MASTER'S THESIS

Task-technology adaptation and decision-making in hospitals

Tuk, W (William)

Award date:
2020

The role of behavioral EMR adaptation

Task-technology adaptation and decision-making in hospitals

Open University of the Netherlands

Faculty of Management, Science & Technology

Master Business Process Management & IT

IM0602 BPMIT Graduation Assignment Preparation

IM9806 Business Process Management and IT Graduation Assignment

Student: William Tuk

Identification number: 852113960

Date: 30-06-2020

Thesis supervisor: Dr. Rogier van de Wetering

Second reader: Dr. Rik Bos

Status: Final version

Abstract

In recent years IS research has given attention to the topic of adaptation strategies or task technology adaptation in the information systems. However, what is missing in those studies are the reasons behind users making those adaptations and how those adaptations will benefit them. By focusing on the usage of the EMR in a health care setting and how it can lead to a more effective decision-making process, this thesis proposes a research model including behavioral EMR adaptation. To gain an understanding of behavioral adaptation, a sample of 133 doctors, nurses, doctor assistants, and other medical professionals that use the EMR for their daily work tasks has been collected. PLS-SEM was used to analyze the dataset. Outcomes demonstrate that behavioral EMR adaptation has a significant effect on decision-making effectiveness. Furthermore, people that are open to new technologies score higher on behavioral EMR adaptation. No mediating effects have been found for behavioral EMR adaption due to the absence of a direct correlation between the independent variables (computer self-efficacy and personal innovativeness) and the dependent variable (decision-making effectiveness). There have been no significant effects found for facilitating conditions as moderator. This suggests that facilitating conditions is better suitable as an independent variable.

Keywords: Behavioral EMR adaptation, facilitating conditions, personal innovativeness, computer self-efficacy, decision-making effectiveness, user coping strategies

Summary

In recent years IS research has been giving attention to the concept of adaptation in explaining the acceptance of new technologies in organizations. However, what is lacking is a clear explanation of why these users start making these changes and what drives those changes. This thesis will focus on the role of behavioral EMR adaptation. The EMR-system inside health care is used for sharing information about patients and their treatments. The EMR has been implemented in the Netherlands and 96% of all medical workers use it. Nonetheless, criticism for the EMR involves that the registration into the system takes too much time. Therefore doctors, nurses, and other users tend to use workarounds to work with EMR. This study will discuss how those workarounds can be used to increase the quality of medical decisions for patients.

The main research question is to what extent does behavioral EMR adaptation influences medical decision-making effectiveness in health care. Differences in patterns between doctors, nurses, and other medical professionals will be examined. Users engage with IT and tend to make small changes to the system. The practical implications for this research are that it can reveal how EMR can be successfully implemented in hospitals. Moreover, the adaptive behavior of medical professionals can increase the effectiveness of their medical decisions.

This research is based on the scientific theory of task-technology fit and its related adaptive structuration theory. Task-technology fit argues that technology should be used to create a match between the technology and the tasks it is supporting. New technologies can allow people to change work processes, perform their routine work, and allows individual decision-making. The adaptive structuration theory examines the reasons for how a fit between technology and tasks can be achieved. Two types of adaptation can be distinguished within this theory; exploitative technology adaptation and exploratory adaptation. Exploitative adaptation refers to users finding new ways to work with the system within the existing IT infrastructure. With exploratory adaptation, users will make adjustments to the system, and therefore the nature of the system changes. Based on this theory the concept of behavioral adaptation is selected in this thesis as the main theory that increases the decision-making process. Decision-making effectiveness is defined by how well a person can make a decision in comparison to their colleagues. This construct is the dependent variable in this thesis. When a user can make adjustments to the system, they are better able to use that system to fit their daily work needs. The concept of behavioral adaptation is new in research and only Wu has written about it. Behavioral adaptation can be described as driving your preferences into the functions of a system and work procedures. This way a fit between tasks and technology can be discovered.

Furthermore, in this thesis reasons are being sought why users would make adaptations to the system. These ideas are based on coping theory. Coping theory identifies that individuals can perceive technology as a threat or opportunity, and looks at the control a user has over the technology. The more freedom an individual has for working with a system in a way they desire, the more benefits a user will get out of this system. Based on these ideas, computer self-efficacy, personal innovativeness, and facilitating conditions were selected as the independent variables in this research. When a person is open to new technologies (personal innovativeness) they are more prone to find new ways to fit the system to their needs. Computer self-efficacy can be distinguished as how well a person perceives his or her abilities to work with computers. Facilitating conditions are the support from the management and the presence of documentation or support for the IT-system. Facilitating conditions would allow an individual to feel more assured if they encounter a problem in the system when they make their adjustments to fit in with their daily tasks.

An online survey has been conducted for two months to nurses, doctors, and other medical workers. A total of 133 useful respondents had been collected. These people were contacted through social media, calling the hospital department, and using the personal network of the researchers. A majority of the respondents access the EMR every day for their work tasks.

A pretest was executed with two medical doctors and two researchers, to guarantee the validity of the questionnaire. Next, common method bias was checked. All the constructs scored a VIF under 3.3. This shows that differences in responses are not caused by the questions themselves and that the beliefs of the respondents have been measured.

For this research, an analysis in PLS-SEM has been conducted. In PLS-SEM the structural and measurement models are tested. The advantage of using PLS-SEM is that it can be utilized to test theories that are still in the developing stage. In this research behavioral EMR adaptation is a new concept that has not yet been thoroughly researched. PLS-SEM does not require theories that have been already tested empirically. Another advantage of PLS-SEM is that it can handle data that has a nonnormal distribution. Since the dataset has an overrepresentation of nurses, females, and hospital workers, PLS-SEM is the preferred method of analysis.

A measurement model was made for the constructs of computer self-efficacy, personal innovativeness, behavioral EMR adaptation, facilitating conditions, and decision-making effectiveness. All the measurements were based on research that is empirical and validated. The measurement model was reviewed for the constructs of computer self-efficacy, personal innovativeness, facilitating conditions, behavioral EMR adaptation, and decision-making effectiveness. All the constructs had a Cronbach's Alpha above .8, a Composite Reliability above .8, and the AVE above .5. Thus, there were no issues with reliability or convergent validity. The items in the constructs explain at least fifty percent of the variance within them. Furthermore, the Fornell-Larcker criterion and the HTMT scores of the items, prove that the constructs are diverse from each other and there is no issue with discriminant validity. As a robustness check, CTA-PLS was performed. This check determines if items in the measurement model are reflective or formative. For facilitating conditions and behavioral EMR adaptation the CTA-PLS proves that they are reflective. Facilitating seems to be formative and personal innovativeness has items that both scored on reflective and formative. Since the measurement of these constructs is based on existing research that has been used multiple times by researchers, it was decided to keep all the items reflective in the model.

The next step was to assess the structural model. First, the VIF scores were reviewed. All scores were below 5. No constructs were overlapping and no multicollinearity was found. To calculate the significance of the relationships between constructs in the model, the bootstrapping procedure of 5000 was performed. T-scores of 1.65 with a confidence level of 90% was used. In other words, the significant scores that were calculated have a probability of 90% that they are correct. A significant effect between personal innovativeness and behavioral EMR adaptation ($\beta = .236$, $t = 2.567$, $p < 0.01$) was discovered. Moreover, the correlation between behavioral EMR adaptation and decision-making effectiveness ($\beta = .156$, $t = 1.722$, $p < 0.1$) was significant. The R^2 values show that 10% of the variance can be explained by behavioral EMR adaptation and 5.9% of the variance for decision-making effectiveness. To determine if these R^2 are meaningful, the effect f^2 was calculated. The score for personal innovativeness to behavioral EMR adaptation and the score from behavioral EMR adaptation to decision-making effectiveness was above 0.02, which states that it is a small effect. Additionally, the Q^2 is measured which looks at the predictive power of the data that is not included in the model. The score of Q^2 is negative 1.4% for decision-making effectiveness and behavioral EMR adaptation scored 4.4%. Therefore, the effect size q^2, which uses Q^2 in its calculation, was low as well. This indicates that the model lacks predictive relevance.

There is a model fit in this structural model. An SRMR score of 0.78 was calculated which is below the threshold of 0.8. No significant mediating effect of behavioral EMR adaptation was found for the independent variables computer self-efficacy or personal innovativeness. Furthermore, no moderating effects for facilitating conditions could be discovered as well.

The multigroup analysis shows that the research model made no difference for age, education, type of institution, and years of experience with the EMR. Women score high on the relationship between computer self-efficacy and decision-making effectiveness. The same relationship is discovered for nurses. Moreover, there is a significant correlation for medical professionals, excluding nurses, between personal innovativeness and behavioral EMR adaptation. This would suggest that nurses are not engaged in making changes in the EMR system to find harmony between the technology and their tasks.

The findings in this research oppose the views of Wu. He discovered no relationship between behavioral adaptation and post-adoption IT use. In this thesis, a significant relationship has been established. Thus, behavioral adaption is a concept worth exploring further in future research. Another result contradicts research conducted by Venkatesh in which he claimed that doctors do not engage with new technologies at work. It was established in this thesis that nurses do not show adaptive behavior when working with the EMR.

In practice, hospitals should encourage people working with the EMR to engage in making changes to the system to make their work more effective. Furthermore, the EMR should be designed in a less complicated manner, so that the system can be utilized to make diagnoses to improve the quality of the decision-making process.

Future research should focus on acquiring a more focused and bigger sample group. There was a lack of predictive power in the model and this in part can be explained by the diversity of the sample group. Data was collected at hospitals and other medical facilities, between different departments and different professions. Other research could also include different types of adaptation to discover if these appear at the same time.

In short, this thesis has put behavioral EMR adaptation central. This can be a valuable tool in explaining how users engage inside hospitals and other workplaces with the EMR and it has opened new directions for future exploration.

Contents

1. Introduction

1.1. Context

Medical personnel has to deal with organizational, administrative, and technological changes in hospitals. The latest of these innovations has been the Electronic Medical Record (EMR) system and all the hospitals in the Netherlands have adopted this new technology due to governmental regulations. The implementation of the EMR reduces the number of paper-based medical files, makes it easier for health care professionals to share medical data about a patient and thus accuracy of medical decisions can be improved. In 2017 96% of all general practitioners in the Netherlands started to use an EMR and share patient data this way with hospitals, laboratories, and other general practitioners (Nivel, 2018).

However, there has also been criticism of the EMR by health care professionals. Research commissioned by the NVZ Dutch Hospitals Association showed that doctors and doctor's assistants complain that the registration of data into the EMR takes too much time (NOS, 2016). In designing the EMR the hospitals rely on the input of one or more doctors. In reality, each doctor has their preferences on what to add to the system. They experience this registration as a burden and they look for ways to work with the EMR in their way. This can be by workaround like using the note option in the EMR to add the data instead of in all the data fields. Furthermore, there has been a lack of standardization of digital patient data exchange (ICT & Health, 2019). Different hospitals use different systems for the EMR that each has their way of filling in data.

