Radboud University

Acceptance of MOOCs by Dutch university students

Extending the *unified theory of acceptance and use of technology* (UTAUT) model with the *technology acceptance model* (TAM)

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Abstract

Massive Open Online Courses (MOOCs) have gained educators' and technology researchers' interests in recent years as MOOCs could be the future of online education. Previous research has shown how MOOCs' acceptance could be improved by using technology acceptance models. Little research has been done on university students' acceptation of MOOCs and intention to use MOOCs as well as the degree to which a technology acceptance model could influence this acceptance process. The purpose of this study is therefore to examine Dutch university students' intention to use MOOCs and their acceptance of MOOCs explained by the *Unified Theory of Acceptance and Use of Technology* (UTAUT) model and *Theory of Acceptance Model* (TAM). These models combined are called the extended UTAUT model. The extended UTAUT model consists of several factors that affect peoples' intention to use MOOCs. These factors are *performance expectancy, effort expectancy, attitude towards use of MOOCs, social influence, facilitating conditions and behavioural intention to use MOOCs*. A sample of 305 Dutch university students took part in this study. *Structural equation modelling* (SEM) implemented via *partial least squares* (PLS) was used to test the research hypotheses. The results showed that the extended UTAUT model provides a comprehensive understanding of students' intention to use MOOCs. *Performance expectancy* and *effort expectancy* positively influence students' *attitude towards use of MOOCs*. Next to this, students' *attitude towards use of MOOCs* positively influence students' *behavioural intention to use MOOCs*. Unexpectedly, *social influence* had no significant influence on *behavioural intention to use MOOCs. Facilitating conditions* had no significant influence as well on *behavioural intention to use MOOCs.* This study, although interpreted carefully, adds to literature on educational innovations, technology acceptance models and behavioural intentions. Furthermore, the findings of this study could be interesting for educators in dealing with students' enrolment in a MOOC course.

Table of Contents

1. Introduction

Online education is a relatively new approach to teaching and studying, it has been gradually developing across the globe over the years (Harasim, 2000). The World Wide Web was invented in 1992, this made online education more accessible. Great innovations and expansions were developed in online education in the 80s and 90s. The developments in online education made it easier to communicate and collaborate and also made it easier to gain access to new knowledge. The 21st century began with an open attitude towards online education.

The next step for providing online course content and resources were *Open Educational Resources* (OER). Open Educational Resources are the digitized materials that are free and open to educators, students and self-learners. Users of OER can use these educational resources, as well as re-use these resources for teaching, learning and research (Hylén, 2006).

A logical continuation to *Open Educational Resources* (OER) is *Massive Open Online Courses* (MOOCs). MOOCs are a relatively new model for the delivery of online courses to learners made by top-educators (Onah, Sinclair, & Boyatt, 2014; Coursera, 2019). MOOCs are available for everyone with an interest in the topics that the MOOCs provide (RUG, 2017). A MOOC course is defined by Coursera (2019, p.1) as follows: "*Each course is like an interactive textbook, featuring pre-recorded videos, quizzes, and projects.*"

Massive and *Open* stand for the intention of the online courses to be accessible to a large number of learners and students that are not reachable by conventional teaching methods. MOOCs are open, free and are not restricted to location. The coursework of the subject should be participatory, shared with all the people taking the course and should be easily distributed (Pisutova, 2012). MOOCs are furthermore free to use as a way of obtaining more in-depth knowledge of a certain topic. MOOCs offer the learner a chance to develop themselves further from anywhere across the globe through internet. Some courses provided by MOOCs include a test at the end of the course and learners receive certificates when they pass these tests. Even though learners get certificates for tests, they will not be able to get an official diploma of a MOOC since none of the platforms providing MOOCs have officially been accredited (Werkstudent, n.d.). A MOOC is an ideal tool for learners to review certain material or for further developing themselves alongside their current major or job.

MOOCs do not have a long history. The term first appeared in 2008 and was created by Stephen Downes and George Siemens. In 2011 the first online educational courses were developed by professors from Stanford University. In that same year, MOOCs became more popular around the world and the number of online courses increased rapidly (Baturay, 2015).

MOOCs began to become even more popular since 2012, as a result of the introduction of well-known online learning platforms such as edX, Coursera and Udacity, with around 200 online courses. These courses were made available for everyone who had access to the internet (Ahrache, Badir, Tabaa, & Medouri, 2013).

MOOCs development appeared to go in two different directions: cMOOCs and xMOOCs. XMOOCs stands for *eXtended Massive Open Online Courses and* cMOOCs stands for *Connected Massive Open Online Courses*. CMOOCs focus on connectivity and tries to achieve this by creativity, autonomy, social network learning, knowledge creation and generation, while xMOOCs are focussed on knowledge duplication and are based on traditional university courses (Pisutova, 2012). A difference between a xMOOC, compared to a cMOOC, is that the lecture is delivered by an instructor to the student. CMOOCs focus more on interaction and involve groups of people learning together (Extension Engine, 2019). To prevent confusion the umbrella term MOOCs will be used in the rest of this thesis.

1.1 Acceptance issues regarding MOOCs

Although this movement seems to be going fast, MOOCs are still in development and empirical research remains thin (Castillo, Lee, Zahra, & Wagner, 2015). Some universities are hesitant to accept MOOCs' course format. This hesitation has led to discussions about the future of education and the role MOOCs will play within education (Gao & Yang, 2015).

Acceptance of a system is an important part of analysing a new technology. Acceptance means *the willingness of people to use a new product or service or to believe a new idea* (Cambridge Dictionary, 2019). In this study acceptance can be defined as the willingness of students to use MOOCs.

Acceptance studies focus on the factors that affect people's actual use of a system, with behavioural intention to use as a predictor for actual use. It can be carefully stated that when people have intentions to use a system, they accept this system. Behaviour intention and acceptance are thus interlinked.

There are some difficulties for universities and students to accept MOOCs (Griffiths, Mulhern, Spies, & Chingos, 2015). The first difficulty is the content fit because the MOOCs reflect the priorities of the creator. Not all offered MOOCs are made by educators that give a course on the same subject. Therefore, there is a difference in content because the educator of the conventional course may have other priorities than the creator of the MOOC. This could also pose a challenge for the educator who then might need to change his or her existing course to fit the online content.

The researchers in Griffiths et al. (2015) asked administrators and faculty members to describe a goal or problem that might arose through use of the online content of MOOCs. A criterion from faculty members on the content fit was that students did not yet had the required level of prior knowledge and quantitative skills to follow the MOOCs, or the opposite, that the expected level of expertise was too low. As a result, a growing number of educators have started creating their own MOOCs that fit their course better than the existing MOOCs. However, not all instructors have the time and expertise to develop a MOOC.

Another difficulty of the acceptance of MOOCs is technology integration (Griffiths et al., 2015). Some MOOCs are difficult to include into local learning management systems of universities, because of incompatibility between the MOOCs and school technology. As a result, MOOCs sometimes did not work and even if they did, students had difficulties accessing the appropriate version of the MOOC. More research is needed to shed light on the acceptance of MOOCs and the factors that influence this acceptance process.

1.2 MOOCs and acceptance technology models

A way of examining people's acceptance of new technologies is by using technology acceptance models. The *Technology Acceptance Model* (TAM) is based on concepts from social psychology and is a tool to examine the intention of individuals to use new technology (Kim, Lee, Hwang, & Yoo, 2015). Additionally, students' intention to use MOOCs can be analysed by using the *Unified Theory of Acceptance and Use of Technology* (UTAUT) model. UTAUT is based on concepts of various human behaviour theory models and contains social concepts as well as individual. Previous research has suggested to combine different hypothesis of different existing models into an adjusted model (Kim et al., 2015). However, it appears that results reported based on these analyses have internal discrepancies, which need to be researched in future studies.

The factors that influenced the intentions of Dutch university students to use MOOCs were analysed in this study. The factors analysed were a combination from the TAM and UTAUT models. Combined these models form the extended UTAUT model. This term, the extended UTAUT model, will be used in the rest of this research.

1.3 Introducing current research

Introducing and implementing MOOCs could lead to a new way of sharing information. Information in the previous sentence refers to obtaining knowledge as well as the transformation of information into gaining new competences. MOOCs, with its enormous potential, offer a new way of organizing traditional education (Jacoby, 2014). MOOCs only date back a few years ago and are still in development. The chapter above showed that there are still difficulties in the acceptance of MOOCs. Although the importance of MOOCs is clear, there is still little research done on university students' acceptance of MOOCs and the factors that could influence this. This thesis will focus on the potential factors that affect Dutch university students' acceptance of MOOCs from the perspective of both the *Theory of Acceptance* (TAM) and the *Unified Theory of Acceptance and Use of Technology* (UTAUT).

The *Theory of Acceptance* model is used to explain user behaviour and was first introduced by Davis in 1986 (Davis, Bagozzi, & Warshaw, 1989). TAM will be used in this research to predict and explain user acceptance of system-based technology. The objective of TAM is to provide an explanation of the factors of system acceptance. These factors are general and capable of explaining user behaviour across a wide range of end-user computing technologies and user population (Davis et al., 1989).

The *Unified Theory of Acceptance and Use of Technology* model is used to explain technology behaviour and acceptance. UTAUT is used in this research to predict and explain user acceptance of MOOCs. Both the TAM and the UTAUT model describe and explain the acceptance of a technology (Carlsson, Carlsson, Hyvonen, Puhakainen, & Walden, 2006).

1.4 Focus of this research

It appears that there are some difficulties with the acceptance of *Massive Open Online Courses*, such as content fit and technology integration (Griffiths et al., 2015). It is interesting to look at why this implementation of MOOCs seem to have hurdles. To analyse this implementation, it is necessary to figure out the underlying factors that influence MOOCs acceptance. MOOCs acceptance can be analysed by students' intention to use MOOCs. Both terms are used in this thesis when explaining MOOCs acceptance. The current focus on MOOCs presents an opportunity for researchers to figure out which factors lead to MOOCs' acceptance (Zheng, Rosson, Shih, & Carroll, 2015). According to the research of Zheng et al. (2015), a quantitative study with a more varied and larger population would be a useful tool of researching the acceptance of MOOCs. A deeper understanding of users' needs can be found by studying the underlying factors that influence MOOCs acceptance. This deep understanding of users' needs is critical for future development of MOOCs (Zheng et al., 2015). This leads to the following research question:

> "*To what extent do the combined UTAUT and TAM models explain Dutch university students' intention to use MOOCs?* "

The combined UTAUT and TAM models consists of several factors that influence students' intention to use MOOCs and thus acceptance of MOOCs. That is why the following sub-questions are formulated:

(1) *What potential factors could affect students' intention to use MOOCs?*
(2) *Will performance expectancy and effort expectancy influence attitude towards use of MOOCs?*
(3) *Will attitude towards use of MOOCs influence behavioural intention to use MOOCs?*
(4) *Will social influence and facilitating conditions influence behavioural intention to use MOOCs?*

To answer the research question and sub-questions, a quantitative research design is applied. A quantitative design (survey method) was chosen because data collected from surveys lead to quantitative, factual and descriptive data that can be used when comparing variables (Stork, 2017; Vaus, 2002). The survey method can help predict and understand a phenomenon at large (Stork, 2017; Swanborn, 2013). By conducting a survey, it was also possible to involve many respondents and in this way the representativeness of the study increases.

1.5 Research purpose

The scientific merit and objective of this research is to find out to which extent factors of the extended UTAUT model influences the acceptance of MOOCs by university students. This research strives to fill the gap in current scientific knowledge regarding the possible factors that influence the acceptance of MOOCs since little research has been done on the acceptance of MOOCs. Even more specifically, little to no research has been done on the acceptance of MOOCs by Dutch university students. The main goal of this research is to increase understanding in the acceptance of MOOCs by students. This research shows societal relevance since it is about innovation of education. This thesis aims to shed new light on the future of (online) education and hopes to provide a solution to educators and universities on how to successfully implement MOOCs. MOOCs may expand or enhance teaching practices, such as providing students with better and more varied teaching, compared to the traditional teaching practices offered by individual instructors, which is more limited. MOOCs could also increase interests of students to pursue higher education by offering access to good teaching methods and interesting subjects.

1.6 Research outline

The rest of the thesis is organized as follows. The theoretical framework is reviewed in chapter 2 and consists of a literature review and a research model. The literature review will offer a short overview of MOOCs, TAM and UTAUT. Section 3 consists of the methodology and research design and section 4 presents the most relevant findings obtained from this thesis. These results are discussed in Section 5. Section 5 also draws conclusions, summarizes the contributions of this study and outlines research limitations and suggestions for future research.

2. Theoretical framework

The theoretical framework consists of two parts. The first part concerns the literature review where previous research on the topic of Massive Open Online Courses (MOOCs) will be evaluated and an explanation of technology acceptance models will be given. The second part of the theoretical framework consists of the research model. The research model might be a solution to the gap in the knowledge about the acceptance of MOOCs, which this research attempts to fill.

2.1 Literature review

Massive Open Online Courses (MOOCs) are the logical next step in open, online education. Online education emphasizes the way that resources and tools can improve the quality of education. Open online education platforms, such as Coursera and edX, provide technological innovations in the form of interactive videos. These videos allow educators to present MOOCs to a large number of students. The use of MOOCs allows students to receive their education without having to be physically present and without having to pay a large amount of money. Students are able to overcome physical and financial barriers with the use of MOOCs. Students will also have the ability to pursue their own learning goals. It comes as no surprise that the advantages of MOOCs are of great interest to educators and technology researchers, since MOOCs could be the future of online education (Zheng et al., 2015).

MOOCs differ from traditional courses on four characteristics, namely autonomy, diversity, openness and interactivity. When MOOCs scored high on all four of the characteristics students' potential to learn was high. In this way, the limitations that are normally associated with an online course, such as the lack of structure, support and moderation are exceeded (Mackness, Mak, & Williams, 2010).

An important part of online education and MOOCs is the acceptance of these new technologies. The first stage of the acceptance process starts when people are confronted with a new technology. In this stage they will go through a process of gathering information about the new technology. Next, people will test the technology and decide whether it offers a worthily improvement. It takes time and energy for people to add a new technology to their range of knowledge and skills (Rogers, 1995).

The acceptance of online education by universities is going slow. Universities are faced with difficulties, such as resistance, which they have to overcome before they can accept new technologies (Griffiths et al., 2015). This can be partly explained by Rogers' diffusion of technological innovation model (1995). The results from this model show that universities, and people in general, are relatively slow in adopting technological innovations (see Appendix 1).

Although the acceptance process of online education is quite slow, there are several ways universities have accepted MOOCs. Some universities actively develop MOOCs themselves and may therefore be called *producers*, while other universities use MOOCs that are developed by other institutions. These institutions are called *consumers*. Another form of acceptance of MOOCs is the wait-and-see approach, where universities wait before getting involved with MOOCs. Some universities do not want to engage with MOOCs at all or do not have the support from faculty members to develop or implement them (Hollands & Tirthali, 2014).

There are several reasons for universities to use MOOCs (Allen & Seaman, 2014). It appears that, of the 140 MOOC-offering institutions, the main reasons for using MOOCs are: institution's visibility (27%), increase of student recruitment (20%), innovation of pedagogy (18%) and providing flexible learning opportunities (17%). Faculty members also identified other benefits of students using MOOCs (Griffiths et al., 2015). These benefits are: replacement of lectures, augmenting or replacing of secondary materials, filling gaps in expertise, exposing students to other styles of teaching and class discussions, and reinforcement of key skills such as critical thinking.

The abovementioned advantages have created an increase in Dutch universities' interest in MOOCs. Dutch universities have started developing their own MOOCs. In February 2013 the first Dutch made MOOC by the University of Amsterdam (UvA) was introduced in the Netherlands. This course is taught in English and is available to students all over the world. The TU Delft also developed a MOOC with a focus on primary education. Other universities in The Netherlands have also shown interest in MOOCs. This indicates that MOOCs are slowly growing in importance in Dutch educational programs and will therefore play a bigger role in educational programs in the future (Mediawijsheid, n.d.).

2.1.1 MOOCs and Technology Acceptance Models

Some research inspirations of this study are drawn from existing theories that examine the acceptance of new technologies and the acceptance of innovations. The acceptance of innovations has been a common research topic for many years. A technology acceptance model is needed to find the factors that influence student's attitudes and intentions to use MOOCs (Wu & Chen, 2017).

