

# Adding Technology Acceptance to E-learning Information Systems Success within an Organizational Setting.

Improving the prediction of use

Student Name: Matthijs van der Graaf  
Student Number: 451759

Supervisor: dr. J. S. Lee

Master Media Studies - Media & Business  
Erasmus School of History, Culture and Communication  
Erasmus University Rotterdam

Master's Thesis  
21 June 2018

# Adding Technology Acceptance to E-learning Information Systems Success within an Organizational Setting.

## ABSTRACT

Because of the speed in which the world is changing, businesses are in need of a fast and cost-effective way to train their employees. E-learning systems can provide this and therefore many business organisations are adopting these systems. Consequently, there is a need to measure the success of these systems to justify investments in them. However, current models that measure the success of an e-learning system cannot accurately predict the use of the system and are not tailored to e-learning within a business environment. Therefore, this study focusses on making improvements on predicting the use of the system and on verifying the model within business organisations. It does this by developing a conceptual model that consist of the D&M model, which focusses on measuring the success of an e-learning system, added with elements of the TAM, which is entirely focused on predicting the use of a technology system. This study uses a specific case, namely an e-learning system used by the Dutch Police Academy, and mixed research methods including surveys, interviews and usage data to find if the added TAM elements improve the predictability of the use of the system. Simultaneously, this data was used to verify the conceptual model within a business organisation. Multiple regression analyses were conducted with the quantitative data to test the relationship between the variables of the two models. The qualitative data was analysed thematically and was used to find explanations for the linkages among variables in the two models within a business organisation setting. The qualitative results rendered it possible to propose alterations on the model to make it more suitable for measuring the effectiveness within a business organisation setting. The results show that the TAM can be added to the D&M model and improve the variance explained in both *user satisfaction* and *intention to use*, two critical elements of the D&M model. When exploring the best fit of combining both models, it becomes clear that overall the TAM variables are more predictive over *intention to use* than the D&M model variables. This shows that it is more important how e-learning participants in a business organisation setting perceive the use of the system than how they perceive the quality of the system.

**KEYWORDS:** *Measuring e-learning success, D&M model, Measuring e-learning adoption, TAM, Intention to use*

# Table of Contents

<b>1. Introduction .....</b>	<b>5</b>
1.1. Relevance.....	8
1.2. Organization Cooperation .....	9
1.3. Thesis outline.....	9
<b>2. Theoretical Framework.....</b>	<b>10</b>
2.1. D&M model .....	10
2.2. Technological Acceptance Model.....	14
2.3. Combining TAM and D&M model.....	17
2.4. Conceptual model.....	18
<b>3. Method .....</b>	<b>22</b>
3.1. Case.....	22
3.2. Research Method .....	23
3.2.1. Quantitative methods .....	23
3.2.2. Qualitative Methods .....	24
3.3. Procedure .....	24
3.4. Sample .....	25
3.4.1. Sample surveys.....	25
3.4.2. Sample interviews .....	26
3.5. Operationalization .....	27
3.5.1. Surveys .....	27
3.5.2. Qualitative Interviews .....	30
3.6. Data analysis.....	31
3.6.1. Quantitative .....	31
3.6.2. Qualitative .....	33
3.7. Validity and Reliability .....	33
3.7.1. Qualitative .....	33
3.7.2. Quantitative .....	34
<b>4. Results and Discussion .....</b>	<b>37</b>
4.1.1. Descriptive statistics.....	37
4.1.2. Descriptive interviews.....	37
4.2. Self-reported vs. user data (H1) .....	38
4.3. How does exposure time effect the models? (H2 and H3).....	39
4.4. Validating the TAM and D&M in business organisations (H4 and H5) .....	40
4.4.1. D&M model (H4) .....	40
4.4.2. Discussion validation of D&M with qualitative results .....	43
4.4.3. TAM (H5) .....	45
4.4.4. Discussion validation of TAM with qualitative results .....	48

4.4.5. Difference between higher education and business setting with qualitative results .....	50
4.5. Adding TAM to D&M model (H6 – H11) .....	52
<b>5. Conclusion.....</b>	<b>57</b>
5.1. Theoretical implications .....	59
5.2. Practical implications.....	60
5.2.1. System quality .....	60
5.2.2. Communication .....	60
5.2.3. Sharing.....	61
5.2.4. Personalization .....	61
5.2.5. Work pressure .....	61
5.3. Limitations .....	62
5.4. Future research.....	63
<b>References .....</b>	<b>64</b>
<b>Appendix 1: Survey metrics .....</b>	<b>69</b>
<b>Appendix 2: Survey.....</b>	<b>72</b>
<b>Appendix 3: Interview Guideline .....</b>	<b>75</b>
<b>Appendix 4: Coding Tree.....</b>	<b>76</b>
<b>Appendix 5: Transcribed interviews .....</b>	<b>77</b>
Interview 1.....	<b>Error! Bookmark not defined.</b>
Interview 2.....	<b>Error! Bookmark not defined.</b>
Interview 3.....	<b>Error! Bookmark not defined.</b>
Interview 4.....	<b>Error! Bookmark not defined.</b>
Interview 5.....	<b>Error! Bookmark not defined.</b>
Interview 6.....	<b>Error! Bookmark not defined.</b>
Interview 7.....	<b>Error! Bookmark not defined.</b>

# 1. Introduction

Companies are in great need to effectively and efficiently train their employees (Zhang & Nunamaker, 2003). Back in 2013, 41,7% of the 500 most profitable companies in the world used e-learning systems for online training purposes (IBIS Capital, 2013). Since 2013, the market for corporate e-learning systems has grown 13% each year (Roland Berger, 2014) and in the time period 2016 to 2020 it is expected to grow even more with an annual of 11.41% (Docebo, 2016). But what are e-learning systems and why is it engaged with by so many companies? E-learning is defined as *'the process of extending learning or delivering instructional materials to remote sites via the Internet, intranet/extranet, audio, video, satellite broadcast, interactive TV, and CD-ROM'* (Holsapple & Lee-Post, 2006 p. 68). E-learning has become popular because it is more flexible and cost-effective than face-to-face education. Because of its mobility, people can learn anywhere at any time. E-learning has been a major trend within higher education since early 2000 (Ray, 2004). Later, organisations also saw the possibilities e-learning systems offered. Training employees has always been an aspect within organisations, but nowadays the business world is changing in a lightning-fast pace which makes it hard to keep the employees up-to-date (Wang, Wang & Shee, 2007). The flexibility and cost-effectiveness of E-learning makes it very attractive for organisations. Also, when successfully applied, e-learning systems have equal or even higher learning outcomes than face-to-face education (Means, Toyama, Murphy & Baki, 2013). With the growing amount of e-learning systems, there is an increasing need to measure their success. Organisations need to evaluate the effectiveness of an e-learning system to justify further investments, determine their added value and to understand the overall effect within the organisation (Dorobãt, 2014).

Over the years, many researches have researched different ways to measure the success of e-learning systems. As a result, two main ways of measuring the success of an e-learning system have emerged (Dorobãt, 2014). The first way focuses on how successful the e-learning system is. This benchmark can be seen as a list of requirements that maximize the success of the system. The model originates from the information system literature and is defines success as the benefits the information system offers. This can vary between systems. For an e-learning system, the benefits can be saving cost and increasing learning outcomes (Wang, Wang, & Shee, 2007). The success model was initially developed by DeLone and McLean and is referred to as the D&M model (DeLone & McLean, 1992). By 2003, this model had been employed in over 300 articles, but information systems had changed substantially since the model's introduction (DeLone & McLean, 2003). Consequently, DeLone and McLean updated their model after reviewing more than 100 D&M model articles. The updated model focuses on measuring the success of an information system through *system quality, system information, system service, user satisfaction, use and user satisfaction* (DeLone & McLean,

2003). This model is the basis of many other alterations that focused on a specific use for an information system, such as e-commerce (Wang, 2008) or e-learning (Holsapple & Lee-Post, 2006; Wang et al., 2007; Hassanzadeh, Kanaai & Elahi, 2012). Hence, the model more successfully measured the success of an e-learning system. However, Holsapple & Lee-Post (2006) concluded that the variable *intention to use*, which is directly related to *system use* needed more attention as it was a primary indicator of the success of a system. Furthermore, the D&M model struggles to predict *intention to use* and *system use*. However, there is another model that solely focusses on explaining the use of a system, or in a broader sense, the adoption of a technology.

This model is the second way to measure the success of an e-learning system. The adoption of a technology can be measured by the TAM, which is short for Technology Acceptance Model, created in 1989 by Fred Davis (1989). This model was initially focused on technology systems and how users accept and use this new technology system. Davis (1989) stated that users are influenced by certain factors that determine if, when and how they are going to use the new technology. The factors are *perceived usefulness* and *perceived ease-of-use*. *Perceived usefulness* is defined as the extent to which the user believes the new technology will increase their professional performance. The *perceived ease-of-use* focuses on the user's belief that the new technology will result in less effort to fulfil his tasks. More recently, this model was updated by its original author, in collaboration with Vankatesh (Davis & Venkatesh, 2000). The main update was that perceived usefulness and perceived ease-of-use were influenced by many external factors, including *job relevance*, *demonstrability*, *experience* and *voluntariness* (Davis & Venkatesh, 2000). This model has been widely adapted and many have attempted to extend this model (Roca, Chiu & Martínez, 2006; McFarland & Hamilton, 2006; Lee, Hsieh & Hsu, 2011; Svendsen, Johnson, Almås-Sørensen & Vittersø, 2013; Dorobät, 2014). For example, Roca et al. (2006) added *computer self-efficacy* and *system design* and Wagner, Hassanein and Head (2010) added *age* as external factors on *perceived ease-of-use*.

The two models can be combined, as the D&M model has limitations in addressing the *system use* and the TAM is completely devoted to improving this construct (Holsapple & Lee-Post, 2006). The two models also show some overlaps. One is that both models share the variables *intention to use* and *system use*. Secondly, some researches state that system design variables, such as *system quality* and *information quality* are considered external variables of the TAM (Roca et al., 2006). Therefore, Pai & Huang (2010) tried to combine elements of both models by incorporate external factors, namely the *system quality*, *information quality* and *service quality* into the TAM. They found that *information quality* positively impacts *perceived usefulness*, *service quality* positively impacts *perceived usefulness* and *perceived ease-of-use* and lastly *system quality* positively impacts *perceived ease-of-use*. Other studies, that also combined the two models, had similar findings which were focused on adoption of e-learning within higher education (Roca et al., 2006; Mohammadi,

2015). However, none of these studies focused on e-learning systems within business organisations. There can be an appreciable difference between these two settings because the users of the system vary in age which happens to be a predictor of a separate construct: *computer self-efficacy* (Charness & Boot, 2010), defined as the users' belief in his or her ability to succeed in computer tasks. Also, the *voluntariness*, the extent to which the users are obligated to use the system, can differ between these two settings (Roca et al., 2006). While users of an e-learning system who are students of a course must engage with the system as it is their only option to achieve learning objectives of a course. Within business organisations, the system is often a tool to make the job easier; however, its use is not compulsory. This difference in obligation can significantly impact the adoption of an information system (Roca et al., 2006; Arning & Ziefle, 2007; Charness & Boot, 2010). Furthermore, most of these studies measured *system use* through surveys instead of empirical usage data, extracted directly from the application, and self-reports in surveys can be biased and may have influenced the outcomes (Gong, Xu & Yu, 2004). Lastly, most studies had no longitudinal elements and therefore had only measured the effects at one moment in time and did not account for exposure time of the application.

This research will follow the example of Roca et al. (2006), Pai and Huang (2010) and Mohammadi (2015) and will combine the TAM and D&M model. By adding the variables from the TAM to the D&M model, this study will focus on improving the predictability of the variable *intention to use*. Also, the predictability of system use needed improvement (Holsapple & Lee-Post, 2006). However, not all studies used *system use*, and if so it was measured by self-reported survey which might be affected by social desirability. Therefore, this study will focus on improving the predictability of only the variable *intention to use*. This research will use mixed research methods including surveys, interviews and usage data to find relationships among the constructs of the two models. The goal is to validate the combination of the two models within a business organisation setting. This leads us to the research question:

*To what extent does adding TAM variables to the D&M model increase the predictability of intention to use within a business organisation setting?*

## 1.1. Relevance

Organisations are in great need for effective and efficient e-learning systems in the fast-changing business landscape (Zhang & Nunamaker, 2003; Wang et al., 2007). As a result, organisation need to be able to measure the success of an e-learning system, so they can determine their added value, justify further investment into the system and know which aspects need to be improved. Combining the two most used models for measuring e-learning system success will give organisations greater insight in the success of their e-learning system (Pai & Huang, 2010). With a combination of both models, organisations can both measure the adoption and net benefits of the e-learning system and acquire insight in which aspects need to be improved to then increase the adoption of the system. Therefore, this research is socially and practically relevant because it provides organisations with needed information about their e-learning systems. It is both relevant for organisation which use e-learning systems and organisation which develop e-learning systems (Wang et al., 2007). The better an organisations e-learning system, the more knowledgeable their employees are and the better the organisation's chances on survival become.

The academic relevance for this research is that it measures the relationship between the TAM and D&M model in a new context, and does so longitudinally and with a higher degree of empiricism. By measuring the relationship between the models, the most predictive elements can be combined in a new model. Heretofore, several researchers have attempted to combine elements of the two models. However, this either only concerned adding a few variables of one model to another model, for instance adding system design variables of the D&M Model to the TAM (Roca et al., 2006; Pai & Huang, 2010; Mohammadi, 2015) or creating a hypothetical new model, which lacked constancy between the studies and had no empirical proof on why certain model elements should be included or excluded (Elmorshidy, 2012; Mohammadi, 2015). Lastly, all these attempts have been in a higher educational setting, which can differ significantly from a business organisation setting (Roca et al., 2006; Arning & Ziefle, 2007; Charness & Boot, 2010). In general, there is a lack of validation of success and adoption models e-learning systems within areas beside a higher education setting (Gong et al., 2004; Holsapple & Lee-Post, 2006; Wang et al., 2007; Mohammadi, 2015). Therefore, this research will be the basis for developing an empirically tested model that incorporates the best elements of both models within a business organisation setting.

Secondly, this research relies on a mixture of data sources and mixed methods to heighten reliability - both data from surveys, data from the application and interviews - while most previous studies relied on only one research method, namely surveys, which yields self-reported data on usage. However, the actual adoption of a technology can substantially differ from the self-reported extent of adoption in a survey due to social desirability (Lee, Hsieh & Chen, 2013). Thus, the findings of this



thesis, particularly those that pertain to actual usage, will have more fidelity than those of previous studies.

## 1.2. Organization Cooperation

This research was carried out in collaboration with both the Police Academy of the Netherlands and Superbuff (a software development company). The police academy has started to employ an e-learning system, developed by Superbuff, in its training of their employees in managerial positions. Hence, the immediate goal of the police academy is to properly measure the success of their e-learning system to justify further investments. Superbuff has developed multiple e-learning systems; however, they have never conducted research on the success and adoption of their systems. They seek insight into what elements of their systems could be improved to better the whole e-learning system. Thus, both organisations clearly have vested interest in measuring the success and adoption of their e-learning system. This research will provide them with insight into the adoption and success of their system from their direct users.

## 1.3. Thesis outline

This study focuses on the effectiveness of an e-learning system in a business organisation setting. It does so by combining two different models, namely the TAM and D&M model, that both have previously been used to measure the effectiveness of an e-learning system. In the chapter theoretical framework, both models will be thoroughly reviewed. As both models have countless extensions, this chapter explores which extensions are relevant for e-learning systems in a business organisation setting. Furthermore, some several researches have attempted to merge several elements of the both models together. Based on the review of previous literature a conceptual model, accompanied by a set of hypotheses, is presented in order to answer the main research question.

Thereafter, the chapter Method presents the methodology used to test the hypotheses and answer the research question. This study uses mixed methods and therefore all the subsections in this chapter are divided in a qualitative and quantitative part. The subsections will describe the case used in this study and elaborate how the data was collected, operationalized and analysed.

In the chapter results and discussions, the subsections are also divided in a qualitative and quantitative part. First the quantitative data is used to answer this study's hypotheses followed by a discussion and explanation of the results based on the qualitative data.

Finally, the last chapter, the conclusion, answers the research question and gives theoretical and practical implication. Lastly this chapter will discuss the limitations of this study and the direction for future research.

## 2. Theoretical Framework

First, the two main models used in this thesis will be discussed. Thereafter, academic literature that has tried to combine the two models will be critically reviewed. The last part of this chapter will explain the conceptual model that will be tested within this research. This part will also cover the hypotheses that will be tested in order to answer the research question of this thesis.

### 2.1. D&M model

Around 1980, the field of management information systems had difficulties in finding the factor that defined and captured the success of an information system (DeLone & McLean, 1992). Researches strived to capture success in this manner; however, they all concluded that there was no single dependent variable, and that information system success was a multidimensional construct (Mason, 1978; Zmud, 1979; DeLone & McLean, 1992). Single variables like user satisfaction or system use were not sufficient to measure the information system success. Therefore, DeLone and McLean (1992) developed a model, later referred to as the D&M model, which incorporated multiple dependent variables from previous studies. Their goal was to develop a universal model to define and measure information system success, a model that allowed for comparison between different systems. In their model, the definition of success depends on what the benefits of the particular information system are. In e-learning, success entails, for example, an increase in learning outcomes and/or reduction of education and time costs (Wang et al., 2007). The D&M model consists of six interrelated dimensions namely, *system quality*, *information quality*, *use*, *user satisfaction*, *individual impact* and *organizational impact*. *System quality* and *information quality* were found to be predictors of *use* and *user satisfaction*. In their turn these variables predicted the success of the information system measured by the variables *individual impact* and *organizational impact*. Their model was well-received and has been one of the most used models in measuring information system success (Dorobãt, 2014). Within ten years, this model had been studied in more than 300 articles, and many variations had been made by other researches (Pitt, Watson & Lee, 1995; Kettinger & Lee, 1995; Seddon 1997; DeLone & McLean, 2003; Holsapple & Lee-Post, 2006; Dorobãt, 2014).

As the information system landscape is continually changing, the model requires constant updates. For example, around 2000, the rise of the internet and internet-based applications made a big impact on the information system landscape. This resulted in an increasingly number of information systems that became available for the public which allowed the public to choose a system instead of being obligated to use the only one available to them. In other words, information systems were no longer mandatory but were mostly voluntary (Wang et al., 2007). Therefore,

Sheddon (1997) stated that the dimension *use* needed to be redefined. He stated that *use* can be a behaviour and an intention. Therefore, he replaced the undefined dimension *use* with *perceived usefulness* and argued that *perceived usefulness* in combination with *user satisfaction* resulted in the actual *system use*. This is the first indication that the D&M model overlaps with other models, in this case the Technological Acceptance Model (TAM), as perceived usefulness is one of the main variables of this model. Furthermore, another result of the rise of the internet and internet-based applications was that information systems became, not solely information providers but also service providers (Pitt et al., 1995; Kettinger & Lee, 1995). Therefore, *service quality* could also influence the success of an information system. Due to these changes the original D&M model became less relevant. Therefore, DeLone and McLean (2003) revised their information system success model and incorporated the feedback their model had received from previous studies (Sheddon, 1997; Pitt et al., 1995; Kettinger & Lee, 1995). They added *intention to use* and *service quality* to their model and merged *individual impact* and *organizational impact* in to one dimension namely, *net benefits*. Consequently, the revised model consisted of seven dimensions namely, *system quality*, *information quality*, *service quality*, *intention to use*, *system use*, *user satisfaction* and *net benefits*.

This revised model became the new standard for measuring information system success and has been used on many different information systems (Holsapple & Lee-Post, 2006; Wang et al., 2007; Wang, 2008; Hassanzadeh et al., 2012; Mohammadi, 2015). Over the years information systems became more divers and many different types of information systems emerged. Therefore, the D&M model needed to be altered slightly for each different type of information system. With the rise of e-learning, researches sought ways to measure the success of the e-learning systems with the D&M model. The e-learning system is the application that is used to remotely distribute information to the participants of an educational course. However, it is also a way for fellow students and the teacher to communicate with one another. Therefore, besides being an information system, e-learning systems are also a communication system. Thus, according to Wang et al. (2007), the revised D&M model lends itself to measure the success of an e-learning system. However, in assessing its success, certain adjustments need to be made to the method and model. The questions in the questionnaire posed to the users (for assessing the system) should be specifically tailored to e-learning systems and not to information systems in general. Furthermore, some additional aspects must be taken into consideration like, culture, e-learning attitudes, goals and loyalty of the users (Holsapple & Lee-Post, 2006; Lin & Lee, 2006; Beldagi & Adiguzel, 2010; Hassanzadeh et al., 2012). These aspects are the reason why some researches have criticised the updated D&M model for measuring e-learning systems (Holsapple & Lee-Post, 2006; Hassanzadeh et al., 2012).

