights for both MOOC educators as well as MOOC- learners (via MOOC educators) that can support them in their strive for the best possible learning results.

Samenvatting

Leven lang leren is het nieuwe paradigma in het onderwijslandschap. Leren beperkt zich niet langer tot traditionele klassikale leeromgevingen, maar wordt beschouwd als een doorlopend proces dat in alle levensfasen relevant is. Hoewel de mogelijkheden om te leren zich uitbreiden, is leren in de traditionele klassikale context nog steeds het meest gebruikelijk. Veel lerenden komen echter barrières tegen die het voor hen moeilijk of zelfs onmogelijk maken om aan deze vorm van leren deel te nemen. Open onderwijs in de vorm van Massive Open Online Courses (MOOCs), die voor iedereen, waar en wanneer dan ook, openlijk toegankelijk zijn, kan voor deze groep (leven lang) lerenden een interessant alternatief zijn. Tegelijkertijd lijken de uitvalpercentages van MOOCs zeer hoog te zijn en kan juist de open, flexibele en minder begeleide vorm van leren in MOOCs grote uitdagingen met zich meebrengen.

Het doel van dit onderzoeksproject was om bij te dragen aan onderzoek naar open onderwijs en MOOCs door het beantwoorden van de volgende hoofdvraag: Hoe kan de definitie van succes in open onderwijs en MOOCs genuanceerd worden en welke barrières belemmeren lerenden in het behalen van hun individuele leerdoelen?

Het eerste onderzoek in hoofdstuk 2 presenteert een alternatieve typologie voor succes en drop-out in MOOCs. Deze typologie neemt de perspectieven van de lerenden als uitgangspunt en is gebaseerd op hun intenties en daadwerkelijk gedrag. Om de toepasbaarheid van de typologie te testen is een verkennende studie uitgevoerd in twee MOOCs. Volgens de traditionele benadering, die gebaseerd is op de afronding van een cursus en het behalen van een certificaat, bedroeg het succespercentage 6,5 en 5,6%. Het succespercentage vanuit het perspectief van de lerende, waarbij de intentie van de lerende leidend was, bedroeg 59 en 70%. Deze resultaten toonden aan dat het niet voldoende is om in het kader van MOOCs alleen maar te kijken naar het afronden van een cursus als maatstaf voor succes. Deze bevindingen duiden op mogelijke dynamiek in het proces van intentie naar gedrag. De volgende twee studies, hoofdstuk 3 en 4, gaan hier verder op in. In hoofdstuk 3 wordt een model geïntroduceerd dat het mogelijke dynamische proces van individuele intentievorming en de vertaling van deze intentie naar daadwerkelijk gedrag vastlegt en visualiseert. Om het model te valideren en ons inzicht in leren in MOOC's te bevorderen, is er een korte vragenlijst met open en gesloten vragen opgesteld, gebaseerd op dit theoretisch onderbouwde intentie-gedragsmodel. De resultaten toonden aan dat de meeste lerenden met een specifieke intentie aan een MOOC beginnen, maar dat bijna een derde van deze lerenden deze initiële intentie op een bepaald moment herformuleert al dan niet als gevolg van barrières die ze tijdens het leren in een MOOC tegenkomen.

Het onderzoek in hoofdstuk 4 gaat verder in op het bereiken van doelen, omdat het bereiken van doelen die verder in de toekomst liggen, zoals dat met leren in een MOOC vaak het geval is, uitdagend kan zijn. Dit onderzoek was gericht op het krijgen van inzicht in het proces van het bereiken van doelen en om ons inzicht in het gedrag van de lerende te vergroten. Twee onderzoeksvragen werden hiervoor onderzocht: 1) Welke doelen stellen lerenden zichzelf en slagen zij erin deze doelen te bereiken? en 2) Op welke manier doorlopen lerenden een MOOC als Gollwitzer's Rubikon model van actiefasen als richtlijn genomen wordt? Wij ontdekten dat, hoewel de lerenden hun doelen vaak niet bereikten, ze over het algemeen toch tevreden waren met de kennis die ze hadden opgedaan. Daarnaast doorliepen de lerenden min of meer intuïtief het grootste deel van de getheoretiseerde actiefasen, maar namen ze vaak niet de tijd om hun leerproces bewust te plannen (voor de start) en te evalueren (na het beëindigen van het leerproces). Dit inzicht kan als startpunt dienen voor het ontwikkelen van ondersteunende tools zoals gepersonaliseerde dashboards, die lerenden op de juiste momenten zouden kunnen voorzien van de benodigde hulpmiddelen om zodoende het leerproces te bevorderen.