The *Technology Acceptance Model* (TAM) is one of the most widely used and accepted models in researching the acceptance of innovations (Jeyaraj, Rottman, & Lacity, 2006; Gao & Yang, 2015). The model consists of a theoretical basis that underlies two key beliefs: *perceived usefulness* (PU) and *perceived ease of use* (PEOU). These two beliefs are followed by users' *attitude*s, *intentions* and *actual system acceptance behaviour*, as can be seen in Figure 1.

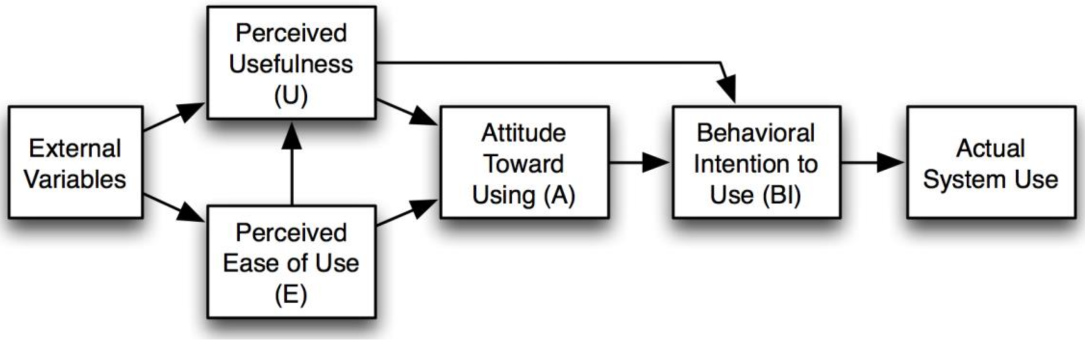

Figure 1. Theory of Acceptance Model (Davis et al., 1989).

TAM was built on the *Theory of Reasoned Action* (TRA). The TRA has its roots in social psychology and states that behaviour is explained by people's *behavioural intention*, *attitude*s, *subjective norms*, and *beliefs* (Aharony & Bar-Ilan, 2016; Fishbein & Ajzen, 1975). Social cognitive theory (Bandura, 1977) and innovation diffusion theory (Rogers, 1995) are both theories that have influenced these acceptance models. Next to TRA, TAM also compares favourably with the *Theory of Planned behaviour* (TPB) (Venkatesh & Davis, 2000). The TPB adds a measure of *perceived control* to the base model of the TRA. In this way the TPB model "*extend the domains of behaviour covered by the TRA to behaviours that are not totally under a person's control"* (Sparks & Shepherd, 1992, p.389).

TAM has some limitations, these are extensibility and explanation power (Benbasat & Barki, 2007). That is why the *Decomposed theory of planned behaviour* (DTPB) was formed. The DTPB model is a combination of the TAM and TPB models and has better explanation power (Taylor & Todd, 1995). Another model, *task-technology fit* (TTF), explains how technology leads to performance impacts and highlights the importance of a fit between task and technology (Goodhue & Thompson, 1995). An extension to this model is the *Technology-to-Performance Chain* (TPC) model, which is a comprehensive model of a linkage between the insights of both user attitudes as predictors of utilization and task-technology fit as a predictor of performance.

A logical sequence to this is the *integrated TAM and TFF* model, which is an extension to the TAM model with some TTF constructs. The variable attitude from the TAM model is combined with the variable fit from the TTF model and together provide a better explanation of *information technology* (IT) utilization (Dishaw & Strong, 1999). Using the TAM model with additional variables to create a stronger model was already suggested by other researchers (Gao, Krogstie, & Siau, 2011; Gao & Yang, 2015; Legris, Ingham, & Collerette, 2003). Another model that extends the TAM model is the *extended technology acceptance model* (TAM2). The TAM model is extended by the collected influence of social influence prosses as well as cognitive instrumental processes on perceived usefulness. TAM2 expands the TAM model with five factors influencing perceived usefulness and two moderating factors, which are experience and voluntariness.

It is no surprise that researchers try to enhance the TAM model, since the two factors of the TAM model (*user's perceived usefulness* and *perceived ease of use*) only explain 30 to 40% of the variance in *behavioural* intention to use a technology (Mendoza, Mak, & Williams, 2017; Venkatesh & Davis, 2000). The TAM model has also been criticised by Lee, Kozar and Larsen (2003) for focusing mainly on personal factors without regarding social influence.

A response to these criticisms was the proposed *Unified Theory of Acceptance and Use of Technology* (UTAUT) model (Mendoza et al., 2017; Venkatesh, Morris, Davis, & Davis, 2003). This model explains 70% of technology acceptance success (Schaper & Pervan, 2007). The UTAUT model has become the leading model of IT and software acceptance (Wrycza, Marcinkowski, & Gajda, 2017). The UTAUT model by Venkatesh et al. (2003) addresses both the personal and social factors for explaining technology acceptance (Mendoza et al., 2017). UTAUT research is mostly focused on e-learning, such as educational webcast acceptance (Giannakos & Vlamos, 2011), as well as mobile learning acceptance (Prieto, Miguelanez, & Garcia-Penalvo, 2014). Most models that explore users' technology acceptance behaviours are derived from innovation theory, sociology, computer utilization and psychology. Some examples of the most representative models are *innovation diffusion theory* (IDT) and *social cognitive theory* (SCT). However, they fail to provide complete explanation of technology acceptance behaviours. A solution to this is the UTAUT model, which offers a more comprehensive exploration.

The UTAUT model is an integrative theory that explores the dimensions that affect users' *behavioural* intention (Venkatesh et al., 2003). The UTAUT model consists of four core variables: *performance expectancy*, *effort expectancy*, *social influence* and *facilitation conditions*, as can be seen in Figure 2. These four variables have been validated in previous research (Im, Hong, & Kang, 2011), which showed that the UTAUT is a suitable framework for critically reviewing findings of previous research in the field of MOOC acceptance (Mendoza et al., 2017). The model also consists of four control variables: gender, age, experience, and voluntariness of use (Im et al., 2011). These four control variables are used to provide a better understanding of the complexity of individuals' technology acceptance (Carlsson et al., 2006).

A more elaborate description of each acceptance model or theory can be found in Appendix 1. A summary of the characteristics, advantages, disadvantages and the origin of each model are put together in a Table that can be found in Appendix 2.

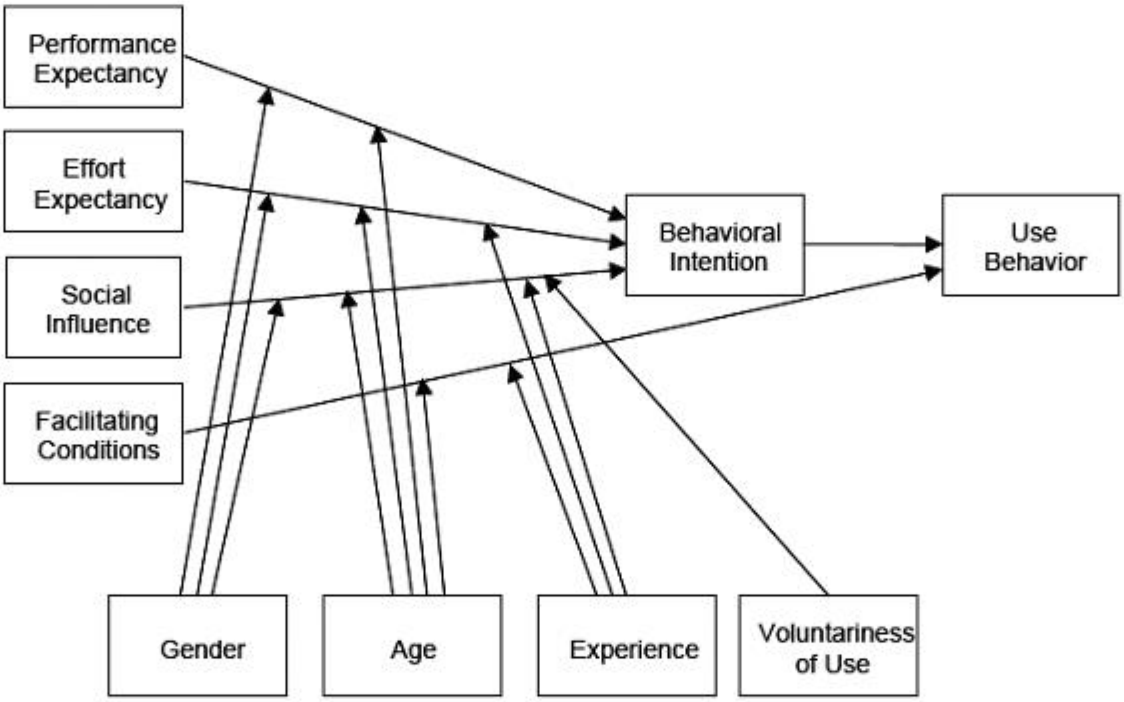

Figure 2. UTAUT Model (Im et al., 2011)

2.1.2 The extended UTAUT model

This study aims to analyse students' acceptance of MOOCs with the *Technology of Acceptance model* (TAM) and the *Unified Theory of Acceptance and Use of Technology model* (UTAUT). The combination of these two models will be referred to as the extended UTAUT model (Figure 4).

From the analyses in the previous chapter it appears that TAM and UTAUT are the most frequently used theory acceptance models. When comparing the TAM and UTAUT models it appears that there are a lot of similarities between the models, as can be seen in Figure 3. The UTAUT model was constructed by extracting 3 variables that influence *behavioural intention to use*, 1 variable that influences action, and 4 moderating variables that mediate the effects of the process. The TAM model was constructed by two independent variables that both influence *attitude* and *behaviour intention.* Some variables are similar in meaning with the variables of the TAM (Kim et al., 2015). As can be seen in figure 3, *perceived usefulness* of the TAM model is similar to *performance expectancy* of the UTAUT model. *Perceived ease of use* of the TAM model is similar in meaning to *effort expectancy* of the UTAUT model. *Intention to use* and *actual use* are also both similar concepts in both models. The TAM model has one other (moderating) variable, which is *Attitude.* The UTAUT model has two other independent variables, which are *social influence* and *facilitating conditions.*

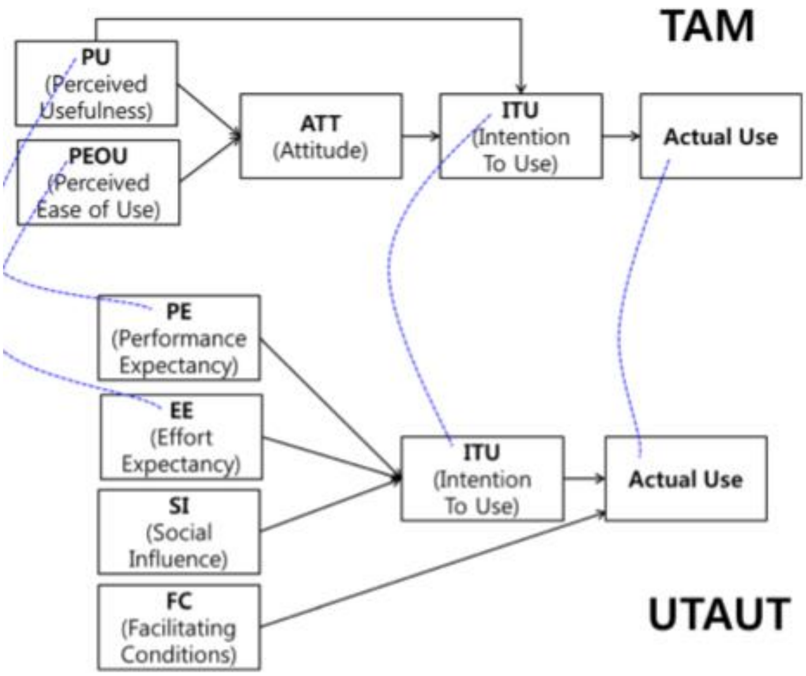

Figure 3. Comparison between the TAM and UTAUT models

The variable *performance expectancy* of UTAUT corresponds with the variable *perceived use* of TAM. *Performance expectancy* stands for the degree to which an individual believes that using the system will increase his or her performance. *Effort expectancy* is comparable to the *perceived ease of use* of the TAM model. *Effort expectancy* stands for the degree of ease associated with the use of the new technology. The other two variables, *social influence* and *facilitating conditions* of the UTAUT model differ from the TAM model. Nevertheless, they are valuable variables for examining MOOCs' acceptance. *Social influence* is the degree to which an individual believes that people important to the individual want them to use the new system. *Facilitating conditions* are the degree to which an individual believes that organizational and technical infrastructures exist in order to support the use of the new technology (Jen, Lu, & Liu, 2009).

Previous research found that some control variables, (1) gender, (2) age, (3) experience and (4) voluntariness of use, had an influence on the acceptance of new technologies, as can be seen in Figure 2. These control variables were also analysed if they were usable for the UTAUT model and it appeared that experience, gender and age had an effect on the acceptance of MOOCs (Im, Kim, & Han, 2008). According to Venkatesh et al., (2003) these four control variables had mediating effects on the relationships between the influences of each variable of the UTAUT model.

Although the TAM and UTAUT models are appropriate models to analyse technology acceptance, there are some implications for further research by previous research. Only a few studies have verification on UTAUT, and its appropriateness still need further research and confirmation of its significance and effect (Jen et al., 2009). The UTAUT model was developed in order to analyse and explain acceptance of new technologies. Other studies could analyse the acceptance of new technologies with the use of the UTAUT model (Carlsson et al., 2006). Further research should also be conducted with larger groups of respondents to verify the research model of TAM (Gao & Yang, 2015).

The abovementioned comments show that the UTAUT and TAM models need more verification, especially when combining the two models in order to test MOOCs' acceptance. This combined model will be discussed further in the Research Model chapter.

2.2 Research Model

The research model is based on the analyses of various models of technology acceptance as can be seen in the previous chapter as well as in Appendix 2. Partly based on these analyses was chosen to use *the Unified Theory of Acceptance and Use of Technology* (UTAUT) (Venkatesh et al., 2003) in combination with the *Technology of Acceptance* model (TAM) (Davis, 1986). These models can be viewed in Figure 1 and Figure 2 respectively. Previous research indicates that the "*combination of many different existing models into an adjusted model is appropriate for a study"* (Kim et al., 2015, p.2).

The variables of the TAM and UTAUT models were most frequently used in studies that looked at the acceptance and intention of people to use new technologies. The UTAUT model has therefore been used as basic framework of the research model with the construct *Attitude towards use of technology* added from the TAM model (see Figure 3). This variable *Attitude towards use of technology* is a powerful predictor of the construct *behavioural intention* according to previous research (Teo & Zhou, 2014).

UTAUT and TAM are similar to one another and can therefore be used simultaneously in a new model. This combination of both models was already made in previous research (Kim et al., 2015). These similarities are as follows. *Performance expectancy* of the UTAUT model is similar to *Perceived Use* of the TAM model. *Performance expectancy stands* for the degree to which an individual believes that using the system will increase their performance. *Effort expectancy* of the UTAUT is comparable with the *Perceived ease of use* of the TAM model. *Effort expectancy* stands for the degree of ease associated with the use of the system (Jen et al., 2009). These similarities of these two models can be seen in Figure 3.

The following variables were used in this study. The independent variables are *performance expectancy* (PE), *effort expectancy* (EE) and *social influence* (SI) and *facilitating conditions* (FC). The moderating variable is *Attitude towards use of MOOCs.* The dependent variable is *behavioural intention to use MOOCs.* The control variables are age, gender, experience of online courses and MOOCs and voluntariness of use.

In the original UTAUT and TAM models, actual use was being analysed. However, in previous research it appeared to be difficult to analyse actual actions, e.g. the actual use of a technology (Kim et al., 2015; Venkatesh et al., 2003). Furthermore, the variable actual use from the TAM and the UTAUT model could not be analysed because the questionnaire did not include questions regarding the actual use variable (Kim et al., 2015). That was the reason why was decided to test the *behavioural intention to use MOOCs* instead of actual use.