### 2.1.1. Success Model for E-learning

With their study, Holsapple and Lee-Post (2006) were the first to try to form a universal e-learning Success Model (ELSM). This model was not solely for evaluating the success of current e-learning systems but also to help design, development and delivery of future successful e-learning initiatives (Holsapple & Lee-Post, 2006). The ELSM is based on the updated D&M model and incorporates previous literature about measuring e-learning systems. Holsapple and Lee-Post (2006) kept all the original dimensions, except for *intention to use*, from the updated D&M model. They argued that it wasn't necessary to measure both *intention to use* and *system use*. However, after conducting the study *system use* showed considerable room for improvement. They advised future studies to use both *intention to use* and *system use* and measure the dimension through access logs instead of self-reported means. Another alteration Holsapple and Lee-Post (2006) made was, that they divided the model into three stages namely, *system design*, *system delivery* and *system outcome*. The first stage is *system design* and included the dimensions: *system quality*, *information quality* and *service quality*. The second stage is *system delivery* and included the dimensions: *system use* and *user satisfaction*. The last stage is *system outcome* and included the dimension *net benefits* which they split in positive and negative aspects. For all these dimensions, they included sample metrics which were specifically tailored for e-learning systems. For example, *system information* had metrics that assessed to what extent the system was well-organized, how much the information in the system is of the right length, clearly written, useful, etc.

Many of these metrics have been used by other studies that have also tried to adopt the updated D&M model to e-learning system (Lin & Lee 2006; Wang et al., 2007; Hassanzadeh et al., 2012). Whereas, Holsapple and Lee-Post (2006) and Wang et al. (2007) excluded the dimension *intention to use*, Lin and Lee (2006) and Hassanzadeh et al. (2012) included this dimension. Lin & Lee (2006) even took it a step further and included *loyalty to the system*. This is an extension to the dimension *system use* which focuses on involvement and participation rate in the online discussions within the e-learning system. Holsapple and Lee-Post (2006) found that their online students had a desire for a human touch within the e-learning system. They suggested improvements like a chat facility for student-to-teacher and inter-student interaction. As e-learning systems are becoming more socially-oriented with these features, involvement and participation rate on the communication environments within the system can increase the *net benefit* of the e-learning system, and it is therefore important to include *loyalty to the system* in an e-learning success model (Hassanzadeh et al., 2012).

Furthermore, Holsapple and Lee-Post (2006) found that there are some personal characteristics that can influence the success of an e-learning system. One of the main characteristics is the participants' *attitude towards e-learning*. This attitude hugely influences the outcome of the

ELSM. Holsapple and Lee-Post (2006) found that it is necessary to assess the attitude from the participants towards e-learning before measuring the success of the e-learning system through the ELSM. They did this through an online readiness survey and a course expectation survey. Consequently, Holsapple and Lee-Post (2006) found that student characteristics such as a higher GPA, having taken previous online courses or spent more time on the course, better expected performance and good technical competencies influenced the respondents *attitude towards e-learning* and therefore the outcome of the ELSM. Therefore, these characteristics are important to measure before applying an information system success model to measure the success of an e-learning system.

Furthermore, Holsapple and Lee-Post (2006) was the only one that empirically tested their model with experiments and it confirmed that assessing e-learning success from information success approach was beneficial. They improved their e-learning system through the feedback from their users via the ELSM surveys. Users' perceptions of the e-learning system statistically improved after the improvements on many dimensions such as *system quality, system information, system service, user satisfaction* and *net benefits*. On the other hand, the dimension *system use* did not statistically improve, and so it still had considerable room for improvement. Holsapple and Lee-Post (2006) suggested that this dimension needed extra attention to improve the whole e-learning system. As all the other dimensions had a success rate of around 90% in the feedback of the users, *system use* only had an average success rate of 70%. This indicates that there are other factors which influence the dimension *system use*. Additionally, Hassanzadeh et al. (2012) found that *system use* has a great positive impact on the *net benefit* which proves the importance of the former dimension. Other studies did not use experiments, because of they did not have access to a specific case. However, they did use expert interviews to determine which metrics could best be used to measure the different dimensions (Wang et al., 2007; Hassanzadeh et al., 2012). Furthermore, they also surveyed students who had used e-learning systems to measure the interrelation between the dimensions. However, they did not focus on measuring causal relations between the dimensions, because their sample and method did not let them. Lastly, all these studies were performed in a higher education setting except for the study by Wang et al. (2007) (Holsapple & Lee-Post, 2006; Lin & Lee 2006; Hassanzadeh et al., 2012). As there are considerably more studies conducted within a higher education setting, the demand for further research in areas other than higher education settings to explore its applicability persists.

To conclude, the D&M model has successfully been adapted to measure the success of an e-learning system (Holsapple & Lee-Post, 2006; Lin & Lee 2006; Wang et al., 2007; Hassanzadeh et al., 2012). As e-learning systems are becoming more social/interactive, the dimensions *intention to use* and *system loyalty* need to be incorporated within an e-learning success model. This is because these

dimensions have positive effect on the *net benefits* of the e-learning system (Hassanzadeh et al., 2012). Holsapple and Lee-Post (2006) also found external variables which can influence the outcome of the e-learning success model. These variables are clustered around the dimension *attitude towards e-learning* and need to be taken in to account when applying the e-learning success model. Furthermore, the one dimension that needs more attention to further improve the model is the dimension *system use*. This can be done to include *intention to use* and by using data from access logs to accurately measure the actual *system use*. Furthermore, other models can be used to determine what other variables can influence *system use* and *intention to use*. Lastly, there is a need to empirically validate the e-learning success model and to test it in other areas besides higher educational settings.

## 2.2. Technological Acceptance Model

The Technological Acceptance Model (TAM) has been developed to acquire insights into how users accept and use new technologies or information system. This theory is an extension of the Theory of Reasoned Action by Fishbein and Ajzen (1975), which is one of the most influential and extensive research programs within the field of social psychology (Trafimow, 2009). The Theory of Reasoned Action states that one first has a behavioural intention before performing a behaviour. TAM uses this notion and connects it to the behaviour, i.e. using a new technology or information system. Within this study this behaviour will be referred to as *system use*. The original TAM developed by Davis (1989) suggested that users of an information system are influenced by two dimensions which eventually leads to their behavioural intention to use a system. These dimensions are *perceived usefulness* and *perceived ease-of-use*. *Perceived usefulness* is the extent to which the user feels the information system will improve their professional performance. *Perceived ease-of-use* is the extent to which the user feels the information system use will be effortless. These two dimensions result in an *intention to use* the information system and eventually the *system use*. Finally, Davis also stated that *perceived usefulness* and *perceived ease-of-use* are influenced by system design characteristics and other external variables. However, he did not define these system design characteristics and external variables (Davis, 1989).

Between the introduction of the TAM and 2000, the model received much attention from the scientific field, with over 424 studies empirically demonstrating its predictive accuracy of technology adoption (Venkatesh, 1999; Venkatesh & Davis, 2000). Furthermore, several attempts have been made to find external variables which influenced *perceived usefulness* and *perceived ease-of-use* (Hartwick & Barki 1994; Venkatesh & Davis, 1996; Venkatesh, 1999; Venkatesh & Davis, 2000). For example, Venkatesh and Davis (1996) included user training and nature of the implementation

process. In 2000, Davis and Venkatesh (2000) presented an updated version of TAM, namely TAM2, which incorporated external variables found in other studies. Since they found that *perceived usefulness* had a much larger impact on *intention to use* than *perceived ease-of-use*, they excluded certain system design characteristics, as these mostly influence *perceived ease-of-use* and instead included other antecedent variables that significantly influence *perceived usefulness*. These external variables were 1) *subjective norm* (influence from others), 2) *image* (desire to have a favourable standing among others), 3) *job relevance* (if the technology was applicable), 4) *output quality* (does the technology perform the required task) and 5) *result demonstrability* (showing results). Furthermore, Venkatesh and Davis (2000) found that *subjective norm* had a direct impact on the *intention to use* and was mediated by previous *experience* and *voluntariness* of the system.

Around the publishing of the TAM2, more and more organisations began using information systems (Venkatesh & Davis, 2000). This resulted in more attention towards the TAM and TAM2 and many researches trying to extend this model or to apply it to different types of information systems (Wixom & Todd, 2005). Park et al. (2007) and Farahat (2012) used the original TAM for measuring the *system use* of an e-learning system in a higher education setting. Park et al. (2007) focused on the *system use* of teachers and Farahat (2012) focused on the *system use* of students. Both found that the original TAM is applicable for e-learning systems in a higher education setting. Other used the updated version of the TAM (TAM2) on studying e-learning systems (Gong et al., 2004; Roca et al., 2006; Zhang, Zhao & Tan, 2008; Cheung & Vogel, 2013; Abdullah & Ward, 2016). Gong et al. (2004) focused on bachelor students and included an additional external variable *computer self-efficacy*. They characterized this as: '*An individual's perception of a particular system's ease of use is anchored to her or his general computer self-efficacy at all times*' (Gong et al., 2004 p. 367). They concluded that *computer self-efficacy* had a strong effect on *intention to use* and *perceived ease-of-use*. Roca et al. (2006) stated that *user satisfaction* was the best indicator for e-learning continuance intention, i.e. the intention to keep using the system. Satisfaction was dependent on several dimensions such as *perceived usability* (*perceived usefulness* and *perceived ease of use*) *subjective norm*, *computer self-efficacy* and *system design* (*system quality*, *service quality* and *information quality*). The *subjective norm* was the only dimension which had no significant impact on *users' satisfaction*. However, Roca et al. (2006) confirmed that *computer self-efficacy* had an effect on *perceived ease-of-use* which is in line with Gong et al. (2004). Furthermore, Roca et al. (2006) also found a significant effect from *system design* on *satisfaction*. This is in line with the updated D&M model (DeLone & McLean, 2003). Finally, Cheung and Vogel (2013) confirmed a significant direct effect of *self-efficacy* on *intention to use* and indirect on *system use* of the e-learning system. Furthermore, they discovered another external component namely *sharing*. This can be *sharing* from knowledge, opinions and documents with other users. This variable had a significant impact on *perceived*

*usefulness, attitude to the system, intention to use* and system usage and is an important factor in the TAM within e-learning settings. All these researches show that TAM can be used to determine the adoption of e-learning within a higher education setting (Gong et al., 2004; Roca et al., 2006; Zhang et al., 2008; Cheung & Vogel, 2013).

In other areas where the TAM has been tested, more external variables were discovered. Examples of these external variables are *attitude towards the technology, cultural diversity, trust* and individual characteristics such as *age* and *gender* (Davis, Bagozzi & Warshaw, 1989; Huang, Lu & Wong, 2003; Gefen, Karahanna & Straub, 2004; Wagner et al., 2010; Charness & Boot, 2010). In the context for e-learning within business organisations, age becomes an important external variable, as students in higher education are considerably younger than employees of organisations. According to Wagner et al. (2010) and Charness and Boot (2010), age plays a major role in the adoption of new technologies. Furthermore, age is a strong predictor of cognitive abilities like processing speed and memory abilities (Arning & Ziefle, 2007) which in turn affect the users' *perceived ease-of-use* and *perceive usefulness*. Roca et al. (2006) was the only study that had older respondents, namely an average of 33.7 years old, in their validation of the TAM in an e-learning setting.

To conclude, the TAM has successfully been applied within an e-learning setting, mostly in higher education with young students. Several external variables have been identified which have a significant impact on the TAM model. These variables are: *subjective norms, self-efficacy, age, attitude towards the technology, sharing* and *system design*. For e-learning systems within a business organisation setting, external variables like *subjective norms, self-efficacy* and *age* become increasingly important because these can vary between a higher education setting and business organisation setting. They can vary because within a business organisation setting, the e-learning course can be *voluntary*, which influences the *subjective norms* (Venkatesh & Davis, 2000), and the users of the e-learning system are considerably older, which influences the *self-efficacy*. As the gross amount of studies are employed within a higher education setting, the TAM hasn't been validated within a business organisation setting, which should be done first. Furthermore, the TAM and D&M model clearly overlap as they share similar dimension, such as *intention to use* and *system use*. Moreover, system design dimensions are used in the D&M model and the social aspect and attitude towards an e-learning system, which both influences the *system use* were also addressed by Holsapple and Lee-Post (2006). These point to the clear overlap between the TAM and D&M model.



### 2.3. Combining TAM and D&M model

As previously mentioned, several dimensions within the TAM and D&M model overlap one another. Furthermore, the D&M model had problems with improving the *intention to use* and *system use* whereas the TAM is completely developed to improve these dimension (Davis, 1989; Holsapple & Lee-Post, 2006). As not all the studies used system use, and if so this variable was measured through self-reported surveys, the main element that needs improving is *intention to use*. Finally, D&M model system design dimensions have been used as external variables within the TAM model (Roca et al., 2006; Pai & Huang, 2010). Consequently, several researches have attempted to combine the two models (Roca et al., 2006; Pai & Huang, 2010; Elmorshidy, 2012; Wong & Huang, 2015). Seddon (1997) was the first to incorporate an element from the TAM into the D&M model. He changed *use* to *perceived usefulness*, one of the main dimensions in the TAM. However, in the updated D&M model, DeLone and McLean (2003) changed it to *intention to use* and *system use*. This has become the standard within information system success models. Later, Roca et al. (2006) incorporated *system design* (D&M variables *system quality*, *information quality* and *service quality*) into the TAM as external variables and found a significant correlation between *system design* and *perceived usefulness* and *perceived ease-of-use*. Pai and Huang (2010) and Mohammadi (2015) followed Roca et al.'s (2006) example and also incorporated *system design* into the TAM. Both researches found a significant correlation. Finally, Elmorshidy (2012) presented a hypothetical model which tried to fully incorporate the TAM into the D&M model. However, this model has never been empirically tested. Moreover, all these researches were focused on either generic information systems in organisations or, specifically, e-learning systems within higher educational settings. None of them focused on e-learning systems outside of the higher educational settings. In this thesis, the specific context or setting will be called a 'e-learning in a business organisation settings'. Furthermore, these researches also did not incorporate important external variables of TAM. Therefore, this research will focus on adding the TAM to the D&M model and incorporating all the external variables which are important within a business organisation setting.

## 2.4. Conceptual model

A conceptual model has been developed in this thesis, on the basis of the academic literature presented in the theoretical framework. An analysis of this model will offer an answer to the research question:

*To what extent does adding TAM variables to the D&M model increase the predictability of intention to use within a business organisation setting?*

Before the presentation of the conceptual model, it should be noted that the research design of this study allows to control for two limitations that have often been mentioned by previous studies (DeLone & McLean, 2003; Holsapple & Lee-Post, 2006; Cheung & Vogel, 2013; Mohammadi, 2015). The first limitation that several studies have given is that they measured *system use* with self-reported surveys. This can lead to a self-reporting bias (Holsapple & Lee-Post, 2006; Cheung & Vogel, 2013). Instead, this thesis uses user data collected directly from the e-learning application, which ensures that the real *system use* is measured. Therefore, the following hypothesis is formed:

**H1:** Self-reported *system use* is different than *system use* derived from user data from the application.

Another limitation that can be controlled for because of the methodological design of this study is exposure time. Several studies have mentioned that their lack of having a longitudinal design prevents them to control for the variable exposure time. Exposure time is when users use the system for a longer period of time and therefore achieve more experience with it. Due to this, users are likely to change their perceptions of the system (Mohammadi, 2015). This study has a longitudinal design and therefore the following hypotheses are formed:

**H2:** Exposure time influences all the variables of the D&M model.

**H3:** Exposure time influences all the variables of the TAM.

Furthermore, the TAM and D&M model, when employed for e-learning systems, have mainly been used in a higher educational setting. Both models therefore demand verification in other contexts, i.e. in a business organisational setting, before adding the TAM variables to the D&M model. A conceptual model of original D&M model, with the inclusion of the variable *loyalty to the system* is shown in figure 2.1. this model will be tested by the following hypothesis.

**H4:** The D&M model maintains its predictions in an e-learning system in a business organisational setting.

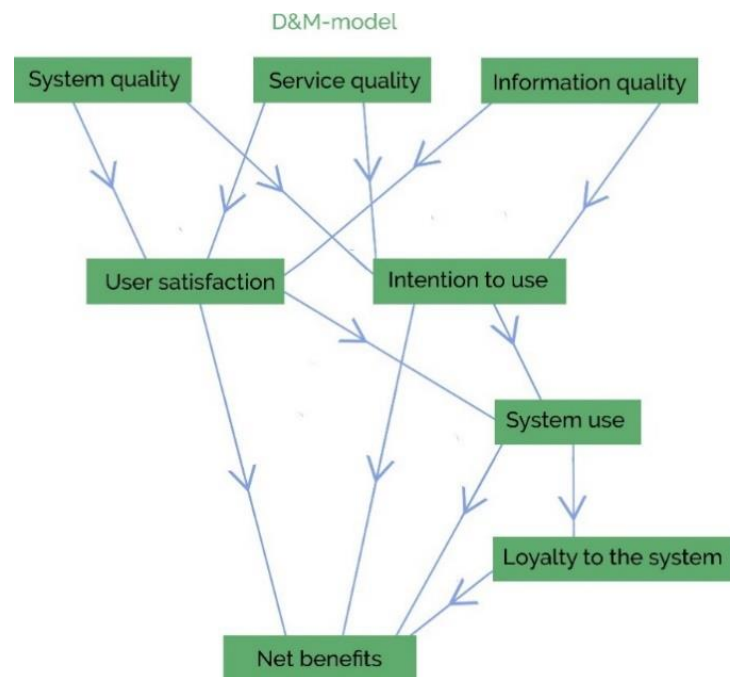


Figure 2.1 D&M model

A conceptual model of original TAM, with the inclusion of the variables *subjective norm*, *self-efficacy*, *age* and *attitude towards using* is shown in figure 2.1. this model will be tested by the following hypothesis.

**H5:** The TAM maintains its predictions in an e-learning system in a business organisational setting.

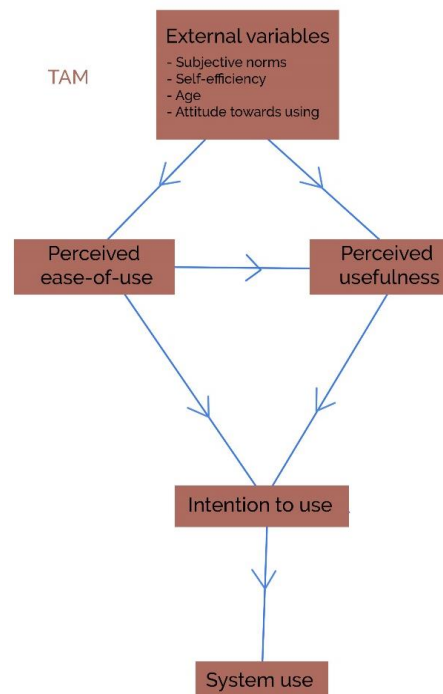


Figure 2.2 TAM

The next hypotheses will be devoted to adding TAM variables to the D&M model. Based on literature discussed in the theoretical framework, the two models will be merged. According to this literature the TAM and D&M model share similar dimensions namely, *system use* and *intention to use* and they both focus on information systems (Davis & Venkatesh, 2000; DeLone & McLean, 2003). Furthermore, several studies have already focused on the relationship between the TAM and D&M model (Roca et al., 2006; Pai & Huang, 2010; Mohammadi, 2015). Some studies use D&M model's system design variables (*System quality, Information quality and Service quality*) as external variables for the TAM. Other studies add TAM variables as predictors of D&M variables (Seddon, 1997; Roca et al., 2006). This study will follow their lead and based on these previous studies a conceptual model is presented. The model can be found in figure 2.1

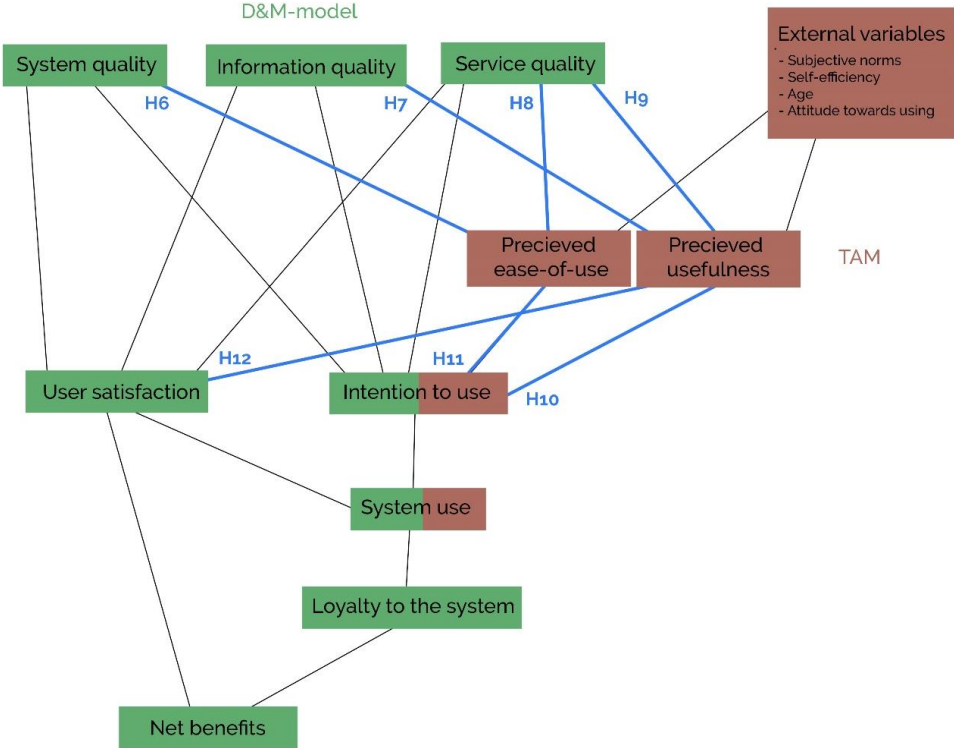


Figure 2.3 – Conceptual Model

The following hypotheses are formed to test this conceptual model. According to Roca et al. (2006), Pai and Huang (2010) and Mohammadi (2015), D&M model *system design* variables have an effect on the TAM variables *perceived usefulness* and *perceived ease-of-use*. To be more precise, *system quality* influences *perceived ease-of-use*.