This research will focus on how the medical professionals inside hospitals and other health care facilities work with the EMR and how they adjust this new technology to be able to make better decisions. Health care is an information-intensive environment. By having all the medical files in one place, doctors and their assistants should be able to make better judgments on the treatment of a patient. However, there has been little research on how clinicians use the EMR and how it can aid their decision-making (Liew, Poh, Koh, French, & Teh, 2018). In this thesis, the concepts of computer self-efficacy, personal innovativeness, facilitating conditions, behavioral EMR adaptation, and decision-making effectiveness are introduced. Computer self-efficacy can be defined as the perception that an individual has of his or her skills in performing computer-related tasks (Marakas, Johnson, & Clay, 2007). Personal innovativeness is the will of an individual to try any new technology (Agarwal & Prasad, 1998). Facilitating conditions signify whether an individual believes that the technological and organizational infrastructure in an organization exists to support the use of the new technology (Sun, 2012; Venkatesh, Morris, Davis, & Davis, 2003). The more help and support an individual gets, the more he or she is willing to do with a new system. Facilitating conditions can therefore be seen as a moderator (Sun, 2012). Behavioral EMR adaptation is interpreted as the exploration of the use of the EMR and to modify work processes to find a fit between medical tasks and the EMR system (Wu, Choi, Guo, & Chang, 2017). The goal here is to attain a fit between daily work processes and technology (Barki, Titah, & Boffo, 2007). In IS-literature decision-making effectiveness is defined as the speed in which a decision is made and whether an organization understands its customers (Wang & Byrd, 2017; DeLone & McLean, 1992).

1.2. Relevance

It is thus important to get a clear idea of how IT is implemented after its adoption. Since the system after its implementation is a different system than a year later. Different users add their own work processes into the system. How this process of adaptation is functioning in an EMR setting, will reveal how the EMR can be successfully implemented in hospitals. Moreover, it will be interesting to see how these changes in the EMR by medics can lead to more effective decision-making. The main focus is on how doctors and other members of staff in a health care setting make subtle changes in the EMR to improve the quality of the medical decisions. The EMR in the Netherlands has been recently implemented and there are still debates inside hospitals, but also in politics on how to standardize the information in the EMR system. By having a clear image of how medics are working with EMR daily, the implementation of the next-generation systems of EMR can be better guided.

1.3. Research questions

Based on the reasons mentioned above, the following research question is proposed:

To what extent does behavioral EMR adaptation influence medical decision-making effectiveness in health care?

The research objectives are as follows:

1. To examine the role of behavioral EMR adaptation as a mediator of personal innovativeness and computer self-efficacy on decision-making effectiveness.
2. To examine the moderating effect of facilitating conditions on behavioral EMR adaptation through personal innovativeness and computer self-efficacy.
3. To examine differences in patterns between doctors, nurses, and other medical professionals working with the EMR and their willingness to adapt this new technology.

1.4. Thesis outline

The first chapter describes the background and relevance of behavioral EMR adaptation. Plus, the research question was introduced. In the next chapter existing literature on task-technology fit, adaptive structuration theory, and coping theory is reviewed. There is a need for a theory on behavioral adaptation with EMR. Furthermore, the research model will be presented here with the hypotheses. The third chapter describes the methodology. As a research method, a survey has been developed to collect data from health professionals working in hospitals or health care centers respectively. The data collection strategy describes how these health professionals were found. The measurement model with all the constructs is further elaborated. For the data analysis, a combination of SPSS and PLS-SEM was used. In chapter four the results from the survey will be tested on the research model. The final chapter will conclude this thesis by discussing the implications of the results and the research objectives will be reviewed.

2. Theoretical framework

This theoretical framework aims to formulate a conceptual model that can explain the relationship between behavioral EMR adaptation and decision-making effectiveness. This chapter will begin by clarifying which methods were used to find relevant literature. It will then proceed to present the main theories concerning the acceptance of technology and the role of technology adaptation within this. Next, the conceptual model will be displayed. Finally, the hypotheses will be presented and explained with the existing literature.

2.1. Research approach

This critical literature review was conducted by searching for relevant papers related to the central research question: To what extent does behavioral EMR adaptation influences the medical decision-making effectiveness in hospitals? The first step was to search through the AIS eLibrary and Google Scholar. The collected articles had a publication date from 1992 to 2019. As search queries a combination of the main concepts was used (i.e. “behavioral EMR adaptation”, ‘Behavioral AND EMR AND adaptation'). Models that were found in that literature gave the inspiration to search further for antecedents and mediators in combination with EMR (for example; EMR "personal innovativeness"). An overview of all the search queries with all the related concepts can be found in Appendix A.

The next step was to look into Google Scholar and take one article as a starting point to find more publications by checking the related articles and who cited the article. This method is called forward snowballing. Relevant literature was selected by reading the abstracts. Up to this point, a total of eighty-two articles were found.

A third step in the literature review was to check if any of the literature found was published in the eight top journals in the field of information systems. Some articles were in the AIS database. However, the sources were different. Since these articles were featured and thus endorsed by the AIS board, these articles have been included in the final literature list. These journals included ECIS, AMCIS, ICIS, PACIS, and ICEB. As a final result, thirty-seven articles were selected to find the gap in current research into behavioral EMR adaptation and to develop a model from.

The last step was to look into those thirty-seven selected articles and examine which theories those articles base their research on and to search for the original authors of those theories. An additional six articles were found this way.

2.2. Literature review

Information technology use in health care is a central topic in information system research (Venkatesh, Zhang, & Sykes, 2011; Ilie, 2013, Anja, Heiko, & Ulrich, 2014; Cocosila & Archer, 2016; Goh, Gao, & Agarwal, 2011; Holden, 2010; Hung, Yu, Tsai, & Yen, 2013; Liew et al., 2018; Mettler, 2012; Weigel, Landrum, & Hall, 2009; Weeger & Gewald, 2013). New technologies are developed and designed to make work faster and more efficient. However, these new technologies remain underused (Venkatesh & Davis, 2000). Understanding how new technology like the EMR, can lead to better and/or faster medical decision-making by medical professionals, is an important research issue. To explain how this can be achieved; this thesis will concentrate on task-technology fit and the related adaptive structuration theory.

2.2.1. Task-technology fit

Goodhue and Thompson (1995) posit that it is crucial for technologies and the tasks it is supporting to have a fit to reach individual performance from information technology. They developed the task-technology fit model which incorporates both the utilization of technology and the match between the technology and the task it is assisting. Goodhue and Thompson (1995) also mention that task-technology fit research should focus on decision-making since new technologies can provide better opportunities to make individual decisions, changing work processes, and perform routine tasks.

2.2.2. Adaptive structuration theory

Adaptive structuration theory (AST) goes one step further than the task-technology fit theory by also explaining how this fit can be achieved. AST argues that work processes can change as a result of the structures that are shaped by the technology itself and by the social interaction users have with the technology (DeSanctis & Poole, 1994, p.143/144). When users become involved with IT they have two choices. Either they perform the task with the technology as the technology was designed for, or they can supplement this technology and attempt making small changes to the technology. Schmitz, Teng, & Webb (2016) make a distinction between two types of adaptation: Exploitive technology adaptation and exploratory technology adaptation. Exploitive adaptation means that the users add their ideas to the existing infrastructure. They make incremental improvements so the needs of the user can be better fulfilled. An example is adding photos of products in an ERP system; then other users know what product code belongs to which product. Exploratory adaptation is to use IT in a way as it was not originally designed to. This can lead to divergent structures (Schmitz et al., 2016). To illustrate this, a company app that was originally designed for suppliers to quickly contact the company in case of an emergency can be used by employees to arrange private meetings. Benlian (2015) investigates how IT-use changes over time. His main focus is on IT-use after implementation when capability-broadening (using current knowledge of technology) and capability-deepening patterns (learning new skills) may arise (Argyres, 1996). IT skill acquisition decreases over time. The more time someone spends on using IT, the less involved they will become (Benlian, 2015).

2.2.3. Coping theory

Coping theory originated from psychology and explains that people will develop different methods to deal with stress. One of those methods is adaptation (Lazarus, 1993). Scholars have brought these concepts into the field of IS research by looking at user adaptations (Beaudry & Pinsonneault, 2005; Wu et al., 2017; Kashefi, Abbott, & Ayoung, 2015) and feature usage (Sun, 2012). New technologies can be disruptive for the existing processes in an organization. Beaudry and Pinsonneault (2005) see adaptation as a coping strategy. The researchers make a distinction between four types of coping behaviors depending on whether the technology is perceived as a threat or opportunity, and whether the user has the authority to change the technology itself or not. To get the benefits out of technology, users would need to make adaptations to it. This can be by making changes in the information system (for example modify, add, delete screens, by personalization or changing the functionalities), the work processes (by changing operational procedures or prioritizing the workload), or in themselves (get training, put effort in learning how to operate the system) (Beaudry & Pinsonneault, 2005). Sun (2012) investigates how and why individuals revise their system use at a feature level. He proposes the concept of adaptive system use as the main driver. Adaptive system use is the revisions a user will make into the system, such as trying new features, feature substituting, combining features, and give features a new meaning (Sun, 2012).

Ilie (2013) looked at how users in health care handle complex IT systems. To deal with complex systems users will try to work around a problem. Bypasses occur when users cannot do their job effectively and if the workaround can be achieved in a short time (Ilie, 2013). Workarounds can be defined as alternative methods to achieve the same goals (Goh et al., 2011). The study from Wu et al. (2017) tries to understand the mechanism behind the post-adoption of a new EMR system. User coping strategies are divided into cognitive adaptation (users focus on the positive effects of IT to confront changes by that IT system), affective adaptation (users try to dissociate themselves from the IT system and avoid engaging with it) and behavioral adaptation (making personal preferences in the functions of a system and work procedures). In the study from Wu et al. (2017) behavioral adaptation is not significant. Nonetheless, the other two strategies are significant. Behavioral adaptation is a concept that has been overlooked by researchers. Most research focuses on an umbrella term of adaptation such as task technology adaptation (Schmitz et al., 2016) or adaptation strategies (Sun, 2012). This thesis will give behavioral EMR adaptation a central role to see if the concept has explanatory power.

2.3. Hypotheses and model development

The research model contains five constructs with related hypotheses. Figure 1 displays the research model that will be tested. Computer self-efficacy and personal innovativeness are independent variables. Facilitating conditions is the moderator and behavioral EMR adaptation is the mediator in the model. Finally, decision-making effectiveness is the dependent variable. Below an elaboration of the hypotheses will be given.

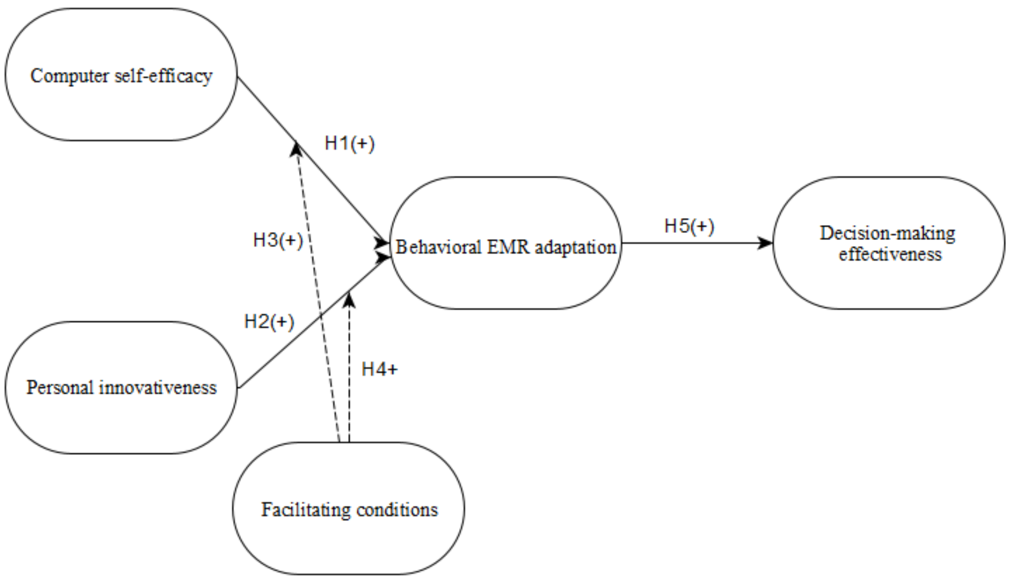


Figure 1 Research model

2.3.1. Computer self-efficacy

Computer self-efficacy is the belief of the individual in his or her own ability to use computers in a competent manner (Compeau & Higgins, 1995). If a user of a system has good computer literacy, he or she will have the knowledge and skills to make adaptations into the system (Marakas et al., 2007). This person knows what the possibilities and limitations are of a system. Several studies found a significant effect between computer self-efficacy and the intention to use EMR (Hung et al., 2013; Ilie, Seha, & Sun, 2009; Weeger & Gewald, 2013). Doctors claiming to have high computer skills found working with the EMR easier (Hung et al., 2013). Physicians who think they possess computer skills would be better able to add information into the EMR. Those people would not experience the system as a barrier to their work. Benlian (2015) tested that people with high computer self-efficacy more slowly discover new features in a system, than individuals with low computer self-efficacy. However, Gaskin, Godfrey, and Vance (2018) found that adaptive behaviors mediate the effect of computer self-efficacy on the perceived added value of a technology.