Facilitating conditions in the UTAUT model has a relation with *actual use*, in the extended UTAUT model the relation between *facilitating conditions* and *behavioural intention* will be analysed, since actual use will not be part of the analyses. Other studies have hypothesized that FC has an influence on behavioural intention to use that is similar to that of the other independent variables (Kim et al., 2015; Heselmans et al., 2012; Duyck et al., 2008). This means that FC could have a similar effect on behaviour intention as *social influence.* This leads to the following research model which can be viewed below in Figure 4.

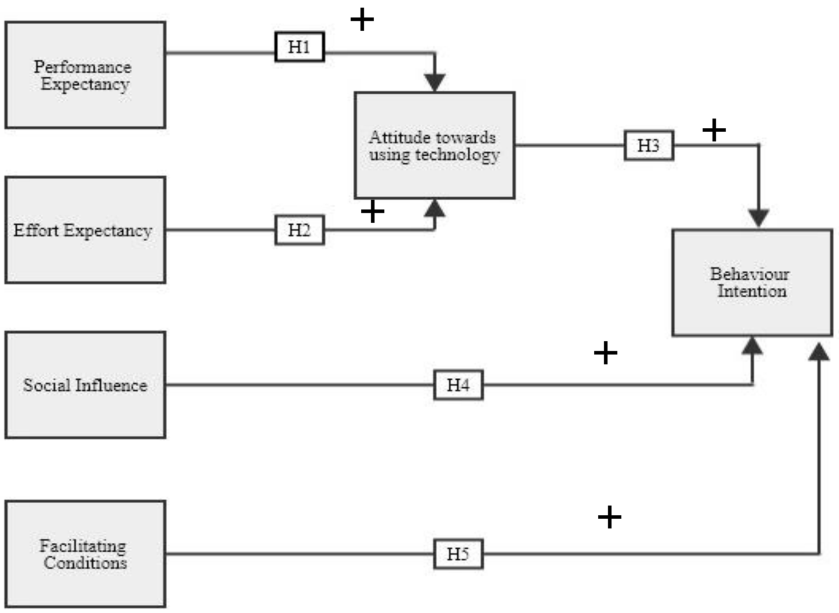

Figure 4. Extended UTAUT model

2.2.1 Hypotheses

This chapter discusses the hypotheses that have been derived from the literature review. Analysing the relationship between the variables in the extended UTAUT model lead to several hypotheses, which can be found in the research model of the previous chapter (Figure 3).

2.2.1.1 Performance expectancy and effort expectancy on attitude towards use of MOOCs

The UTAUT model suggests that *performance expectancy* (PE) and *effort expectancy* (EE) positively influence attitude (Venkatesh et al., 2003). The concepts of the TAM model *perceived ease of use* (PEOU) and *perceived use* (PU) are also expected to have a positive influence on attitude (Davis, 1989). PE and EE in the UTAUT model are similar to the concepts PEOU and PU in the TAM model (Kim et al., 2015). *Perceived usefulness* reflects peoples' beliefs of whether using a particular system would enhance their job performance (Davis et al., 1989), the same definition counts for *performance expectancy* (Venkatesh et al., 2003). The *perceived usefulness* or *performance expectancy* of MOOCs can be described as *"the extent to which a person believes that MOOCs can be a driving force towards achieving learning goals"* (Wu & Chen, 2017, p. 223). *Perceived usefulness* is a construct that has repeatedly been revealed to positively influence attitude (Kim et al., 2015; Lee, Hsieh, & Chen, 2013; Wu & Chen, 2017).

Perceived ease of use of the TAM model, similar to *effort expectancy* of the UTAUT model, has in the context of MOOCs been defined as *"the extent to which a person believes that using MOOCs will be free of effort"* (Wu & Chen, 2017, p. 223). An example of *effort expectancy* is the ease of acquiring skills using MOOCs. Previous studies found evidence that *perceived ease of use* positively influenced users' attitudes (Hong, Suh, & Kim, 2009; Kim et al., 2015). The following hypotheses are therefore: *performance expectancy* (PE) and *effort* *expectancy* (EE) from the UTAUT model, similar to the variables *PEOU* and *PU* from the TAM model, have a positive effect on *attitude*.

H1. *Performance expectancy will positively influence attitude towards use of MOOCs*

H2. *Effort expectancy will positively influence attitude towards use of MOOCs*

2.2.1.2 Attitude towards use of MOOCs on behavioural intention to use MOOCs

The variable *attitude* that was suggested by the TAM model will be used in this model and it was expected that attitude would have a positive influence on students' *behavioural intention to use MOOCs* (Kim et al., 2015). The relation between *attitude towards use of MOOCs* and *behavioural intention to use MOOCs* has its origin in Davis' TAM model (1989). *Attitude towards use of MOOCs* stands for the extent to which an individual has positive or negative feelings towards MOOCs (Wu & Chen, 2017). *Behavioural intention to use MOOCs* is the perceived likelihood of students that they will act in a certain way (Speaking of Health, 2002*)*. In the context of MOOCs, this means that students will accept and use MOOCs when studying. Attitude seems to be a powerful predictor of behaviour intention to use technology (Teo & Zhou, 2014). Previous research showed a significant effect of attitude on behaviour intention (Kim et al., 2015; Wu & Chen, 2017). Consequently, the following hypothesis can be made:

H3. *Attitude towards use of MOOCs will positively influence behavioural intention to use MOOCs*

2.2.1.3 Facilitating conditions and social influence on behavioural intention to use MOOCs

Social influence and *facilitating conditions* are variables from the UTAUT model and seem to have an influence on *behavioural intention to use MOOCs*. *Social influence* is the degree that students feel that important others believe that they should use the new system (MOOCs) (Venkatesh et al, 2003). An example of *social influence* is peer pressure. *Facilitating conditions,* in the context of MOOCs, are students' beliefs that an organizational and technical infrastructure exists on campus to support the use of MOOCs. An example of a *facilitating condition* is the technical support offered by a university for MOOCs.

In previous research *social influence* appeared to have a significant effect on *behavioural intention to use* (Chang, Hwang, Hung, & Li, 2007; Im et al., 2011; Kijsanayoting, Pannarunothai, & Speedie, 2009; Venkatesh & Davis, 2000). In previous research was found that *facilitating conditions* did not have a significant effect on *behavioural intention* (Birch & Irvine, 2009; Venkatesh et al., 2003). However, in a recent study by Kim et al. (2015) *Facilitating Conditions* did appear to have a significant effect on *behavioural intention*. Since this study analyses the same model (the extended UTAUT model) as Kim et al. (2015), a hypothesis is formed that FC will positively influence *behavioural intention.* The following hypotheses were formulated based on the previously mentioned information:

H4. *Social influence will positively influence behavioural intention to use MOOCs*

H5. *Facilitating conditions will positively influence behavioural intention to use MOOCs*

2.2.1.4 Control variables

The UTAUT model suggests that four control variables, (1) gender, (2) age, (3) experience with MOOCs and (4) voluntariness of use, mediate effects of the acceptance process (Kim et al., 2015; Venkatesh et al., 2003). The variable *experience with online courses* was added to the existing control variables in this study and was therefore also considered when analysing the extended UTAUT model. The control variables play an important part within this study because they can affect the results and are therefore considered when conducting the analyses.

3. Methodology

This chapter focusses on the chosen research method and discusses the analyses conducted in order to be able to answer the hypotheses. This chapter contains the research method, data collection, reliability and validity, measures, research ethics and data analyses of this study. This study aims to explain Dutch university students' intention to use MOOCs analysing the combined UTAUT and TAM models (extended UTAUT model)**.**

3.1 Research method

The aim of this study was to discover the degree to which the extended UTAUT model influenced Dutch university students' intention to use *Massive Open Online Courses* (MOOCs) by conducting a questionnaire. A quantitative design (survey method) was used to identify and verify the factors affecting the acceptance of MOOCs. There are various reasons why a survey method was chosen in this study. The first is that data collected from surveys lead to quantitative, factual and descriptive data that can be used when comparing variables (Stork, 2017; Vaus, 2002). The survey method can help predict and understand a phenomenon at large (Stork, 2017; Swanborn, 2013). A quantitative study with a more varied and larger population was also a useful tool for researching MOOCs' acceptance (Zheng et al., 2015).

The evidence presented in this section justified the use of the survey method as this study wanted to quantitatively understand and predict the effect of several factors on the acceptance of MOOCs. This study tested whether the extended UTAUT model is a good measurement model for explaining Dutch university students' acceptance of MOOCs.

3.2 Data collection

The new acceptance technology addressed in this study are MOOCs. Dutch university students were the focus of this study, since the goal was to analyse students' acceptance of MOOCs. The respondents of this study had to be students that studied at a Dutch university at the time the survey was distributed. The students did not need to have experience with MOOCs since the aim of this study was to find out if students were willing to accept MOOCs. The control variable experience with MOOCs was therefore added to the questionnaire. This made it possible to conduct an analysis whether students' experience with MOOCs affected their level of acceptance towards MOOCs. Students' opinions on MOOCs could provide valuable insight into their intentions to use MOOCs.

Data were collected by a survey via Qualtrics, which is a survey program available for members of the Radboud University. Since respondents only needed to meet the requirement of being a Dutch university student, they were randomly selected, and a convenience sampling was used. The convenience sampling method does not consciously take representativeness into account and thus by choosing this technique it was accepted that the sample would not be fully representative. The survey was distributed by posting a link to the questionnaire on several social media platforms via the personal network of the researcher (Linked-In, Facebook, Instagram and WhatsApp) in order to get a high response rate. Students were invited through the means of messages on social media to participate in the study. The questionnaire was formed based on the questions/statements of the UTAUT model that were derived from Venkatesh et al. (2003). An example of such a statement/item is *I would find MOOCs useful in my study*. All statements of the extended UTAUT model can be found in Appendix 3. Likert-scales were used for respondents to specify their level of agreement or disagreement for the series of statements formulated in the questionnaire (1= totally disagree, 5= totally agree).

Some survey questions had been altered to better fit the population study of this research. Question 4 of the variable performance expectancy was originally*: If I use the system, I will increase my chances of getting a raise*. Since students' aim was not to get a raise but to pass their course, this question was changed into: *If I use MOOCs, I will increase my chances of passing the course*. Similar to this, the following question of the variable Attitude toward using technology: *The system makes work more interesting*, was changed into: *MOOCs make studying more interesting.*

The survey was originally in English but was translated into Dutch. The full Dutch survey can be found in Appendix 4. The questionnaire was pre-tested by two people before it was distributed to make sure there were no unclarities in terms of grammar, spelling and comprehensibility. After the pre-test several adjustments were made, and the questionnaire was distributed.

After distributing the surveys and obtaining the information from them, the invalid questionnaires were deleted from the dataset (114). These invalid questionnaires included incomplete answers (105) or respondents who did not meet the criteria of being a Dutch university student (9). After deletion of the invalid questionnaires, 305 valid questionnaires remained suitable for analyses. Respondents also received questions regarding their demographic information (gender, age, university, major) as well as questions regarding their experience with MOOCS and online courses.

3.3 Reliability and validity

Internal consistent reliability was tested by means of Cronbach's alpha. This is a measure of reliability that was used in this study. Cronbach's alpha was used to evaluate the degree to which different test items, that examined the same construct, produced similar results. Construct validity was also tested. Validity refers to how well a variable measure what it is supposed to measure. The construct validity was measured by examining the convergent and discriminant validity in *Partial Least Squares* (PLS), which will be further elaborated on in the Result section.

The UTAUT variables of Venkatesh et al. (2003) in previous research appear to be reliable ($\alpha > 0.70$) and had an acceptable convergent and discriminant validity (Wang & Yang, 2005). Four types of analyses were conducted to analyse the validity and reliability of the reflective measurement model in PLS. These types of analyses were (1) construct reliability, (2) indicator reliability, (3) convergence validity and (4) discriminant validity. Further elaboration on these analyses can be found in the Result section.

3.4 Research ethics

The objective of this research was to analyse the effect of several factors on the acceptance of MOOCs by Dutch university students. To analyse this effect a questionnaire was conducted. The current research was conducted with regard to the principles of research ethics of APA (Smith, 2003). |Such as informed-consent rules, which was done properly by informing the individuals of their voluntarily participating in the research and telling them that their participation benefits academic research. The respondents were also informed of the purpose of the research and the expected duration (5-10 min). If the respondents had any questions, they were able to contact this studies researcher. Next to this, confidentiality and privacy were respected. This means that respondents rights to confidentiality and privacy were uphold. An example is when respondents felt uncomfortable during the questionnaire questions they could stop at any time (Smith, 2003).

The questionnaire was distributed via social media. Respondents first read a short introduction to the survey which informed them that their data would be used for academic purposes. The introduction also explained the aim of the study and that they were able to withdraw from the research at any time. Respondents' participation was anonymous and completely voluntary. Furthermore, the data was treated with confidentiality to secure the privacy of the respondents.

3.5 Measures

All variables were of (quasi-)metric measurement level, except for the five control variables which were transformed into dummy variables. A 5-point Likert scale (1 = totally disagree, 5 = totally agree) was used for all (quasi-)metric latent variables.

All variables of the research model have a specific family code (e.g. *Performance expectancy*), which were further divided into several answer categories, e.g. *Using MOOCs increases my productivity* (Appendix 3). The latent variables along with their definition are presented in Table 1.

Table 1. *Operationalization of the Research Model*

Factor	***Definition***
Performance expectancy[a]	"*The degree to which an individual believes that using the system will help him or her to attain gains in job* performance" (*Venkatesh et al., 2003, p.477). *In this study: *study performance*
Effort expectancy[a]	"*The degree of ease associated with the use of the system"* (Venkatesh et al., 2003, p.450)
Social influence[b]	"*The degree to which an individual perceives that important others believe he or she should use the new system" (*Venkatesh et al., 2003, p.4750)
Facilitating conditions[b]	"*The degree to which an individual believes that an organizational and technical infrastructure exists to support use of the system" (*Venkatesh et al., 2003, p.452)

Attitude towards use of MOOCs[c]	"*The degree to which an individual perceives a positive or negative feeling related to MOOCs" (*Wu & Chen, 2017, p. 224)
Experience	"*Prior use/experience with* MOOCs (Evers, 2014, p. 3; Venkatesh et al., 2003)
Voluntariness of use	"*The extent to which potential adopters perceive the acceptance decision to be nonmandated"* (Agarwal & Prasad, 1997, p.564*)*
Behavioural intention to use MOOCs	"*A person's perceived likelihood or subjective probability that he or she will engage in a given behaviour"* (Speaking of Health, 2002, p.31)
Notes	[a] Direct relationship to *attitude towards use of MOOCs* [b] Direct relationship to *behavioural intention to use MOOCs* [c] Moderating effect

The dependent variable of this study is *behavioural intention to use MOOCs* and is shown in Table 1. The four independent variables are *Performance expectancy, Effort expectancy, Social influence* and *Facilitating conditions* and can also be seen in Table 1. *Attitude towards use of MOOCs* is a moderating variable. These variables, along with their existing item-scales, were derived from the UTAUT model by Venkatesh et al. (2003).

For the survey tools, the UTAUT model and a part of the TAM model were integrated. A questionnaire was created to analyse the factors that influenced acceptance. Next, 22 questions from the UTAUT questionnaire were extracted (4 PE questions, 4 EE questions, 3 ATT questions, 4 SI questions, 4 FC questions, and 3 questions regarding *behavioural intention to use MOOCs*) (Venkatesh et al., 2003). A question regarding the experience of MOOCs, another regarding the online course experience, three questions regarding the *voluntariness of use*, and some demographic questions (gender, age, university and major) were also added to the questionnaire. The final questionnaire consisted of 32 questions.

3.6 Data analyses

The data was analysed by first using *exploratory factor analyses* (EFA) and then *partial least squares* (PLS) modelling. It can be difficult to understand a large dataset without tools that assist in simplifying and summarising that data (Oshlyansky, Cairns, & Thimbleby, 2007). The best way to simplify data is by using Factor Analysis. *"Factor analysis simplifies a matrix of correlations into more easily comprehensible factors "(*Oshlyansky et al., 2007, p. 84). These factors are the summary of the relationships between sets of variables.

Items measuring each individual variable should group together on factors and show that they measure a particular aspect of technology acceptance (Kline, 2014; Oshlyansky et al., 2007). The rules of thumb according to factor analysis is that the factors selected should either have an eigenvalue of 1 or more or the variables' percentage should be around 60%. If this is the case, the variables are considered to have a significant influence on the factor.