**H6:** System quality has a positive effect on perceived ease of use within a business organisation setting.

Information quality positively influences users' perceived usefulness.

**H7:** Information quality has a positive effect on perceived usefulness within a business organisation setting.

And lastly, service quality positively influences users' perceived usefulness and users' perceived ease-of-use.

**H8:** Service quality has a positive effect on perceived ease-of-use within a business organisation setting.

**H9:** Service quality has a positive effect on perceived usefulness within a business organisation setting.

In the original TAM *perceived ease-of-use* and *perceived usefulness* are predictive over *intention to use*. Furthermore, according to Seddon (1997) and Roca et al. (2006), *perceived usefulness* is also predictive over D&M model's *user satisfaction*. To validate these claims the following hypothesis are formed

**H10:** Perceived usefulness has a positive effect on intention to use within a business organisation setting.

**H11:** Perceived ease-of-use has a positive effect on intention to use within a business organisation setting.

**H12:** Perceived usefulness has a positive effect on user satisfaction within a business organisation setting.

Testing all the above hypotheses will make it possible to fully answer the research question.

## 3. Method

This chapter provides a thorough description of the methods used to answer the research question. This chapter will start with a brief description of the case that has been used for this study. Next, the research methods will be described followed by an argumentation on why these methods are chosen to answer the research question. After this, the sample of the study will be discussed followed by an operationalization of the TAM and D&M model. The last subsection will discuss the reliability and validity of the study.

### 3.1. Case

The Police Academy of The Netherlands developed, in collaboration with Superbuff (a software development company), an e-learning system for mobile use called the 'Innovation Expeditie'. The e-learning system was still in development and therefore it is considered to be a prototype. The e-learning system was an application for the mobile phone and was part of a voluntary blended learning course offered by the police academy to those in managerial roles within the Dutch police located all over the Netherlands. Employees that have a managerial role could enrol themselves into the 'Innovatie Expeditie' course. There was a maximum of around 60 spots available per course, and once people have started the course, they were highly encouraged to finish it; however, the course was not compulsory. The first trial-class of 60 students was offered in 2017. This course started in April and when the course had finished in September, 15% of the participants had dropped out of the course. Furthermore, it was unsure how many courses will occur yearly because the course was still in its testing phase. So far, two classes (tracks) have started in 2018, one started on January 11<sup>th</sup> and one, which was delayed, started May 15<sup>th</sup>. It was intended to include both classes in this study. However, because the May 15<sup>th</sup> class was delayed, this class could not be included in this thesis. Therefore, the January 11<sup>th</sup> was the only class that has been analysed in this study. Further information on both the case and the sample will be discussed in the sample subsection.

All the content of the blended learning 'Innovation Expeditie' course appeared in a mobile e-learning application, and once every 8 weeks the participants met face-to-face for discussions and cases about the material. These face-to-face meetings are called 'inspiration days'. The length of the whole course was 6 months and consists of 4 face-to-face meetings.

As stated in the introduction, the police academy endeavours to know the application's effectiveness, so they can justify further investment in the application. Also, information on how the mobile e-learning application could be improved would be invaluable to them. Hence, the activities and attitudes of the students surrounding this e-learning application will be the case used to measure the relationship between the two e-learning success models, the TAM and D&M model.

## 3.2. Research Method

This analysis used a combination of quantitative and qualitative research methods, also known as mixed methods. The quantitative research objective was to verify the TAM and D&M model in a business organisation setting and to test the relationship between the variables of the two models. The qualitative research objective was to find explanations for the linkages among variables in the two models within a business organisation setting. The qualitative results rendered it possible to propose alterations on the model to make it more suitable for measuring the effectiveness within a business organisation setting. The quantitative research methods that have been used are surveys and user data from the application, and the qualitative method that has been used are interviews.

### 3.2.1. Quantitative methods

For this study a quantitative method was appropriate to use because it can measure the relationships between the D&M model and TAM. Quantitative research methods produce quantifiable data that makes it possible calculate relationships and predictive patterns between variables. (Punch, 2003; Sapsford, 2007). Furthermore, there was already sufficient research done with these variables which made it possible to define variables and develop a questionnaire to measure them (Rowley, 2014)

The initial quantitative research design for this study (i.e. intended design) was an experimental longitudinal design. A longitudinal experiment is conducted by having a pre-test, apply a manipulation to the experiment group, controlling all variables for the control group and finally have a post-test. This way casual relations can be measured. However, due to time restrictions, only the 11<sup>th</sup> January group (i.e. the group that started the course on January 11) could be analysed. This eliminated the research design which included 11<sup>th</sup> January group's being the experiment group and the 15<sup>th</sup> May group's being the control group. The manipulation for this pseudo-experimental study was improving the system design variables, which would make it possible to measure a causal relationship between the system design variables and the TAM. Furthermore, due to technological restrictions of the applications and money issues the 11<sup>th</sup> January group could not be split into two parts with one part using an updated application and one group using the original application. Also, minimum respondent restrictions for adequate statistical analysis (and also set by the guidelines of the Media and Business programme) made it impossible to split the 11<sup>th</sup> January group into two. Therefore, another research design was opted.

The research design that was eventually used for the overall research - qualitative methods, both the survey and the user data from the application - is an observational longitudinal research design. This means that one group is measured twice, through a survey and user application, to measure the relationship between the D&M model and the TAM and the effect that application

exposure time has on both models. It is an observational design because the researcher did not apply any manipulations.

All the data during the stages were collected through an identical survey and user application data. The survey was identical for both data gathering moments so that the results can be compared. Furthermore, surveys were appropriate for this research because the two models have clear dimensions, which require solicitation from respondents (i.e. course participants) (Neuman, 2013). It will not deeply elaborate on their motivations or beliefs, which is generally associated with qualitative interviews (Neuman, 2013).

### 3.2.2. Qualitative Methods

After conducting the quantitative methods, the results showed clear variables and relationships between these variables. However, not all of them were in line with previous research. Therefore, this thesis engages in qualitative analysis to explain the discrepancies between the theoretical expectations and the empirical, quantitative findings of these thesis. Furthermore, it was also used to acquire a deeper understanding of the difference between a higher education setting and a business organisation setting. Quantitative research is well suited for this as it focusses on the reason why and can uncover complex social phenomena (Baum, 2002). The quantitative research method that has been used in this thesis is semi-structured interviews. This quantitative research method focussed on revealing meaning and uncovering decision making processes (Weiss, 1995).

A technical reason for the qualitative interviews was that the number of survey respondents unfortunately failed to achieve the minimum required for the MA thesis. The qualitative method, semi-structured interviews were held with the participants of the Innovation Expedition e-learning course that commenced on January 11, 2018. Semi-structured interviews were appropriate because most of the TAM and D&M model were already explained by the quantitative data. Therefore, it was only necessary to acquire some in-depth knowledge about specific linkages. However, the semi-structure allowed the interviewee to go into more depth on specific answers if they seemed relevant to the study in any way.

### 3.3. Procedure

The quantitative data for this research has been gathered during two face-to-face meetings, and for the qualitative data, during a follow-up set of interviews. The in total four face-to-face meetings between the student participants and course teacher were already part of the course (i.e. not explicitly part of this research agenda). The first data gathering moment was during the second face-to-face meeting held on 15<sup>th</sup> March. During this meeting, the course participants had already used



the application for 8 weeks. At the end of the face-to-face meeting, all the course participants were asked to fill out the survey. The survey was constructed in Qualtrics and thoroughly tested for mobile phone use. This enabled the course participants to fill out the survey on their mobile phone. Another advantage of a digital survey was that the data was immediately available to the researcher. In case of technical complications, several paper copies of the survey were printed for respondents who could not fill out the survey on their phones. Not all the course participants were present on the 15<sup>th</sup> March face-to-face meeting. Therefore, absent students were sent an e-mail with a link to the Qualtrics survey that asked if everyone could fill out the survey.

The second data gathering moment was on the 23<sup>th</sup> May during the third face-to-face meeting. At this moment, the course participants had used the application for 16 weeks. Before the meeting, several survey respondents were selected for interviews based on several criteria, which will be explained in the sample section. At the beginning of the meeting, the course coordinator made clear that the researcher would ask several course participants a few questions about the e-learning application. Throughout the day, these selected participants were asked to be interviewed by the researcher. The interviews were held in a separate room that was only available for the researcher. The interviews were recorded with an application on the researcher's phone. In total seven course participants were interviewed. At the end of the day, all the present course participants were asked to fill out the survey on their phone. Absent course participants were sent an e-mail that asked if everyone could fill out the survey.

All the participants signed a consent form before attending the course. This consent form asked permission for their application data to be measured. Additionally, for this research an informed consent form was made to ask permission to analyse the application data on a personal level and to use their survey data and interview data for analysis for this research. After the survey data was gathered, they were anonymized to ensure privacy (Babbie, 2011). Furthermore, the participants were not informed that the second survey was to measure the effect of exposure time as this can influence the results (Christensen, Johnson, Turner & Christensen, 2011).

## 3.4. Sample

### 3.4.1. Sample surveys

The unit of analysis for this research were the participants of the 11<sup>th</sup> January 'Innovation Expeditie' e-learning course given by the police academy. The course participants were policemen who are in management functions within their respective police stations. While the course was voluntary, the course coordinator stated there was some social pressure to apply to the course and to finish it.

On 11<sup>th</sup> January 2018, 58 people started with the course; however, some did not finish. By the first survey administration, 50 people were still enrolled in the ‘Innovation Expeditie’ course but some did not attend any face-to-face meeting and did not use the application. Therefore, these are not considered active participants of the course. Within the sample for this analysis, there are 42 respondents. The sample criteria are, being a participant of the 11<sup>th</sup> January ‘Innovation Expeditie’ course and have at least opened the app 5 times. This last criterion is to ensure that the respondents can give reasoned answers to the survey question about the application. During the data gathering not all the 42 filled out the survey. During the first data gathering, 35 participants filled out the survey and during the second time 30 filled it out. Descriptive statistics surrounding these samples will be discussed in the Results chapter.

3.4.2. Sample interviews

The semi-structured interviews were held with participants of the ‘Innovation Expedition’ e-learning course, which makes them the population. Based on the quantitative data a few important characteristics were found such as gender, age and minutes of system use, that could impact the results of the model in a meaningful way. To get a representative sample of the participants of the ‘Innovation Expedition’ a stratified sampling technique needed to be used (Robinson, 2014). In the population of the ‘Innovation Expedition’ there were considerably more males (68.4%) than females (31.6%). To make the sample representative of the population, the male female ratio should be similar to the population ratio. Secondly system use of participants of the ‘Innovation Expedition’ ranged from 0 to 1762.77. To get a represented sample, the system use of the sample should also have a comparable range. Lastly the age of the participants ranged from 29 to 65. To make it representable the sample should also have a comparable range. Lastly, the interviews were held on the third face-to-face meeting. Therefore, the last criteria for the sample is to be present on that day. A sampling framework was made to be able to recruit the right interview respondents (Table 3.1). However, because of time restrictions and the male female ratio, not every female category could be interviewed. Descriptive statistics surrounding the interview sample will be discussed in the Results chapter.

Male				Female			
Heavy users (750-1750)		Light users (0-750)		Heavy users (750-1750)		Light users (0-750)	
Old (45-65)	Young (29-45)	Old (45-65)	Young (29-45)	Old (45-65)	Young (29-45)	Old (45-65)	Young (29-45)
1	1	1	1	1	1	1	1

Table 3.1 Stratified sample framework for the interviews

### 3.5. Operationalization

#### 3.5.1. Surveys

The dimensions in both the D&M model and TAM were measured through the survey. The dimensions of the original D&M model include: *system quality, information quality, service quality, system use, intention to use, user satisfaction and net benefit*. The dimensions of the original TAM model include: *perceived usefulness, attitude towards the system and perceived ease of use*. Besides the original dimensions of these models, a few dimensions from extended versions of both models were included. These dimensions include *subjective norm, age, and computer self-efficacy*.

While formulating the definitions, some dimensions showed similarities. For instance, *perceived ease-of-use* has similarities with *system quality*. Furthermore, *perceived usefulness* has similarities with *information quality*. It was therefore important to make a clear distinction between these variables. Roca et al. (2006) operationalises the TAM variables more abstractly and the D&M *system design* variables more on the practical level. For instance, *perceived usefulness* of an e-learning system is the way how the technology as distributor of information is useful for learning and their job. The *information quality* is how the information is formulated, for instance the length, format and completeness. Mohammadi (2015) made the same distinction as Roca et al. (2006), and therefore this research followed their examples. In table 3.2, all the different dimensions are defined as in accordance with material presented earlier in the theoretical framework.

	<i>Dimension</i>	<i>Definition</i>	<i>Reference</i>
<b>D&amp;M Model</b>	Service quality	The quality of the support that users receive from IS systems staff and how face-to-face meetings are integrated	(Mohammadi, 2015)
	System quality	The desirable characteristics and features of IS system. The technical quality of the system	(Mohammadi, 2015)
	Information quality	The way the information is displayed and described	(Mohammadi, 2015)
	Satisfaction	The extent to which user believe that their needs, goals, and desires have been fully met	(Holsapple & Lee-Post, 2006)
	Intention to use	Key likelihood that an individual will use a technology	(Holsapple & Lee-Post, 2006)
	Actual use	The recorded use of an individual	(Mohammadi, 2015)
	Net benefits	The total benefit of using the IS system	(Hassanzadeh et al, 2012)

	<i>Dimension</i>	<i>Definition</i>	<i>Reference</i>
<b>TAM</b>	Perceived ease usefulness	The degree to which a person believes that using a particular system would enhance his or her job performance but also his learning performance	(Venkatesh & Davis, 2000)
	Perceived ease of use	The degree to which a person believes that using a particular system would be free of effort for him or her	(Venkatesh & Davis, 2000)

	Intention to use	Key likelihood that an individual will use a technology	(Venkatesh & Davis, 2000)
--	------------------	---	---------------------------

<i>Dimension</i>	<i>Definition</i>	<i>Reference</i>
<i>Loyalty to the system</i>	Involvement and participation rate on the communication environment within the system	(Lin & Lee, 2006)
Computer self-efficacy	The self-assessment of individual ability to apply computer skills to complete specified tasks	(Roca et al., 2006)
Subjective Norm	The degree to which someone is influenced by others to use the system	(Roca et al., 2006)
Age	Individuals age	
Attitude towards the system	Attitude someone has towards e-learning in general	(Venkatesh & Davis, 2000)

Table 3.2 TAM and D&M model dimensions

Both models have been used numerous times in literature (Holsapple & Lee-Post, 2006; Roca et al., 2006; Wang et al., 2007; Pai & Huang, 2010; Cheung & Vogel, 2013; Hassanzadeh et al., 2012; Mohammadi, 2015). However, they have not used the same survey questions or even the same metrics within their surveys. To ensure that all the questions in the survey were derived from previous literature while maintaining to be relevant for the specific case of this research, all the survey questions were first broken down into metrics. Metrics are the aspects that are measured through a specific question. For instance, the question ‘does the application has a fast response time’ measures the metric speed of the application. Furthermore, the metric speed in combination with other metrics such as, attractiveness, user-friendliness, structure and reliability can measure the dimension *service quality*. The operationalisation of both models will be discussed separately. In papers that used the D&M model, some researchers included their survey in their paper (Roca et al., 2006; Wang et al., 2007) and some only included the metrics (Hassanzadeh et al., 2012). Therefore, first all the questions were broken down into metrics which resulted in 34 metrics. Some of these metrics showed close resemblance such as, clear and understandable. Similar metrics were therefore merged into one which resulted in 22 metrics. All the metrics concerning the D&M model can be found in appendix 1. The survey questions were formulated by using these metrics and the surveys of previous papers (DeLone & McLean, 2003; Roca et al., 2006; Wang et al., 2007; Mohammadi, 2015). After selecting the most common question for each metric, the questions were tailored to the specific case used in this research. Consequently, 24 questions were formulated to measure all the dimensions within the D&M model, which all can be found in appendix 1. Similar to the papers that used the D&M model, TAM papers did also not consistently include the survey they used. Therefore, the same “deconstruction” approach was used to formulate the

questions measuring the dimension of the TAM. For the TAM, 10 overarching metrics were found. All the metrics concerning the TAM can be found in appendix 1. The survey questions were formulated by using the metrics and the surveys of previous papers (Venkatesh & Davis, 2000; Roca et al., 2006; Cheung & Vogel, 2013; Mohammadi, 2015). Also, these questions were tailored to the 'Innovatie Expeditie' case used in this research. Consequently, 11 questions were formulated to measure all the dimension within the TAM. The questions can be found in appendix 1.

Lastly, some dimensions not mentioned in the original TAM and D&M model were included in the survey as previous literature had shown these external dimensions influenced the individual models (Holsapple & Lee-Post, 2006; Lin & Lee, 2006; Roca et al., 2006; Cheung & Vogel, 2013). The external variables which were included in the survey were, *subjective norms*, *self-efficacy*, *age*, *member loyalty*. These variables will be measured by the metric provided by the studies who discovered these external variables (Holsapple & Lee-Post, 2006; Lin & Lee, 2006; Roca et al., 2006; Cheung & Vogel, 2013). The questions in the survey were derived from these metrics and can be found in appendix 1.

Furthermore, there were some questions included in the survey which measured other external variables that were proposed by either the police academy or the game developer, Superbuff. They proposed these variables based on feedback they had received from their course participants during the first trial course. They believed these variables could influence the use of the e-learning system. These variables were occupation, location and type of mobile phone they used for using the e-learning system. Additionally, gender was also included in the questionnaire. All the questions in the questionnaire can be found in appendix 2.

#### **3.5.1.1. Scales**

All questions were merged in to one survey and was tailored to the e-learning system used by the police academy. Furthermore, all the questions will be translated into Dutch as the respondents are Dutch. After these alterations the survey will be used for both the data gathering moments. The survey questions constituted five-point Likert scales. While seven-point Likert scales are commonly used, this survey will consist of many questions so to make it easier for the respondents a five-point Likert scale was used. According to Berdie (1994), a seven-point Likert scale increases the difficulty and confusion for respondents to check their right answer. It also increases the time used to finish the survey, which might result in answers near the end of the survey not being answered correctly. Furthermore, Pai and Huang (2010), who also studied both models, also used a five-point Likert scale. The scale that will be used is as followed: 1 is strongly agree, 2 is agree, 3 is neutral, 4 is disagree, and 5 is strongly disagree. An abridged version, with scale, can be found in table 3.3.

Variable	Question	Strongly agree	Agree	Neutral	Disagree	Strongly disagree
<i>Mobiel self-efficacy</i>	I am really good with using my mobile phone	○	○	○	○	○
<i>Subjective norm</i>	My peer students expect from me that I use the application	○	○	○	○	○
<i>Service quality</i>	The application provides a proper online explanation	○	○	○	○	○
<i>Information quality</i>	The application provides sufficient information	○	○	○	○	○

Table 3.3 Abridged version of item scale

### 3.5.2. Qualitative Interviews

The themes of the semi-structured interviews were based on the results of the quantitative data. Furthermore, several questions concerned the linkages between the TAM and the D&M model and how these linkages affect the system use. The interview questions were divided in three sections. The first set of questions concerned how respondents perceived the D&M model system design variables, what should be improved about them and how they affected their system use and how it could be improved. During these questions, linkages between D&M model *system design* variables and the TAM *perceived ease-of-use* and *perceived usefulness* variables were explored. An example of a question used in this section of the interviews is: ‘*How do you perceive the system quality?*’. The second set of questions concerned if and why their use of the system changed overtime. An example of a question used in this section of the interviews is: ‘*Have you been using the application less or more than before?*’. The last set of questions concerned their overall attitude towards the Innovation Expedition e-learning course. In this section e-learning was compared to traditional learning and it was explored what made e-learning different in a business organisation setting compared to a higher educational setting. An example of a question used in this section of the interviews is: ‘*What makes corporate e-learning different from e-learning for higher education?*’ The full interview guide can be found in appendix 3.