Therefore, in this thesis, it is hypothesized that a high level of computer self-efficacy will more likely allow people to figure out how their tasks and the EMR system can be aligned.

Hypotheses 1: ***Computer self-efficacy is positively associated with behavioral EMR adaptation.***

2.3.2. Personal innovativeness

Scientists interpret personal innovativeness as the willingness to try out new applications or technologies (Agarwal & Karahanna, 2000; Cocosila & Archer, 2016). In the paper from Agarwal and Karahanna (2000), personal innovativeness has a strong significant effect on cognitive absorption. They define cognitive absorption as a strong mental connection with technology (Agarwal & Karahanna, 2000). One of the indicators is if someone feels they have control over the technology. There is an overlap between the construct of cognitive absorption and technology adaptation as defined in this thesis. Personal innovativeness also has a positive effect on behavioral intention to adopt EMR (Cocosila & Archer, 2016; Kashefi, Nuhu, Abbott, Ayoung, & Alwzinani, 2018). For Ebner, Bassellier, & Smolnik (2019) innovation of IT is strongly related to feature adaptation. According to Gaskin et al. (2018), innovative users will more easily play with the new technologies they encounter and are more likely to discover new ways of using technology for their benefits. Furthermore, these users are also more likely to take risks and in return get more benefits out of technology. In their study, they discovered that adaptive behavior has a mediating effect for personal innovativeness on successful system use (Gaskin et al., 2018). Li, Hsieh, and Rai (2013) posit two usage behaviors. Namely using IT routinely (routine use) or finding new ways to work with the IT (innovative use). These scholars use personal innovativeness as a moderator for innovative use.

Hence, it is hypothesized that people with high personal innovativeness are more willing to explore all the options a new system has to offer and are therefore more likely to make adjustments to that system.

Hypotheses 2: ***Personal innovativeness is positively associated with behavioral EMR adaptation.***

2.3.3. Moderating effect of facilitating conditions

Facilitating conditions are defined as the extent to which a person believes that the infrastructure of the company exists to support the use of the system (Venkatesh et al., 2003). This can either be by training, the availability of a helpdesk, or by support from supervisors (Sun, 2012). The control someone has over his or her work is closely related to facilitating conditions. A person that feels he or she has the freedom to explore all the options that new technology offers and senses the support from his or her organization, will be more favorable towards making small adaptations in the way of work or to the system itself (Venkatesh et al., 2003). Zhou (2003) discovered that the more developmental feedback supervisors gave to their employees, the more likely those employees would show creativity at their work. Computer self-efficacy is used in the IS-literature to explain the adoption of new technologies or can be used to reinforce the value of learning to administer IT in an organization (Marakas et al., 2007).

In the literature facilitating conditions have been used as independent variable (Venkatesh, Brown, Maruping, & Bala, 2008; Anja et al., 2014; Cocosila & Archer, 2016; Mettler, 2012) or as moderator (Sun, 2012; Haake, Schacht, & Maedche, 2018).

Facilitating conditions have no direct significant effect on the behavioral intention to use IT (Venkatesh et al., 2003, p.468; Venkatesh et al., 2008; Mettler, 2012). In their research Anja, Heiko, & Ulrich (2014) show that physicians who claim to have high computer self-efficacy, use the medical digital archive system inefficiently. This is due to the lack of training with the new system. Huang, Chen, & Hsieh (2014) examined the effect of training on computer self-efficacy. They found a positive relationship and advised hospitals to give training to their employees. Cocosila and Archer (2016) found no significant relationship for facilitating conditions and the expected performance of the EMR. One explanation they give is that not all the functionalities of the EMR system are being used since doctors are not aware of the existence of those functionalities.

Sun (2012) discovered that facilitating conditions is a moderator for adaptive systems use. If people feel they are supported by their supervisors, they are inclined to do more with a new system and are more willing to explore all the options (Zhou, 2003). Other research from Haake et al. (2018) used facilitating conditions likewise as a moderator on adaptive system use. Nonetheless, as an independent variable, they used situations where an individual has to learn and adapt the new technology. As a result, this research found no significant moderating effect for facilitating conditions (Haake et al., 2018).

Based on the arguments in the literature, the choice was made for facilitating conditions to be used as a moderator for computer self-efficacy and personal innovativeness in the research model. It seems likely that computer self-efficacy becomes stronger if the facilitating conditions are favorable. On the occasion that a company supports an employee in exploring new technologies, an individual will have more confidence in working with the technology. In return, this person will think highly of his or her computer skills.

It is further theorized that even if an individual is competent in using new technologies, but the organization does not provide the resources to use that technology effectively, the individual will not attempt to make adaptations to that system.

Hypotheses 3: ***The higher the degree of facilitating conditions, the stronger the positive relationship between computer self-efficacy and behavioral EMR adaptation.***

Hypotheses 4: ***The higher the degree of facilitating conditions, the stronger the positive relationship between personal innovativeness and behavioral EMR adaptation.***

2.3.4. Mediating effect of behavioral EMR adaptation on decision-making effectiveness

The EMR can be used to make more effective medical decisions if the EMR would provide the necessary information (Holden, 2010). The system holds the power to reduce human mistakes and improve medical diagnoses (Liew et al., 2018). In the medical field making the right decision is important for doctors to give high-quality care to their patients (Wang & Byrd, 2017). In the literature, decision-making effectiveness is referred to if a decision leads to the desired outcome (Cao, Duan, & Cadden, 2019). Research on decision-making mostly focuses on the role of IT (DeLone & McLean, 1992; Boulesnane & Bouzidi, 2013; Sun, 2017). There is a lack of literature that describes the link between decision-making effectiveness and IT adaptation. Venkatesh (2006) mentions that research on IT usage should pay more attention to why a certain IT is not being used in a certain field. For instance, if someone believes that the EMR is difficult to use and will not make their lives easier, then they will also not try to work with the EMR (Liew et al., 2018). Liew et al. (2018) discuss the acceptance of the EMR by doctors working in an Intensive Care Unit. Those doctors need a holistic view to treat their patients and the EMR can provide that. They see decision-making effectiveness as part of increased productivity. Sun (2017) discovered that the use of IT does improve decision-making effectiveness. However, Liew et al. (2018) and Sun (2017) do not look into what kind of adaptation behaviors people perform.

Wu et al. (2017) is the only research that makes a distinction between three different types of adaptation behaviors; cognitive adaptation, affective adaptation, and behavioral adaptation. However, their research shows no significant effect on behavioral adaptation and post-adoption IT use (Wu et al., 2017). Also, the study from Weigel, Landrum, & Hall (2009) shows that if there is no perfect fit between an EMR and a user, this person will make adaptations to the technology if possible. Nonetheless, the paper from Weigel et al. (2009) did not delve into what drives a doctor or assistant to start making adaptations.

Barki et al. (2007) assert that researchers must include task-technology and individual adaptation behavior when researching the interactions with IT. They found no relationship between task-technology adaptation and IS-use related activities (Barki et al., 2007). Schmitz et al. (2016) explain that there is a difference between task adaptation behaviors and technology adaptation behaviors. In the work of Sun, Wright, & Thatcher (2019) adaptive system use will first lead to lower task productivity. These are short term effects since users that make adaptations to the system would at first require more time to finish their tasks. Eventually, the long-term positive benefits will follow.

To conclude, the behavioral adaptation of the EMR could be a possible explanation for how physicians would achieve high-quality medical decisions. After all, if they would make adjustments to the EMR that would make their task easier or they can do their job faster, their decision-making would also improve.

Hypotheses 5: *Behavioral EMR adaptation is positively associated with decision-making effectiveness.*

3. Methodology

To research the main research question, an online survey was picked as the research method. Explanations will be given why this is the best way to investigate the research model. Next, the data collection strategy is discussed. How are the research questions researched and where does the data come from? This is followed by the measurement model. It will be explained how the constructs are measured and from which existing research the indicators are adapted. An analysis of the data was done with SmartPLS 3.3.2 and IBM SPSS Statistics 26. The analysis in the measurement model and structural model are explained. Lastly, a justification for the use of PLS-SEM can also be found here.

3.1. Research method

In this study, a deductive approach was followed. The research is designed to test the main research question and therefore follows a top-down approach (Saunders, Lewis, & Thornhill, 2016, p.51). First, the theory has been crafted and out of this theory, the hypotheses followed. Next, the hypotheses of the model are tested. This is also a cross-sectional study. Only one point in time is being researched (Saunders et al., 2016, p.200).

An online survey was chosen, so a large sample group of medical professionals, who work with the EMR daily, could be collected in a short period. Secondly, a large sample is needed to check if the results would be significant. For the type of research, a sample group of at least 130 respondents would be desirable if the significance level of 1% would be tested because there are two independent variables in the research model in this thesis (Hair, Hult, Ringle, & Sarstedt, 2017, p.26).

An online survey tool named LimeSurvey was used to collect the data. The online questionnaire was self-completed by the respondents. This way a large sample could be found that was geographically dispersed. Questionnaires can be used for explanatory research to explain the causal relationship between variables (Saunders et al., 2016, p.176). A questionnaire with closed questions was developed. The goal of this research was to discover if doctors and nurses in a hospital make adjustments to the EMR and how it affects the quality of the decision making.

Educational level, age, gender, occupation (specialized doctor, AIOS, nurse or doctors assistant, general practitioner), hospital or non-hospital, years of experience with the EMR, and frequency per week that the EMR is consulted or adjusted, were collected, to be used as control groups in the research model. The full questionnaire can be found in both sections of Appendix B.

3.2. Data collection strategy

Several strategies were used to recruit respondents. The first method of collecting respondents was by calling the policlinic departments of hospitals in the Netherlands to ask them whether they could spread the questionnaire to doctors or assistants within their organization. Another method that was used was snowball sampling, by asking within the personal network on Facebook, Linkedin, or by e-mail, if they could forward the questionnaire to doctors, nurses, and/or assistants and ask those to help forward the survey to their colleagues. A further strategy was using Facebook. Facebook has the option to join community groups. In those groups in which nurses are mostly active, the questionnaire was posted. The last method to recruit medical professionals for the survey was by using LinkedIn. LinkedIn has the option to send people private messages. This was exploited to search for medical professionals and send them a message in which was asked to cooperate with the survey and to forward it to their coworkers. Several of the respondents posted the survey in the private Facebook groups that they were active in or forwarded the questionnaire to their colleagues. This method can be called convenience sampling (Saunders et al., 2016, p.303). Anybody who comes in contact with the EMR at their workplace was eligible to be contacted. The survey was opened online for 8 weeks between April 2020 and June 2020 and in that period 136 people responded to the survey.