Both exploratory as confirmative factor analyses were used in this study. Exploratory factor analyses were conducted in SPSS to identify the structure of the variables. Since the statements in the questionnaire were translated into Dutch it was useful to check them again with an exploratory factor analysis. Confirmatory factor analyses are part of PLS and could be used since the variables were derived from previous research and have been previously validated. CFA is used to make sure that the variables in the sample from the current study load onto the factors the same way they did in the original research. The results of both the EFA and the CFA can be found in the Results section.

Next, *Partial Least Squares* (PLS) modelling was used to find relations between the independent variables, the moderating variable and the dependent variable. The software ADANCO was used for the statistical analyses of the questionnaire since this is an approach to variance-based *Structural Equation Modelling* (SEM). PLS is an alternative technique for *Structural Equation Modelling* (SEM). The PLS model consists of a structural part, which shows the relationships between the latent variables. The PLS model consists of a measurement component as well, which reflects how the latent variables are related to their indicators. PLS also contains a third component, the weight relations, which are used to estimate case values for latent variables (Haenlein & Kaplan, 2004). PLS was used to analyse the data and compute the reliability and validity of the extended UTAUT model variables. PLS was an appropriate analysis tool to analyse this study's research model, since the model contains multiple latent variables.

4. Results

The analyses in this chapter are based on the results of an exploratory factor analysis as well as a partial least squares analysis. The first part of this chapter consists of a univariate analysis of the data, followed by the results of the exploratory factor analysis and ends with the results of the partial least squares modelling.

4.1 Univariate Analysis

A survey was held among 419 Dutch University students to inspect students' degree of acceptance of MOOCs. Missing and incorrect data, such as incorrect answers related to type of university (9) and incomplete questionnaires (105), were deleted from the data set. As a result of the data gathering and the validation process, 305 complete questionnaires were collected.

The variable *Voluntariness of use* contained an item (VoU3) whose polarity needed to be reversed. Among the three items, this was the only one that was positively formulated and therefore needed its polarity to be reversed. The reversed item received the name VoU3Rev. All items of *Voluntariness of use* are now negatively coded. No variables had missing values and all frequency distributions looked plausible (see Appendix 5). The age of respondents ranged from 18 to 29 (M = 21.75 and SD = of 2.28) as this study focussed on students. More women (75.1%) participated than men (24.3%), and a small group (.7%) belonged to the category other (neither man nor woman).

A total of 155 Bachelor and 150 Master students participated in this study. Most of the students studied at Wageningen University (40%) and Radboud University (29.5%), as can be seen in Appendix 5. The largest group majored in Health and Environment studies (25.6%), followed by Business studies (18.4%). An overview of students' majors can be viewed in Figure 5.

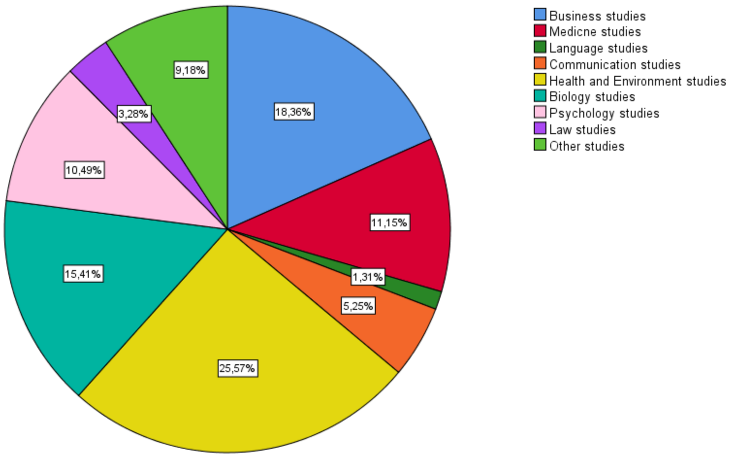

Figure 5. Students' major

The majority of the respondents had experience doing online courses (70.5%), others did not have experience doing online courses (26.2%) and some were not sure if they had experience doing online courses (3.3%). There is a difference between doing online courses and MOOCs. A MOOC course is defined by Coursersa (2019, p.1) as follows: "*Each course is like an interactive textbook, featuring pre-recorded videos, quizzes, and projects.*" This definition shows that MOOCs provide more than just online courses, so a distinction between the two is made. A small group of students had experience with MOOCs (21.3%), while the majority did not have experience or did not know if they had experience with MOOCs (78.7%).

A 5-point Likert scale was used to analyse *voluntariness of use* (M = 4.08, SD = .71) These results show that that most respondents are able to voluntarily do a MOOC and it was not obligatory in their university.

4.2 Exploratory factor analyses

Multiple exploratory factor analyses were conducted in SPSS to measure the validity of the variables. The KMO and Bartlett's tests of sphericity were performed to check if the factor analyses could be conducted. The results of the KMO tests were between 0.609~0.777, which is greater than the threshold of .5, and Bartlett's test of sphericity should be significant, which was the case with $p < 0.001$.

An exploratory factor analysis was performed for each variable. The results showed that most of the latent variables contained items above the threshold of .20 after extraction. However, an item (FC4) of the latent variable *Facilitating Conditions* was .17, which is below the threshold of .20 and was therefore deleted from the variable. After the deletion of FC4, all variables were good enough to go through the PLS analysis.

4.3 Partial Least-Squares - Modelling

4.3.1 Ensuring requirements

The extended UTAUT model was the subject of an overall model assessment. The software program ADANCO was used to conduct the *partial least squares* (PLS) modelling. PLS modelling was conducted in order to analyse the factors that had an effect on the acceptance of MOOCs.

In order to perform a PLS two data requirements had to be met. These are (1) a sufficient sample and (2) some data requirements. According to the rule of thumb, a sample size should be 10 times the number of maximum arrowheads pointing on a latent variable (Hair, Hult, Ringle, & Sarstedt, 2013). As shown in the measurement model (Figure 6), the largest number of arrowheads is 8 and these arrowheads are pointing at behavioural intention to use MOOCs. The recommended sample size was thus 80 (10 times 8). The sample size of this study (305) was higher than the minimum requirement and PLS could therefore be conducted. The second data requirement was that no missing data should be present in the final dataset and all measures should be of quasi metric data. There was no missing data and all answers were measured with 5-point Likert scale items. The use of 5-point Likert scale items resulted in quasi-metric data.

4.3.2 Assessing the measurement model

The extended UTAUT model with control variables was analysed. The measurement model of the extended UTAUT model with latent variables, control variables and indicators can be seen in Figure 6. The number of **, in Figure 6, shows the significance of the relationship between the variables in the measurement model. For example, the relationship of *Attitude towards use of MOOCs* on *behavioural intention to use MOOCs* is really significant (**), while the relationship between *age* and *behavioural intention to use MOOCs* is significant (*).

The extended UTAUT model consists of six latent variables and five control variables. The six latent variables are *performance expectancy* (PE), *effort expectancy* (EE), *social influence* (SI), *facilitating conditions* (FC), *attitude towards use of technology* (ATUT) and *behavioural intention to use MOOCs* (BI). The five control variables are *voluntariness of use* (VoU), age, gender, experience with MOOCs and experience with online courses. The indicators are the items that belong to the variables, e.g. *facilitating conditions* has three items FC1, FC2 and FC3.

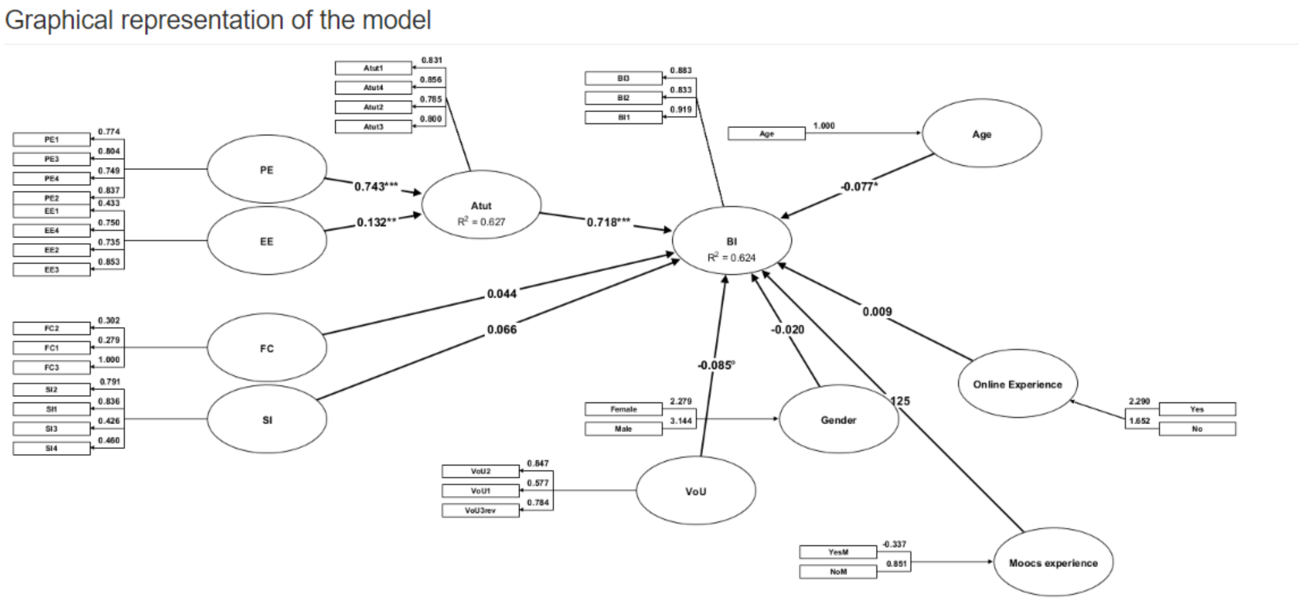

Figure 6. Extended UTAUT model with latent variables, indicators and control variables in ADANCO

4.3.3 Approximate fit

Several fit indices, such as the SRMR measurement method, were applied to assess the approximate fit. The start of the model assessment is to check the overall goodness of fit of the model, which can be analysed by SRMR. The SRMR of both the goodness of model fit of the saturated model and estimated model should be below the threshold of .08. The decision, based on the analyses of the measurement model, is that there is not a good model fit. The outcomes for the saturated model (.0825) and the estimated model (0.0837) are both above the threshold of .08. This means that the model does not fit the data and the data conveys more information than the model conveys (Henseler et al., 2016). A bad model fit can lead to meaningless estimates as well as questionable conclusions drawn from them.

The outer measurement model needed to have acceptable levels of reliability and validity in order to proceed to the inner structural model. Four types of analyses were conducted to analyse the validity and reliability of the reflective measurement model. These types of analyses were construct reliability, indicator reliability, convergence validity and discriminant validity.

The items, which are the statements from the questionnaire, included in the measurement model were assessed to see if they are reliable. Cronbach's Alpha was used to analyse the construct reliability. The Cronbach's Alpha values for all the factors were between .50 and .85 (see Table 2). The colours in the Tables (Table 2 and 3) indicate if the outcome is poor, questionable or acceptable to good. The colour red stands for poor, orange stands for questionable and black stands for acceptable to good. Most factors met the threshold of 0.6 (Wrycza et al., 2017). The reliability of *Social influence*, consisting of 4 items, was poor $\alpha = .540$. The reliability of *facilitating conditions,* consisting of 3 items, was also poor $\alpha = .599$. In three cases (PE, ATUT and BI), Cronbach's Alpha was at >.80, which is considered a good reliability.

Table 2. Data reliability and convergent validity

Variable	**Number of indicators**	**Cronbach's Alpha >.6 / .7**	**Convergent validity AVE >.5**
Performance expectancy	4	.802	.6268
Effort expectancy	4	.661	.5045
Social influence	4	.540	.4295
Facilitating conditions	3	.599	.3895
Attitude	4	.836	.6697
behavioural intention to use MOOCs	3	.853	.7731
Voluntariness of use	3	.692	.5555

The indicator reliability contains the proportion of indicator variance that is explained by the respective latent variable, as can be seen in Appendix 5. An observation was made that the variance that is explained by the respective latent variable is average, with a range from 0.0781 towards 0.9991.

The convergence validity was assessed using the average variance extracted (AVE) which is comparable to the proportion of explained variance in factor analysis. The critical value for convergence validity is an AVE of above .5. It appeared that the AVE for the variables *facilitating conditions* and *social influence* were below the threshold of .5, while the other variables are all above .5, as can be seen in Table 2. The Discriminant validity or Heterotrait-monotrait Ratio of correlation (HTMT) is an estimate of the construct correlation. In order to determine discriminant validity, the AVE-value between the different variables is checked and should have an AVE-values of below .85. The AVE value is checked for the latent variables that are on the same level such as *performance expectancy*, *effort expectancy*, *facilitating conditions* and *social influence*. It appears that *facilitating conditions* and *effort* *expectancy* have a higher AVE of 1.0786, which means that they are highly correlated with each other, as can be seen in Appendix 5. It appears that the model is insufficient and to continue to the structural model measurement, some changes had to be made. The variables *effort expectancy*, *social influence*, *facilitating conditions* and *voluntariness of use* all had a construct reliability of an alpha below .7. The convergence validity was checked with AVE, and it appeared that the variables *facilitating conditions* and *social influence* scored below the threshold of .5 with .3895 and .4295 and the construct *Effort expectancy* just barely exceeds the threshold with .5045. When looking at the factor loadings, which is a part of confirmatory factor analyses, it appeared that some items that loaded really low (below .5) were not sufficient enough (see Appendix 5). These items are EE1 with .433, SI3 and SI4 with .426 and .460, FC1 and FC2 with .302 and .279. These items were deleted, and a new measurement model was run through the PLS analysis, as can be seen in Figure 7.

4.3.4 Assessing the new measurement model

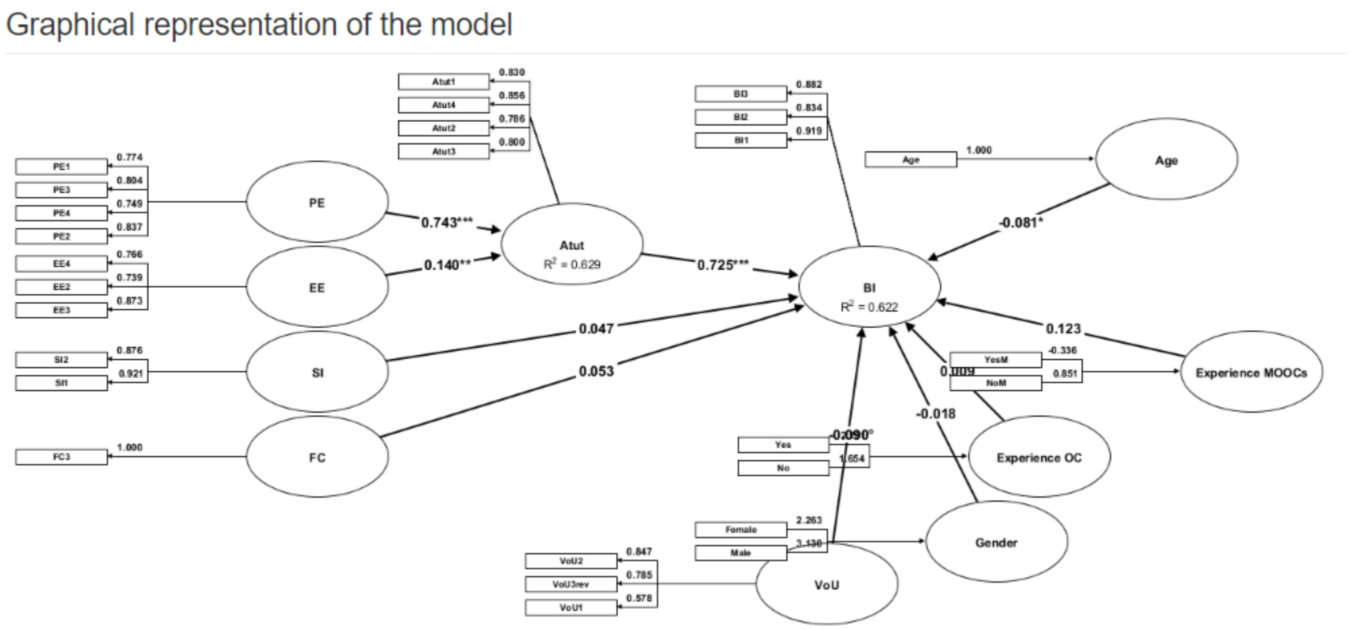

Figure 7. Extended UTAUT model with latent variables, indicators and control variables in ADANCO after deletion of insufficient items

4.3.5 Approximate fit

Several fit indices, such as the SRMR measurement model, were applied to assess the approximate fit. The SRMR of both the goodness of model fit of the saturated model and estimated model should be below the threshold of .08. The decision was made that there was a good model fit for the saturated model (.0662) and the estimated model (.0683).