The respondents for the interviews were sampled using stratified sampling, as mentioned in the sample subsection. The interviews were on average 30 minutes, ranging between 20 and 40 minutes. Because, the interviews were a follow up on the quantitative data and were focussed on specific themes found in this data, broader themes were not discussed which made the that the interviews were not very long. However, in the last few interviews similar answers were given, which is a sign of data saturation. The transcribed interviews can be found in appendix 5. In total seven course participants were interviewed of which two were female and five were male. The full description of the interviewees can be found in the Results section.

## 3.6. Data analysis

### 3.6.1. Quantitative

Before conducting the statistical test on the quantitative data, the reliability of the survey needed to be tested. This was done with the Cronbach's Alpha reliability test and is necessary to ensure the reliability and relevance of the data that has been collected through the survey. A minimum Cronbach's Alpha of .70 was needed to ensure the scale for a construct was reliable (DeVellis, 2003; Pallant, 2010). However, the variable would still be used as the scales were derived from previous literature in which these scales were already tested on reliability. However, the result of the Cronbach's Alpha test does have consequences for the interpretation and discussion surrounding this construct as the construct is less reliable.

The surveys were constructed in Qualtrics, which made it possible to export the raw data immediately into a statistical data analysis program. The program that has been used to conduct the statistical test for this research was SPSS. Some adjustments had to be made to the raw data to make it easier to process it. Furthermore, Superbuff, the game development company, made the user data from the e-learning system available for this research. The data was presented in an Excel document and derived on the same day the surveys were conducted. The data in the Excel document showed the total use of the system for each course participant. This number was divided by the number of weeks the course participant had been exposed to the application. This number is the *system use* per week. At the end the first user data *system use* was the average use of the first 8 weeks and the second user data *system use* was the average use of the second 8 weeks. This data was added to the data set in SPSS.

Several statistical test have been conducted within SPSS to answer the 12 hypotheses. The tests that have been used are Paired-sample T-tests, Repeated Measures T-tests, MANOVAs, Multiple Linear Regressions and Linear Regressions. For each hypothesis will be explained which statistical test has been used and argued why this test was appropriate.

**H1:** Self-reported *system use* is different than *system use* derived from user data from the application.

To answer this hypothesis a Paired-sample T-test was run. This test can compare the mean of one group which have been tested twice (Ross & Willson, 2017). Usually this means a group has been tested in two different points of time. However, in this case the group has been tested through two different methods, through a survey and user data.

**H2:** Exposure time influences all the variables of the D&M model.

**H3:** Exposure time influences all the variables of the TAM.

To answer these hypotheses two MANOVAs were run. On the longitudinal data concerning the D&M model and one on the longitudinal data concerning the TAM. A MANOVA is in essence an ANOVA with several dependent variables (Meyer, Gampst, & Guarino, 2006). In this case all the individual variables of the D&M model and TAM model are dependent on the exposure time. A MANOVA will test if the means of the two moments in time are the same. In other words, if the exposure time has an effect on the variables of the two models.

**H4:** The D&M model maintains its predictions in an e-learning system in a business organisational setting.

**H5:** The TAM maintains its predictions in an e-learning system in a business organisational setting.

**H6:** System quality has a positive effect on perceived ease of use within a business organisation setting.

**H7:** Information quality has a positive effect on perceived usefulness within a business organisation setting.

**H8:** Service quality has a positive effect on perceived ease-of-use within a business organisation setting.

**H9:** Service quality has a positive effect on perceived usefulness within a business organisation setting.

**H10:** Perceived usefulness has a positive effect on intention to use within a business organisation setting.

**H11:** Perceived ease-of-use has a positive effect on intention to use within a business organisation setting.

**H12:** Perceived usefulness has a positive effect on user satisfaction within a business organisation setting.

To answer hypothesis 4 to 12 several Linear Regression and Multiple Linear Regressions were run. A Linear Regression measures the relationship between two ratio variables. The goal is to calculate if one independent variable is predictive over one dependent variable. In some cases, a dependent variable was predicted by several independent variable. In this case A Multiple Linear Regressions was used, as it calculates if multiple independent variables are predictive over a dependent variable (Seber & Lee, 2012). These tests were calculated for hypothesis 4 and 5, if the relationships between the variables within both models still hold within a business organisation setting. For hypothesis 6 to 12 the regressions were calculated the relationship between TAM variables and D&M model



variables to measure the relationship between the two models. For all the regressions within this research the standardized coefficients have been reported. By reporting these the effect sizes of the variables can be compared. Furthermore, the significance of the tests will be reported one-tailed as previous research indicate a directional effect.

### 3.6.2. Qualitative

After conducting the interviews, the recordings were transcribed. The data has been analysed through a thematic analysis. This data analysis technique makes it possible to find patterns/themes within the data (Braun & Clarke, 2006). Furthermore, it organises the dataset in themes which can be connected to the theory. The theory in this case is the data from the quantitative research methods. Therefore, the coding process was based on the TAM and D&M model, and in particular about the results of the quantitative research of this thesis.

The six analysing steps by Braun and Clarke (2006) were used. The first step becoming familiar with the data. This was done by simultaneously listening to the recordings and reading through the transcripts. Next, some interesting phenomenon were already coded accordingly. Thereafter, all the sections were only coded per sentence. From these open codes themes were established. After reviewing these themes there were placed in the preconceived themes based on the quantitative results. Sections that did not fit in these themes were given their own theme. Lastly the results were written up. The coding tree can be found in appendix 4 and all the transcripts can be found in appendix 5.

## 3.7. Validity and Reliability

### 3.7.1. Qualitative

Reliability is to what extent this research can be replicated under the same conditions (Silverman, 2016). This study uses a specific case to gather its data from, which makes it very difficult to replicate this exact study. Furthermore, one of the research method uses is qualitative interviews, which is hard to make reliable. However, this research elaborately describes the research process in the Method chapter. This improves the transparency of the study, which makes it more reliable (Golafshani, 2003). However, exactly replicating it stays impossible. Furthermore, according to Silverman (2016) the reliability of qualitative research can be improved through asking interview questions in the same way. This research used semi-structured with a clearly defined topic list, which will improve the reliability.

### 3.7.2. Quantitative

To ensure the reliability and validity of the quantitative methods the scales were derived from previous studies and thereafter a reliability test was conducted. As previously mentioned, to measure the effectiveness of the e-learning system two models were used, namely the TAM and the D&M model. The original TAM model consists of three main variables, namely *perceived usefulness*, *perceived ease-of-use*, *intention to use* and *system use* (Venkatesh & Davis, 2000). Also, a few external variables were added such as *subjective norm*, *age*, *attitude towards using* and *mobile self-efficacy*. To measure these variables, the scales of previous research were used (appendix 1). This increases the validity as it makes sure that the survey measures what it is intended to measure. These scales were slightly modified to better fit the case studied in this analysis. The scales were aggregated using its average to test the hypotheses. In order to verify that the modifications did not affect the reliability of the scales, a reliability test was conducted for each individual variable. The variables *age* and *system use* are not included as these. Lastly, these scales used in the whole survey is as followed, 1=strongly agree, 2=agree, 3=neutral, 4=disagree, 5=strongly disagree). This means the scale is in reversed direction. This is important to consider when comparing this scale to normal direction variables such as *age* and *system use*. The results of the Cronbach's reliability test are shown in table 3.4.

#### *Reliability test for original TAM variables*

	Cronbach's Alpha	Mean
Perceived usefulness	.882	2.20
Perceived ease-of-use	.854	2.37
Intention to use	.991	2.06

#### *Reliability test for external TAM variables*

	Cronbach's Alpha	Mean
Subjective Norm	.225	2.45
Subjective Norm (updated)	.691	2.27
Attitude towards using	.879	1.99
Mobile Self-efficacy	.825	1.94

Table 3.4 TAM reliability test

All the variables had a Cronbach's Alpha higher than .70, which makes them reliable (DeVellis, 2003; Pallant, 2010), except for subjective norm. The results of reliability test of the subjective norm scale

show that if the question ‘Is the use of innovation expedition voluntarily’ were to be deleted the Cronbach’s Alpha would be 0.69, which is considerably higher. When taking a closer look at the other questions it seems like the ‘Is the use of innovation expedition voluntarily’ is a reversed question, to be more specific, it is the only reversed variable in the whole survey. When reversing this question, it still does not fit in the scale, likely because it was the only reversed variable in the survey. This is a mistake made by the researcher. To conclude Subjective Norm’s Cronbach’s Alpha is 0.69, which is still not higher than .70. The updated Subjective Norm variable will be used in the analysis however, the variable is less reliable, and this should be taken in to account when analysing this variable.

The other model used to measure the effectiveness of the e-learning system is the D&M model. The original D&M model consist of seven main variables, namely *system quality, information quality, service quality, satisfaction, intention to use, system use* and *net benefits* (DeLone & McLean, 2003). For this model an external variable was added also, namely *loyalty to the system*. To measure these variables the scales of the original model were used, supplemented with the scales from recent research using the D&M model with a focussed on e-learning systems (appendix 1). These scales were slightly modified to fit the case used in this analysis. A reliability test was conducted to ensure the reliability of the scales. The variables *intention to use* and *system use* are not included in this table because the reliability of these variables was already tested in the reliability test of the TAM variables. The results of the Cronbach’s reliability test are shown in table 3.5.

*Reliability test for original D&M model variables*

	Cronbach’s Alpha	Mean
System quality	.736	2.78
System quality (updated)	.760	2.78
Information quality	.850	2.18
Information quality (updated)	.856	2.19
Service quality	.599	2.36
Satisfaction	.904	2.14
Benefits	.885	2.55

*Reliability test for external D&M model variables*

	Cronbach’s Alpha	Mean
Loyalty to the system	.833	3.17

Table 3.5 D&M reliability test

Both the variables *system quality* and *information quality* became more reliable when deleting one question. For *system quality* this was 'does the application look appealing'. When comparing this question to the other *system quality* question it seems like the others are more focussed on technical aspects of the system and not the appearance. The question that has been deleted in the *information quality* scale is 'the text in the modules are not too long'. The only other variable that needs to be discussed is *service quality*. This variable cannot be improved by deleting any question. A Cronbach's Alpha of .60 is low and this makes the variable less reliable. However, the variable will still be included in the analysis, but the results concerning this variable are less reliable. Furthermore, from now on the updated version of *system quality* and *information quality* will be used. The average of the items of each variable will be used during the data analysis. Furthermore, all the items can be found in appendix 1, including the items that were deleted.

## 4. Results and Discussion

In this chapter, the nine hypotheses will be tested by using several different quantitative analyses and their findings supplemented through both qualitative and quantitative data. The quantitative analyses will test the hypothesis and the qualitative data will discuss and give an explanation on the results. First, descriptive statistics are presented, then the reliability of the survey will be tested, followed by several subsections that answer the corresponding hypotheses. For each individual hypothesis, the type of analysis will be described followed by the analysis itself. The analysis will show if the hypothesis is rejected or supported and finally the qualitative data will attempt to offer further explanations regarding the outcomes of the hypothesis tests.

### 4.1.1. Descriptive statistics

Before answering the hypotheses, some descriptive statistics of the sample, including age, gender, function within the police and work location, are provided. These descriptive statistics are important to obtain a sense of the diversity of the group. The number of respondents in the first survey sample (T1) is  $N=38$ . The number of respondent in the second survey sample (T2) is  $N=31$ . Of the sample, 68.4% is male and 31.6% is female. Within the sample, the age ranges from 29 to 65 with an average of  $M = 46$  years old and a standard deviation of  $SD = 8.64$ . This means the group is very age diverse. All the people in the sample have a managerial function; however, their functions still differ much from each other. Respondents' specific managerial role was obtained through an open question in the survey and cannot be easily quantified. However, answers ranged from local team manager of a unit (less than 10 persons) to director of national security. Other answers included advisor, teacher leadership, project manager and coordinator of master. Also, the work location of the respondents varied hugely. The work locations were ascending from most respondents to least, Apeldoorn ( $N=11$ ), Amsterdam ( $N=11$ ), Den Haag ( $N=8$ ), Groningen ( $N=5$ ), Rotterdam ( $N=5$ ), Utrecht ( $N=5$ ), Tiel ( $N=4$ ), Enschede ( $N=4$ ), Dordrecht ( $N=2$ ), Eindhoven ( $N=2$ ), Helmond, ( $N=2$ ), Hoogezand ( $N=2$ ), Zwolle ( $N=2$ ), Driebergen ( $N=1$ ), Epe ( $N=1$ ), Hengelo ( $N=1$ ), Wassenaar ( $N=1$ ), Woerden ( $N=1$ ), Zoetermeer ( $N=1$ ). This shows that respondents come from all over The Netherlands.

### 4.1.2. Descriptive interviews

To find explanations for the quantitative results, seven interviews were held. Two female and five male respondents were included in the sample. The respondents were selected based on their system use and their age. This way several different perspectives were gathered. In table 4.1 the characteristics of the interview respondents are shown.

	<i>Gender</i>	<i>System use in minutes</i>	<i>Age</i>
<i>Respondent 1</i>	Male	946	38
<i>Respondent 2</i>	Female	871	31
<i>Respondent 3</i>	Male	20	43
<i>Respondent 4</i>	Female	105	50
<i>Respondent 5</i>	Male	553	36
<i>Respondent 6</i>	Male	1479	60
<i>Respondent 7</i>	Male	77	55

Table 4.1 Interview sample discriptives

## 4.2. Self-reported vs. user data (H1)

This study had two ways of calculating the *system use* of the sample. The first was through the survey where the respondents self-reported their *system use* (*self-reported system use*). The second was through user data directly from the e-learning system statistics (*user data system use*). To answer hypothesis 1, self-reported *system use* differs from *system use* derived from user data from the e-learning system, the two variables were compared.

First, the means of both categories were calculated. The mean of *self-reported system use* is 64.74 minutes per week. The app user data shows something completely different. The mean of the *user data system use* is 41.94. There is a significant difference between the two variables ( $M_{\text{difference}} = -22.79, p < .001$ ). This means that people over-estimate their *system use* with on average 22.79 minutes or 35.21% per week. However, the two variables do significantly correlate with each other ( $r = .440, N = 66, p < .001$ ). Overall, there is a moderate, positive correlation between *self-reported system use* and *user data system use* derived from user data. To conclude, respondents overestimate their *system use* when self-reporting it, and there is a correlation between application data and self-reported data, but its moderate. As *system use* derived from the user data is the more accurate *system use*, this variable will be used in all forthcoming the tests. Furthermore, H1 is confirmed.

But, there remains the question is the *self-reported system use* unintentional over estimation or wilful exaggeration? Most of the interview respondents admitted that they did not spend enough time on the application. However, two of the respondents indicated that they spend much time on the application, but when comparing this with the *user data* they hardly spend any time on the application. This might be due to respondents' wanting to give social desirable answers, in other words a social desirability bias (Fisher & Katz, 2000). Social desirability is common among self-reported data on sensitive topics (Davis, Thake & Vilhena, 2010) or on media use (Prior, 2009). *System use* is surely the use of media but can also be perceived as a sensitive topic as there is a high *subjective norm* surrounding the use of the system according to some respondents.

### 4.3. How does exposure time effect the models? (H2 and H3)

The sample of this study was measured twice. Once after using the application for 8 weeks, referred to as T1 ( $N=35$ ), and one after using the application for 16 weeks, referred to as T2 ( $N=30$ ). This makes it possible to measure if exposure time of the application has an effect of on the TAM and D&M model. To answer this, two hypotheses are formed (H2 and H3). To measure these two MANOVA, also known as a multivariate ANOVA, was conducted. The reason for this is because each model has multiple dependent variables. One of the assumptions of a MANOVA is that the dependent variables correlate with each other in a moderate range (Meyers, Gampst, & Guarino, 2006). In subsection 'Validating the TAM and D&M in business organisations' regression analysis between the dependent variables of this MANOVA were performed. In figure 4.1 (in subsection 4.4) the correlations between the variables of D&M can be found and in figure 4.3 the correlation between the variables of TAM can be found. Both figures show that most of the variables have meaning full correlation patterns, which suggest appropriateness for a MANOVA when using these variables.

In order to answer hypothesis 2, which states that exposure time of the e-learning system has an effect on the D&M model, a one-way multivariate analysis of variance (MANOVA) was conducted with *system quality*, *information quality*, *service quality*, *user satisfaction*, *intention to use*, *system use*, *loyalty to the system*, *net benefits* as dependent variables and exposure time as independent variable. A statistically significant MANOVA effect was obtained, Wilks' Lambda = .79,  $F(7,62) = 2.357$ ,  $p = .034$ . The multivariate effect size was estimated at .210, which implies that 21.0% of the variance in the dependent variables was accounted for by exposure time. None of the variables were significant which means that homogeneity of variance is assumed. The MANOVA shows that only *system quality* is significant ( $p = .016$ ). Next, an independent sample t-test was conducted to compare *system quality* in T1 and T2 conditions. There was a significant difference in the scores of *system quality* T1 ( $M = 2.72$ ,  $SD = .70$ ) and *system quality* T2 ( $M = 3.17$ ,  $SD = 0.76$ );  $t(69) = -2.61$ ,  $p = .011$ . To conclude, time has a significant negative effect on the D&M model, but only on the variable *system quality*. System quality went down. This means that the more the course participants used the system, the less optimistic they felt towards its quality. Therefore, H2 is confirmed.

In order to answer hypothesis 3, which states that exposure time of the e-learning system has an effect on the TAM model, a one-way multivariate analysis of variance (MANOVA) was conducted. No statistically significant MANOVA effect was obtained, Wilks' Lambda = .903,  $F(6,63) = .919$ ,  $p = .487$ . This means that the time of exposure to the application has no significantly effect. To

verify this, independent t-test were conducted on all the TAM variables. In table 4.2 the results of these tests are shown. No variable showed a significant difference and therefore, H3 is not confirmed.

	8 weeks exposure		16 weeks exposure		t-test
	<i>M</i>	<i>SD</i>	<i>M</i>	<i>SD</i>	
<i>Perceived ease-of-use</i>	2.23	.67	2.45	.75	.158
<i>Perceived usefulness</i>	2.09	.82	2.34	.88	.222
<i>Intention to use</i>	1.92	.74	2.15	.85	.227
<i>System use</i>	36.33	35.78	35.38	37.38	.906
<i>Mobile self-efficacy</i>	1.96	.75	1.88	.83	.666
<i>Subjective norm</i>	2.17	.76	2.34	.94	.355
<i>Attitude towards using</i>	1.97	.82	1.98	.73	.995

Table 4.2 Sample discriptives using independent t-test

To conclude, the only variable that has been affected by exposure time is *system quality*. The results of the qualitative interviews give some indication on why only the results of *system quality* are negatively affected by exposure time. For example, respondent 1 expressed that he used the application a lot and that after a while he received more and more errors. He recently stopped using the system because it freezes most of the time. These results partly support the concerns about the effect of exposure time on the D&M model by Mohammadi (2015). He stated that attitude and perceptions of an e-learning system can change overtime and therefore a longitudinal design should be used to assess the effectiveness of an e-learning system. However, this research studies an e-learning system which is still a prototype. The reason why the *system quality* had changed overtime might be due to the instability of the prototype.

#### 4.4. Validating the TAM and D&M in business organisations (H4 and H5)

##### 4.4.1. D&M model (H4)

Hypotheses 4 to 12 are all based on previous literature. The literature state that all these hypotheses are directional, to be more precise the independent variable positively predicts the dependent variable. Therefore, all the p-values concerning hypotheses 4 to 12 are reported as one-tailed.

The goal of this research is to join the TAM model to the D&M model. However, most researches that used the TAM and/or D&M model on e-learning systems did this in a higher education environment (Holsapple & Lee-Post, 2006; Roca et al., 2006; Mohammadi, 2015). The case



used in this study is not in a higher education environment but in a business organisation environment. Therefore, the two models should first be validated in this environment before measuring the relationship between the two models. In order to test this, hypothesis 4 and 5 are proposed. Hypothesis 4, which states that the D&M model can accurately measure the effectiveness of an e-learning system within a business organisation setting, will be answered by using several linear multiple regressions. This analysis is most suitable for answering this hypothesis as the variables are impacted by several predictors (Pallant, 2010).

For tests concerning only one predictor, linear regression analysis will also be used; its standardized coefficient is equivalent to a Pearson correlation. The first dependent variable that was predicted is *user satisfaction*. A multiple linear regression was run to test if *system quality*, *information quality* and *information quality* ratings significantly predicted *user satisfaction*. A significant regression equation model was found ( $F(3, 68) = 12.184, p < .001, R^2 = .350$ ). This model explains 35% of the variance in *user satisfaction*, which indicates the model is moderately predictive. To compare the effect sizes, the standardized coefficients of the independent variables within the regression models are reported. This holds for all the regression analyses within this study. It was found that *service quality* ( $b^* = .468, p < .001$ , one-tailed) and *information quality* ( $b^* = .210, p = .025$ , one-tailed) significantly predicted the *user satisfaction*. *System quality* ( $b^* = .063, p = .270$ , one-tailed) was not significantly predictive over *user satisfaction*. So, service quality has the largest effect (but moderate) on satisfaction such that a 1 standard deviation increase in service quality can yield a .47 standard deviation improvement in user satisfaction.