3.2.1. Demographics of the sample

The sample of this study consisted of 136 medical professionals. On average thirteen minutes and sixteen seconds was spent by the respondents on the questionnaire. There was no missing data in the collected dataset. In LimeSurvey, the option was selected that people could only upload the response if every question had been answered.

Three respondents were deleted due to unengaged responses. Two people answered every question as neither agree nor disagree. They were found by looking in Excel at the standard deviation. For those respondents, the standard deviation was 0. For another respondent, the standard deviation was 0.333 with most answers being neutral. Also, the time spent on the questionnaire by these three respondents was below four minutes. After inspection of the dataset, no other respondents were found that answered the survey within four minutes.

For the question regarding the educational level, eight respondents answered with other. They supplied answers ranging from HBO, post-HBO to courses from the Open University. After looking through the answers, it was decided to replace their answers by the option most related to their answer. For instance, the answer HBO was replaced by Bachelor's degree, post-HBO by Master's degree, opleiding A verpleegkundige plus banaba spoed en IZ were replaced by MBO and the answer for additional courses by Bachelor’s degree. This way the data was not negatively influenced by these answers and within the variable education, two control groups could be created.

For the question ‘in what type of institution do you work with the EMR?’ the first five type of answers referred to a type of hospital (academic hospital, general hospital, specialized hospital, etc.) and the possible answers from number six to nine identify workplaces outside the hospital, such as general practice center, revalidation center, or nursing home. To analyze the data a new dummy variable was created that would make a dichotomy between hospital and other medical centers. Respondents that answered with other (nineteen in total) were further investigated and divided into hospital and non-hospital.

One question inquired about the occupation of the respondents. They could answer that they identify themselves as a doctor, nurse, assistant doctor, general practitioner, a doctor in training or other. Of the 133 respondents, thirty-one replied with other. When cross-examining their answers, a wide range of professions could be discovered. For example anesthetist, dietician, paramedic, midwife, or nurse in a nursing home. Over twenty-one, different categories could be distinguished. In the class doctor, all people that are specialized doctors are included. In the category assistant doctor, the following job titles were included such as an assistant doctor, doctor in training, and doctor in training with a specialization. The next category was the nurses and these include nurses, nurses in training, EVV’s, and specialist nurses. Only nurses working inside a hospital were included in this category. As a consequence of the scope of this research, the categorization was simplified into two groups;

one for nurses and one for doctors, assistant doctors, and other medical professionals. The sample size of doctors and assistants was below 25. With the inclusion of other medical professionals, these three groups made a sample of 48. The group of nurses contained 85 samples. Hence, a multigroup analysis could be performed.

	Mean	Median	Std. Dev.	Kurto-sis	Skew-ness
Age	3.47 (3 = 36-45 years)	4 (4 = 46-55 years)	1.335	-0.867	-0.344
Education	3.05 (3 = Bachelor)	3	0.999	-0.400	-0.544
Frequency of EMR use	1.24(1 = every day)	1	0.709	15.119	3.766
Years of experience with EMR	2.60 (2 = between 1 and 5 years)	2	0.945	-1.020	0.222

Gender	28% male, 72% female
Institution	65% hospital, 35% other medical institution
Occupation	9% doctor, 64% nurse, 5% assistant doctor, 22% other

Table 1 Demographics of the sample (N=133)

Table 1 shows the demographics of the 133 final participants. Almost two-thirds of the participants were nurses. Doctors and assistant doctors accounted for fourteen percent of the respondents. A fifth of the respondents had different occupations. Over seventy percent was female. Nearly two-thirds of the sample consists of people working inside a hospital. Slightly more than a third worked in other medical institutions, for instance, general practice centers or nursing homes. A majority of the respondents were between 46 and 55 years old. The distribution of age is nonnormal and skewed to the left. In the sample group, most of the respondents had completed a Bachelor's degree on either HBO or university level. Education has a nonnormal distribution with also skewness to the left. This was expected since doctors and nurses need to be highly qualified to get their credentials. By focusing on experience with EMR, the most common group has between one and five years of experience. Again a nonnormal distribution of the data can be found. Furthermore, the sample mostly consists of medical professionals using the EMR every day. The kurtosis shows a score of 15.119, which is high. Additionally, this distribution is strongly skewed to the right. Since this research focuses on doctors and nurses working with the EMR, it is acceptable to have this type of distribution in the data.

3.2.2. Ethical issues

To ensure the anonymity of the respondents is an ethical issue. LimeSurvey was used for collecting the data in a way that it was not possible to recognize the respondents. All the answers were grouped into classes. LimeSurvey is designed for the use of collecting anonymous data. The respondents had freedom of choice to complete the questionnaire. They were not forced by the HR-departments or their supervisors to join this research. They could withdraw their participation at any time during the questionnaire without further investigation. Only filled in questionnaires were saved. Before respondents started the questionnaire they would get a disclaimer about their privacy and that the answers to the questions would only be used for scientific research. Moreover, EMR is a topic that is closely related to the privacy of patients. No questions about patient data were asked. Therefore, this research complies with the General Data Protection Regulation (GDPR) within the European Union.

3.3. Measurements

The research model and its constructs are based on former empirical and validated research. In this thesis, five constructs are researched e.g. computer self-efficacy, personal innovativeness, facilitating conditions, behavioral EMR adaptation, and decision-making effectiveness. To be able to measure these constructs a Likert scale of 1 to 7 was developed. In Table 10 of Appendix B, the reflective measurement model can be found inside the questionnaire. All the constructs in the model are reflective. The reflective measurement model indicates that the direction of the construct is to the measures. Furthermore, the measures are correlated and are interchangeable. Removing one measure would not change the nature of the indicator (Hair et al., 2017, p.43/44). A formative measurement model would have no expected measures that are correlated, the indicators are not interchangeable and the direction is from the measures to the construct (Hair et al., 2017, p.47). In the literature, these five constructs are regarded as reflective. Thus, in this thesis, the constructs stayed reflective.

Each indicator was build up by several questions from the survey. For computer-self efficacy, ten items were incorporated from the research of Compeau and Higgens (1995). The questionnaire had statements such as “I could complete any particular job using the software if someone showed me how to do it first” to measure computer self-efficacy. Personal innovativeness was measured with four items (Agarwal & Karahanna, 2000). Statements regarding personal innovativeness included “If I heard about new information technology, I would look for ways to experiment with it”. The work from Venkatesh et al. (2003) was adapted to design the construct of facilitating conditions. Three items were utilized for the moderator facilitating conditions. Statements were provided that looked into guidance or manuals that are available to the staff (e.g. “guidance was available to me for the use of the EMR”). Behavioral EMR adaptation is a mediator in the model and was measured by exploring the effort users put to change the functions of the EMR (e.g. “I spent efforts (in time and energy) so that the EMR and my tasks fit each other”). For this construct, a synthesis between the work of Wu et al. (2017) and Barki et al. (2007) was developed. Decision-making effectiveness is the dependent variable and was examined with statements about the ability to respond quickly to changes, understanding patients, and making real-time decisions (e.g. "I am more capable than my colleagues in responding quickly to change"). The items were adapted from the analysis of Cao et al. (2019) to fit the concept of decision-making into the field of health care.

3.3.1. Reliability and validity

A pretest has been performed, to ensure the validity of the questionnaire. The survey was pretested on two researchers that both have written articles about the EMR and two medical doctors to establish whether the research subjects would understand the questions and how medical professionals would answer them. An explanation of the goal of the research and definitions of the constructs were included in the questionnaire to ensure that every interviewee would understand the question at hand. According to the results of the pre-test, two questions were regarded as too similar by the doctors. These two questions were related to the variable behavioral EMR adaptation; ‘I spent efforts (in time and energy) so that the EMR and my tasks fit each other’ and ‘I spent efforts (in time and energy) so that the EMR and my tasks would be in harmony with each other’. For this reason, the question 'I spent efforts (in time and energy) so that the EMR and my tasks fit each other' has been deleted from the final questionnaire.

To warrant the reliability alternative form was used. Thus, the same question has been asked twice (in a separate form) in the questionnaire to spot if the answer would be the same. To avoid respondents' fatigue, only two questions have been asked twice. In particular for the concepts of behavioral EMR adaptation and facilitating conditions these control questions have been asked. The question 'there is an instruction note for extending or modifying the system' is an alternative for 'specialized instruction concerning the EMR system was available to me'. Sixty-four participants gave the same answer on both the control question as to the original question. More than half of the respondents gave a different answer. This proves that the control question and the original question have different meanings to the people who undertook the survey. Besides, in the pretest, it was not mentioned that these questions were too similar. It was decided to keep the control question in the analysis since it also increased the Cronbach's Alpha of facilitating conditions. Furthermore, in the literature, it is recommended to use four indicators if possible (Hair, Black, Babin, & Anderson, 2010, p.678)

For behavioral EMR adaptation, the control question was 'I'm using the EMR in a different way than when I began using the EMR'. This question was added to verify if medical professionals are aware that they are using the EMR differently now.

The last step was to control for the common method bias. Common method bias (CMB) occurs if differences in responses are caused by the instrument instead of measuring the beliefs that the instrument should unravel (Kock, 2015, p2). The CMB can exist in reflective factors. Formative factors rarely suffer from CMB (Gaskin, 2017). Kock (2015) claims that if the factor level VIF occurs to be lower than 3.3, then the model can be considered free of common method bias. He reasons that high collinearity leads to inflated path coefficients (Kock, 2015, p.5). The VIF proves if the independent variables are correlated and were measured by connecting one factor with the remaining factors. For example, the VIF for CSE was calculated by connecting BEA to CSE, DME to CSE, FC to CSE, and PI to CSE. Every factor got this treatment. As shown by Table 2 all VIF scores are below 3.3 and thus no common method bias is present.

	BEA	**CSE**	**DME**	**FC**	**PI**
BEA		1.094	1.063	1.039	1.058
CSE	1.040		1.026	1.016	1.036
DME	1.062	1.046		1.047	1.059
FC	1.062	1.063	1.045		1.057
PI	1.038	1.054	1.059	1.021	

VIF < 3.3 = no common method bias

Table 2 Common method bias

3.4. Data Analysis

For the data analysis, IBM SPSS Statistics 26 and SmartPLS 3.3.2 were used. With SPSS the data was cleaned up. For the variable personal innovativeness the question 'in general, I am hesitant to try out new information technology' needed to be recoded. A negative answer signifies that the respondent scores high on personal innovativeness while the other questions in this variable suggested that a positive answer would express high personal innovativeness. Moreover, the variables institution and occupation have been made into new variables that can be utilized for the multigroup analysis.

Next, with SPSS the distribution of the variables was examined for skewness and kurtosis. The majority of the items had skewness between 1 and -1. This is within the norm for the data (Hair et al., 2017, p.61). The items CSE_2, BEA_2, PI_2, gender, experience, and the institution had negative skewness to the left (>-1). While CSE_4, CSE_5, FC_3, and frequency were positively skewed to the right. Except for frequency (kurtosis of 15.119) and FC_3, none of them were bigger than 2.2. Based on the published threshold of 2.2, there were no kurtosis issues (Sposito, Hand, & Skarpness, 1983). Besides, FC_3 scored 2.605. In the literature, it is mentioned that a threshold of 7 can be used for SEM (Byrne, 2013, p.103). The kurtosis for FC_3 can be interpreted as not an extreme value. It was opted to retain this variable to keep the integrity of the scale and as noted by Byrne (2013) SEM can handle a high kurtosis without further issues.