Four types of analyses were conducted to analyse the validity and reliability of the reflective measurement model. These types of analyses were construct reliability, indicator reliability, convergence validity and discriminant validity. To evaluate the construct reliability, the calculation of Cronbach's Alpha is used. The Cronbach's Alpha values for all the factors were between .69 and .85, as can be seen in Table 3. All the factors met the threshold of 0.6 (Wrycza et al., 2017). *Facilitating conditions* was left with only one indicator, after deletion of the insufficient items, and thus no Cronbach's Alpha was given.

Table 3. Data reliability and convergent validity

Variable	**Number of indicators**	**Cronbach's Alpha >.6**	**Convergent validity (AVE) >.5**
Performance expectancy	4	.802	.6268
Effort expectancy	3	.709	.6315
Social influence	2	.765	0.8081
Facilitating conditions	1	-	1.000
Attitude	4	.836	0.6697
behavioural intention to use MOOCs	3	.853	0.7732
Voluntariness of use	3	.692	0.5557

The indicator reliability contains the proportion of indicator variance that is explained by the respective latent variable, as can be seen in Appendix 5. An observation can be made that the variance that is explained by the respective latent variable was average, with a range from 0.3338 towards 1.0000.

The convergence validity was assessed using the average variance extracted (AVE) which is comparable to the proportion of explained variance in factor analysis. The critical value for convergence validity is an AVE of above .5. It appeared that most variables had a good AVE of above .6, and the construct *voluntariness of use* was acceptable with 0.5557, as can be seen in Table 3.

The Discriminant validity or Heterotrait-monotrait Ratio of correlation (HTMT) is an estimate of the construct correlation. In order to determine discriminant validity, the AVE-value between the different variables is checked and should have an AVE-values of below .85. The AVE value is checked for the latent variables that are on the same level such as *performance expectancy*, *effort expectancy*, *facilitating conditions* and *social influence*. It appears that all variables that are on the same level have an AVE-value of below .85 (see Appendix 5). All factor loadings of the variables were now above .5, as can be seen in Appendix 5.

4.3.6 Assessing the structural model

The structural model was then examined with PLS in ADANCO. The bootstrapping procedure was used to analyse the statistical significance (Yang, Shao, Liu, & Liu, 2017). Several parameters were used for assessing the structural model. The first parameter was the adjusted R2 of the variables. *Attitude towards use of MOOCs* had an adjusted R2 of .6262. This means that the model explained 62.62% of the variable *attitude towards use of MOOCs*. *Behavioural intention to use MOOCs* had an adjusted R2 of .6120, which means that the model explained 61.20% of that variable. The path coefficients indicate the direction and strength of a relation between the variables, which can be seen in Table 4.

Cohen's f2 was calculated to determine the effect size of each effect. While the effect size of *performance expectancy* on *attitude towards use of MOOCs* (1.3723) and of *attitude towards use of MOOCs* on *behavioural intention to use MOOCs* (1.0830) were strong, the effect size of *effort expectancy* on *attitude towards use of MOOCs* was low (.0488). The effect size of *facilitating conditions* (.0063) and *social influence* (.0043) on behaviour intention were low. The effect sizes of all control variables (Voluntariness of use (.0191), Gender (.0008), Online experience (.0002), MOOCs experience (.0368) and age (.0158)) on *behavioural intention to use MOOCs* were low.

A bootstrap analysis was used in order to determine the significance of the effect size. The results of the bootstrap analysis showed that most relations between variables are significant ($p < .05$). The direct relations, path coefficients and significance of the relationships between the variables can be seen in Table 4. Based on the Bootstrap analyses, it can be concluded that most relations are significant, based on an p value of <.05, as can be seen in table 4. A non-significant relationship has a red colour in Table 4 and 5.

Table 4. Path Coefficients, strength and direction of relation between variables as well as significance and results of verification

Relation direct effect	Path Coefficient	Strength (High/Low)	Direction (Positive/Negative)	Sign.	Result of verification
PE → ATUT	0.7427	High	Positive	<.001	Accepted
EE → ATUT	0.1401	Low	Positive	0.0010	Accepted
FC → BI	0.0534	Low	Positive	0.0853	Rejected
SI → BI	0.0466	Low	Positive	0.1364	Rejected
ATUT → BI	0.7251	High	Positive	<.001	Accepted

Gender → BI	-0.0204	Low		Negative	0.3617	Rejected
Age → BI	-0.0805	Low		Negative	0.0156	Accepted
Online experience → BI	0.0088	Low		Positive	0.4316	Rejected
MOOCs experience → BI	0.1228	Low		Positive	0.0985	Rejected
VoU → BI	-0.0902	Low		Negative	0.0377	Accepted
Relation indirect effect						
PE → BI	0.5386	High	Low	Positive	<.001	Accepted
EE → BI	0.1016			Positive	<.001	Accepted

4.3.7 Model elaboration and validation

The results of the model hypothesis verification can be found in Table 5. The table contains the hypotheses verifying the relationships between the individual variables. The individual hypotheses were examined based on their significance levels (hypotheses with $p < .05$ were accepted). Hypotheses H1 and H2 were found to be very significant, H2 was considered significant while H4 and H5 were rejected due to the fact that the significance level exceeded the predefined threshold ($p < .05$).

Table. 5 Hypotheses verification results

Hypothesis	**Interconnection**	**Significance**	**Result of verification**
H1	PE → ATUT (+)	<.001	Accepted
H2	EE → ATUT (+)	<.01	Accepted
H3	ATUT → BI (+)	<.001	Accepted
H4	SI → BI (+)	0.1364	Rejected
H5	FC → BI (+)	0.0853	Rejected

Considering the results of the measurement model presented in Table 5, the final UTAUT research model took the following form, see Figure 8.

As presented in Figure 8, when no significant support for the individual hypotheses was found, the accompanying relationships were drawn using dotted lines.

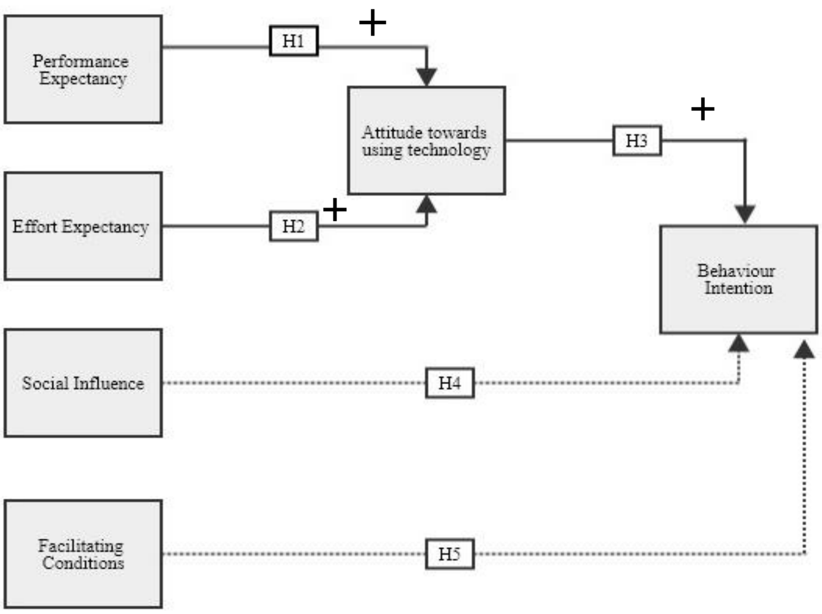

Figure 8. Enriched UTAUT model with (non) significant hypotheses

5. Discussion & Conclusion

This discussion chapter will discuss the outcomes presented in the previous chapter. The discussion will be based on the quantitative analysis and will restate the aim of the study. Previous literature will be discussed and compared with the results from this study. Next, the conclusions chapter will give an answer to the research question and the sub-questions as well as state the limitations and further research and theoretical and practical implications.

5.1 Discussion

The purpose of this study was to examine Dutch university students' intention to use MOOCs and their acceptation of MOOCs explained by a combined model of the *Unified Theory of Acceptance and Use of Technology* (UTAUT) model and *Theory of Acceptance Model* (TAM). In this research, these models combined were called the extended UTAUT model. It appeared that there were some difficulties with the acceptance of *Massive Open Online Courses*, such as content fit and technology integration (Griffiths et al., 2015). It was interesting to look at why this implementation of MOOCs seem to have hurdles. To analyse this implementation, it was necessary to figure out the underlying factors that influence MOOCs acceptance.

MOOCs acceptance could be analysed by students' intention to use MOOCs. The current focus on MOOCs presented an opportunity for researchers to figure out which factors lead to MOOCs' acceptance (Zheng, Rosson, Shih, & Carroll, 2015). According to the research of Zheng et al. (2015), a quantitative study with a more varied and larger population would be a useful tool of researching the acceptance of MOOCs. A deeper understanding of users' needs can be found by studying the underlying factors that influence MOOCs acceptance. This deep understanding of users' needs is critical for future development of MOOCs (Zheng et al., 2015). These reasons were the basis for conducting analyses on students' acceptance of MOOCs.

5.1.1 Extended UTAUT model and acceptance of MOOCs

Previous research has shown that the UTAUT model is a reasonable model to predict acceptance of MOOCs. The UTAUT model appeared to explain 70% of technology adoption success (Schaper & Pervan, 2007). Studies suggested that further research on the acceptance of new technologies, with the use of the UTAUT model, was needed (Carlsson et al., 2006).

The current study extended the UTAUT model with the variable *attitude* of the TAM model. The explanation power was tested for the extended UTAUT model. The findings of the current study show that 62.62% of the variable *attitude towards use of MOOCs* was explained by the research model. This means that the research model explained 62.62% of the variance in *attitude towards use of MOOCs.* The research model also explained 61.20% of the variance in *behavioural intention to use MOOCs*. These findings show, that the extended UTAUT model is a reasonable model to explain the acceptance of MOOCs because the previously mentioned percentages of explained variance were quite high. However, it appears that the original UTAUT model still had a higher explanation power with 70%.

Addressing the study hypotheses, three of the five proposed hypotheses were accepted. The first two (H1 and H2) support the extended UTAUT model, suggesting that the more students believed MOOCs would help them attain gains in study performance, the higher their *attitude towards use of MOOCs*. It also suggests that the more students perceive that MOOCs are easy to use, the higher their *attitude towards use of MOOCs*. These findings were expected as previous research also indicated that PE and EE were significant predictors of Attitude (Hong et al., 2009; Kim et al., 2015; Lee et al., 2013; Wu & Chen, 2017). Results also suggest that PE had a greater influence on *Attitude towards use of MOOCs* than EE. This finding was not surprising since previous research has already shown that PE has a stronger effect on technology acceptance than EE (Aharony & Bar-Ilan, 2016). The results from this study indicate that students will use MOOCs if they belief that the usage is beneficial towards their study performance and if they belief MOOCs will help them study better and improve their learning outcomes (Aharony & Bar-Ilan, 2016). If educators want to encourage students to accept MOOCs and enrol in a MOOC course, they should present MOOCs' ease of use as well as inform them that MOOCs can improve their study performance.

The third hypotheses (H3) that *attitude towards use of MOOCs* will positively influence students' *behavioural intention to use MOOCs*, was accepted. This means that when students had a positive feeling towards MOOCs, they were more likely to use MOOCs. This finding was not surprising since *attitude* already seemed to be a powerful predictor of *behavioural intention* (Teo & Zhou, 2014).

The hypotheses H4 and H5, that focus on social influence and facilitating conditions, were not accepted. Results show that *social influence* did not significantly correlate with the *behavioural intention to use MOOCs*. This finding is surprising since previous research showed that social influence has significant effect on *behavioural intention* (AlAwadhi & Morris, 2008; Chang et al., 2007; Im et al., 2011; Kijsanayoting et al., 2009; Kim et al., 2015, Venkatesh & Davis, 2000). However, in previous research about the prediction of preservice teachers' intention to use ICT, facilitating conditions and social influence also appeared not significant (Birch & Irvine, 2009). A possible explanation for the finding of social influence being not significant, could be students' misinterpretation or misunderstanding of the questions from the questionnaire. In the PLS analyses two items of a total of 4 items of social influence had to be deleted since their factor's loadings were too low. In future uses of the UTAUT survey in the field of education, researchers could consider re-evaluation of these two items. For example, the statement "people who influence my behaviour" may have been too vague and could have let to misinterpretation by the respondents. A solution might be to specify the people to consider when answering these questions (Brick & Irvine, 2009).

Facilitating conditions did not correlate significantly with *behavioural intention to use MOOCs*. The variable facilitating conditions, in the UTAUT model, has a relation towards actual use and not behaviour intention as is the case in the extended UTAUT model. Venkatesh et al. (2003) hypothesized that facilitating conditions would have an influence on actual use and would not have an influence on intention. This hypothesis was confirmed in the study of Birch and Irvine (2009) and in this study as well. Further research should add the variable actual use and draw a relation between facilitating conditions and actual use instead of a relation with behavioural intention.

Another interesting finding was that only age and voluntariness of use of the control variables showed a significant, though small, effect. The respondents were all students, and it comes as no surprise that the effect of age on *behavioural intention to use MOOCs* was quite small as there was no big age difference (18-29) among participants. Perceived voluntariness may be an important indicator of initial acceptance behaviour because of the extent of behaviour modification required. However, people will only continue to use the system if they view the benefits as useful (Agarwal & Prasad, 1997).

5.2 Conclusions

MOOCs have attracted a great amount of interest in the past few years as a new technology (Yang et al., 2017) and is becoming the future of online education (Zheng et al., 2015). The importance of educational innovation and the significant gap in previous literature regarding MOOCs acceptance by Dutch university students was the motivator behind this research. Another motivator was to analyse technology acceptance models and then in particular a combination of the UTAUT and TAM models.

This research was conducted to answer the following research question: "*To what* *extent do the combined UTAUT and TAM models explain Dutch university students' intention to use MOOCs?"*

To answer the research question, the extended UTAUT model explains Dutch university students' intention to use MOOCs by 61.20%. Although this percentage is quite high, the original UTAUT model explained 70% (Schaper & Pervan, 2007). This means that the UTAUT model has a better explanation power but the explanation power of the extended UTAUT model might be improved by further verification of the model and the variables.

The extended UTAUT model consisted of several factors that influence students' intention to use MOOCs. That is why the following sub-questions were formulated and analysed:

(1) *What potential factors could affect students' intention to use MOOCs?*
(2) *Will performance expectancy and effort expectancy influence attitude towards use of MOOCs?*
(3) *Will attitude towards use of MOOCs influence behavioural intention to use MOOCs?*
(4) *Will social influence and facilitating conditions influence behavioural intention to use MOOCs?*

The results of the current research identify a comprehensive set of factors relevant to the acceptance of MOOCs and explain their influence on students' *behavioural intention to use MOOCs*. The findings showed that hypothesis 1 and 2 were accepted, that *performance expectancy* and *effort expectancy* had a large influence on the *attitude towards use of MOOCs*. To answer sub-question 2 this means that PE and EE indeed influence *attitude towards use of MOOCs.* In addition, hypothesis 3 was also accepted that *attitude towards use of MOOCs* has a major influence on the *behavioural intention to use MOOCs*. This confirms sub-question 3 that indeed *attitude towards use of MOOCs* did influence *behavioural intention to use MOOCs*. However, hypotheses 4 and 5 were not accepted and no significant influence was found of *social influence* and *facilitating conditions* on *behavioural intention to use MOOCs.*

Thus, the answer to sub-question 4 is that social influence and facilitating conditions do not influence behavioural intention to use MOOCs. These findings lead to the answer of sub-question 1 and this means that PE, EE and *attitude towards use of MOOCs* are potential factors that could affect students' intention to use MOOCs.