The second dependent variable that was predicted is *intention to use*. For this analysis, a multiple linear regression was used as well. The test calculated if *system quality*, *information quality* and *information quality* ratings significantly predicted participants' *intention to use*. A significant regression equation model was found ( $F(3, 68) = 18.379, p < .001, R^2 = .448$ ) that explains 44.8% of the variance in *intention to use*, which indicates the model is strongly predictive. It was found that *information quality* ( $b^* = .482, p < .001$ , one-tailed) and service quality ( $b^* = .360, p < .001$ , one-tailed) significantly predicted the participants' *intention to use*. *System quality* ( $b^* = -.101, p = .146$ , one-tailed) was not significantly predictive over *intention to use*. Thus, *information quality* has the strongest, although moderate, effect on *intention to use*.

The second layer in the model states that *user satisfaction* and *intention to use* are predictive of *system use*. To test this a multiple linear regression was run. A significant regression equation model was found ( $F(2, 68) = 5.440, p = .003, R^2 = .138$ ). The model explained 13.8% of the variance in *system use*, which indicates the model is moderately predictive. It was found that only *intention to use* ( $b^* = -.434, p = .0235$ , one-tailed) significantly predicted participants' *system use*. *User satisfaction* ( $b^* = .076, p = .362$ , one-tailed) was not significant predictive. Furthermore, the

standardized coefficient is negative because the scale decreases in agreement with higher values (1=strongly agree, 2=agree, 3=neutral, 4=disagree, 5=strongly disagree) and with the *system use*, the positive (more use) the higher the value (minutes of use). Thus, *intention to use* has a positive, moderate effect on *system use*.

One external variable has been added to the model as it was significantly predictive according to previous literature (Lin & Lee, 2006). This variable is an extension of *system use* and is called *loyalty to the system*. The literature states that *system use* is predictive of *loyalty to the system* and in its turn, *loyalty to the system* is predictive of *net benefits*. A significant regression equation model was found for *loyalty to the system* ( $F(1, 69) = 5.642, p = .010, R^2 = .076$ ) with *system use*. The model with the predictor *system use* explained 7.6% of the variance, which indicates the model is weakly predictive. It was found that *system use* ( $b^* = -.275, p = .010$ , one-tailed) significantly predicted participants' *loyalty to the system*. Again, the scale of the survey and therefore *loyalty to the system* was reversed. The standard coefficient of *system use* is negative; however, this must be interpreted as positive. Thus, system use has a positive, weak effect on *loyalty to the system*.

Furthermore, the model states that *net benefits* is predicted by *system use*, *user satisfaction* and *loyalty to the system*. To test this, a multiple linear regression was run. A significant regression equation model was found for *net benefits* ( $F(4, 67) = 22.299, p < .001, R^2 = .578$ ) with *intention to use*, *system use*, *loyalty to the system* and *user satisfaction*. The model explained 57.8% of the variance in *net benefits*, which indicates that the model is strongly predictive. It was found that *user satisfaction* ( $b^* = .566, p < .001$ , one-tailed) significantly predicted participants' *net benefits*. Both *loyalty to the system* ( $b^* = .090, p = .145$ , one-tailed), *intention to use* ( $b^* = .166, p = .149$ , one-tailed) and *system use* ( $b^* = -.070, p = .218$ , one-tailed) had no significant predicted value over *net benefits*. Thus, the only variable that has an effect on *net benefits* is *user satisfaction*. The effect is moderately positive.

To conclude most of the model behaves according to expectations and can be found in figure 4.1. However, there are some discrepancies in the model. The *net benefits* is not predicted by *intention to use*, *system use* or *loyalty to the system*,

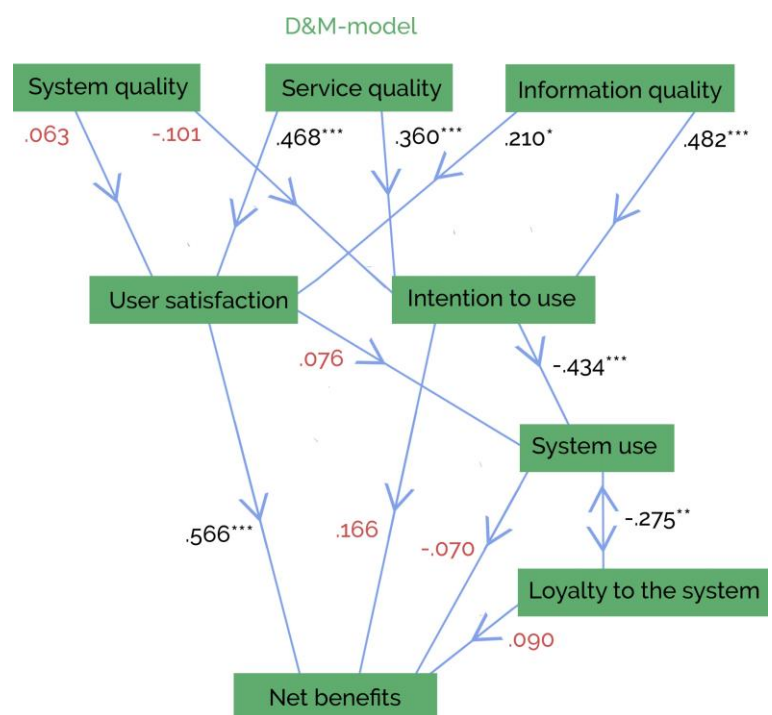


Figure 4.1 D&M model coefficients

and *user satisfaction* does not predict *system use*, which they should according Delone and McLean (2003) and Lin and Lee (2006). This means that an increase in the variables concerning *system use* does not lead to an increase in *net benefits*. This is not in line with previous research as it states that *system use* has a great positive impact on the net benefits (Hassanzadeh et al., 2012). An explanation for this can be that the *net benefits* are not achieved through using the e-learning system but through the face-to-face meetings. This explication is supported by the fact that *service quality*, which partly concerns the face-to-face meetings, has the strongest effect on *user satisfaction*. The fact that the course is a blended learning course might have affected the results of D&M model, as most previous literature used it to assess courses which were fully dependent on e-learning systems (DeLone & Mclean, 2003; Holsapple & Lee-Post, 2006; Roca, et al. 2006; Mohammadi, 2015). Furthermore, it seems that *loyalty to the system* is predicting *system use* instead of the other way around. Lastly, the variable *system quality* does not significantly predict any variable and is the only variable that does not fit in the model. These abnormalities may be better explained from qualitative interviews.

#### 4.4.2. Discussion validation of D&M with qualitative results

The first thing that will be discussed is the separation between *net benefits* and *system use*. In the interviews, it became clear that people see the application as addition to the face-to-face meetings. Respondent 5 stated that you need the e-learning system to understand everything within the course and to be able to participate in the face-to-face meetings. This indicates that the application in combination with the face-to-face meetings give the benefits such as increase problem solving ability (survey question). However, as a standalone application the benefits might be less clear because the interview respondents see the blended learning course as a whole.

The second variable that needs some more explaining is *loyalty to the system*. As mentioned in the Method, *loyalty to the system* is the involvement and participation rate on the communication environment within the system. In this case the communication environment is called Slack, however it is not within the system, but it is a standalone application. In the model, *loyalty to the system* should be predicted by *system use* and be predictive of *net benefits*. However, it only correlates with *system use*. Most interview respondents report that they do not use Slack often. The reason for this is that there is not enough activity on the platform. "I've noticed that not a lot of people are on Slack which made me also not use Slack" (Respondent 3). 'I don't use Slack for the inspiration expedition that often because not a lot of people post on it' (Respondent 2). This indicates that if people use the Slack less it will result in even less people using it. However, five of the interviewees stated that if there was more activity on the Slack they would use it more, because they would like to discuss their

answers on the question in the application with others. As respondent 1 stated 'If everyone should post their answers on Slack it would make it a lot more interesting and I think the more answers or activity on Slack the more people are going to use it' (respondent 1). According to respondent 3, more activity on Slack would help her learn better. This way she can discuss things and ask questions to others. Respondent 2 and 3 are in other Slack communities which they find very interesting and beneficial. Furthermore, respondent 2 also stated that whenever she reads comments on Slack she is also opens the e-learning app, 'and if I use Slack, I also have a look on the application' (Respondent 2). This shows that *loyalty to the system* is an important variable, both for increasing the *system use* and *net benefits*. These results are supported by previous literature which state that *loyalty to the system* has a significant effect on *net benefits and system use* (Hassanzedeh et al., 2012). However, the results of the interviews are only partly supported by the results found through the quantitative data, as *loyalty to the system* has a significant correlation with *system use*, but not with *net benefits*. However, previously was already established that the nature of the e-learning course, being a blended learning course, might have affected the variable *net benefits*.

Furthermore, the interview respondents gave a few suggestions on how to increase the variable *loyalty to the system* (the activity on Slack). According to respondent 1, 2, 5 and 7, Slack should be integrated within the application and not a standalone application, because 'the step to Slack is really irritating' (Interview 5). Furthermore, more activity on Slack is the key to getting more people involved in Slack. This could be achieved by moderators posting up-to-date and relevant information to keep people engaged according to respondent 2. Lastly, the answers given in the application should be posted on Slack. This way people can discuss about the answers.

The last variable that will be discussed is *system quality*. This variable was not significantly predictive in the case that has been studied. However, in the D&M model it is a significant predictor. During the interviews, many interview respondents indicated that the system quality is bad. To give a few examples; 'the stability is very bad (respondent 4); the system is too slow, I think it needs to be much faster (respondent 5); the stability is really a critical point of the application (respondent 6). All this critique is supported by the surveys as *system quality* had the worst score of the *system design* variables (table survey reliability). The interview respondents revealed many different bugs the application had, such as not being able to start the next learning module, not getting a checkmark when finishing a module and that the application only worked well when connected with WIFI. Some even indicated that the bad system quality is a reason to stop using the system. 'The stability is very bad, and I think this is the reason why many people stop using it' (respondent 4). 'I have used it with pleasure, however when you get that moment [many errors and freezes] you quit using it' (Respondent 1). This indicates that *system quality* should have a direct relation with *system use*. However, system quality does not have a significant effect on intention to use ( $b^* = -.101, p = .145$ ,

one-tailed), moreover it is even negative. Furthermore, when adding *system quality* to a multiple regression with predictors *intention to use* and *user satisfaction* predicting *system use*, a significant regression model is found ( $F(3, 67) = 8.512, p < .001$ ). In this model *user satisfaction* is still not a significant predictor ( $b^* = -.016, p = .469$ , one-tailed). However, *system quality* ( $b^* = .352, p = .001$ , one-tailed), and *intention to use* ( $b^* = -.424, p = .019$ , one-tailed), have become a significant predictor. Interestingly, *system quality* has a positive correlation. As the survey scale is reversed (1=agree and 5=disagree) and the scale for *system use* is normal, this means that the better one perceives the *system quality* the less you use the system. This is contradictory with the statements of the interview respondents and previous literature (DeLone, McLean, 2003). The interview respondents explicitly said that the bad system quality has led them to stop using the system (Respondent 1) or use the system less (Respondent 2). However, there is one small clue on why *system quality* has a reversed correlation. The only interview respondent that said the *system quality* was good is Respondent 3. "I find the system quality very good, I have never experienced any problems" (Respondent 3). However, when looking at Respondent 3 user data *system use*, it shows that Respondent 3 only had used the e-learning application a total of 30.20 minutes during the past 16 weeks. Furthermore, Respondent 7 did not mention anything about the quality of the system, even though when explicitly asking it. He also has a low system use, namely 77.63. Therefore, an explanation of the reversed correlation between *system quality* and *system use* can be that if people hardly use the system they will not experience any problems with the system. This might be because system errors only happen after using the system a while or that the more you use it the more you get annoyed with the system speed and stability. This is in line with earlier finding in this study where the results showed that the *system quality* was negatively affected by exposure time.

#### 4.4.3. TAM (H5)

In order to answer hypothesis 5, which states that the TAM can accurately measure the adoption of an e-learning system within a business organisation setting, several (multiple) linear regression were used. First, the original variables will be tested, where after the external variables will be tested. The first variable that was predicted is *intention to use*. The TAM model indicates that only *perceived usefulness* and *perceived ease-of-use* were predictive of *intention to use*. However, conducting stepwise multiple regressions with the external variables (*age*, *self-efficacy*, *attitude towards using* and *subjective norm*) showed that also *subjective norm* is a predictor of *intention to use*. Therefore, a multiple linear regression was run to test if *perceived usefulness*, *perceived ease-of-use* and *subjective norm* significantly predicted participants' *intention to use*. A significant regression equation model was found ( $F(3, 67) = 29.960, p < .001, R^2 = .573$ ) with *subjective norm*, *perceived usefulness* and *perceived ease-of-use*. The model which explained 57.3% of the variance, which indicates the

model is strongly predictive. It was found that *perceived usefulness* ( $b^* = .586, p < .001$ , one-tailed) *perceived ease-of-use* ( $b^* = .223, p = .008$ , one-tailed) and *subjective norm* ( $b^* = .283, p < .001$ , one-tailed) significantly predicted the participants' *intention to use*. Thus, *perceived usefulness* has the strongest positive effect on *intention to use*.

The TAM model also states that *perceived ease-of-use* is predictive of *perceived usefulness* (Venkatesh & Davis, 2000). A significant regression equation model was found ( $F(1,69) = 11.407, p = .001$ , one-tailed) with *perceived ease-of-use* ( $b^* = .377, p = .001$ , one-tailed) significantly predicting *perceived usefulness*. This can be a sign of that *perceived usefulness* partially or fully mediates the effect of *perceived ease-of-use* on *intention to use*. The literature did not mention this mediation and therefore this was not hypothesised in the conceptual

model. To test this mediation effect, an additional hypothesis was formed, which states that the relationship between *perceived ease-of-use* and *intention to use* is mediated by *perceived usefulness*, was formulated. To test this a several regression analyses were run. First the individual effect of *Perceived ease-of-use* ( $b^* = .413, p < .001$ , one-tailed) and *perceived usefulness* ( $b^* = .671, p < .001$ , one-tailed) on *intention to use* was calculated. When comparing this to the

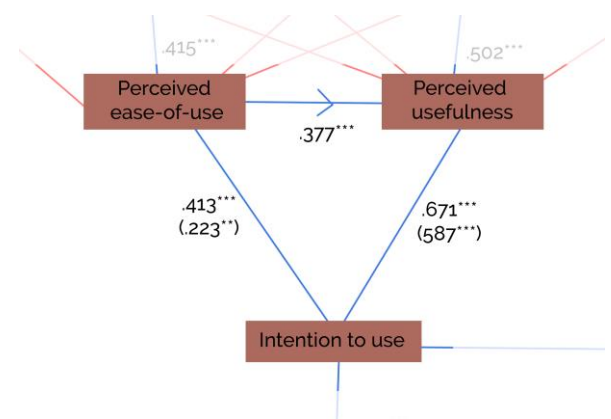


Figure 4.2 Mediation in TAM

multiple regression model of *perceived ease-of-use* and *perceived usefulness* as predictors of *intention to use*, the predictive ability from *perceived ease-of-use* drops from  $b^* = .443, p < .001$  (one-tailed) to  $b^* = .223, p = .008$  (one-tailed), and the predictive ability from *perceived usefulness* drops from  $b^* = .671, p < .001$  (one-tailed) to  $b^* = .587, p = .008$  (one-tailed). In the multiple regression model *perceived ease-of-use* is still significant, which indicates a partial mediation. To test if the mediation is significant a Sobel's Z-test was conducted. The mediation effect was found to be significant ( $z = 2.98, p = .003$ ). This confirms the additional mediation hypothesis, thus the relationship between *perceived ease-of-use* and *intention to use* is partially mediated (because still significant in multiple regression model) by *perceived usefulness* which is visualized in figure 4.2. In this figure the irrelevant coefficients are intentionally obscured in order to highlight the relevant coefficients. This finding is supported by previous literature (Venkatesh & Davis, 2000).

The last original variable is *system use*. Aforementioned, all the TAM and D&M model variables are reversed expect for *system use* and *age*. This must be taken into consideration when comparing *system use* and or *age* to the other variables. A linear regression was run to test if *intention to use* significantly predicted participants' *system use*. A significant regression equation model was found ( $F(1, 69) = 10.893, p = .001, R^2 = .136$ ). This model explained 13.6% of the variance,

which indicates that the model is weakly predictive. It was found that *intention to use* ( $b^* = -.369, p = .001$ , one-tailed) significantly predicted the participants' *system use*. Thus, *intention to use* has a strong positive effect on *system use*.

Furthermore, external variables (*age*, *self-efficacy*, *attitude towards using* and *subjective norm*) have been mentioned in the literature that might influence the TAM variables (Venkatesh & Davis, 2000; Gong et al, 2004). Previously these external variables were already tested on *intention to use*, however this analysis has tested if the external variables are predictors of *perceived ease-of-use* and/or *perceived usefulness*. A multiple linear regression was run to test if just the set of *subjective norm*, *age*, *attitude towards using* and *mobile self-efficacy* significantly predicted participants' *perceived ease-of-use*. A significant regression equation model was found ( $F(4, 63) = 3.596, p = .011, R^2 = .186$ ). This model with the explained 18.6% of the variance, which indicates that the model is moderately predictive. The variables *age* ( $b^* = .038, p = .381$ , one-tailed), *subjective norm* ( $b^* = -.111, p = .180$ , one-tailed) and *attitude towards using* ( $b^* = .014, p = .455$ , one-tailed) were not significantly predictive. The only variable that significantly predicted *perceived ease-of-use* was *mobile self-efficacy* ( $b^* = .433, p < .001$ , one-tailed). Even though *age* did not predict *perceived ease-of-use*, it does predict *mobile self-efficacy*. A linear regression was run to test if *age* predicted *mobile self-efficacy*. A significant regression equation model was found ( $F(1, 67) = 10.083, p = .001, R^2 = .131$ ) with *age*. This model with the explained 13.1% of the variance, which indicates that the model is weakly predictive. It was found that *age* ( $b^* = .362, p = .001$ , one-tailed) significantly predicted the participants' *mobile self-efficacy*. This can be a sign of a mediation of *mobile self-efficacy* on *perceived ease-of-use*. To test this additional hypothesis, which states that the relationship between *perceived ease-of-use* and *age* is mediated by *mobile self-efficacy*, a regression analyses was conducted. However, there was no significant model ( $F(1,67) = 2.952, p = .045$ ) and no significant prediction ( $b^* = .205, p = .045$ , one-tailed) found between *age* (only) and *perceived ease-of-use*. Therefore, the mediation hypothesis is rejected, which means that the relationship between *perceived ease-of-use* and *age* is not mediated by *mobile self-efficacy*.

Next, a multiple linear regression was run to test if the external variables *subjective norm*, *age*, *attitude towards using* and *mobile self-efficacy* were not significantly predictive over participants' *perceived usefulness*. A significant regression equation model was found ( $F(4, 63) = 6.033, p < .001, R^2 = .227$ ). The model explained 22.7% of the variance, which indicates the model is moderately predictive. It was found that *attitude towards using* ( $b^* = .512, p < .001$ , one-tailed) and *mobile self-efficacy* ( $b^* = .232, p = .030$ , one-tailed) significantly predicted *perceived usefulness*. *Age* ( $b^* = -.036, p = .338$ , one-tailed), and *subjective norm* ( $b^* = -.109, p = .169$ , one-tailed) was not significantly predictive. In figure 4.3 all the standardized coefficients are shown.

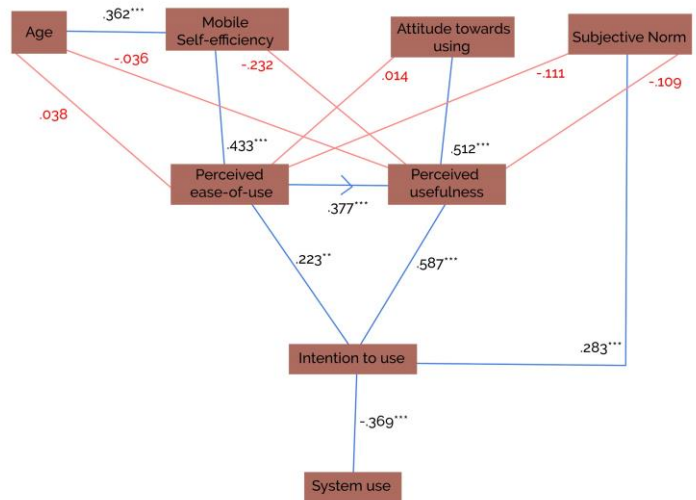


Figure 4.3 TAM coefficients

#### 4.4.4. Discussion validation of TAM with qualitative results

The four main variables, *perceived ease-of-use*, *perceived usefulness*, *intention to use* and *system use*, are in line with the literature. Within the interviews, respondents expressed the relevance of the variables, *perceived ease-of-use* and *perceived usefulness*. Respondent 1 expressed that he likes that the information goes from 'abstract to specific information for your role in the company' (Respondent 1). Also, other interview respondents expressed their positive attitude towards the usefulness of the information in the application; 'the theory does really fit the real world' (Respondent 3); 'I really feel that it [the information] helps me with my job, it is another way of thinking' (Respondent 5); 'Because you use it every day you really change your way of thinking which is important for your work. This way the things you learn can be immediately used for you work' (Respondent 2). There was also someone that did not think the theories were useful, 'I used many theories in the application, but some do really not fit the organisation, so those make it [the application] less relevant for me' (Respondent 6). This shows that usefulness impacts the relevance of the application. This corresponds with the findings in the survey, as *perceived usefulness* is a strong predictor of *intention to use* ( $b^* = .586, p < .001$ , one-tailed). Furthermore, this is supported by previous research as *perceived usefulness*, in most studies, has the largest effect on *intention to use* (Roca, et al. 2006; Svendsen, et al., 2013; Mohammadi, 2015)



Furthermore, the TAM theory and the surveys state that *perceived ease-of-use* is also a predictor of *intention to use*. However, the only interview respondent that mentioned characteristics of this variable was Respondent 7. He stated that; 'There are so many buttons which do not make sense'; 'I find the navigation in the application hard to understand' and 'sometimes I get lost in the application' (Respondent 7). When he showed the thesis author the application, it was clear that he had a low *mobile self-efficacy* as he struggled to find the app and open modules within the application. Even the age of the Respondent 7 is in line with the survey findings, as he was 55 years old, the oldest interview respondent.