A PLS path model was created in SmartPLS 3.3.2 consisting of the structural model and the measurement model. The structural model is formed by the constructs and the underlying relationships between them (inner model or path model). The measurement model contains the indicators for the constructs (outer model or factor model). To assess the measurement model indicator loadings are calculated. These factor scores determine the influence of an indicator on the construct. The closer to 1 the stronger the influence. Next, the internal consistency reliability is tested by inspecting the Cronbach's alpha and composite reliability. Internal consistency reliability refers to if the test is performed again, whether the same outcomes would be measured. Following, the AVE is tested for convergent validity. Convergent validity checks if the measures in the model are related to each other. Following is the discriminant validity in which is reviewed if the constructs that should not correlate, do not correlate. To demonstrate the discriminant validity the Fornell-Larcker Criterion and the Heterotrait-Monotrait Ratios are calculated. The final step is to determine if the measurement model is reflective or formative. Therefore the CTA-PLS is applied.

The structural model is assessed by reviewing the collinearity to see if the independent variables of personal innovativeness and computer self-efficacy are correlating with each other. Next, to calculate the significance of the regression coefficients, a bootstrapping confidence interval was used. Hence, the standard error can be acquired (Hair et al., 2017, p.195). The bootstrapping procedure takes the original sample group and resamples them into a new sample group (Hair et al., 2017, p.149). Bootstrapping of 5000 was executed. T-scores above 1.65 are significant at the 90% confidence level for exploratory research (Hair et al., 2017, p.153). Thereupon, the R^2 was estimated. This is the coefficient of determinant and will tell about the predictive power of the model (Hair et al., 2017, p.198). From the R^2, the effect size f^2 can be computed. This is a technique where the exogenous construct is removed to discover what its impact is on the endogenous constructs (Hair et al., 2017, p.201). The f^2 determines if a significant effect is a meaningful effect. As a guideline an effect size of higher than 0.02 is a small effect, higher than 0.15 is a medium effect, and higher than 0.35 shows a large effect (Cohen, 1988).

An examination of the Stone-Geisser's Q^2 value followed. This value proves the predictive power of the data that is not included in the model (Hair et al., 2017, p.202). An omission distance of 8 was selected for the blindfolding procedure. The default setting in SmartPLS is 7. However, since there are 133 respondents, the omission distance of 7 could not be used. It is not allowed to have an integer value when the sample size is divided by the omission distance. There is currently no standard for the omission distance value in the literature (Evermann & Tate, 2012, p.3). Furthermore, the lower the distance, the higher number of the sample will be discarded. A value of between 5 and 10 is recommended (Hair et al., 2017, p.204). By performing a blindfolding procedure on the model and applying the cross-validated redundancy approach, the Q^2 scores were enumerated. From the Q^2, the effect size q^2 can be quantified. SmartPLS does not provide a calculation for q^2 and therefore this had to be done manually with the following formula:

$$q^2 = \frac{Q^2_{included} - Q^2_{excluded}}{1 - Q^2_{included}}$$

To check if the data fit the model, the Standardized Root Square Residual (SRMR) needs to be calculated. SRMR is the square-root difference between the residuals of the sample and the hypothesized model.

Next, the research model was tested by evaluating the mediating effects and moderating effects. At last, a multigroup analysis (MGA) was employed to test the research model for different groups of respondents. MGA can be used to verify the stability of the research model. Ideally, the model has the same significant relationships in the total sample as in each subgroup of the sample. If the p-value is significant then there is a significant difference in traits instead of measurements. A significant parametric test shows that this significance has meaning. MGA can assess at most two distinct groups at the same time (Hair et al., 2017, p.42/43).

SmartPLS is designed to test models with Partial Least Squares Structural Equation Modeling (PLS-SEM). This method can be applied when the theory is less developed and the goal is to explain why something is happening (Hair et al., 2017, p.15). For PLS-SEM it is not necessary to have theories that are already empirically supported (Lowry & Gaskin, 2014, p.131). In this thesis, the focus is on behavioral EMR adaptation. Both Wu et al. (2017) and Barki et al. (2007) use the concepts of task-technology adaptation or behavioral adaptation in their investigations, but not in the context of the EMR. This thesis is a new type of exploration of the construct. For PLS-SEM the data distribution can either be normal or nonnormal since PLS-SEM is a nonparametric statistical method (Hair et al., 2017, p.60). This means that it can be applied to the data that was discovered by the questionnaire, since age, frequency of use, education, and years of experience with EMR had nonnormal distributions. Each question or statement in the questionnaire was coded from 1 to 7. To apply PLS-SEM, the points had to be equidistant. That way the Likert scale can come close to an interval-level measurement and then PLS-SEM can be applied (Hair et al., 2017, p.10).

4. Results

The analysis in PLS-SEM was divided into three sections. First, the reflective measurement model was reviewed by testing for reliability, convergent validity, and discriminant validity. Additionally, PLS-SEM was used to examine the structural model to establish the relationships between the variables and how strong this relationship is (Hair et al., 2017, p.191). To conclude the analysis a multigroup analysis was performed to see if the structural model is different for certain groups.

4.1. Assessment of reflective measurement model

The first step in the assessment of the reflective measurement model is to focus on the indicator loadings. Ideally, the loadings of the items are higher than 0.708 (Hair et al., 2019, p8) The factor-loadings for all the constructs were above 0.708 apart from BEA_5 and seven items in computer self-efficacy. This construct has an issue with item reliability. BEA_5 scored 0.703 and this difference between the recommended score can be disregarded. In Appendix C an overview can be found of the item loadings and their corresponding mean and standard deviation.

Next, the internal consistency reliability was tested by applying Cronbach's alpha. Cronbach's alpha (α) looks at the intercorrelations between the indicator variables. It is recommended to have an α between 0.70 and 0.90 (Fornell & Larcker, 1981). The lowest Cronbach's Alpha calculated was for computer self-efficacy (α is 0.744) and the highest α is 0.854 for facilitating conditions. These are all in the acceptable range.

Following, the composite reliability (CR) was measured for all the constructs. CR can be used as an alternative to review internal consistency reliability. CR verifies the outer loading of the indicator variables (Hair et al., 2017, p.111). The composite reliability should also be higher than 0.70. Computer self-efficacy did not meet this requirement, because of the score of 0.498. Fornell and Larcker (1981) have said that a score of 0.5 for the composite reliability is acceptable if the convergent validity (AVE) is higher than 0.6.

Afterward, the AVE was scrutinized by evaluating the outer loadings of the indicator and the variance between them (Hair et al., 2017, p.114). In the literature, a threshold of 0.50 is common for AVE (Fornell & Larcker, 1981). At least fifty percent of the variance of the items in the construct is explained. All the items met the criteria of at least 0.50, except for computer self-efficacy. Computer self-efficacy scored an AVE of 0.319

The construct of computer self-efficacy needed to be further investigated, because there were problems with the composite reliability and the convergent validity. After looking over the outer loadings, four items of computer self-efficacy were removed from the construct. These include CSE_1, CSE_2, CSE_3 and CSE_8, which each had a loading of -.496, -638, -.043 and .015. Meanwhile, the remaining items had positive loadings. Removing these items has increased the AVE to .562, the Cronbach's Alpha to .847, and the Composite Reliability to .882 for the construct computer self-efficacy. Besides no issues with discriminant validity were detected after removing the four items. Removing more items than these four items did not improve the AVE. Moreover, in Appendix D the outer loadings can be found for the final analysis.

The discriminant validity was tested next to check if the constructs are distinctive from each other by using cross-loadings. More specifically, if an indicator's outer loading on a construct is higher than its correlation on other constructs (Hair et al., 2017, p.115). For all the items the Fornell-Larcker Criterion shows a higher score on the construct itself than on the other constructs. Therefore, the constructs are all different. Table 3 summarizes all this data.

	BEA	CSE	DME	FC	PI
1. Behavioral EMR adaptation (BEA)	.777				
2. Computer self-efficacy (CSE)	-.134	.749			
3. Decision-making effectiveness (DME)	.168	.139	.855		
4. Facilitating conditions (FC)	.193	-.062	.220	.831	
5. Personal innovativeness (PI)	.242	-.192	.059	.023	.809
Cronbach's Alpha	.838	.847	.834	.854	.830
Composite Reliability	.883	.882	.893	.899	.883
AVE	.602	.562	.737	.692	.655

Table 3 Convergent and discriminant validity of reflective constructs

The next step is to calculate the Heterotrait-Monotrait Ratios (HTMT). The HTMT calculates the mean value of correlations of items across constructs in comparison with the average correlations of the items within the same construct. The HTMT ratio must be less than 0.85 for conceptually different constructs (Hair et al., 2019, p.9). Table 4 shows that the HTMT ratios were all below the 0.85 thresholds.

	BEA	CSE	DME	FC
Computer self-efficacy	0.228			
Decision making-effectiveness	0.170	0.222		
Facilitating conditions	0.206	0.135	0.258	
Personal innovativeness	0.249	0.378	0.097	0.104

Table 4 Heterotrait-Monotrait Ratios

A robustness check was done to determine if the items of all the constructs are formative or reflective by applying a confirmatory tetrad analysis for PLS-SEM (CTA-PLS). This technique calculates tetrads for all the items in a construct. A score that is significantly different from zero supports the claim that the measurement is formative. A score of zero between the confidence interval low adjustment and the confidence interval high adjustment proves to be a reflective model (Hair et al., 2017, p. 287). The results of the CTA-PLS can be found in Appendix E. In the research model the constructs computer self-efficacy and behavioral EMR adaptation are reflective. Facilitating conditions seems to be a formative model. Personal innovativeness has one tetrad making the statement for reflective measurement and another tetrad states that it is a formative measurement model. It should be noted that even if the CTA-PLS claims that a tetrad is formative instead of reflective or reversed, it does not necessarily mean that the measurements should be reversed. The measurement model is based on existing research and it can be claimed that the items personal innovativeness (Agarwal & Karahanna, 2000), computer self-efficacy (Compeau & Higgins, 1995), facilitating conditions (Venkatesh et al., 2003), behavioral EMR adaptation (Wu et al., 2017; Barki et al., 2007) and decision-making effectiveness (Cao et al., 2019) are all reflective.

4.2. Assessment of structural model

The first step in assessing the structural model is to check the collinearity with the variance inflation factors (VIF). The VIF scores were all below 5. Plus, only four items scored between three and five. This indicates there is sufficient construct validity in the model and there is no multicollinearity.

It was observed that there is a significant effect between personal innovativeness and behavioral EMR adaptation (β = *.236, t = 2.567, p < 0.01*). Furthermore, a significant correlation was distinguished between behavioral EMR adaption and decision-making effectiveness (β = *.156, t = 1.722, p < 0.1*). There was no significant effect from computer self-efficacy to behavioral EMR adaptation. Additionally, no direct effects between computer self-efficacy and personal innovativeness to decision-making effectiveness exist. This implies that there is no direct effect of the independent variables on the dependent variable. Since there is a significant effect between the dependent variable and the mediating variable plus a significant effect between the mediating variable and the dependent variable, there could be a cross-over interaction. A further assessment of the model is required, to see if there is a significant mediating effect between personal innovativeness and decision-making effectiveness for behavioral EMR adaptation. Moreover, the moderating effect of facilitating conditions has not been tested yet.

Subsequently, the result of the R^2 analysis shows that behavioral EMR adaptation explains 10% of the variance when it is impacted by computer self-efficacy and personal innovativeness (R^2 = 0.10). The impact of computer self-efficacy, personal innovativeness, and behavioral EMR adaptation explains 5.9% of the variance of decision-making effectiveness. In addition, a calculation of the effect size f^2 was performed. The effect size for the relationship between personal innovativeness and behavioral EMR adaptation is 0.053, which indicates a small effect. Behavioral EMR adaptation to decision-making effectiveness scores a small effect size of 0.033.