Voorgaande studies tonen aan dat intentie geen perfecte voorspeller is voor gedrag, aangezien niet alle lerenden hun intentie vertalen naar daadwerkelijk gedrag. Het lijkt erop dat lerenden geconfronteerd worden met barrières die hen hinderen om hun individuele leerintenties te behalen en hun doelen te bereiken. Hoofdstuk 5 presenteert een verkennend onderzoek naar de soorten barrières die het succes van de lerende in de weg staan. Er werden gegevens van twee MOOCs gebruikt om het MOOC-succes vanuit twee perspectieven te illustreren (zoals in de eerste studie ook gedaan is) en om de barrières te identificeren die lerenden in de MOOCs tegenkwamen. De resultaten lieten zien dat barrières die niet aan de MOOC gerelateerd waren het meeste voorkwamen. Met name gebrek aan tijd in het algemeen en problemen op het werk waren veel voorkomende barrières. Het volgende onderzoek, dat in hoofdstuk 6 beschreven wordt, gaat een stap verder. Het doel was om barrières die van invloed zijn op het bereiken van de intentie in MOOCs, te identificeren en vervolgens empirisch te classificeren. De factor-analytische aanpak resulteerde in een model met 4 verschillende componenten; 1. Technische en online-leren gerelateerde vaardigheden, 2. Sociale context, 3. Cursusontwerp/verwachtingsmanagement, 4. Tijd, ondersteuning en motivatie. De belangrijkste bevinding van dit onderzoek was dat de meeste barrières waar lerenden hinder van ondervonden, niet gerelateerd waren aan de MOOC. Deze bevinding sluit aan bij de resultaten van het voorgaande onderzoek en is vooral interessant en waardevol voor MOOC-ontwerpers en opleiders. Inzicht in het soort barrières waar lerenden tegenaan lopen, kan namelijk voorkomen dat MOOCs onnodig herontworpen of aangepast worden.

Het volgende onderzoek, in hoofdstuk 7, bouwt voort op het onderzoek in hoofdstuk 6. Dit onderzoek had als doel het ontwikkelen van een zelfrapportage-instrument voor lerenden wat door MOOC-aanbieders en -ontwerpers gebruikt kan worden als diagnostisch instrument om informatie te verzamelen die de verdere ontwikkeling van MOOCs ten goede kan komen. De resultaten van de zelfrapportage kunnen vervolgens ook ingezet worden om lerenden te ondersteunen bij het bereiken van hun persoonlijke leerdoelen. Voor de instrumentontwikkeling zijn een aantal factoranalyses uitgevoerd die veelbelovende resultaten hebben opgeleverd. De gestandaardiseerde factorladingen wezen op een goede meetkwaliteit, wat in combinatie met de samenhangende diagnostische categorieën, op een goede construct-validiteit duidde en dus op een goede bruikbaarheid van het instrument.

Het laatste onderzoek, dat beschreven wordt in hoofdstuk 8, gaat in op de vraag of leeftijd, geslacht, opleidingsniveau en online leerervaring van invloed zijn op de barrières waar lerenden tegenaan lopen. De resultaten tonen aan dat het lastig is om werk en gezinsleven te combineren met leven lang (online) leeractiviteiten. Dit gold in het bijzonder voor lerenden in hun vroege volwassenheid (20-35 jaar) en mid-life (36-50 jaar). Meer ervaring met online leren heeft echter een positief effect op het vermogen van lerenden om deze uitdagingen aan te gaan. Als laatste lieten de resultaten zien dat lerenden met een lager opleidingsniveau problemen met de inhoud van MOOCs kunnen krijgen wegens een gebrek aan kennis.

Met dit onderzoeksproject wilden wij een bijdrage leveren aan open onderwijs en MOOC-onderzoek door het beantwoorden van de hoofdvraag: Hoe kan de definitie van succes in open onderwijs en MOOCs genuanceerd worden en welke barrières belemmeren lerenden in het behalen van hun individuele leerdoelen?

Dit doel werd bereikt door een alternatieve, empirisch onderbouwde, kijk op MOOC-succes voor te stellen, die MOOC-opleiders bewust kan maken van het belang van het individuele perspectief en gedrag van de lerende. Dit individuele perspectief kan als aanvulling gezien worden op het institutionele perspectief bij het beoordelen MOOC-succes. Daarnaast werd in de studies ingezoomd op redenen waarom lerenden niet of minder succesvol waren dan ze aanvankelijk gehoopt hadden. Dit resulteerde in empirisch onderzoek naar barrières die leren in MOOCs kunnen hinderen en naar welke determinanten mogelijk van invloed zijn op het tegenkomen van bepaalde barrières. Hoewel er een aantal beperkingen in acht genomen moeten worden en verder onderzoek naar deze onderwerpen noodzakelijk is om de generaliseerbaarheid van de studies te vergroten, bieden de resultaten van dit proefschrift kansen en inzichten voor zowel MOOC-ontwerpers en opleiders als MOOC-lerenden.

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Stay sane and keep learning☺

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