Some interview respondents mentioned that they had used e-learning systems before and that they really like this way of learning. However, compared to their previous experience the system of this application is very bad. Respondent 4 stated 'It could work very good and I think it is the right way to educate everyone. However, the app [system] is not good enough' and 'I love e-learning and used many other e-learning systems. However, this system is really bad compared to the other'. This shows that she sees the usefulness of e-learning; however, this particular system is judged to be less effective than other e-learning systems. This finding is supported by the survey data. *Attitude towards using* is a strong predictor of *perceived usefulness* ( $b^* = .512, p < .001$ , one-tailed). Furthermore, when a Pearson product-moment correlation coefficient was computed to assess the relationship between *attitude towards using* and *system quality*, a negative correlation was found between the two variables ( $r = -.260, N = 71, p = .003$ ). This shows that when people have positive experience with previous e-learning systems they perceive this system as useful; however, they also think the *system quality* is bad.

The final variable that will be discussed is *subjective norm*. The interview respondents do support the fact that subjective norm can make sure people use the application. 'However, the pressure to deliver an innovative product after the whole learning is very high. This makes sure that people do their best.' (Respondent 6). However, the respondents do not feel you should obligate, but you should motivate the people to use the application. 'You can't force people to use the app, it is more of a discipline thing, it needs to be an intrinsic motivation' (Respondent 1). 'You should not obligate people to use it. But you should motivate people to use it' (Respondent 3). The interview respondents are also concerned that not everyone is being motivated enough. 'I really don't like that not everyone is motivated to finish the course. Because the attendance is so low now' (Respondent 6). This shows that *subjective norm* has an effect on *intention to use*.

#### 4.4.5. Difference between higher education and business setting with qualitative results

##### 4.4.5.1. Sharing and using information

The interview results also gave useful information on what makes an e-learning system in a business setting different from a higher education setting. Respondent 1 feels that e-learning systems for higher education is to only educate the person who uses it. On the contrary, he asserts that e-learning systems for businesses typically aim to educate the whole organisation, not only the ones that use the system or are enrolled in a course. It is less about one person passing a test and more about establishing a movement within the company, especially with this particular e-learning course. According to him, the goal of this e-learning system is to make everyone in the police aware of innovation, and not just the people following the course. Therefore, the user should be able to share the information in the application with his colleagues which should both increase the use of the application and the goals of the application. Cheung and Vogel (2013), who used and extended TAM to assess the effectiveness of an e-learning system, also concluded that the possibility for sharing, for instance documents, can increase ones uses of the system. The importance of sharing the information with course participants is shared by the other interview respondents. Some statements are; 'I would like to share the information' (Respondent 4); 'I have a need to share the videos with my colleagues' (Respondent 3) and 'If you can share it, it will live more in the workplace' (Respondent 1). This last statement shows that the course does not live in the workplace. Because the course participants are from all over the country they cannot discuss the information within the learnings. And as the face-to-face meetings are only once every 8 weeks, there is not a lot of opportunity to discuss the information face-to-face. 'Because the participants are from all over the country, you can't discuss face to face with your project group on tasks. This means you are not engaged with it all the time. (...) Usually you talk with each other at the coffee machine about these things but that does not happen now because we are so far apart' (Respondent 6). As Holsapple and Lee-Post (2006) mentioned, e-learning system users have a desire for a human touch and a social aspect. This is in line with the results of the interviews. A solution for this can be a communication platform (Holsapple and Lee-Post (2006), but as mentioned earlier just a fraction of the participants uses the applications communication platform. Furthermore, another interesting finding is that the interview respondents also would like to find information that they have learned earlier in the application. The reason for this is that sometimes they directly need the information in the job. 'I would like to be able to search all the information that I have already learned so that I can look up something if I need it and have forgotten it' (Respondent 2). A search function would also help to share the relevant information with colleagues and educate them. 'A search function will improve the speed in which you can share stuff in every day conversation about work. It will result in people talking more to people in the workplace' (Respondent 5). This shows that besides being an e-learning

system it is also a library with information to use on the job and to share with colleagues. Cheung and Vogel (2013), who used and extended TAM to assess the effectiveness of an e-learning system, also concluded that sharing is an important variable that can improve the effectiveness of an e-learning system. According to them, sharing had direct effect on *perceived usefulness*, *intention to use* and *system use*.

#### 4.4.5.2. Time pressure

Another major difference between e-learning in a higher education setting and in a business setting, is that the main focus of people in a business setting is work and not education. This means that the time is prioritized on work and after that on education. When asked why the interview respondents do not use the system more they say; 'The reason why it decreased is that I do a study besides this and my job is very busy. I would like to do it, but I literally do not have the time' (Respondent 5); 'Work pressure increased' (Respondent 2); 'because of work, vacation and also the low quality of the system it is hard to keep motivated'. (Respondent 6). This last statement shows that keeping people motivated is a key aspect. If people do not see the importance of the e-learning or are not motivated to use it, they are easily included to use their spare time on work and not on using the e-learning system. Furthermore, it also shows the low *system quality* and the importance of having a good *system quality*. 'When we do find a time to use it we want it to work flawlessly' (Respondent 5). Moreover, because people have a really high work pressure, they are very positive about how the e-learning application enables them to work everywhere whenever they have time. 'Therefore, it is very good of the app that you can learn whenever where ever you want' (Respondent 5).

#### 4.4.5.3. Diversity of the group

The last major difference is the diversity of the group. The descriptive statistics show that the participants of the course come from all over the country. This is important because, according to Respondent 3, cultures within the department differ significantly. According to (Hassanzadeh et al., 2012) cultural differences has an effect on *system use*. Besides that, the participants are from all over the country there is also a big difference between occupation, education and previous knowledge. 'I already am in a change team which means that already know many of the things that I read and see in the app' (Respondent 3). Other participants have difficulty with the information 'It is a lot of information and sometimes you forget things' (Respondent 2); it is a lot of information in a small time period' (Respondent 6). Furthermore, participants are from all different educational backgrounds. According to respondent 3, the police is an organisation with many people from different educational backgrounds. The majority of the employees is MBO with only some being HBO or even WO. In managerial functions people can be all three because some start on the street as

police and work themselves up to managerial functions, usually people with an MBO educational background, and other HBO or WO employees start in managerial functions. This is however not tested within the survey so therefore there are no descriptive statistics on educational background of the sample. Nonetheless, the different educational backgrounds result in some participants being better in learning than others. To keep both motivated information should not be too easy, but also not too hard. To achieve this information should be personalized, according to Xu, Huang, Wang, and Heales (2014) personalized information improves *user satisfaction*.

#### 4.5. Adding TAM to D&M model (H6 – H11)

Now, that the two models are validated within a business organisation setting, they can be merged. Previous research states that D&M model system design variables, *service quality*, *information quality* and *system quality* are external variables of the TAM (Roca et al, 2006; Pai & Huang, 2010; Mohammadi, 2015). To be more specific, *service quality* and *system quality* are predictors of *perceived ease-of-use*, which will be tested by hypothesis 6 and 8, and *service quality* and *information quality* are predictors of *perceived usefulness*, which will be tested by hypothesis 7 and 9. In order to test hypothesis 6 and 8 a multiple linear regression was used for the dependent variable *perceived ease-of-use*. *Mobile self-efficacy* was already found as a predictor of *perceived ease-of-use* and therefore should be included in this regression model. A significant regression equation model was found ( $F(4, 67) = 9.595, p < .001, R^2 = .364$ ) for *perceived ease-of-use*. This model explains 36.4% of the variance, which indicates the model is strongly predictive. It was found that *mobile self-efficacy* ( $b^* = .350, p = .001$ , one-tailed) and *system quality* ( $b^* = .411, p < .001$ , one-tailed) significantly predicted the participants' *perceived ease-of-use*. The variables *service quality* ( $b^* = .114, p = .137$ , one-tailed) and *information quality* ( $b^* = -.039, p = .370$ , one-tailed) were not significantly predictive.

To test hypothesis 7 and 9 a multiple linear regression was used for the dependent variable *perceived usefulness*. *Attitude towards using* and *mobile self-efficacy* were already found as a predictor of *perceived usefulness* and will therefore be added to the regression model. A significant regression equation model was found ( $F(5, 65) = 8.535, p < .001, R^2 = .396$ ). This model explains 39.6% of the variance, which indicates the model is strongly

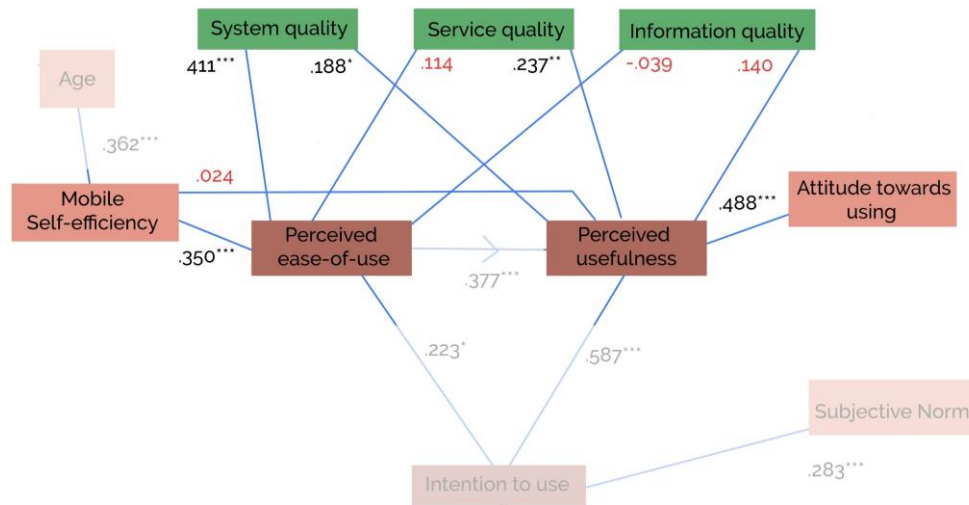


Figure 4.4 Adding system design to TAM

predictive. It was found that *attitude towards using* ( $b^* = .488, p < .001$ , one-tailed), *system quality* ( $b^* = .188, p = .042$ , one-tailed) and *service quality* ( $b^* = .237, p = .014$ , one-tailed) significantly predicted the participants' *perceived ease-of-use*. *Information quality* ( $b^* = .140, p = .232$ , one-tailed) and *mobile self-efficacy* ( $b^* = .024, p = .414$ , one-tailed) were not significantly predictive. These results are visualized in figure 4.4. In this figure the irrelevant coefficients are intentionally obscured in order to highlight the relevant coefficients.

Finally, the models share two similar variables, namely *intention to use* and *system use*. To test if the TAM is of added value to the D&M model, all the predictors of *intention to use* from both the TAM and the D&M model, which are *information quality*, *service quality*, *perceived usefulness*, *perceived ease of use* and *subjective norm*, have been tested with a multiple linear regression. A significant regression equation model was found ( $F(6, 64) = 23.282, p < .001, R^2 = .686$ ). This model explains 68.6% of the variance, which indicates the model is strongly predictive. It was found that *perceived*

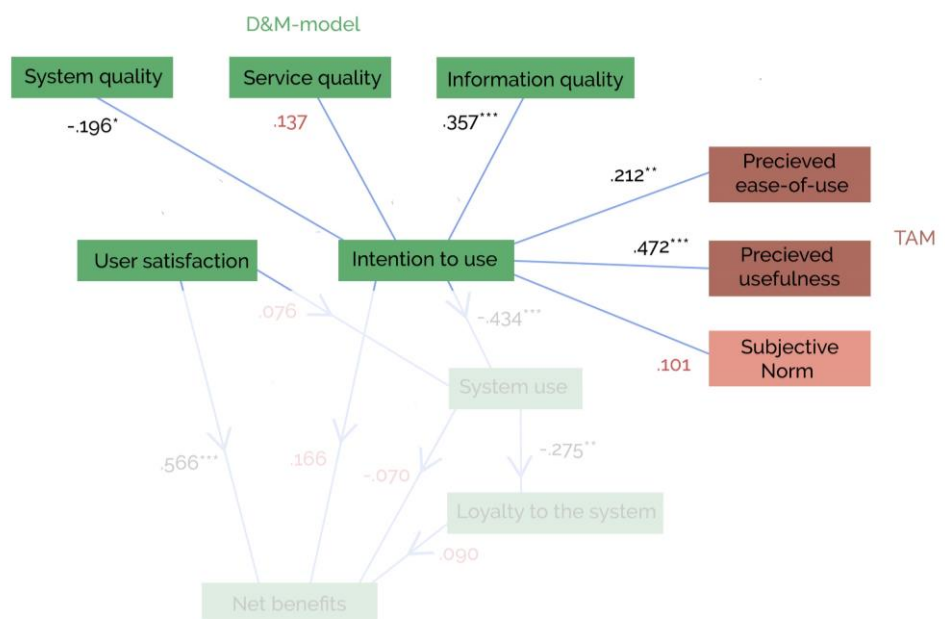


Figure 4.5 Adding TAM to D&M model

*usefulness* ( $b^* = .472, p < .001$ , one-tailed), *perceived ease-of-use* ( $b^* = .212, p = .008$ , one-tailed) and *information quality* ( $b^* = .357, p < .001$ , one-tailed) and *system quality* ( $b^* = -.196, p = .011$ , one-tailed) significantly predicted the participants' *intention to use*. The variables and *subjective norm* ( $b^* = .101, p = .109$ , one-tailed) and *service quality* ( $b^* = .137, p = .052$ , one-tailed) were not significantly predictive. These results are visualized in figure 4.5. In this figure the irrelevant coefficients are intentionally obscured in order to highlight the relevant coefficients.

The goal of combining the two models is that more variance would have been explained. When comparing the  $R^2$  of the multiple regression model of the TAM and D&M model combined ( $R^2 = .656$ ) against the  $R^2$  of the multiple regression model of the D&M ( $R^2 = .435$ ) individually there is a significant increase of variance explained of 25.1% ( $R^2$  change = .251,  $p < .001$ ). This supports the hypothesis that including the TAM to the D&M model will increase the variance explained of *intention to use*.

#### 4.5.1. Discussion of adding the TAM to D&M model

Whereas *system quality* is negatively and significant predictive in the original D&M model on *user intention* and *intention to use*, it is positively and significantly predictive over TAM variable *perceived ease-of-use*. This is in line with the findings in the interviews as many interview respondents stated the low *system quality* made it hard to use the system. Respondent 1 said that the low *system quality* resulted in them not using the application anymore. However, in light of the results of the multiple linear regressions it seems like the interview respondents did not talk about *system quality* but more about *perceived ease-of-use* of the system. The *system quality* resulted in finding the application hard to use. For example, 'the structure makes me lose a sense of navigation' (Respondent 4) and 'All these small system flaws lead to irritation which makes me stop using the application for a little while' (Respondent 5). This shows that *perceived ease-of-use* is a better predictor of *intention to use* than *system quality*, definitely in this case because the *system quality* was so low that people did not even use the system. Furthermore, *service quality* loses its significant prediction over *intention to use*. This indicates a mediation *perceived usefulness* between *service quality* and *intention to use*. Lastly, *subjective norm* loses its significant prediction. This might be because it is partly captured by other variables.

Some of the results correspond with the results found in previous literature. For instance, *perceived usefulness* is the strongest predictor of *intention to use*, just as in previous studies (Roca, et al. 2006; Svendsen, et al., 2013; Mohammadi, 2015). This shows the importance of this variable in predicting the *intention to use*. Furthermore, the result of the design variable *information quality* is not in line with previous studies, as it is not predictive over neither *perceived ease-of-use* or

*perceived usefulness* (Roca et al., 2006; Pai and Huang, 2010; Mohammadi, 2015). Instead *information quality* maintains its direct prediction over *intention to use*.

#### 4.5.2. The final model

The results of all the previous analyses showed that not all the linkages proposed in the conceptual model are significantly predictive. For instance, *system quality* and *service quality* lose their prediction over *intention to use* when adding the models together. Therefore, this subsection explores how the models could fit together using the data from the case. When adding the complete models together it becomes clear that the most predictive variables over *intention to use* are TAM variables *perceived ease-of-use* and *perceived usefulness* and D&M model variable *information quality*, which is supported by the results of Roca et al. (2006). The other D&M model variables are either not significant or have a negative correlation. Therefore, these are not relevant for predicting *intention to use*. *Subjective norm* is also not significant. When analysing which variables are significant of the TAM variables *perceived ease-of-use* and *perceived usefulness*, the predictive variables are the external TAM variables *attitude towards using* and *mobile self-efficacy* and the D&M model variables *service quality* and *information quality*. In figure 4.6, the model, which is made through incorporating the most predictive variables. As some variables are excluded new multiple regressions are run to calculate the standard correlation of each variable. A multiple regression analysis was conducted for *perceived usefulness*, which is predicted by *attitude towards using* and *service quality*. A significant regression equation model was found ( $F(2, 68) = 16.820, p < .001, R^2 = .331$ ). It was found that *attitude towards using* ( $b^* = .411, p < .001$ , one-tailed) and *service quality* ( $b^* = .333, p = .001$ , one-tailed) were statistically significant. Likewise, a multiple regression analysis was conducted for *perceived ease-of-use*, which is predicted by *mobile self-efficacy* and *system quality*. A significant regression equation model was found ( $F(2, 68) = 18.795, p < .001, R^2 = .353$ ). It was found that *mobile self-efficacy* ( $b^* = .346, p < .001$ , one-tailed) and *system quality* ( $b^* = .417, p = .001$ , one-tailed) were statistically significant. According to previous results the variables predicting *intention to use* are; *information quality*, *perceived usefulness*, *perceived ease-of-use* and *subjective norm*. A multiple regression analysis was conducted for *perceived usefulness* with these variables. A significant regression equation model was found ( $F(4, 66) = 30.344, p < .001, R^2 = .648$ ). It was found that *perceived usefulness* ( $b^* = .535, p < .001$ , one-tailed), *perceived ease-of-use* ( $b^* = .137, p = .049$ , one-tailed), *information quality* ( $b^* = .319, p < .001$ , one-tailed) and *subjective norm* ( $b^* = .160, p = .026$ , one-tailed) were statistically significant.

The only variable that is now not predicted is *user satisfaction*. A multiple regression analysis was conducted with *information quality*, *perceived usefulness* and *perceived ease-of-use* to find the

significant predictors of *user satisfaction*. A significant regression equation model was found ( $F(2, 68) = 54.229, p < .001, R^2 = .621$ ). This model explained 62.1% of the variance, which indicates that the model is strongly predictive. It was found that *perceived usefulness* ( $b^* = .712, p < .001$ , one-tailed) and *information quality* ( $b^* = .193, p = .008$ , one-tailed) were statistically significant. The variable *perceived ease-of-use* ( $b^* = .088, p = .294$ , one-tailed) showed no significant prediction on *user satisfaction*. These results are visualized in figure 4.6. In this figure the irrelevant coefficients are intentionally obscured in order to highlight the relevant coefficients. Compared to the original model, this new combination of variables explains more variance of *user satisfaction*. To compare the variance explained the adjusted  $R^2$  is used, as this accounts for the increase in number of predictors. The original D&M model explained 32.1% of the variance in *user satisfaction*; however, the new model explains 60.4% of the variance.