By applying the cross-validated redundancy approach the Q^2 was calculated. The Q^2 value for behavioral EMR adaptation scored 0.044. A score larger than 0 indicates that the model has predictive relevance (Hair et al., 2017, p.207). Nonetheless, decision-making effectiveness had a Q^2 value of -0.014 which suggests a lack of predictive relevance. The effect size q^2 were computed to examine the relevance of the model (Hair et al., 2017, p.208). The q^2 is evaluated for its relative impact of predictive relevance. Personal innovativeness on behavioral EMR adaptation achieved a score of 0.042. This means that personal innovativeness has a small predictive relevance for behavioral EMR adaptation. All other constructs scored below 0.02 and therefore have no predictive relevance. Table 5 presents an overview of the findings.

Relationship	**Std Beta**	**Std Error**	**t-value**	**f^2**	**q^2**	**95% CI LL**	**95% CI UL**
BEA -> DME	0.156	0.105	1.722*	0.033	-0.02	-0.031	0.314
CSE -> BEA	-0.069	0.186	0.402(ns)	0.006	0.005	-0.320	0.279
CSE -> DME	0.154	0.210	0.837(ns)	0.031	-0.001	-0.252	0.393
FC -> BEA	0.194	0.104	1.785*	0.038	0.012	0.029	0.338
PI -> BEA	0.236	0.087	2.567**	0.053	0.042	0.100	0.364
PI -> DME	0.048	0.115	0.422(ns)	0.002	-0.023	-0.145	0.233

*** p<0.001 ** p<0.01, *p<0.1, (ns) not significant
R^2 (Behavioral EMR adaptation = 0.100; Decision-making effectiveness = 0.059)
Q^2 (Behavioral EMR adaptation = 0.044; Decision-making effectiveness = -0.014)

Table 5 Direct causal model coefficients

To check the model fit, the SRMR was calculated. The SRMR in the final structural model was 0.078, which indicates there is a model fit since the SRMR should be below 0.080 (Gaskin et al., 2018, p.68).

In the structural model, behavioral EMR adaptation is the mediator. To measure the effect of this mediator, the indirect effects had to be calculated from the independent variables computer self-efficacy and personal innovativeness to the dependent variable decision-making effectiveness. The mediating effects can be found in Table 6. The effect of personal innovativeness on decision-making effectiveness does increase when it goes through behavioral EMR adaptation. The t-value increases from 0.422 to 1.376. However, the t-value is lower than 1.65 and is therefore not significant. For computer self-efficacy, the effect even shrinks. The t-value of 0.837 drops to 0.379 when behavioral EMR adaptation is used as a mediator. In conclusion, there is no significant mediating effect of behavioral EMR adaptation on decision-making effectiveness for computer self-efficacy as well as personal innovativeness.

Relationship	Std Beta	Std Error	t-value	95% CI LL	95% CI UL
CSE -> BEA -> DME	-0.015	0.036	0.379(ns)	-0.083	0.036
FC -> BEA -> DME	0.032	0.029	1.164(ns)	-0.002	0.096
PI -> BEA -> DME	0.037	0.029	1.376(ns)	0.002	0.102

** p<0.01, *p<0.05, (ns) not significant

Table 6 Indirect causal model coefficients

It is theorized that the relationship between computer self-efficacy and behavioral EMR adaptation is positively moderated by facilitating conditions. For moderation, also a bootstrapping of 5000 was executed. The moderating effect of facilitating conditions for computer self-efficacy is slightly negative with a standardized beta of -0.067. This implies that the higher someone scores on computer self-efficacy and the lower on facilitating conditions, the less likely they are going to make adaptations in the EMR. The standardized beta for facilitating conditions as a moderator of personal innovativeness is 0.049. The results of the moderation analysis are presented in Table 7.

Relationship	Std Beta	Std Error	t-value	95% CI LL	95% CI UL
BEA -> DME	0.149	0.105	1.645(ns)	-0.029	0.314
CSE -> BEA	-0.026	0.155	0.147(ns)	-0.249	0.262
CSE -> DME	0.149	0.214	0.800(ns)	-0.257	0.396
FC -> BEA	0.161	0.090	2.362**	-0.005	0.290
FC*CSE -> BEA	-0.067	0.158	1.199(ns)	-0.253	0.207
FC*PI -> BEA	0.049	0.108	1.026(ns)	-0.137	0.170
PI -> BEA	0.215	0.089	2.250**	0.069	0.350
PI -> DME	0.045	0.122	0.426(ns)	-0.159	0.239

*** p<0.001 ** p<0.01, *p<0.1, (ns) not significant

Table 7 Moderation analysis

This is also shown in the simple slope analysis in figure 1. If facilitating conditions are present and someone scores low on computer-self efficacy they will score high on behavioral EMR adaptation. Nonetheless, there is no moderating effect of facilitating conditions on computer self-efficacy to behavioral EMR adaptation due to the t-value not being significant.

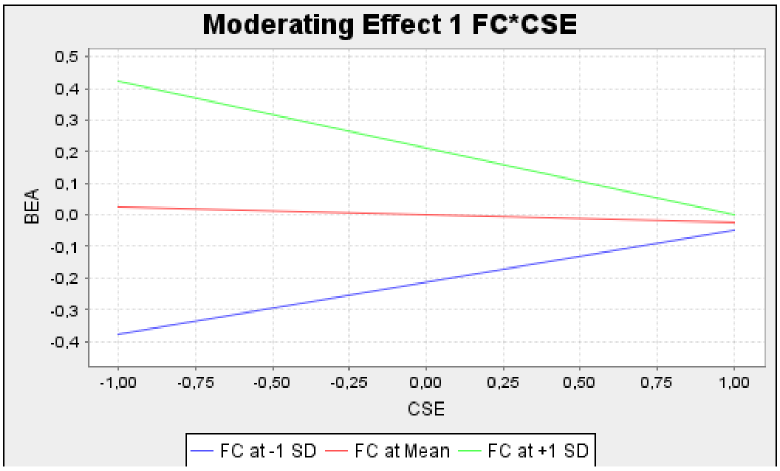


Figure 2 Simple slope analysis for the moderating effect of FC on CSE

The simple slope analysis in figure 2 depicts that facilitating conditions has a slight positive effect between personal innovativeness on behavioral EMR adaptation. This proves that facilitating conditions allow personal innovative doctors or nurses to make adaptations in the EMR. The effect is not significant, and no meaningful moderating effect can be established.

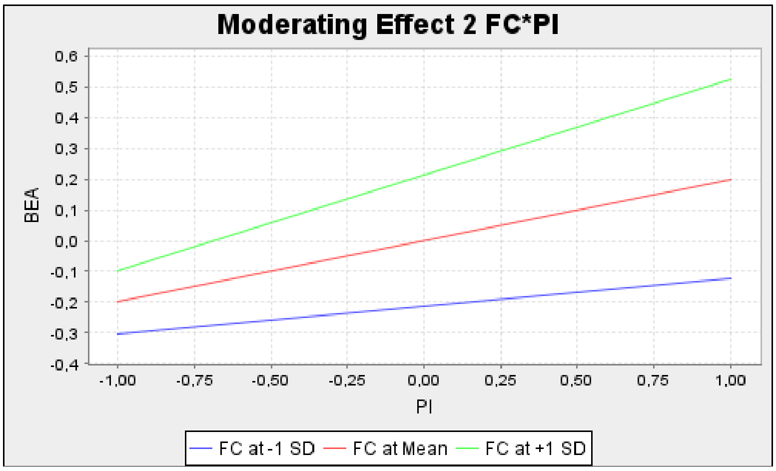
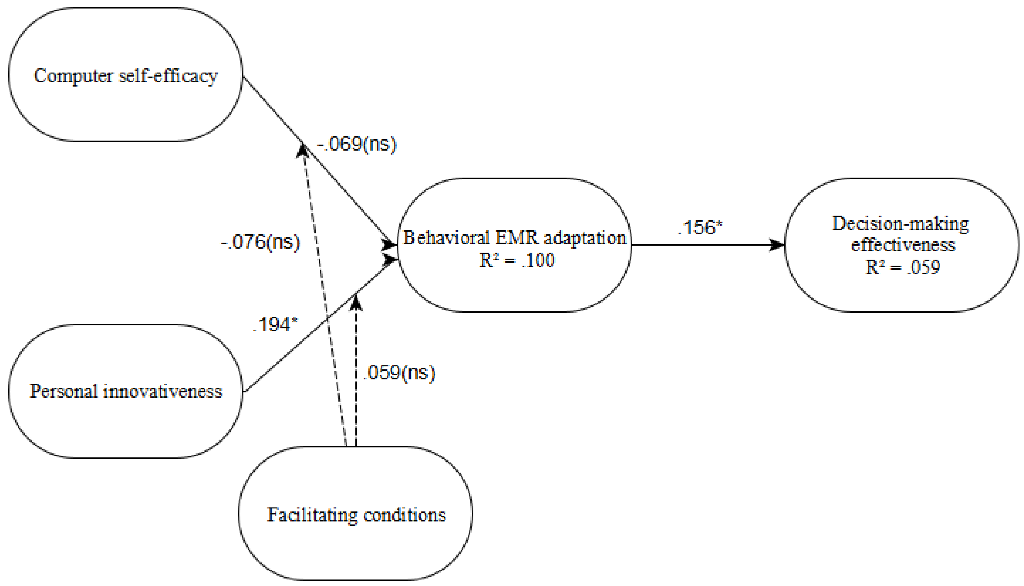


Figure 3 Simple slope analysis for the moderating effect of FC on PI

The analysis of the structural model is compiled in figure 4. In conclusion, there was support for two of the five hypotheses. Personal innovativeness affects behavioral EMR adaptation (hypothesis 2). Furthermore, behavioral EMR adaptation has a significant correlation with decision-making effectiveness (hypothesis 5). No support was found for the link between computer self-efficacy and behavioral EMR adaptation (hypothesis 1). Facilitating conditions present no moderating effects between computer self-efficacy and behavioral EMR adaptation (hypothesis 3) or between personal innovativeness and behavioral EMR adaptation (hypothesis 4).



*** p<0.001 ** p<0.01, *p<0.1, (ns) not significant

Figure 4 Indirect mediated moderation model

4.3. Multigroup analysis

By focusing on different groups within the sample to discover if the research model is significant, new patterns could be discovered. With PLS-MGA the significant relationships in the demographics of the respondents for the variables occupation, age, gender, the frequency of use of EMR, education, institution, and experience with the EMR can be demonstrated.

The frequency of the use of EMR, however, could not be tested in PLS since 113 respondents said they are using the EMR every day. The group that is working less with EMR in the workplace is too low to perform MGA on. MGA requires at least 25 cases. For age, there was no significance between people younger and older than 45 years old. Also, experience with EMR showed no significance for people working longer than 5 years and for those who worked less than 5 years with the EMR. The level of education made no difference in the model. The parametric test showed no significance between people who have a Bachelor's degree or higher and medical staff who have a lower educational background. A similar result was discovered for the institution. There was no difference between hospital workers and people working at other medical institutions.

Only for gender and occupation, the parametric test showed several significant results. According to Table 14 in Appendix F, there is a strong correlation between computer self-efficacy and decision-making effectiveness for females (β = .397, t = 3.208, p < 0.001). Women tend to make better decisions due to computer self-efficacy. The parametric test was also significant (t = 2.111, p < 0.1).