These findings not only enrich academic understanding of MOOCs but also provide an important message to universities' faculty members and MOOCs developers. Faculty members should inform students on MOOCs' benefits, its ease of use and the fact that MOOCs will result in the improvement of students' study performance. The developers of MOOCs, which can also be educators from universities, can use these results to better attract students and convince them to use MOOCs. Developers can use these results to design and implement more effective MOOCs with a focus on the factors that highly influence MOOCs acceptance (Yang et al., 2017).

5.2.1 Limitations and further research

This study has some limitations that should be addressed in future studies. The first is that the current study is only focused on Dutch university students. The findings are therefore context-specific and cannot be generalized to other countries. It would be helpful to carry out similar studies in other countries as to gain an international perspective on MOOCs acceptance. Future studies should collect and analyse data from other countries and compare their findings with this study to find out whether there are any differences or similarities.

Second, the current study is based on a quantitative research method and a qualitative research method could show deeper reasoning of respondents towards the acceptance of MOOCs. Using a qualitative research method such as an interview would allow students to better explain their choices/opinions concerning acceptance of MOOCs. An addition to this is that the present study was conducted using a short-term period and the variable actual use of

MOOCs was not tested and excluded. A longitudinal study could better measure the intention of users to keep using MOOCS and the actual use of MOOCs.

Third, this study is not generalizable since convenience sampling was used and therefore the characteristics of the entire population was not met. Fourth, this study had to delete some items of several variables since they were insufficient, therefore the variables *social influence* and *facilitating conditions* only had a few indicators. In future research these variables should be analysed further, and new items should be added to improve the measurement validity. The extended UTAUT model also needs further verification, since little research has been conducted using this model. Future research can conduct the extended UTAUT model by testing the research model for different new technologies. Furthermore, research using the extended UTAUT model should lead to a better understanding of choices about using IT.

5.2.2 Theoretical and practical implications

The present study explored the degree to which the extended UTAUT model explains the acceptance of MOOCs by Dutch university students. By addressing this question, this thesis makes a number of theoretical and practical contributions. It expands the current research about the extended UTAUT model by examining it within the context of MOOCs, focusing on Dutch university students. Furthermore, it contributes to the innovation of education. The use of MOOCs allows students to receive their education without having to be physically present and without having to pay a large amount of money. In this way, students are able to overcome physical and financial barriers with the use of MOOCs (Zheng et al., 2015). This will lead to a change of traditional education and a change in the future of education.

Next to this, the results from this study confirms that the extended UTAUT model significantly predicts the likelihood of MOOCs acceptance. *Performance expectancy* and *effort expectancy* contribute greatly to the *attitude towards* (future) *use of MOOCs*. *Attitude towards use of MOOCs* also greatly contributes to students' *behavioural intention to use MOOCs*.

Furthermore, the research shows that universities gain advantages by using MOOCs. These advantages include improving an institution's visibility, increase of student recruitment, innovation of pedagogy and providing flexible learning opportunities for students. A practical implication for educators, is to focus on the way they should present MOOCs, with the aim of encouraging students to accept MOOCs and enrol in a MOOC course. Educators should inform students on the benefits of MOOCs, such as that they can improve their study performance by doing a MOOC course as well as how easy MOOCs are in use. Besides, MOOCs could also increase interests of students to pursue higher education by offering access to good teaching methods and interesting subjects.

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Appendix

Appendix 1. Research models and theories behind technology acceptance

Most models that explore users' technology acceptance behaviours are derived from innovation theory, sociology, computer utilization and psychology. Some of these theories as well as acceptance models will be addressed and explained in this Appendix. First the Social Cognitive Theory (SCT) will be discussed, followed by the Innovation Diffusion Theory (IDT). Then the different acceptance models will addressed in the following order: Theory of Reasoned Action (TRA), Theory of Acceptance Model (TAM), Theory of Planned Behaviour (TPB), Decomposed Theory of Planned Behaviour (DTPB), Task Technology Fit (TFF), Technology-to-Performance-Chain (TPC), integrated TAM/TFF Model, extended Technology Acceptance Model (TAM 2), Unified Theory of Acceptance and Use of Technology (UTAUT) and Extended UTAUT model.

Social Cognitive Theory (SCT)

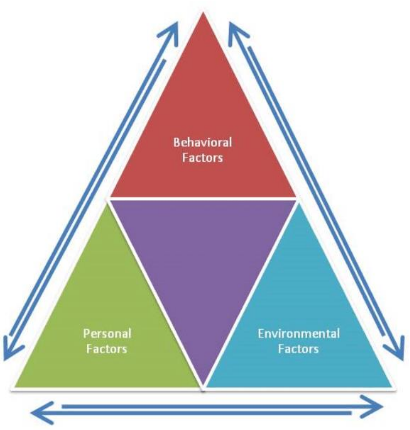

Figure 9. Social Cognitive Theory (SCT) developed by Bandura (1977)

Social cognitive theory (SCT) provides a conceptual framework with determinants and psychosocial mechanisms of human behaviour. SCT analyses social diffusion of human behaviour in terms of psychosocial factors influencing human action, adaptation, and change. The theory states that human thoughts and actions are affected by environmental factors, behavioural factors and personal factors/cognitive factors (Gibson, 2004). An example of environmental factors are social support and barriers. Behavioural factors are the outcome expectations of humans. Examples of personal factors or cognitive factors are knowledge, goal and self-efficacy.

Innovation Diffusion Theory (IDT)

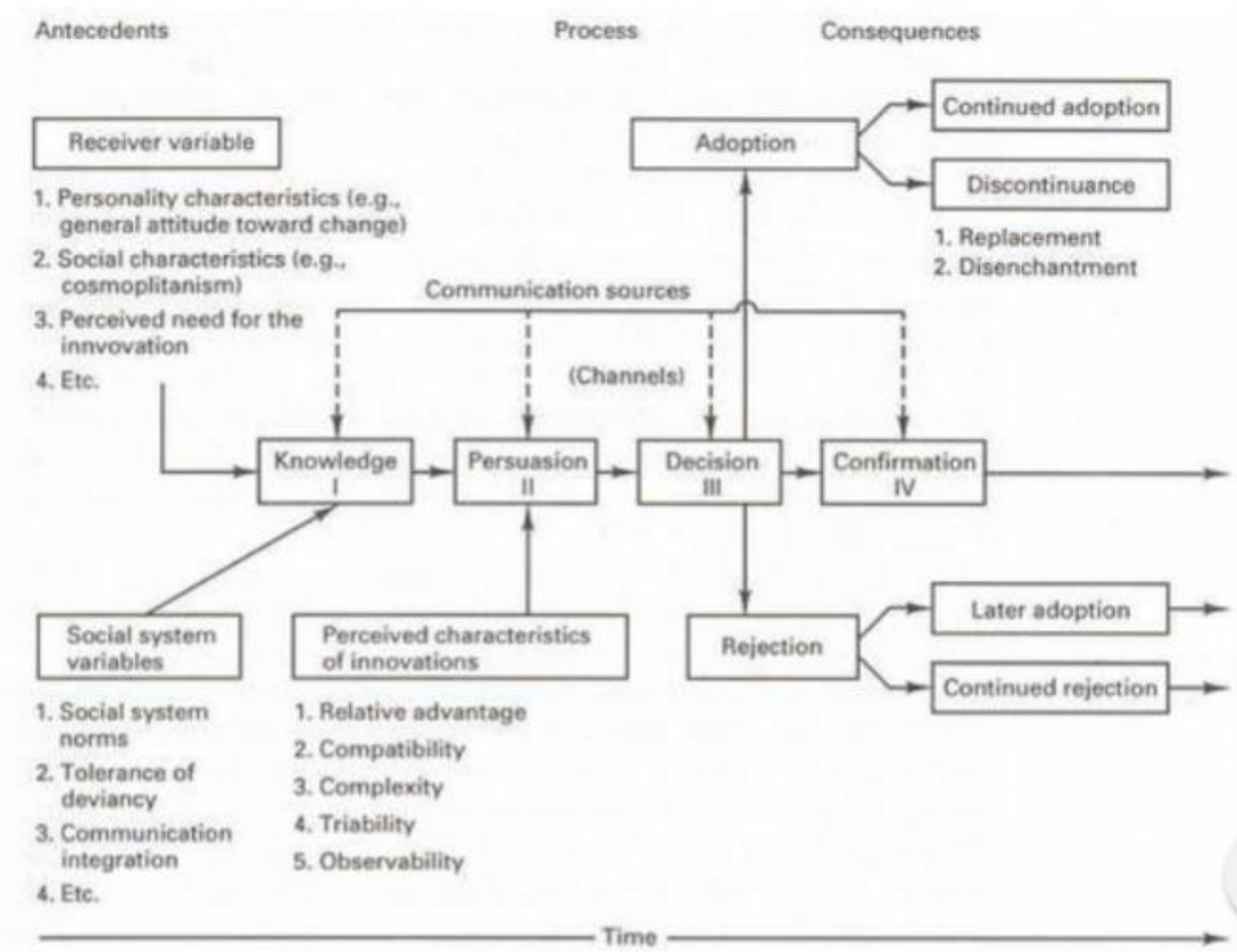

Figure 10. Innovation Diffusion Theory (IDT) developed by Rogers (1995)

The diffusion of innovations is a theory founded by Rogers (1995) that tries to explain how, why, and at what rate new ideas and technology are spread, as can be seen in Figure 9.

Diffusion is defined by Rogers (1995) as the process by which an innovation is communicated over time among people in a social system. In the diffusions of innovations theory as can be seen in Figure 10, there are four stages in the decision of the innovation process. These stages are knowledge, persuasion, decision and confirmation.

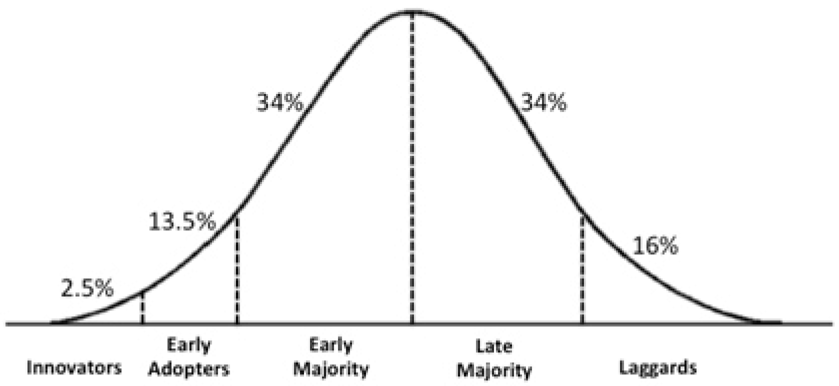

Figure 11. Rogers' diffusion of technological innovation model (1995)

Rogers (1995) also defined adopter categories as a classification of individuals within the social system on basis of their innovativeness, as can be seen in Figure 11. In this Innovation Diffusion model, five types of adopters are categorised: innovators, early adopters, early majority, late majority and laggards.

Theory of Reasoned Action (TRA)

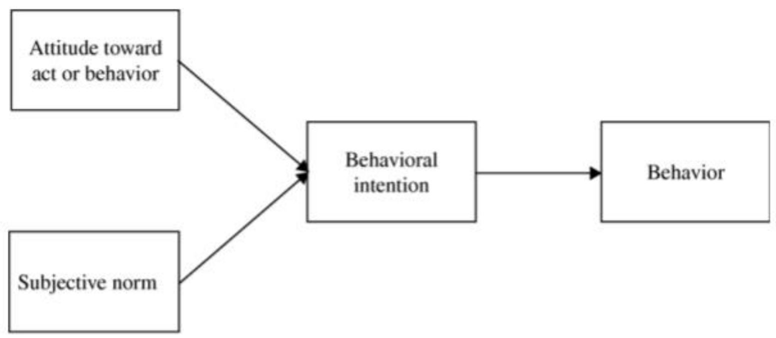

*Figure 12***.** Theory of Reasoned Action (TRA) developed by Fishbein and Ajzen (1975)

The *Theory of Reasoned Action* (TRA) has its roots in social psychology and states that behaviour is explained by people's *behaviour intention*, *attitude*s, *subjective norms*, and *beliefs* (Aharony & Bar-Ilan, 2016; Fishbein & Ajzen, 1975). According to the *Theory of Reasoned Action* (TRA), behaviour is determined by people's behaviour intention. Behaviour intention is according to this model, influenced by two factors. These factors are attitude toward act or behaviour and subjective norm. However, only limited support was found for the basic model of TRA and it was suggested to make modifications to obtain an adequate representation of data (Vallerand, Deshaies, Cuerrier, Pelletier, & Mongeau, 1992). These modifications were made and a causal path from normative beliefs to attitudes as well as noncausal relations among elements of the attitudinal and normative structures were added to the base model. The modified version of the TRA allows for an adequate understanding and prediction of moral behaviour (Vallerand et al., 1992).

Technology Acceptance Model (TAM)

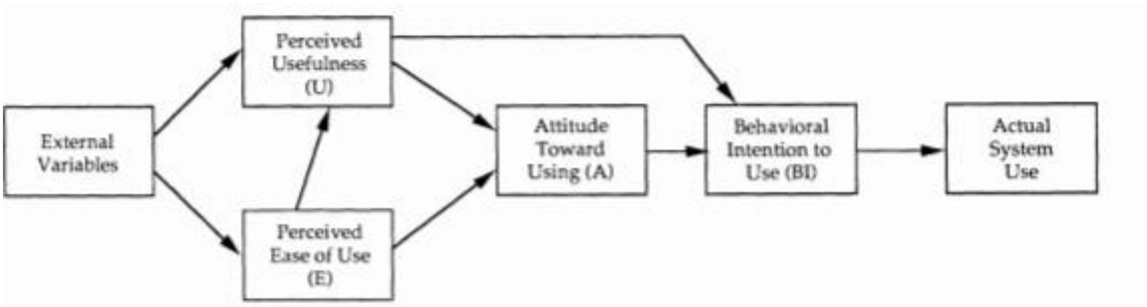

Figure 13. Technology Acceptance Model (TAM) developed by Davis (1986)

The *Technology Acceptance Model* (TAM) is based on concepts from social psychology and is a tool to examine the intention of individuals to use new technology (Kim et al., 2015). TAM was built on the *Theory of Reasoned Action* (TRA) and also compares favourably with the *Theory of Planned behaviour* (TPB) (Venkatesh & Davis, 2000). The *Technology Acceptance Model* (TAM) is one of the most widely used and accepted models in researching the acceptance of innovations (Jeyaraj et al., 2006; Gao & Yang, 2015). The model consists of a theoretical basis that underlies two key beliefs: *perceived usefulness* (PU) and *perceived ease of use* (PEOU). These two beliefs are followed by users' *attitude*s, *intentions* and *actual system acceptance behaviour,* as can be seen in Figure 13.

Theory of Planned Behaviour (TPB)

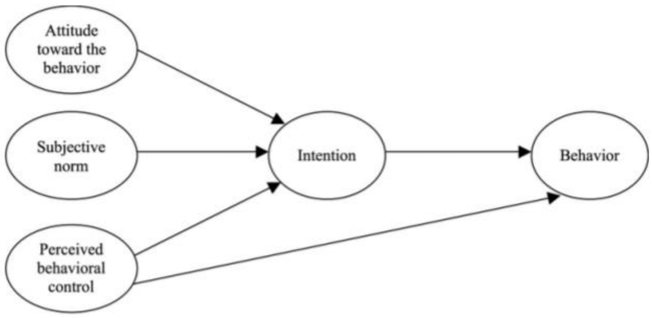

Figure 14. Theory of Planned Behaviour (TPB) developed by Ajzen (1991)

The *theory of planned behaviour* (TPB) has been one of the most frequently cited and influential models of the prediction of human social behaviour (Ajzen, 2011). However, TPB also has received much criticism and debate. Such a critic is for example the question if the model is sufficient enough. The TPB is the expanded version of the *theory of reasoned action* (TRA) (Beck & Ajzen, 1991). The TPB extends the TRA by its prediction of behavioural goals. The TPB adds a measure of *perceived control* to the base model of the TRA. In this way the TPB model "*extend the domains of behaviour covered by the TRA to behaviours that are not totally under a person's control"* (Sparks & Shepherd, 1992, p.389). A central factor of TPB is individual's intention to perform a given behaviour. The TPB has three factors that are determinants of intentions, as can be seen in Figure 14. These factors are *attitude toward the behaviour, subjective norm* and *perceived behavioural control*. However, TPB deals with perceived, rather than actual, behaviour control. In some situations, perceived behavioural control may not be realistic. An example of when this happens is when people have little information about the behaviour.