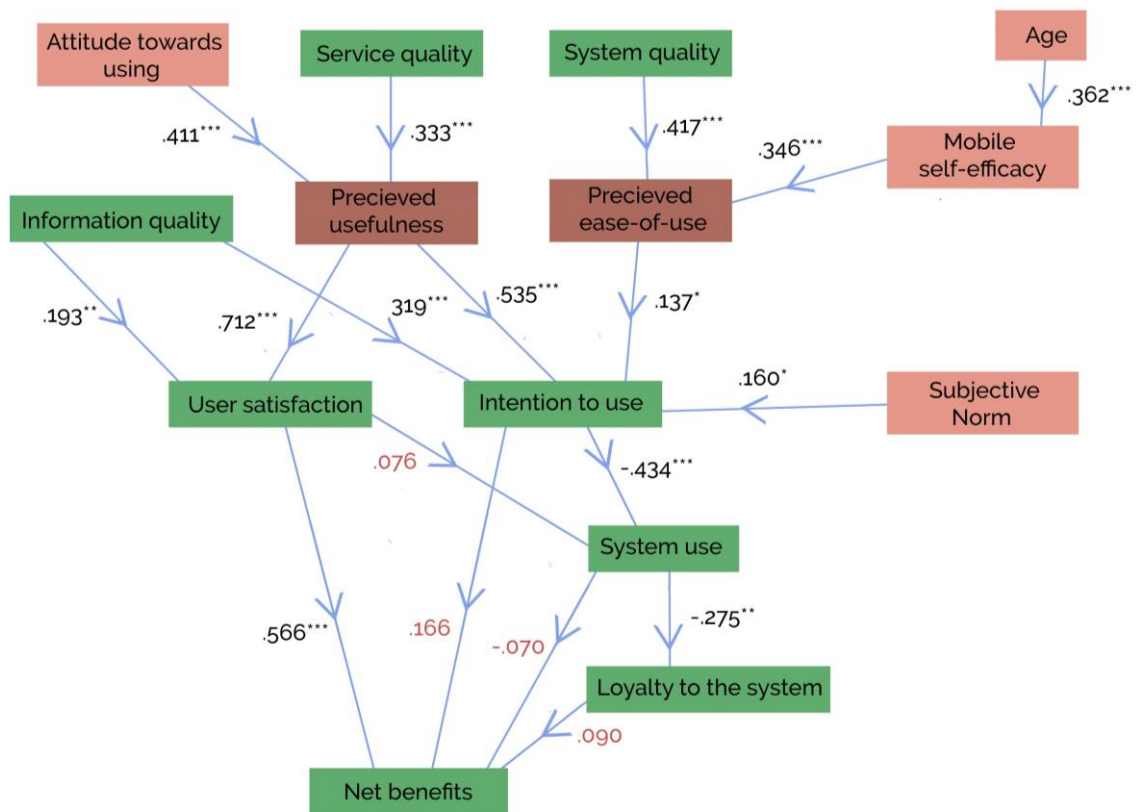


Figure 4.6 Merging TAM and D&M model



## 5. Conclusion

Using both qualitative and quantitative research methods (i.e. mixed methods), an e-learning system used in a business organisation setting has been analysed on its effectiveness. By analysing its effectiveness, this research attempted to answer the following research question: *To what extent does TAM add to the D&M model within a business organisation setting?*

First, two limitations from other studies have been tested and accounted for in this study. The first concerns the variable *system use*, which previous studies measured through self-reported surveys. This study had a second and more accurate way of measuring the variable *system use*, namely through user data directly derived from the e-learning system. This allowed to answer hypothesis 1 (**H1**: self-reported *system use* is different than *system use* derived from user data from the application). The results show that there is a significant difference between *system use* from self-reported surveys and *system use* from user data. The self-reported *system use* was overestimated by 34.55%. It became unclear if the survey respondents overestimated or exaggerated their self-reported *system use*. Overreporting by self-reported surveys is common in media academics (Prior, 2009).

The second limitation of previous studies was that these studies measure the effectiveness of an e-learning system on one moment in time. They did not account for exposure time of the application on the both models. The longitudinal design of this research allowed to answer hypothesis 2 and 3 (**H2**: Exposure time influences all the variables of the D&M model; **H3**: Exposure time influences all the variables of the TAM). The results of this study show that the TAM model is not affected by exposure time. There is generally no significant difference between having used the application for 8 weeks or having used it for 16 weeks. However, in the D&M model one variable did show a significant difference. These results partly support the concerns about the effect of exposure time on the D&M model expressed by Mohammadi (2015). The variable that was negatively affected in this study by exposure time was *system quality*. The reason for this was that the users experienced more bugs and more freezes over time. The more they encountered system failures the more annoyed they became with the *system quality*. However, the application studied was a prototype that still exhibited many bugs and a slow response time. More research should be done if the same effect, due the exposure time, applies to a fully-developed e-learning system.

To answer the main research question, both the TAM and D&M model have first been validated within a business organisation setting. Two hypotheses were formulated to answer this question (**H4**: The D&M model maintains its predictions in an e-learning system in a business organisational setting; **H5**: The TAM maintains its predictions in an e-learning system in a business organisational setting). The results of the D&M model did not entirely match up with the results of

previous studies where the D&M model was applied in a higher education setting. The main difference was *system quality* that was not significantly predictive over *intention to use* and *user satisfaction*, which it should be according Holsapple & Lee-Post (2006). More interestingly, when comparing *system quality* with *system use* it has a reversed correlation. Based on both the qualitative and quantitative results a theory for this phenomenon was formed. Some course participants have only used the e-learning application less than 50 minutes in the last 8 weeks. And results have shown that the more you use, the worse you perceive the *system quality*. This means that people who have used it for just a small amount of time have not encountered as many system failures as heavy users. Another difference is that *system use* does not correlate with the *net benefits* of the system, even though literature state that *system use* strongly and positively correlates with *net benefits* (Hassanzadeh et al., 2012). This seems to be because it is part of a larger blended learning course and the benefits are mainly achieved by the face-to-face meetings and not by the e-learning system itself. Furthermore, it was found that *loyalty to the system* is both predicted and being predicted by *system use*, which is supported by Hassanzadeh et al. (2012).

The original variables of the TAM all showed results that are in line with previous research. Of the external variables, it was found that *age* predicted *mobile efficacy* and, in its turn, predicted *perceived usefulness*. *Age* is however not mediated by *mobile efficacy*. Furthermore, *attitude towards using* predicted *perceived usefulness* and *subjective norm* had a direct prediction over *intention to use*. Lastly the interviews indicated that there are some extra variables that could improve the D&M model within a business organisation setting. These variables are, sharing information, work pressure and personalization. Both sharing information was found a significant predictor in previous literature (Cheung & Vogel, 2013) and personalization was included as an item in both *system quality* and *information quality* in several studies (Delone & McLean, 2003; Wang, Wang & Shee, 2007; Mohammadi, 2015). These variables are further explained in the practical implications.

Finally, the TAM can be added to the D&M model. By doing so hypotheses **H6** to **H12** will be answered. Together the models explain more variance of the variable *intention to use*. Furthermore, when adding the models together *system quality* has significant positive predictive value, even though the *system quality* was a difficult variable because the e-learning system was still a prototype. Also, the external TAM variables still retain their significant values. Therefore, the TAM can be added to the D&M model and it increases its total of variance explained in both *intention to use* and *user satisfaction*, which the literature stated as hard variables to predict (Holsapple & Lee-Post, 2006). To conclude this study shows that it is more important how e-learning participants use the information, services and system than the quality of these individual variables. This might even be more so in a business organisation because of the diversity of the participants.

## 5.1. Theoretical implications

This study has several implications for academic literature. The first implications concern the two methodical approaches that made it possible to account for self-reported *system use* and the effect of exposure time of the e-learning system. DeLone and McLean (2003) and Mohammadi (2015) explicitly stated that the lack of a longitudinal design is a limitation within their studies. However, this study shows that it does not have to be a limitation as exposure time had only an effect on one of the variables of D&M model and none of the TAM. Therefore, the results of previous studies who did not use a longitudinal design are still valid. However, this does not hold for the studies that have relied on self-reported *system use*. Aforementioned, self-reported system use is inaccurate and therefore future research should, when possible, always use actual system use derived from user data. Furthermore, previous research that has measured system use with self-reported methods, might have incorrect results. This might have effect on the relationship between system use and other variables in the model because system use is a particularly important variable for the both the TAM and D&M model.

The last big implication for the academic fields of information systems and e-learning is that adding the TAM to the D&M model improves the explained variance in both *user satisfaction* and *intention to use*, which are the main predictors of *system use* and *net benefits*. Previous studies had difficulties capturing a high variance in *intention to use* (Holsapple & Lee-Post, 2006). So, in the future when academics are to measure the effectiveness of an e-learning system they should add the TAM variables to the D&M model to acquire a wider and more accurate picture of the effectiveness of the e-learning application.

## 5.2. Practical implications

This study surveys a prototype e-learning system developed by Superbuff and used by the police academy. The results of this study can help them to determine if an e-learning system is the right way to educate their employees and if they should invest in improving the system. And if they decided to continue with this project this study helps them to improve their application and add functionalities which will improve the effectiveness of their e-learning system.

### 5.2.1. System quality

The interviews show that most of the respondents reported that e-learning is the right way to educate employees because they can learn whenever, wherever they want. However, the single most important point that holds them back from taking full advantage of the e-learning system is the low quality of the system. All the respondents complained about the quality of the system, and it also received the second worst score in the survey, right after loyalty to the system. Specific points that should be improved upon to increase the system quality are the stability, the reaction speed, the navigational structure and the ability to use the application on the road without any system problems. The system should work flawlessly and not hamper the ability to use the system. Otherwise, it would be difficult to keep busy employees motivated to use the e-learning app; a flawed system makes it even harder.

### 5.2.2. Communication

Most respondents reported that they did not use the communication platform Slack (indicative of Loyalty to the system) because it was integrated in the application and there was not enough activity. However, the respondents did indicate that they would like more activity on Slack and that more activity would help them learn and increase their use of the system, especially as all the participants are scattered over the whole country. Therefore, A good communication platform is key to keep people motivated and engaged with the topic. At the moment, Slack does not achieve this. According to the interview respondents it would work better if the communication platform would be integrated in the application. Furthermore, more activity in the application would ensure that more people will use it. More activity can be achieved through a moderator or making sure that the answers of the open quiz questions after completing a module are directly posted on the communication platform.

### 5.2.3. Sharing

The interviewees indicated that there are some extra elements that could improve an e-learning system within a business organisation setting. Because e-learning systems in business organisation settings are not explicitly to train an individual, but more to educate and establish a movement in the whole company, sharing information is an important characteristic. The respondents saw the e-learning application both as a way to learn, but also as a data base of information which they could use to share information but also to lookup information when they need it on the job. All the respondents stated that they would like to be able to share the information with their colleagues. Cheung and Vogel (2013), who used and extended TAM to assess the effectiveness of an e-learning system, also concluded that sharing is an important element. According to them, sharing has a direct and positive effect on *perceived usefulness*, *intention to use* and *system use*. Therefore, a share and search feature need to be added to the information of the e-learning system. This will increase the *perceived usefulness*, *intention to use* and *system use*, but it will also help to achieve the overall goal of the e-learning application, educate all the employees of the company and establish a movement instead of educating every employee individually.

### 5.2.4. Personalization

Another difference between higher education and a business organisation setting is the diversity of the group. Participants of a course can be from all kinds of different educational backgrounds, ages, locations and occupations. To keep people motivated the e-learning system should be tailored to the individual and therefore personalization of information and learning style is therefore important. To achieve this, levels of difficulty could be added to the learnings. Furthermore, should be able to choose their own learning style (10 minutes every day or 60 minutes in one day per week) that will be linked to a personal notification. Furthermore, insight in their total use and progress can make the application feel more personal to them. It can even function as some sort of subjective norm which will increase their use of the system.

### 5.2.5. Work pressure

Lastly, employees prioritize work before education. This is an important difference between higher education students and employees. Therefore, people need to be motivated, and an e-learning application needs to be as time efficient as possible. Work pressure can therefore be an external variable that could influence the use of an e-learning system in a business organisation setting, as employees with high work pressure have less time to use the system. It is hard to control for this variable, besides clearly stating that the e-learning course is time intensive.

## 5.3. Limitations

Although this thesis offers interesting findings, some limitations should be noted when interpreting the results.

### 5.3.1. Case limitations

Because of many setbacks during the study, the method needed to change half way through the execution of this study. The initial plan was to use quantitative longitudinal experimental research design to measure the effectiveness of two different e-learning groups, both consisting of 60 participants. However, one group, which was planned to start in February did not start until mid-May. Therefore, this sample could not be used for this study. Furthermore, technical limitations in the application did not allow to split the group that did start to be split in two which made it impossible to perform an experiment. Lastly, of the group that did start, 25 participants had quit the course, which left a group of 35 left to analyse. Because this was not enough participants for the requirements of this thesis, interviews were held to get in-depth knowledge in both models. Nonetheless, the number of respondents for the survey. The total number of relevant surveys was 72; however, the measurements were repeated over two time points. This results in a higher margin of error than if there were more respondents (per the initial plan).

Furthermore, the e-learning system within this case was a prototype. This has impacted the results as the system quality of the application was very bad and was not predictive within the D&M model, which it should be according to literature (DeLone & Mclean, 2003; Holsapple & Lee-Post, 2006; Hassanzadeh et al., 2012). The fact that the e-learning system was still a prototype might have impacted other variables as well.

### 5.3.2. Methodological limitations

There are also some methodological limitations that might have influenced the results of this research. The first is that all the interviews and surveys were done in Dutch. With designing the survey questionnaires were used from existing literature about the TAM and D&M model. These questions were translated to Dutch so that the Dutch Innovation Expedition participants could easily fill out the survey. However, some of the essence of questions might have been incorrectly translated. Furthermore, all the interviews were done in Dutch, because all participants were native Dutch speakers and could express themselves better in their own language. After coding the transcripts, the results were translated to Dutch. Also, the quotes used in the results are translated from English to Dutch. Therefore, some of the essence of the quotes and explanations of the respondents also might have incorrectly been translated.

Furthermore, because the sample was very small all the data point of both the 8 weeks exposure time and 16 weeks exposure time were used in the regression. This longitudinal design has not been accounted during the regressions. However, the MANOVA test have shown that exposure time had only a significant effect on system quality.

Another limitation concerns a selection bias for the interviews. The interviews were held after one of the face-to-face meetings, which means that only the motivated participants volunteered for the interviews. Participants that stopped using or were not motivated to come to the face-to-face meeting were not interviewed. This might have influenced the results of the interviews. The same sampling limitation applies to the surveys. These were distributed during the face-to-face meetings. Even though, all the absent people were send an email, not all of them filled out the survey. Therefore, the results to a lesser extent account for the people who were absent during the face-to-face meetings.

Even though this thesis had several limitations, it does have relevant theoretical and practical implications. It proved a limitation from previous researches and it significantly improved on both models in their combining, particularly in improving the explanatory power in *user satisfaction* and *intention to use*.

#### 5.4. Future research

The points for future research were already touched upon throughout the conclusion. Because the nature of this case, the e-learning system being an unstable prototype and a small sample, there are two suggestions for future research. First, future research should be done on the effects of exposure time on both the models with a fully grown e-learning application. Secondly, adding the TAM to the D&M model makes significant improvements for testing the effectiveness of an e-learning system. However, future research should validate the model with a bigger sample group and on a fully grown e-learning system.

## References

- Abdullah, F., & Ward, R. (2016). Developing a general extended technology acceptance model for e-learning (GETAMEL) by analysing commonly used external factors. *Computers in Human Behavior, 56*, 238-256.
- Arning, K., & Ziefle, M. (2007). Understanding age differences in PDA acceptance and performance. *Computers in Human Behavior, 23*(6), 2904-2927.
- Babbie, E. R. (2011). *Introduction to social research*. Belmont, CA: Wadsworth Cengage learning.
- Baum, J. (2002). *Grounded theory research methods, companion to organizations*. Oxford: Blackwell Publishers.
- Beldagli, B., & Adiguzel, T. (2010). Illustrating an ideal adaptive e-learning: A conceptual framework. *Procedia-Social and Behavioral Sciences, 2*(2), 5755-5761.
- Berdie, D. R. (1989). Reassessing the value of high response rates to mail surveys. *Marketing Research, 1*(3).
- Braun, V., & Clarke, V. (2006). Using thematic analysis in psychology. *Qualitative Research in Psychology, 3*(2), 77-101
- Charness, N., & Boot, W. R. (2009). Aging and information technology use: Potential and barriers. *Current Directions in Psychological Science, 18*(5), 253-258.
- Cheung, R., & Vogel, D. (2013). Predicting user acceptance of collaborative technologies: An extension of the technology acceptance model for e-learning. *Computers & Education, 63*, 160-175. doi: 10.1016/j.compedu.2012.12.003
- Christensen, L. B., Johnson, B., Turner, L. A., & Christensen, L. B. (2011). *Research methods, design, and analysis*. Munich: Pearson.
- Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly, 3*, 319-340.
- Davis, F. D., Bagozzi, R. P., & Warshaw, P. R. (1989). User acceptance of computer technology: a comparison of two theoretical models. *Management Science, 35*(8), 982-1003.
- Davis, C. G., Thake, J., & Vilhena, N. (2010). Social desirability biases in self-reported alcohol consumption and harms. *Addictive Behaviors, 35*(4), 302-311.
- DeLone, W. H. & McLean, E. R. (1992). Information systems success: the quest for the dependent variable. *Information Systems Research, 3*(1), 60-95. doi:10.1287/isre.3.1.60.



- DeLone, W.H. & McLean, E.R. (2003). The DeLone and McLean model of information systems success: A ten-year update. *Journal of Management Information Systems*, 19, 9–30.
- DeVellis, R. F. (2003). *Scale development: Theory and applications* (2<sup>nd</sup> ed.). Thousand Oaks, California: Sage.
- Docebo (2016) Elearning market trends and forecast 2017 – 2021 [Report]. *Decebo*. Retrieved from: <https://eclass.teicrete.gr/modules/document/file.php/TP271/Additional%20material/docebo-elearning-trends-report-2017.pdf>
- Dorobăt, I. (2014). Models for measuring e-learning success in universities: a literature review. *Informatica Economica*, 18(3), 77-90
- Elmorshidy, A. (2012). Mobile learning—a new success model. *The Journal of Global Business Management*, 8(02), 18-27.
- Farahat, T. (2012). Applying the technology acceptance model to online learning in the Egyptian universities. *Procedia-Social and Behavioral Sciences*, 64, 95-104.
- Fishbein, M., & Ajzen, I. (1975). *Belief, Attitude, Intention and Behavior: An introduction to theory and research*. Reading, MA: Addison-Wesley.
- Fisher, R. J., & Katz, J. E. (2000). Social-desirability bias and the validity of self-reported values. *Psychology & Marketing*, 17(2), 105-120. doi: 10.1002/(SICI)1520-6793(200002)17:2<105::AID-MAR3>3.0.CO;2-9
- Gefen, D., Karahanna, E., & Straub, D. W. (2003). Inexperience and experience with online stores: The importance of TAM and trust. *IEEE Transactions on Engineering Management*, 50(3), 307-321.
- Golafshani, N. (2003). Understanding reliability and validity in qualitative research. *The Qualitative Report*, 8(4), 597-606.
- Gong, M., Xu, Y., & Yu, Y. (2004). An enhanced technology acceptance model for web-based learning. *Journal of Information Systems Education*, 15(4), 365.
- Hassanzadeh, A., Kanaani, F., & Elahi, S. (2012). A model for measuring e-learning systems success in universities. *Expert Systems with Applications*, 39(12), 10959-10966.
- Hartwick, J., & Barki, H. (1994). Explaining the role of user participation in information system use. *Management Science*, 40(4), 440-465.
- Holsapple, C. W., & Lee-Post, A. (2006). Defining, assessing, and promoting e-learning success: an information systems perspective. *Decision Sciences Journal of Innovative Education*, 4(1), 67-85. doi:10.1111/j.1540-4609.2006.00102.x
- Huang, L., Lu, M. T., & Wong, B. K. (2003). The impact of power distance on email acceptance: Evidence from the PRC. *Journal of Computer Information Systems*, 44(1), 93-101.

- IBIS Capital (2013). Global e-learning investment review [Report]. *IBIS Capital*. Retrieved from: [http://zefly.com/uploads/document/file/55d5a6935562753f22e61900/e-Learning\\_Lessons\\_for\\_the\\_Future.pdf](http://zefly.com/uploads/document/file/55d5a6935562753f22e61900/e-Learning_Lessons_for_the_Future.pdf)
- Kettinger, W. J., & Lee, C. C. (1994). Perceived service quality and user satisfaction with the information services function. *Decision Sciences*, 25(5-6), 737-766.
- Lee, Y. H., Hsieh, Y. C., & Chen, Y. H. (2013). An investigation of employees' use of e-learning systems: applying the technology acceptance model. *Behaviour & Information Technology*, 32(2), 173-189.
- Lee, Y. H., Hsieh, Y. C., & Hsu, C. N. (2011). Adding innovation diffusion theory to the technology acceptance model: Supporting employees' intentions to use e-learning systems. *Journal of Educational Technology & Society*, 14(4), 124.
- Lin, H. F., & Lee, G. G. (2006). Determinants of success for online communities: an empirical study. *Behaviour & Information Technology*, 25(6), 479-488.
- Mason, R. O. (1978). Measuring information output: A communication systems approach. *Information & Management*, 1(4), 219-234.
- McFarland, D. J., & Hamilton, D. (2006). Adding contextual specificity to the technology acceptance model. *Computers in Human Behavior*, 22(3), 427-447.
- Means, B., Toyama, Y., Murphy, R. & Baki, M. (2013). The effectiveness of online and blended learning: a meta-analysis of the empirical literature. *Teachers College Record*, 115, 1-47.
- Mohammadi, H. (2015). Investigating users' perspectives on e-learning: An integration of TAM and IS success model. *Computers in Human Behavior*, 45, 359-374.
- Meyers, L.S., Gamst, G., & Guarino, A. (2006). *Applied multivariate research: Design and interpretation*. Thousand Oaks, CA: Sage Publishers.
- Neuman, W. L. (2013). *Social research methods: Qualitative and quantitative approaches*. Los Angeles : SAGE Publications.
- Pallant, J. (2010). *SPSS survival manual: A step by step guide to data analysis using SPSS (4<sup>th</sup> ed.)*. Buckingham, PH: Open University Press.
- Pai, F. Y., & Huang, K. I. (2011). Applying the technology acceptance model to the introduction of healthcare information systems. *Technological Forecasting and Social Change*, 78(4), 650-660.
- Park, N., Lee, K. M., & Cheong, P. H. (2007). University instructors' acceptance of electronic courseware: An application of the technology acceptance model. *Journal of Computer-Mediated Communication*, 13(1), 163-186.