Table 15 in Appendix G shows the MGA for the occupation. The relationship between computer self-efficacy and decision-making effectiveness is significant for nurses (β = .342, t = 2.372, p < 0.1). In addition, personal innovativeness and behavioral EMR adaptation are significant for other medical professionals (β = .452, t = 3.499, p < 0.001) and so is the parametric test (β = .397, t = 3.208, p < 0.001). By being personally innovative a medical professional other than a nurse will make adaptations to the EMR to align it with their daily work. It was expected that nurses would be more favorable in adjusting the EMR. However, it is the medical professionals that engage in this type of behavior.

5. Discussion, conclusions, and recommendations

5.1. Discussion

Behavioral adaptation and its effect on the decision-making process is underexposed in the literature about IS research, while at the same time studies have shown that users tend to make adjustments in the system (Schmitz et al., 2016; Barki et al., 2007; Sun, 2019; Weigel et al., 2009). It has, however, not been properly researched what drives doctors, nurses, or assistants to make those adaptations. This gap has been addressed in this thesis by proposing a model including behavioral EMR adaptation. The main research question explores to what extent behavioral EMR adaptation influences medical decision-making effectiveness in health care. It was theorized that by adapting the EMR for their tasks doctors, nurses, and assistant doctors will make better medical decisions. Or, by not making any adaptations to the EMR, and instead only use the system as it was originally intended, would not lead to an additional improvement in decision-making. Thus, this study tried to extend the literature on task-technology fit.

The first research objective in this thesis was to examine the role of behavioral EMR adaptation as a mediator of personal innovativeness or computer self-efficacy on decision-making effectiveness. It was discovered in the research model that behavioral EMR adaptation has no mediating effect on decision making-effectiveness. Although, there is a direct significant relationship between behavioral EMR adaptation and decision-making effectiveness. By making adaptations to the EMR, doctors, and nurses do believe that they can make better medical decisions. This outcome contradicts the results of Wu et al. (2017). Wu et al. (2017) did not find any significant effect on behavioral adaptation and post-adoption of IT.

The second research objective was to observe the moderating effect of facilitating conditions on behavioral EMR adaptation through personal innovativeness or computer self-efficacy. No moderating effect could be discovered for facilitating conditions on the relationship between personal innovativeness and behavioral EMR adaptation to decision-making effectiveness. This verifies that when people are more willing to try out new software, they will not need additional support from the hospital or medical facility to make additional changes in the functions of a system. Instead, they will figure out by themselves how to change the functions of the EMR. Facilitating conditions have no moderating effect as well on the relationship between computer self-efficacy and behavioral EMR adaptation. It seems highly probable that facilitating conditions is an independent variable. While testing with SmartPLS, the scores for facilitating conditions were calculated and there was a direct significant effect from facilitating conditions on behavioral EMR adaptation.

The third research objective investigates the different patterns between doctors, nurses, and other medical professionals working with the EMR and their willingness to adapt this new technology. The findings of this thesis demonstrate that personal innovativeness affects behavioral EMR adaptation. Medical professionals that are more open to new technologies have a high probability that they will also make adaptations to the EMR to align the software with their daily tasks. While comparing nurses with all other medical professionals, this relationship is not significant for nurses. It is proven that doctors, doctor assistants, and other medical professionals spent effort on harmonizing the EMR and their tasks. This counters the research from Venkatesh et al. (2011). Venkatesh et al. (2011) point out that doctors with a central role are more negative over a new system and influence the supporting medical personnel around them to think negatively about the systems as well. However, central players in the supporting role, like nurses, influence usage positively. The findings of this thesis do not confirm this view and in fact, nurses are the ones who show less adaptive behaviors with the EMR.

5.2. Recommendations for practice

From a practical standpoint, hospitals should encourage their employees to explore new functions of the EMR and other software packages. For example, trying new features, substituting features, and give new meaning to features (Sun, 2012). Beaudry and Pinsonneault (2005) have argued that to get the advantages out of new technologies, users have to be able to make adjustments to that technology. One respondent wrote that the EMR is too rigid and that they have given up on working with it. Gaskin et al. (2018) claimed that adaptive behaviors are best for unstructured tasks. Therefore, hospitals should motivate their personnel to make adaptations. The system should be designed so that it allows people to make adjustments. There has been evidence that different departments inside hospitals have different information needs en thus have different willingness to work with the EMR (CHIPSOFT, 2020).

Another implication is that with the implementation of the EMR, the system should also be used for complex data entry to improve the diagnostics that can be made with the EMR. This would increase the quality of medical decisions. If the EMR could improve the quality of the data that is entered into the system, it should become easier to make diagnostics for the medical staff and therefore better medical treatments can be provided.

One respondent has said the EMR has improved the quality of work inside the hospital in comparison to the situation before the EMR. This person, additionally, said that it is difficult to use the EMR to make diagnoses with the available data and instead, medics have opted for avoidance instead of showing adaptive behaviors. This demonstrates that health care workers also use affective adaptation and not only behavioral adaptation. This is in line with the research by Wu et al. (2017).

5.3. Recommendations for further research

This research contains some limitations that further research could address. One of the main findings in this research was that there is no mediating effect between behavioral EMR adaptation and decision-making effectiveness. Because there were no direct relationships between the independent variables (computer self-efficacy and personal innovativeness) and the dependent variable (decision-making effectiveness). This might be explained by how the questions were framed regarding the variable decision-making effectiveness. For this variable, three questions were used. Each question states whether the respondent is more capable than his colleagues in responding, quickly to change, making real-time decisions, and understanding patients. It could be that the respondents want to be modest and not claim that they are better than their coworkers. Instead, a more suitable way of framing would be ‘I am more capable now due to the information system than before in responding quickly to change, making real-time decisions and understanding patients’. Thus, it is possible to measure the change in improving the decisions over time.

Furthermore, the low explanatory power of the model in this thesis could be due to medical professionals using different strategies to gain benefit from the EMR. It might be possible that nurses, assistant doctors, or doctors display different kinds of adaptive behaviors. Gaskin et al. (2018) have hinted that adaptive behaviors can be in adapting the content of the IT-system or by making adaptations in the spirit of the system. By including affective adaptation and cognitive adaptation, it could be discovered which type of adaptation correlates with higher quality medical decisions.

Another limitation involves the sample size and sample group in this study. The nature of the data made it difficult to conclude from and the lack of significant correlations can be an indication of a too diverse sample group. By focusing the research on hospitals, perhaps stronger significant correlations could be found. In addition, a different research method could be beneficial. For instance, in-depth interviews or a case study. It might be possible that the respondents misinterpret the questions in the survey. The questionnaire includes themes the respondents are not familiar with. By applying in-depth interviews or case study research, the concept can be better explained by the researchers to the interviewees. Benlian (2015) stated that IT skills decrease over time and that people stop learning new skills. A majority of the respondents work with the EMR every day for the past one to five years. It might be that they made adaptations when they just started to work with the EMR. Yet years later stopped doing this. With in-depth interviews, this could be exposed. With these recommendations, further research might be able to find significant effects between decision-making effectiveness and computer self-efficacy, personal innovativeness, or behavioral EMR adaptation.

Although this current study has a limited scope, the concept of behavioral adaptation is worth further exploring. This study justifies the use of behavioral adaptation in research for the post-adoption of IT-systems, such as the EMR. The significance between personal innovativeness and behavioral EMR adaptation opens avenues for further exploration.

References

Agarwal, R., & Karahanna, E. (2000). Time flies when you're having fun: Cognitive absorption and beliefs about information technology usage. *MIS quarterly*, 665-694.

Agarwal, R., & Prasad, J. (1998). A conceptual and operational definition of personal innovativeness in the domain of information technology. *Information systems research*, *9*(2), 204-215.

Anja, N., Heiko, G., & Ulrich, H. (2014). Why Do They Resist? Examining the Salient Factors of Physicians' IT adoption behavior. *PACIS Proceedings. Paper*, *223*.

Argyres, N. (1996). Capabilities, technological diversification and divisionalization. *Strategic Management Journal*, *17*(5), 395-410.

Barki, H., Titah, R., & Boffo, C. (2007). Information system use–related activity: an expanded behavioral conceptualization of individual-level information system use. *Information Systems Research*, *18*(2), 173-192.

Beaudry, A., & Pinsonneault, A. (2005). Understanding user responses to information technology: A coping model of user adaptation. *MIS quarterly*, *29*(3).

Benlian, A. (2015). IT feature use over time and its impact on individual task performance. *Journal of the Association for Information Systems*, *16*(3), 2.

Boulesnane, S., & Bouzidi, L. (2013). The mediating role of information technology in the decision-making context. *Journal of Enterprise Information Management*.

Byrne, B. M. (2013). *Structural equation modeling with Mplus: Basic concepts, applications, and programming*. Routledge.

Cao, G., Duan, Y., & Cadden, T. (2019). The link between information processing capability and competitive advantage mediated through decision-making effectiveness. *International Journal of Information Management*, *44*, 121-131.

Chipsoft. (2020, February 5). *Erasmus MC gaat gebruik EPD optimaliseren.* https://www.chipsoft.be/nieuws/443/Erasmus-MC-gaat-gebruik-EPD-optimaliseren

Cohen J. E. (1988). *Statistical Power Analysis for the Behavioral Sciences*. Hillsdale, NJ: Lawrence Erlbaum Associates, Inc

Cocosila, M., & Archer, N. (2016). A Blended Model of Electronic Medical Record System Adoption in Canadian Medical Practices. *CAIS*, *39*, 22.

Compeau, D. R., & Higgins, C. A. (1995). Computer self-efficacy: Development of a measure and initial test. *MIS quarterly*, 189-211.

DeLone, W. H., & McLean, E. R. (1992). Information systems success: The quest for the dependent variable. *Information systems research*, *3*(1), 60-95.

DeSanctis, G., & Poole, M. S. (1994). Capturing the complexity in advanced technology use: Adaptive structuration theory. *Organization science*, *5*(2), 121-147.

Ebner, K., Bassellier, G., & Smolnik, S. (2019). The Role of IT Feature Recombinations in Individuals' Innovative Use of IT. In *ICIS 2019.*

Evermann, J., & Tate, M. (2012). Comparing the predictive ability of PLS and covariance models. In *ICIS 2012*.

Fornell, C., & Larcker, D. F. (1981). Structural equation models with unobservable variables and measurement error: Algebra and statistics. *Journal of Marketing Research*, *18*(3), 382-388.

Gaskin, J. (2017). Common Method Bias (CMB) in PLS (partial least squares), Gaskination's Statistics. http://youtube.com/Gaskination

Gaskin, J., Godfrey, S., & Vance, A. (2018). Successful system use: It's not just who you are, but what you do. *AIS Transactions on Human-Computer Interaction*, *10*(2), 57-81.

Goh, J. M., Gao, G., & Agarwal, R. (2011). Evolving work routines: Adaptive routinization of information technology in healthcare. *Information Systems Research*, *22*(3), 565-585.

Goodhue, D. L., & Thompson, R. L. (1995). Task-technology fit and individual performance. *MIS quarterly*, 213-236.

Haake, P., Schacht, S., & Maedche, A. (2018). Adaptive System Use Revisited–A Methodological Replication. *AIS Transactions on Replication Research*, *4*(1), 4.

Hair, J. F., Jr., Black, W. C., Babin, B. J., & Anderson, R. E. (2010). Multivariate data analysis (7th ed.). Upper Saddle River, NJ: Prentice Hall.

Hair Jr, J. F., Hult, G. T. M., Ringle, C., & Sarstedt, M. (2017). *A primer on partial least squares structural equation modeling (PLS-SEM)*. Los Angeles: Sage publications.