Decomposed Theory of Planned Behaviour (DTPB)

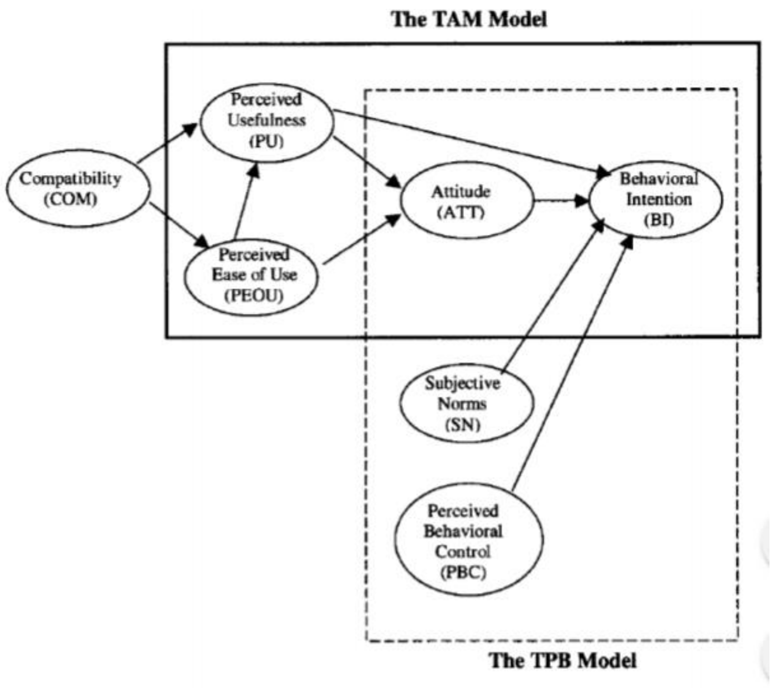

Figure 15. Decomposed Theory of Planned Behaviour (DTPB) developed by Taylor and Todd (1995)

Decomposed theory of planned behaviour (DTPB) derives from social psychology and is formed on the basis of theoretical and empirical findings from prior information systems (IS) usage research (Hsu & Chiu, 2004). The DTPB model has some advantages, it identifies specific salient beliefs that might influence information technology usage and provides a fuller understanding of usage behaviour and intention. The DTPB model is a combination of both the *theory of planned behaviour model* (TPB) and the *theory of acceptance model* (TAM). In comparison to these two models, has the DTPB model a better predictive power. The decomposed TPB model uses constructs from the TPB and TAM models. It contains analyses of *subjective norms, perceived behaviour control, attitudes* and how these elements can influence the individual's *intention to use a technology* (Ndubisi, 2004).

Task-Technology Fit (TTF)

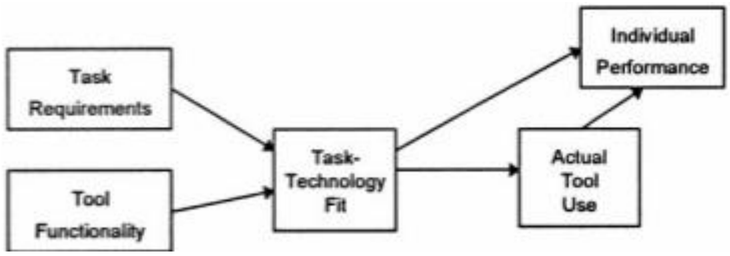

Figure 16. A basic task-technology fit (TTF) model by Goodhue and Thompson (1995)

The aim of the *task-technology fit* (TTF) was to explain how technology can lead to performance impacts. This happens when a technology provides features and support that fit with the requirements of a task. Previous models did not take the construct *task-technology fit* into account or only implicit. This model provides a more explicit explanation of TTF and the links between the constructs provide a better theoretical basis for thinking about several difficulties with the impact of *intelligence technologies* (IT) on performance (Goodhue & Thompson, 1995). The model shows that two variables, *task requirements* and *tool functionality,* influence *task-technology fit* and TTF on its turn has an effect on *individual performance* and *actual tool use. Actual tool use* also influences *individual performance*.

Technology-to-Performance-Chain model (TPC)

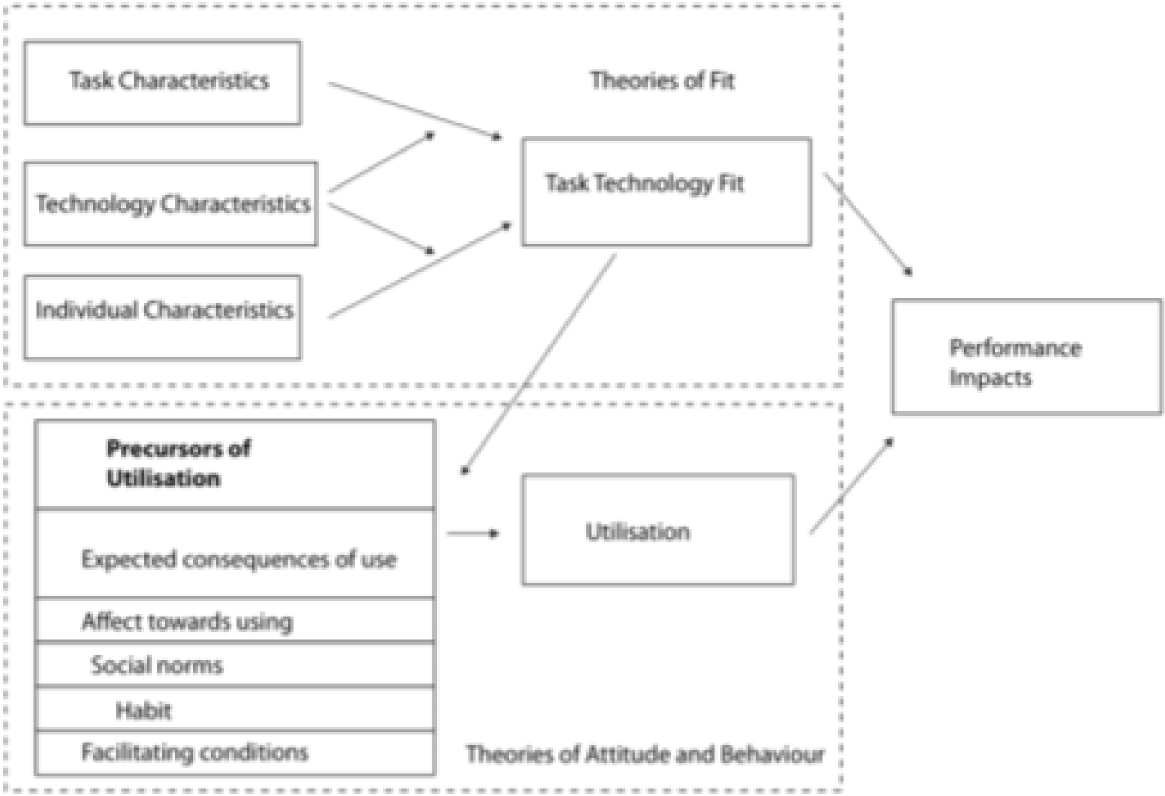

Figure 17. Technology-to-Performance-Chain model (TPC) developed by Goodhue and Thompson (1995)

Technology-to-Performance-Chain model (TPC) is a comprehensive model of a linkage between the insights of two complementary streams of research. These two streams of research are user attitudes as predictors of utilization and task-technology fit as a predictor of performance. The essence of this model is "*that for an information technology to have a positive impact on personal performance, the technology must be utilized, and the technology must be a good fit with the tasks it supports"* (Goodhue & Thompson, 1995, *p.* 213). The TPC model is a combination of utilization and *task-technology fit* (TTF), but also takes technologies, tasks and individuals into account.

Integrated TAM/TFF

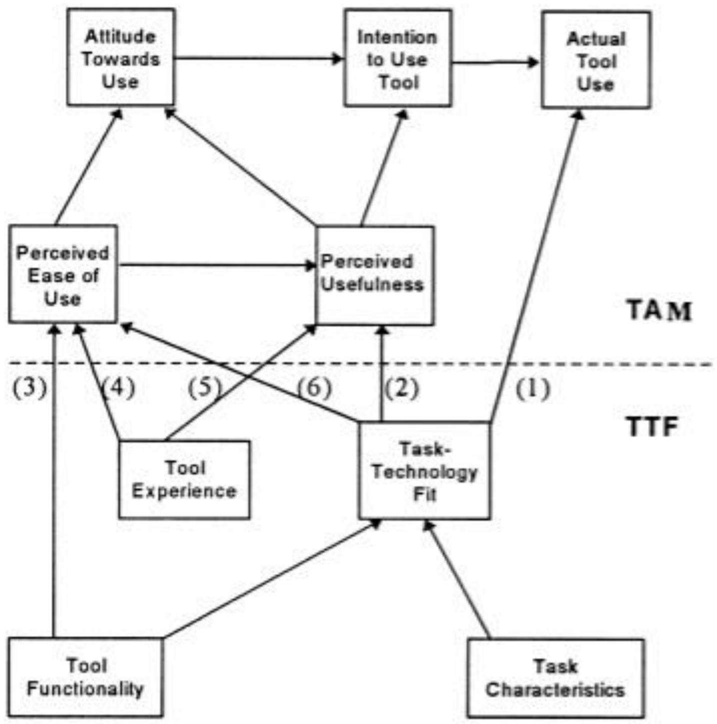

Figure 18. Integrated TAM/TFF model by Dishaw & Strong (1999)

The TAM model and the TFF model both provide significant explanatory power, but by combining these models offers a significant improvement. *The integrated TAM/TFF* model is an extension to the TAM model and include some TTF constructs. Both models were developed from behaviour models to explain technology utilization. The models are combined since they capture two different aspects of users' choices to use IT, which are users' beliefs and attitudes towards a particular technology and users' rationale that using the IT leads to benefits, such as improved job performance. Now attitude from the TAM model is combined with fit from the TTF model and together provide a better explanation of IT utilization (Dishaw & Strong, 1999).

Extended Technology Acceptance Model (TAM 2)

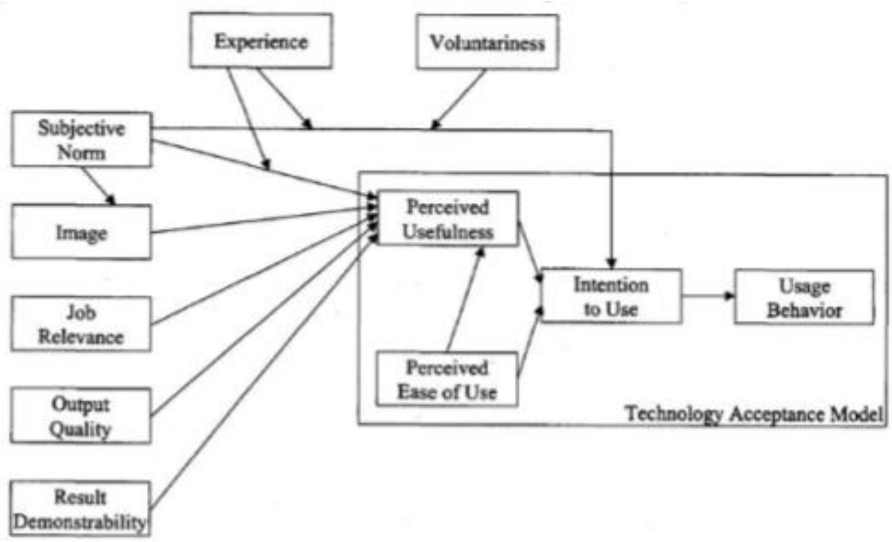

Figure 19. Extended Technology Acceptance Model (TAM 2) developed by Venkatesh and Davis (2000)

The *extended technology acceptance model* (TAM 2) uses TAM as starting point for the model and incorporates additional theoretical constructs covering social influence processes, such as subjective norm, image and voluntariness as well as cognitive instrumental processes, such as job relevance, output quality, result demonstrability and perceived ease of use. TAM2 analyses the effects of several constructs to examine individual's opportunity to adopt or reject a new system. The extended model was supported and explains around 40-60% of variance in usefulness perceptions and 34 – 52% of the variance in usage intentions. The social influence process as well as the cognitive instrumental processes both showed to significantly influence user acceptance. In this way, the TAM2 model advance theory and contributes to future research aimed at improving understanding of user adoption behaviour (Venkatesh & Davis, 2000).

Unified Theory of Acceptance and Use of Technology (UTAUT)

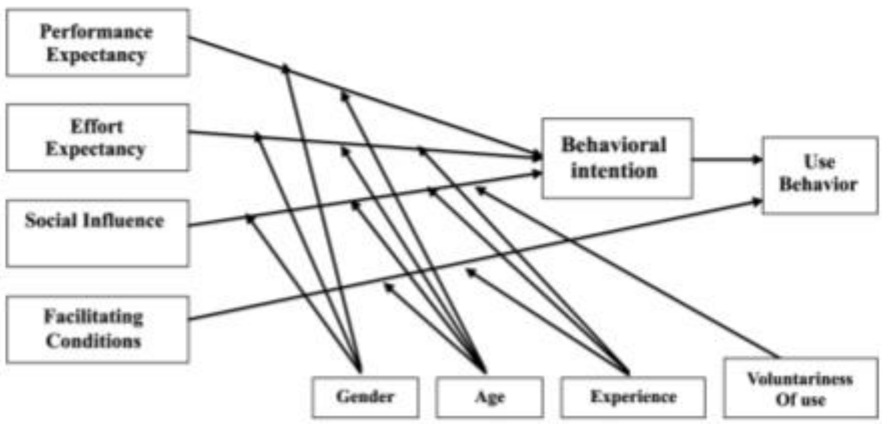

Figure 20. Unified Theory of Acceptance and Use of Technology (UTAUT) developed by Venkatesh et al. (2003)

The *Unified Theory of Acceptance and Use of Technology* (UTAUT) model is based on concepts of various human behaviour theory models and contains social concepts as well as individual for explaining technology acceptance (Venkatesh et al., 2003). The UTAUT model has become the leading model of IT and software acceptance (Wrycza et al., 2017). Previous models have tried to explain acceptance, e.g. TRA, TPB, TAM, however they fail to provide complete explanation of technology acceptance behaviours. A solution to this is the UTAUT model, which offers a more comprehensive exploration.

The UTAUT model is an integrative theory that explores the dimensions that affect users' *behavioural* intention (Venkatesh et al., 2003). The UTAUT model consists of four core variables: *performance expectancy*, *effort expectancy*, *social influence* and *facilitation conditions*, as can be seen in Figure 20. The model also consists of four control variables: gender, age, experience, and voluntariness of use (Im et al., 2011). These four control variables are used to provide a better understanding of the complexity of individuals' technology acceptance (Carlsson et al., 2006).

Extended UTAUT model

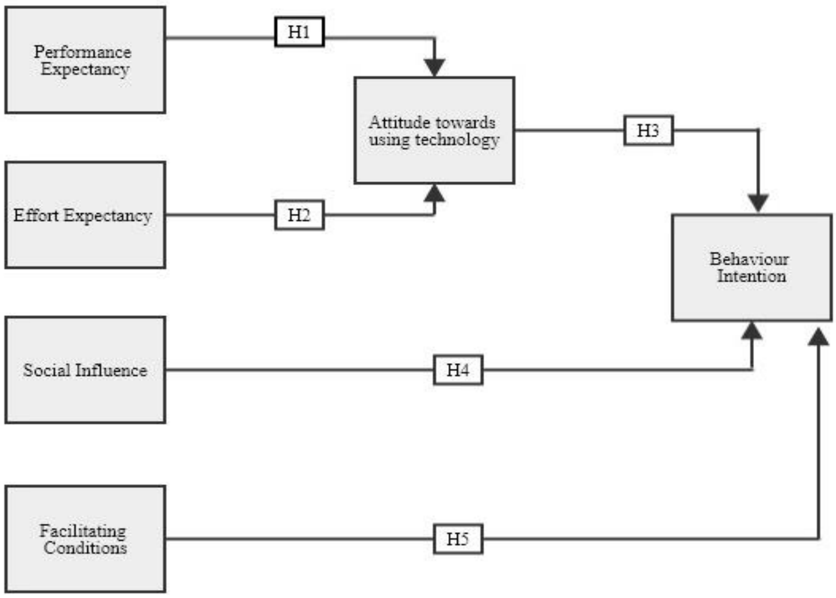

Figure 21. Extended Unified Theory of Acceptance and Use Technology (UTAUT) model

The extended *unified theory of acceptance and use technology (*UTAUT) model is a combination of the TAM and UTAUT models. Both models try to explain user's intention to use a new technology. Several studies have suggested to combine different hypothesis of different existing models into an adjusted model (Kim et al., 2015). In the extended UTAUT model, the construct *attitude* from the TAM model is added to the UTAUT model and several new relations were formed. *Performance expectancy* and *effort expectancy* are now moderated by *attitud*e before influencing *behaviour intention to use*. *Social influence* and *facilitating conditions* now have a direct relation with *behaviour intention to use,* while facilitating conditions in the former UTUAT model directly related to actual use. However, actual use is not measured in this model (Kim et al., 2015).