- Pitt, L. F., Watson, R. T., & Kavan, C. B. (1995). Service quality: a measure of information systems effectiveness. *MIS Quarterly*, 173-187.
- Presser, S., & Stinson, L. (1998). Data collection mode and social desirability bias in self-reported religious attendance. *American Sociological Review*, 137-145.
- Prior, M. (2009). The immensely inflated news audience: Assessing bias in self-reported news exposure. *Public Opinion Quarterly*, 73(1), 130-143.
- Punch, K.F. (2003). *Survey research: The basics*. Los Angeles, CA: SAGE Publications. doi: 10.4135/9781849209984
- Ray, M. (2004). Online education: designing for the future in appraiser education. *The Appraisal Journal* 72(3). 266-273.
- Robinson, O. C. (2014). Sampling in Interview-Based Qualitative Research: A Theoretical and Practical Guide. *Qualitative Research in Psychology*, 11(1), 25-41. doi: 10.1080/14780887.2013.801543
- Roca, J. C., Chiu, C. M., & Martínez, F. J. (2006). Understanding e-learning continuance intention: An extension of the Technology Acceptance Model. *International Journal of human-computer studies*, 64(8), 683-696.
- Roland Berger (2014, May) Corporate learning goes digital, how companies can benefits from online education. *Think Act*. Retrieved from:  
file:///C:/Users/matth/Downloads/roland\_berger\_tab\_corporate\_learning\_e\_20140602.pdf
- Ross, A., & Willson, V. L. (2017). Paired Samples T-Test. In *Basic and Advanced Statistical Tests* (pp. 17-19). Rotterdam: Sense Publishers. doi: 10.1007/978-94-6351-086-8\_4
- Rowley, J. (2014). Designing and using research questionnaires. *Management Research Review*, 37(3), 308-330.
- Sapsford, R. (2007). *Survey Research* (2nd ed). London: Sage Publications.
- Seber, G. A., & Lee, A. J. (2012). *Linear regression analysis* (Vol. 329). Auckland: John Wiley & Sons.
- Seddon, P. B. (1997). A respecification and extension of the DeLone and McLean model of IS success. *Information Systems Research*, 8(3), 240-253.
- Silverman, D. (Ed.). (2016). *Qualitative research*. London: SAGE Publications.
- Svendsen, G. B., Johnsen, J. A. K., Almås-Sørensen, L., & Vittersø, J. (2013). Personality and technology acceptance: the influence of personality factors on the core constructs of the Technology Acceptance Model. *Behaviour & Information Technology*, 32(4), 323-334.
- Trafimow, D. (2009). The theory of reasoned action: A case study of falsification in psychology. *Theory & Psychology*, 19(4), 501-518.

- Venkatesh, V., & Davis, F. D. (1996). A model of the antecedents of perceived ease of use: Development and test. *Decision Sciences*, 27(3), 451-481.
- Venkatesh, V. (1999). Creation of favorable user perceptions: exploring the role of intrinsic motivation. *MIS Quarterly*, 239-260.
- Venkatesh, V., & Davis, F. D. (2000). A theoretical extension of the technology acceptance model: Four longitudinal field studies. *Management Science*, 46(2), 186-204.
- Wagner, N., Hassanein, K., & Head, M. (2010). Computer use by older adults: A multi-disciplinary review. *Computers in Human Behavior*, 26(5), 870-882.
- Wang, Y., Wang, H. & Shee D, Y. (2007) Measuring e-learning systems success in an organizational context: scale development and validation. *Computers in Human Behavior*, 23, 1792-1808
- Wang, Y. S. (2008). Assessing e-commerce systems success: a respecification and validation of the DeLone and McLean model of IS success. *Information Systems Journal*, 18(5), 529-557.
- Weiss, R. S. (1995). *Learning from strangers: The art and method of qualitative interview studies*. New York: Free Press.
- Wixom, B. H., & Todd, P. A. (2005). A theoretical integration of user satisfaction and technology acceptance. *Information Systems Research*, 16(1), 85-102.
- Wong, W. T., & Huang, N. T. N. (2015). The effects of e-learning system service quality and users' acceptance on organizational learning. *International Journal of Business and Information*, 6(2).
- Wu, J. H., & Wang, S. C. (2005). What drives mobile commerce?: An empirical evaluation of the revised technology acceptance model. *Information & Management*, 42(5), 719-729.
- Xu, D., Huang, W. W., Wang, H., & Heales, J. (2014). Enhancing e-learning effectiveness using an intelligent agent-supported personalized virtual learning environment: An empirical investigation. *Information & Management*, 51(4), 430-440.
- Zhang, D., & Nunamaker, J. F. (2003). Powering e-learning in the new millennium: an overview of e-learning and enabling technology. *Information Systems Frontiers*, 5(2), 207-218.
- Zhang, S., Zhao, J., & Tan, W. (2008). Extending TAM for online learning systems: An intrinsic motivation perspective. *Tsinghua Science & Technology*, 13(3), 312-317.
- Zmud, R. W. (1978). An empirical investigation of the dimensionality of the concept of information. *Decision Sciences*, 9(2), 187-195.

## Appendix 1: Survey metrics

<i>Construct</i>	<i>Metric</i>	<i>Question</i>	<i>Source</i>
<i>Service quality</i>	Guidance	The application provides a proper online explanation	(Mohammadi, 2015) (Wang et al., 2007)
	Guidance	The application was carefully explained before first individual use	(Holsapple & Lee-Post, 2006)
	Course management	The application and face-to-face are beneficial/compliment to each other	(Holsapple & Lee-Post, 2006)
	Support	I receive good support when I need help	(Holsapple & Lee-Post, 2006)
<i>System quality</i>	Attractiveness	The application has attractive features that appeal to the user [deleted]	(Mohammadi, 2015) (Wang et al., 2007)
	Speed	The application has a fast response time	(Mohammadi, 2015) (Roca et al, 2006)
	User-friendly	The application is user friendly	(Mohammadi, 2015) (Wang et al., 2007)
	Reliability	The application is reliable	(Mohammadi, 2015)
	Structure	Without going through too many steps I can find the information I am looking for	(Roca et al, 2006)
<i>Information quality</i>	Completeness	The application provides sufficient information	(Wang et al., 2007)
	Understandable	The application provides information that is easy to understand	(Wang et al., 2007)
	Well organised	The application provides well organized information	(Mohammadi, 2015)
	Right format	The application presents the information in an appropriate format	(Roca et al., 2006)
	Right format	The application provides modules with text that are not too long (right length)	(Holsapple & Lee-Post, 2006)
<i>Satisfaction</i>	Satisfied	The application satisfies my educational needs	(Mohammadi, 2015)

	Recommendation	I would recommend using the application to other course participants	(Holsapple & Lee-Post (2006))
	Enjoyment	I enjoyed working with the application	(Mohammadi, 2015)
<i>Intention to use</i>	Intention	I am willing to use the application	(Pai & Huang, 2010)
	Valuable	I believe that using the application is valuable	(Hassanzadeh et al., 2012)
<i>Loyalty to the system</i>	Participation	I am willing to participate in the Slack community	(Lin & Lee, 2006)
	Participation	I am willing to communicate with other members of in the Slack community	(Lin & Lee, 2006)
<i>Perceived ease of use</i>	Ease to use	I find that the application is easy to use	(Mohammadi, 2015)
	Ease to learn	I was able to quickly learn to use the application	(Mohammadi, 2015)
	Ease to use	I find it easy to get the system to do what I want it to do	(Cheung & Vogel, 2013)
	Effortless	Interacting with the system does not require a lot of my mental effort	(Venkatesh & Davis, 2000)
<i>Perceived usefulness</i>	Effectiveness	The application helps me to increase my learning effectiveness	(Roca et al., 2006)
	Learning outcome	The application helps me improve my knowledge	(Mohammadi, 2015)
	Effectiveness	The application is appropriate with my learning style	(Mohammadi, 2015)
	Relevance	The e-learning system provides information that is relevant to your job	(Wang et al., 2007)
<i>Attitude towards using</i>	Good Idea	In general, using e-learning applications is a good idea	(Holsapple & Lee-Post, 2006)
	Like using	In general, I like using e-learning applications	(Holsapple & Lee-Post, 2006)
<i>Net benefits</i>	Job performance	As a whole, the application has improved in my job performance	(wang et al, 2007)
	Job performance	As a whole, the application has improved me in thinking through and solving problems	(wang et al, 2007)

	Learning outcome	I feel that I've learned a lot because of the e-learning system	(Hassanzadeh et al, 2012)
	Flexibility	The e-learning system enables me to learn wherever and whenever I want	(Hassanzadeh et al, 2012)
	Save time	The application has saved me learning time	(Hassanzadeh et al, 2012)
<i>Actual use</i>	Frequency	How much time have you spent using the app on average weekly [in minutes]	(Wang et al, 2007) (Mohammadi, 2015)
	Duration	On average, how long do you use the application each time you use it [in minutes]	(Hassanzadeh, et al, 2012)
<i>Subjective norm</i>	Influenced	My peer students expect me to use the e-learning application.	(Venkatesh & Davis, 2000)
	Influenced	The teacher expects me to use the e-learning application.	(Venkatesh & Davis, 2000)
	Voluntary	The use of the e-learning system is voluntary [deleted]	(Venkatesh & Davis, 2000)
<i>Mobile self-efficacy</i>	Mobile use	I am really good with using my mobile phone	Roca et al. (2006)
	Mobile learning	I experience no problems when learning to use a new mobile application	Roca et al. (2006)

## Appendix 2: Survey

Naam:

Leeftijd:

Geslacht (M/V):

Werk locatie (Stad):

Functie:

Welke telefoon gebruikt u (Merk en Type):

### Gebruik

Hoeveel tijd besteed je aan het gebruik van de applicatie gemiddeld per week? ..... uur en ..... minuten

Hoelang gebruik je gemiddeld de applicatie per keer dat je de applicatie gebruikt? ..... minuten

### Mobiel self-efficacy

Oneens    Neutraal    Eens

Ik kan heel goed overweg met mijn mobile telefoon                    0   0   0   0   0

Het kost mij geen enkele moeite om een nieuwe mobile applicatie in gebruik te nemen                    0   0   0   0   0

### Subjectieve norm

Oneens    Neutraal    Eens

Mijn mede cursisten verwachten van mij dat ik de applicatie gebruik                    0   0   0   0   0

De docent verwacht van mij dat ik de applicatie gebruik                    0   0   0   0   0

Het gebruik van de applicatie is vrijwillig                    0   0   0   0   0

### Service kwaliteit

Oneens    Neutraal    Eens

De applicatie geeft een duidelijke online uitleg                    0   0   0   0   0

De applicatie is duidelijk uitgelegd voordat we hem voor het eerst gingen gebruiken                    0   0   0   0   0

De applicatie en de face-to-face meetings vullen elkaar aan                    0   0   0   0   0

Ik word goed geholpen als ik iets niet snap en hulp nodig heb                    0   0   0   0   0

### Systeem kwaliteit

Oneens    Neutraal    Eens

De applicatie heeft een aantrekkelijke uiterlijk                    0   0   0   0   0

De applicatie heeft een snelle reactietijd                    0   0   0   0   0

De applicatie is gebruiksvriendelijk                    0   0   0   0   0



De applicatie is betrouwbaar	0	0	0	0	0
Ik kan de informatie vinden die ik zoek, zonder door te veel stappen te gaan	0	0	0	0	0
<b>Informatie kwaliteit</b>					
	Oneens	Neutraal	Eens		
De applicatie geeft mij genoeg informatie	0	0	0	0	0
De applicatie voorziet mij van informatie die makkelijk te begrijpen is	0	0	0	0	0
De applicatie is goed gestructureerd	0	0	0	0	0
De informatie in de applicatie wordt in een goed format gepresenteerd	0	0	0	0	0
De tekst in de modules zijn niet te lang	0	0	0	0	0
<b>Tevredenheid</b>					
	Oneens	Neutraal	Eens		
De applicatie voorziet mij in mijn educatieve behoeften	0	0	0	0	0
Ik zou de applicatie aanraden aan anderen	0	0	0	0	0
Ik vind het leuk om met de applicatie te werken	0	0	0	0	0
<b>Intentie tot gebruik</b>					
	Oneens	Neutraal	Eens		
Ik ben bereid om de applicatie te gebruiken	0	0	0	0	0
Ik vind het gebruik van de applicatie waardenvol	0	0	0	0	0
<b>Gebruikers loyaliteit</b>					
	Oneens	Neutraal	Eens		
Ik gebruik het Slack kanaal om te lezen wat anderen vinden	0	0	0	0	0
Ik communiceer met anderen via het Slack kanaal	0	0	0	0	0
<b>Gebruiksvriendelijkheid</b>					
	Oneens	Neutraal	Eens		
Ik vind de applicatie makkelijk in gebruik	0	0	0	0	0
Ik leerde snel hoe de applicatie werkt	0	0	0	0	0
Ik vind het makkelijk om de applicatie te laten doen wat ik wil	0	0	0	0	0
Het gebruiken van de applicatie kost mij weinig moeite	0	0	0	0	0
<b>Bruikbaarheid</b>					
	Oneens	Neutraal	Eens		
De applicatie helpt mij om effectiever te leren	0	0	0	0	0
De applicatie helpt mij om mijn kennis te verbeteren	0	0	0	0	0
De applicatie is geschikt voor mijn leerstijl	0	0	0	0	0
De applicatie voorziet mij met informatie die relevant is voor mijn werk	0	0	0	0	0
<b>Houding tegenover het gebruik</b>					
	Oneens	Neutraal	Eens		
Over het algemeen vind ik het gebruik van e-learning applicaties een goed idee	0	0	0	0	0
Over het algemeen vind ik het leuk om e-learning applicaties te gebruiken	0	0	0	0	0

<b>Totale voordelen</b>	Oneens	Neutraal	Eens
Alles bij elkaar genomen heeft de applicatie mijn werkprestaties verbeterd	0	0	0
Alles bij elkaar genomen heeft de applicatie mijn probleemoplossende capaciteiten verbeterd	0	0	0
Ik heb het gevoel dat ik veel geleerd heb door de applicatie	0	0	0
De applicatie heeft mij in staat gesteld om te leren wanneer en waar ik wil	0	0	0
De applicatie heeft mij leertijd bespaard	0	0	0

Heeft u zelf nog een suggestie om de applicatie te verbeteren:

---



---



---

## Appendix 3: Interview Guideline

# Interview guideline

### Design variables

#### Service quality

How do you perceive the system quality?

What should happen to improve the system quality?

Would an improvement like that result in you using the application more?

#### Information quality

How do you perceive the information quality?

What should happen to improve the system quality?

Would an improvement like that result in you using the application more?

#### Service quality

How do you perceive the information quality?

What should happen to improve the system quality?

Would an improvement like that result in you using the application more?

### Time

Have you been using the application less or more than before?

Is your app usage the same every week?

Why did your app usage change?

### Additional

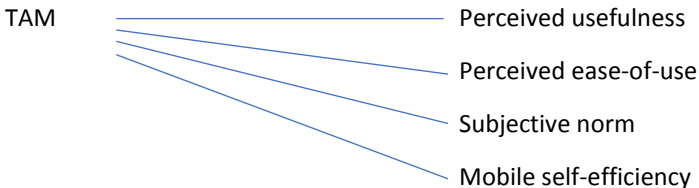
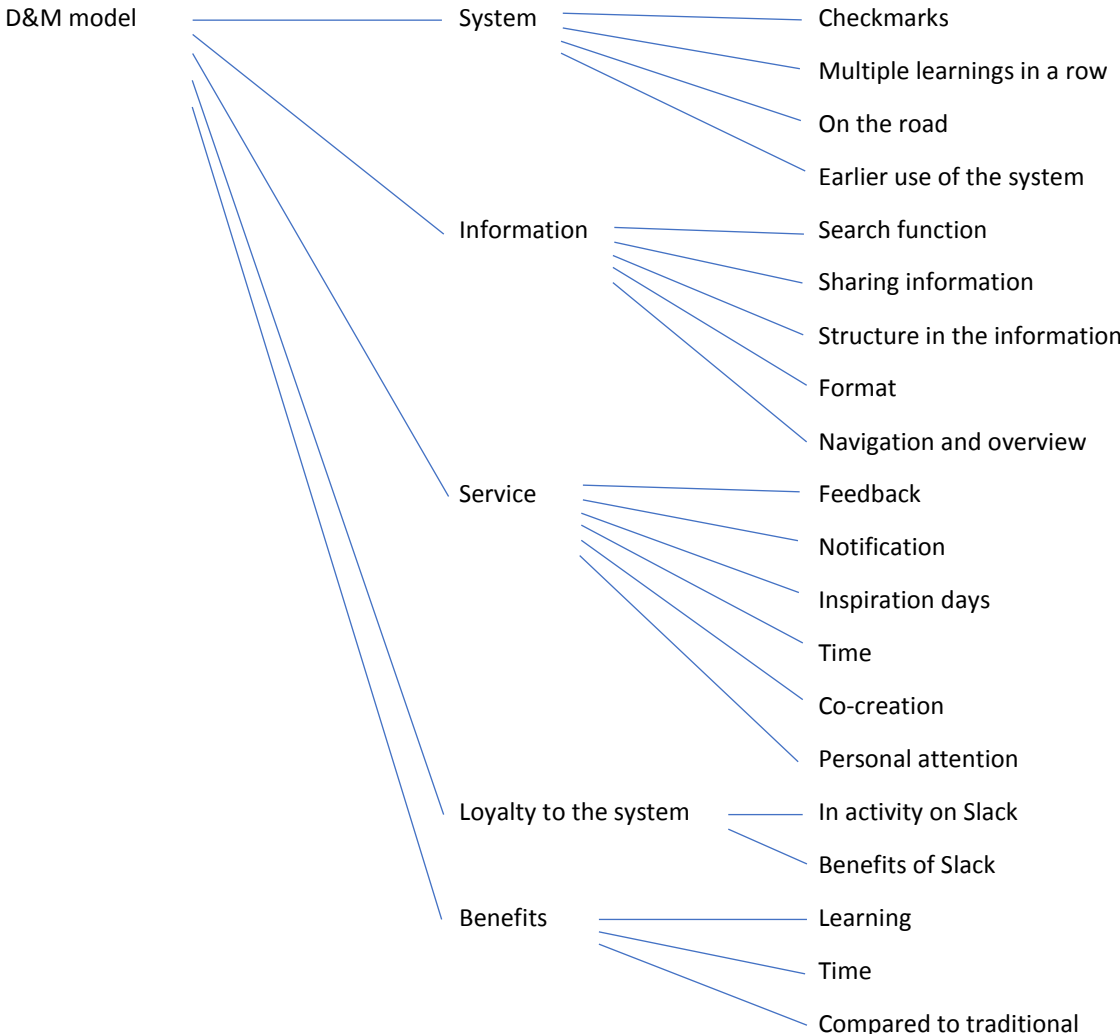
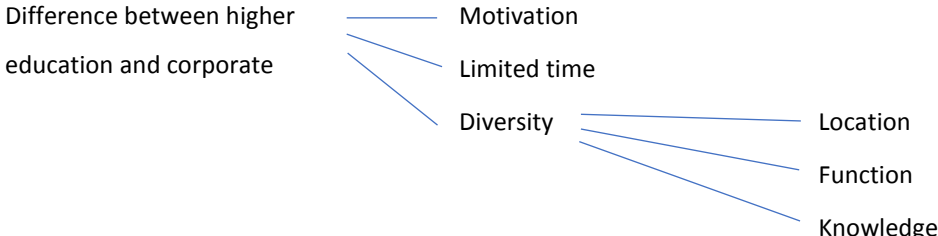
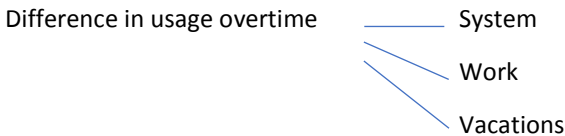
Do you have any other suggestions which would make you use the application more?

Would you prefer traditional courses or e-learning course?

What makes corporate e-learnings different from e-learnings for higher education?

# Appendix 4: Coding Tree

Mobile performance



## Appendix 5: Transcribed interviews

**See data file.**