Appendix 2. Short analyses of research models and theories behind technology acceptance

Table 6

Short analyses of research models and theories behind technology acceptance

Name model	**Characteristics**	**Advantages & Disadvantages**	**Source**
Social Cognitive Theory (SCT)	User behaviour is in a triangle relationship with personal factors and environmental influences	Advantages in the area of organizational behaviour and psychology	Bandura (1977)
Innovation Diffusion Theory (IDT)	IDT characterises people based on their degree of innovativeness and their likelihood to adopt technology	Theory is flawed in overstating the role of technological superiority in the diffusion process (Surray, 1997)	Rogers (1995)
Theory of Reasoned Action (TRA)	Behaviour is determined by *behavioural intention to use MOOCs* and *behavioural intention to use MOOCs* is in turn jointly influenced by *attitude* toward certain behaviour and subjective norms	Both the TAM and TPB are originated from TRA but the TRA model is deprecated	Fishbein & Ajzen (1975)
Technology Acceptance Model (TAM)	TAM is aimed at predicting and explaining the acceptance of information technologies	TAM stems from TRA and is one of the most use technology acceptance models	Davis (1986)

Theory of Planned behaviour (TPB)	The behaviour of an individual is directly influenced by his or her intention and perceived behavioural control	TPB extends TRA by including the construct perceived behavioural control. Useful model to cope with difficulties of human social behaviour	Ajzen (1991)
Decomposed Theory of Planned Behaviour (DTPB)	Adapted model from TAM & TPB	Combination between TAM & TPB; better explanatory power	Taylor and Todd (1995)
Task-technology-fit (TTF)	TTF explains how technology leads to performance impacts	Now the construct task-technology fit is highlighted in stead of implicit in previous models	Goodhue and Thompson (1995)
Technology-to-Performance Chain model (TPC)	TPC tries to predict the effect of an information system on the performance of an individual user	Predictive power but relationships among variables in the model vary depending on the choice of the users to use the system or not (Staples & Seddon, 2004)	Goodhue and Thompson (1995)
Integrated TAM/ TFF model	Combined models which capture two different aspects of users' choices to use IT	Combined models offer a significant improvement in explanatory power	Dishaw and Strong (1999)

Extended Technology Acceptance Model (TAM 2)	Extended TAM by the collected influence of social influence processes and cognitive instrumental processes on perceived usefulness	TAM2 expands TAM with five factors influencing perceived usefulness and two moderating factors: experience and voluntariness	Venkatesh and Davis (2000)
Unified Theory of Acceptance and Use of Technology (UTAUT)	A model that identifies three variables which directly influence the intention to use	Comprehensive synthesis of former technology acceptance theories	Venkatesh et al. (2003)
Extended UTAUT model	Factors that affect people’s intention to use a new system and technology	Model combined TAM and UTAUT and adds to the UTAUT model by adding the construct Attitude	Kim et al. (2015)

Appendix 3. Survey questions from previous research

Demographic/Characteristic questions

1. What is your gender?
2. What is your age?
3. What is the name of your university school?
4. What subject do you study?
5. Do you have experience with MOOCs?
6. Do you have experience with online lectures?

Performance expectancy

PU = Perceived usefulness (Davis, 1989)

RA = Relative advantage (Rogers, 1983)

OE = Outcome expectations (Compeau & Higgins, 1995)

1. I would find MOOCs useful in my study (PU).
2. Using MOOCs enables me to accomplish tasks more quickly (RA).
3. Using MOOCs increases my productivity (RA).
4. If I use MOOCs, I will increase my chances of passing the course (OE).

Effort expectancy

PEU = Perceived ease of use (Davis, 1989)

EU = Ease of use (Moore & Benbasat, 1991)

1. My interaction with MOOCs would be clear and understandable (PEU).
2. It would be easy for me to become skilful at using MOOCs (PEU).
3. I would find MOOCs easy to use (PEU).
4. Learning to operate MOOCs is easy for me (EU).

Social influence

SN = Subjective norm (Ajzen, 1991)

SF = Social factors (Thompson, Higgins & Howell, 1991)

1. People who influence my behaviour think that I should use MOOCs (SN).
2. People who are important to me think I should use MOOCs (SN).
3. The faculty members of university have been helpful in the use of MOOCs (SF).

4. In general, the university has supported the use of MOOCs (SF).

Facilitating conditions

1. I have the resource necessary to use MOOCs.
2. I have the knowledge necessary to use MOOCs.
3. The system is compatible with other computer networks I use.
4. A specific person (or group) is available for assistance with system difficulties.

Voluntariness of use

1. Although it might be helpful, using a MOOCs is certainly not compulsory in my study.
2. My teacher does not require me to use a MOOCs.
3. My superiors expect me to use a MOOCs.

***Attitude* Toward Using Technology**

AtB = *Attitude* toward Behaviour (Fishbein & Ajzen, 1975)
AtU = *Attitude* toward Use (Thomspon, Higgins & Howell, 1991)
A = Affect (Compeau & Higgins, 1995)

1. Using MOOCs is a bad/good idea (AtB).
2. MOOCs makes studying more interesting (AtU).
3. Studying with MOOCs is fun (AtU).
4. I like studying with MOOCs (A).

***Behavioural intentions* to use the system**

PBC = Perceived behavioural control (Davis, 1989)

1. I intend to use MOOCs in the next 12 months (PBC)
2. I predict I would use MOOCs in the next 12 months (PBC)
3. I plan to use MOOCs in the next 12 months (PBC)

Appendix 4. Survey questions from previous research translated in Dutch

Demografische/ karakteristieke vragen aan respondenten

1. Wat is je geslacht?
2. Hoe oud ben je?
3. Wat is de naam van je universiteit?
4. Welk studie volg je?
5. Heb je ervaring met MOOCs?
6. Heb je ervaring met online courses?

Introductie - Massive Open Online Courses (MOOCs) zijn:

- Online gefilmde cursussen gemaakt door professoren met als doel om een groot aantal studenten les te geven in een bepaald vakgebied.
- Interactieve cursussen met onder andere quizzen en testen.
- Toegankelijk vanaf elke locatie en op elk gewenst tijdstip.
- Gratis en op geheel vrijwillige basis.
- Niet verplicht, maar zorgen er wel voor dat de student zich op een breed gebied verder kan ontwikkelen vanuit zijn/haar eigen kamer.
- Een ideale tool om bepaalde stof nogmaals te bekijken of jezelf verder te ontplooien naast je huidige studie
- Verkrijgbaar op platformen die vergelijkbaar zijn met Netflix, al worden er in het geval van MOOCs serieuze cursussen aangeboden die de student zelf kan kiezen

Universiteiten kunnen toegang tot deze cursussen verlenen, waardoor ze gemakkelijk te bekijken zijn als aanvulling op je huidige studie.

Prestatieverwachtingen

1. Ik zou het gebruik van MOOCs nuttig vinden in mijn studie.
2. Door MOOCs te gebruiken, zou ik sneller kunnen leren.
3. Het gebruik van MOOCs zou mijn productiviteit verhogen.
4. Als ik een MOOC zou gebruiken, die aansluit bij een vak dat ik volg, vergroot ik mijn kansen om te slagen voor dat vak

Inspanning-verwachtingen

1. Het is voor mij duidelijk hoe ik een MOOC kan gebruiken/ bekijken
2. Ik zou gemakkelijk vaardig kunnen worden in het gebruik van MOOCs.
3. Ik zou MOOCs gemakkelijk in gebruik vinden.
4. Leren werken met MOOCs is gemakkelijk voor mij.

Sociale invloed

1. Mensen die invloed hebben op mijn gedrag, denken dat het nuttig is voor mij om MOOCs te gebruiken.
2. Mensen die belangrijk voor me zijn, denken dat het nuttig is voor mij om MOOCs te gebruiken.
3. De faculteitsleden van de universiteit zullen behulpzaam zijn mijn gebruik van MOOCs.
4. Over het algemeen zal de universiteit het gebruik van MOOCs ondersteunen.

Voorwaarden vergemakkelijken

1. Ik heb de benodigde middelen om MOOCs te gebruiken.
2. Ik heb de kennis die nodig is om MOOCs te gebruiken.
3. Het MOOCs platform komt overeen met andere computerplatforms die ik gebruik.
4. Een specifiek iemand (of groep) op de universiteit, is beschikbaar voor hulp bij vragen over MOOCs.

Vrijwilligheid van gebruik

1. Hoewel het misschien nuttig zou zijn, is het gebruik van MOOCs zeker niet verplicht in mijn studie.
2. Mijn docenten vereisen niet dat ik MOOCs gebruik.
3. Mijn docenten verwachten dat ik MOOCs ga gebruiken.

Houding tegenover het gebruik van technologie

1. MOOCs gebruiken is een goed idee.
2. MOOCs kunnen studeren interessanter maken.
3. Leren door middel van MOOCs zou leuk zijn.
4. Ik zou graag studeren met MOOCs.

Gedragsintentie om het systeem te gebruiken

1. Als ik de mogelijkheid had, zou ik MOOCs de komende 12 maanden gebruiken.
2. Als ik de mogelijkheid had, zou ik voorspellen dat ik MOOCs zou gebruiken in de komende 12 maanden.
3. Als ik de mogelijkheid had, zou ik van plan zijn om MOOCs te gebruiken in de komende 12 maanden.

Appendix 5. Analyses output from SPSS and ADANCO

Table 7

Statistics and Descriptive statistics

Statistics

		FacilitatingConditions	EffortExpectancy	Performance Expectancy	SocialInfluence	AttitudeTechnology	BehaviouralIntention
N	Valid	305	305	305	305	305	305
	Missing	0	0	0	0	0	0
Mean		3,6287	3,8779	3,6352	3,1754	3,8492	3,5869

Descriptive Statistics

	N	Mean	Std. Deviation
What is your sex?	305	1,26	,452
What is your age?	305	4,71	2,279
Type higer education	305	1,49	,501
What is the name of your University?	305	2,95	2,600
Which study do you currently follow?	305	25,09	20,586
Do you have experience with online colleges?	305	1,33	,536
Do you have experience with MOOCs?	305	2,02	,666
VoluntarinessofUse	305	4,0787	,70943
Valid N (listwise)	305		

Table 8

Type of University frequencies

What is the name of your University?

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Radboud University	90	29,5	29,5	29,5
	Wageningen University	122	40,0	40,0	69,5
	Rijksuniversity Groningen	16	5,2	5,2	74,8
	University Utrecht	13	4,3	4,3	79,0
	University Twente	15	4,9	4,9	83,9
	University Leiden	23	7,5	7,5	91,5
	TU Delft	7	2,3	2,3	93,8
	TU Eindhoven	2	,7	,7	94,4
	University of Amsterdam	5	1,6	1,6	96,1
	Vrije University	1	,3	,3	96,4
	Erasmus University	5	1,6	1,6	98,0
	Tilburg University	2	,7	,7	98,7
	Maastricht University	3	1,0	1,0	99,7
	Open University	1	,3	,3	100,0
	Total	305	100,0	100,0	

Table 9

Indicator Reliability (base model)

Indicator	PE	EE	FC	SI	ATUT	BI	VoU
PE1	0.5998						
PE2	0.7008						
PE3	0.6462						
PE4	0.5603						
EE1		0.1875					
EE2		0.5399					
EE3		0.7284					
EE4		0.5621					
FC1			0.0781				
FC2			0.0913				
FC3			0.9991				
SI1				0.6991			
SI2				0.6264			
SI3				0.1812			
SI4				0.2113			
Atut1					0.6902		
Atut2					0.6158		
Atut3					0.6400		
Atut4					0.7327		
BI1						0.8452	
BI2						0.6947	
BI3						0.7796	
VoU1							0.3334
VoU2							0.7180
VoU3rev							0.6151

Table 10

Factor loadings (base model)

Loadings

Indicator	PE	Atut	BI	Age	EE	VoU	SI	FC
Age				1.0000				
PE1	0.7745							
EE1					0.4330			
PE3	0.8039							
PE4	0.7485							
VoU2						0.8473		
EE4					0.7497			
BI3			0.8829					
Atut1		0.8308						
FC2								0.3022
SI2							0.7914	
Atut4		0.8560						
BI2			0.8335					
EE2					0.7348			
VoU1						0.5774		
SI1							0.8361	
FC1								0.2794
PE2	0.8371							
Atut2		0.7847						
Atut3		0.8000						
SI3							0.4257	
FC3								0.9995
BI1			0.9193					
EE3					0.8534			
SI4							0.4597	
VoU3rev						0.7843		

Table 11

Discriminant Validity, HTMT (AVE <.85) (base model)

Discriminant Validity: Heterotrait-Monotrait Ratio of Correlations (HTMT)

Construct	PE	Atut	BI	Age	EE	VoU	SI	FC
PE								
Atut	0.9331							
BI	0.8030	0.8932						
Age	0.0457	0.1361	0.0063					
EE	0.3992	0.4504	0.2791	0.2010				
VoU	0.1296	0.0023	0.1257	0.2189	0.0413			
SI	0.6401	0.5998	0.5901	0.0712	0.5301	0.3323		
FC	0.3519	0.3255	0.1851	0.2916	1.0786	0.0294	0.6268	

Table 12

Indicator reliability after deletion of several items (extended model)

Indicator	PE	EE	FC	SI	ATUT	BI	VoU
PE1	0.5997						
PE2	0.7009						
PE3	0.6463						
PE4	0.5603						
EE2		0.5463					
EE3		0.7615					
EE4		0.5867					
FC3			1.0000				
SI1				0.8487			
SI2				0.7675			
Atut1					0.6886		
Atut2					0.6173		
Atut3					0.6408		
Atut4					0.7322		
BI1						0.8450	
BI2						0.6960	
BI3						0.7785	
VoU1							0.3338
VoU2							0.7172
VoU3rev							0.6159

Table 13

Factor loadings after deletion several items (extended model)

Loadings

Indicator	PE	Atut	BI	Age	EE	VoU	SI	FC
Age				1.0000				
PE1	0.7744							
PE3	0.8039							
PE4	0.7486							
VoU2						0.8469		
EE4					0.7660			
BI3			0.8823					
Atut1		0.8298						
SI2							0.8761	
Atut4		0.8557						
BI2			0.8343					
EE2					0.7391			
VoU1						0.5778		
SI1							0.9213	
PE2	0.8372							
Atut2		0.7857						
Atut3		0.8005						
FC3								1.0000
BI1			0.9193					
EE3					0.8726			
VoU3rev						0.7848		

Table 14

Discriminant Validity, HTMT (AVE <.85) after deletion several items (extended model)

Discriminant Validity: Heterotrait-Monotrait Ratio of Correlations (HTMT)

Construct	PE	Atut	BI	Age	EE	VoU	SI	FC
PE								
Atut	0.9331							
BI	0.8030	0.8932						
Age	0.0457	0.1361	0.0063					
EE	0.3630	0.4433	0.3052	0.1798				
VoU	0.1296	0.0023	0.1257	0.2189	0.0712			
SI	0.4969	0.4669	0.4626	0.0463	0.3179	0.2655		
FC	0.3456	0.3708	0.3165	0.1592	0.4937	0.0110	0.3095	