Hair, J. F., Risher, J. J., Sarstedt, M., & Ringle, C. M. (2019). When to use and how to report the results of PLS-SEM. *European Business Review*.

Holden, R. J. (2010). Physicians' beliefs about using EMR and CPOE: in pursuit of a contextualized understanding of health IT use behavior. *International journal of medical informatics*, *79*(2), 71-80.

Huang, W. M., Chen, T., & Hsieh, C. W. (2014). An Empirical Study on the Physicians' Behavioral Intention with Electronic Medical Record Systems in Taiwan. In *PACIS*.

Hung, S. Y., Yu, W. J., Tsai, M. F., & Yen, D. C. (2013). What Drives Physicians' Intention to Use Electronic Medical Record System: The Roles of Perceived Service Level, Computer Self-Efficacy, and Perceived Risk. In *PACIS* (p. 194).

ICT & Health. (2019, 9 September). Leveranciers EPD beperken betere uitwisseling gegevens. Retrieved from https://www.icthealth.nl/nieuws/leveranciers-epd-beperken-betere-uitwisseling-gegevens/

Ilie, V. (2013). Psychological Reactance And User Workarounds. A Study In The Context Of Electronic Medical Records Implementations. In *ECIS* (p. 24).

Ilie, V., Seha, S., & Sun, W. N. (2009). Socio-Cognitive Assessment of Physicians' Engagement with Electronic Medical Records (EMR): A Pre-EMR Implementation Study in Developing Countries. *AMCIS 2009 Proceedings*, 558.

Kashefi, A., Abbott, P., & Ayoung, A. (2015). User IT adaptation behaviors: What have we learned and why does it matter. *AMCIS 2015*.

Kashefi, A., Nuhu, K., Abbott, P., Ayoung, D., & Alwzinani, F. (2018). Investigating Users' IT Adaptation Behaviors: A Case of a Computerized Work System. In *ICIS 2018.*

Kock, N. (2015). Common method bias in PLS-SEM: A full collinearity assessment approach. *International Journal of e-Collaboration (ijec)*, *11*(4), 1-10.

Lazarus, R. S. (1993). Coping theory and research: Past, present, and future. *Fifty years of the research and theory of RS Lazarus: An analysis of historical and perennial issues*, 366-388.

Li, X., Hsieh, J. P. A., & Rai, A. (2013). Motivational differences across post-acceptance information system usage behaviors: An investigation in the business intelligence systems context. *Information systems research*, *24*(3), 659-682.

Liew, E. J., Poh, Y. H., Koh, S. G., French, J. A., & Teh, P. L. (2018). The Use of Electronic Medical Record System on Dynamic Capabilities and Physician Productivity. *ICEB 2018 Proceedings*

Lowry, P. B., & Gaskin, J. (2014). Partial least squares (PLS) structural equation modeling (SEM) for building and testing behavioral causal theory: When to choose it and how to use it. *IEEE transactions on professional communication*, *57*(2), 123-146.

Marakas, G., Johnson, R., & Clay, P. F. (2007). The evolving nature of the computer self-efficacy construct: An empirical investigation of measurement construction, validity, reliability and stability over time. *Journal of the Association for Information Systems*, *8*(1), 2.

Mettler, T. (2012, December). Post-acceptance of electronic medical records: Evidence from a longitudinal field study. Association for Information Systems. In *ICIS 2012.*

NIVEL. (2018). E-health in verschillende snelheden: eHealth-monitor Den Haag/Utrecht:Nictiz/Nivel.

NOS. (2016, 12 January). Papierwerk ziekenhuizen gaat ten koste van patiënten. Retrieved from https://nos.nl/artikel/2079947-papierwerk-ziekenhuizen-gaat-ten-koste-van-patienten.html

Saunders, M., Lewis, P., & Thornhill, A. (2016). Research Methods for Business Students (7th edition). Harlow: Pearson.

Schmitz, K., Teng, J. T., & Webb, K. (2016). Capturing the Complexity of Malleable IT Use: Adaptive Structuration Theory for Individuals. *MIS Quarterly*, *40*(3), 663-686.

Sposito, V. A., Hand, M. L., & Skarpness, B. (1983). On the efficiency of using the sample kurtosis in selecting optimal lpestimators. *Communications in Statistics-simulation and Computation*, *12*(3), 265-272.

Sun, H. (2012). Understanding User Revisions When Using Information System Features: Adaptive System Use and Triggers. *MIS quarterly*, *36*(2).

Sun, H., Wright, R. T., & Thatcher, J. (2019). Revisiting the Impact of System Use on Task Performance: An Exploitative-Explorative System Use Framework. *Journal of the Association for Information Systems*, *20*(4), 3.

Sun, J. (2017). The effect of information technology on IT-facilitated coordination, IT-facilitated autonomy, and decision-makings at the individual level. *Applied Economics*, *49*(2), 138-155.

Venkatesh, V. (2006). Where to go from here? Thoughts on future directions for research on individual-level technology adoption with a focus on decision making. *Decision Sciences*, *37*(4), 497-518.

Venkatesh, V., Brown, S. A., Maruping, L. M., & Bala, H. (2008). Predicting different conceptualizations of system use: the competing roles of behavioral intention, facilitating conditions, and behavioral expectation. *MIS quarterly*, 483-502.

Venkatesh, V., & Davis, F. D. (2000). A theoretical extension of the technology acceptance model: Four longitudinal field studies. *Management science*, *46*(2), 186-204.

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS quarterly*, 425-478.

Venkatesh, V., Zhang, X., & Sykes, T. A. (2011). “Doctors do too little technology”: A longitudinal field study of an electronic healthcare system implementation. *Information Systems Research*, *22*(3), 523-546.

Wang, Y., & Byrd, T. A. (2017). Business analytics-enabled decision-making effectiveness through knowledge absorptive capacity in health care. *Journal of Knowledge Management*, *21*(3), 517-539.

Weeger, A., & Gewald, H. (2013). Examining Social And Cognitive Aspects Determining Physician's Adoption Of Electronic Medical Records. In *ECIS* (p. 66).

Weigel, F. K., Landrum, W. H., & Hall, D. J. (2009). Human-technology adaptation fit theory for healthcare. In *Twelfth Annual Conference of the Southern Association for Information Systems (SAIS), Charleston, SC*.

Wu, Y., Choi, B., Guo, X., & Chang, K. T. T. (2017). Understanding User Adaptation toward a New IT System in Organizations: A Social Network Perspective. *Journal of the Association for Information Systems*, *18*(11), 7087-813.

Zhou, J. (2003). When the presence of creative coworkers is related to creativity: Role of supervisor close monitoring, developmental feedback, and creative personality. *Journal of applied psychology*, *88*(3), 413.

Appendix A: Search queries

Construct	Search Term(s)	AIS # of articles	Google Scholar # of articles	Articles used
Behavioral EMR adaptation	behav* AND emr AND adaptation	184	16400	Barki et al., 2007; Beaudry & Pinsonneault, 2005; Benlian, 201; Ebner, et al., 2019; Gaskin et al., 2018; Goh et al., 2011; Ilie, 2013; Schmitz et al., 2016; Sun, 2012; Sun et al., 2019; Venkatesh et al., 2003; Wu et al., 2017
	"behavior* emr adaptation"	0	0	
	individual emr adaptation	249	31700	
	“individual emr adaptation”	262	0	
	"individual adaptation behavior" is	20	33	
	"individual adaptation behavior" it	20	29	
	“task technology adaptation”	13869	55	
	"adaptive system use"	67	253	
	adaptations of electronic health records	2208	152000	
	“IT feature use”	20025	36	
Personal innovativeness	emr "personal innovativeness"	9	374	Agarwal & Karahanna, 2000; Agarwal & Prasad, 1998; Cocosila & Archer, 2016; Ebner et al., 2019; Gaskin et al., 2018; Kashefi et al., 2018; Li et al., 2013; Wu et al., 2017
	"personal innovativeness"	551	9550	
Decision-making effectiveness	emr "decision-making effectiveness"	2	61	Boulesnane & Bouzidi, 2013; Cao et al., 2019; ; DeLone & McLean, 1992; Holden, 2010; Liew et al., 2018; Sun, 2017; Venkatesh, 2006; Wang & Byrd, 2017
	emr adaptation "decision-making effectiveness"	1	115	
	"information technology" adaptation "decision-making effectiveness"	75	1930	
	"information technology" adaptation "better decisions"	490	18100	
	"information technology" adaptation "better decisions" healthcare	115	10900	
	"information technology" "decision*" healthcare	3714	77000	

	adaptive "information technology" "decision*" healthcare	2182	41600	
	adaptive "information technology" "quality of decision*" healthcare	24	1660	
	behavioral expectation system use healthcare decision	2471	95200	
	"it feature use" healthcare decision making	3	12	
Computer self-efficacy	emr "computer self-efficacy"	25	946	Anja et al., 2014; Benlian, 2015; Cocosila & Archer, 2016; Compeau & Higgins, 1995; Hung et al., 2013; Ilie et al., 2009; Marakas et al., 2007; Mettler, 2012; Weeger & Gewald, 2013
	"computer self-efficacy"	1076		
Facilitating conditions	emr "facilitating conditions "	32	674	Ilie et al., 2009; Haake et al., 2018; Huang, Chen, & Hsieh, 2014; Sun, 2012; Venkatesh et al., 2000; Venkatesh et al., 2003; Venkatesh et al., 2008; Venkatesh et al., 2011; Weeger & Gewald, 2013; Zhou, 2003
	emr “facilitating conditions “ adaptation	24	1030	
Task-technology fit	“task-technology fit”	1101	15300	Goodhue & Thompson, 1995
Coping theory	“Coping theory”	91	22700	Beaudry & Pinsonneault, 2005; Ilie, 2013; Kashefi et al., 2015; Lazarus, 1993; Wu et al., 2017
Adaptive Structuration Theory	“Adaptive structuration theory”	15597	5700	DeSanctis & Poole, 1994; Argyres, 1996; Schmitz et al., 2016; Weigel et al., 2009

Table 8 Results research found in AIS and Google Scholar, 1992 – 2019

Appendix B: Questionnaire

Section 1: General questions

Label	***Question***	***Choose an answer***
Profess	What is your current qualification?	○ Specialist doctor (1) ○ Resident (specialist) (3) ○ General practitioner (4) ○ Resident (3) ○ Nurse (2) ○ Doctor’s assistant (3) ○ Other (2 or 4)
Edu	What is your highest educational level?	○ Doctorate (1) ○ Master (2) ○ Bachelor (3) ○ MBO (4) ○ High school (5) ○ Other (2, 3 or 4)
Insti	In what type of medical facility do you work with the EMR? (In case of employment in multiple facilities, please select the one choice in which you work the most with the EMR)	○ General hospital (1) ○ University Medical Center (NL) (1) ○ University Medical Center (BE) (1) ○ Clinical hospital (1) ○ Military hospital(1) ○ Centre for Nursing(2) ○ Rehabilitation Center(2) ○ GGD (NL)(2) ○ Other(1 or 2)
Freq	How many times do you enter data in the EMR or consult the EMR?	○ Every day (1) ○ Several times a week (2) ○ Once a week (3) ○ Less than once a week (4) ○ Never (5)
Exp	How long have you been working with the EMR?	○ Less than 1 year (1) ○ Between 1 and 5 years (2) ○ Between 5 and 10 years (3) ○ Longer than 10 years (4)
Age	What is your age?	○ 18-25 (1) ○ 26-35 (2) ○ 36-45 (3) ○ 46-55 (4) ○ 56-65 (5) ○ 65+ (6)
Gender	What is your gender?	○ Male (1) ○ Female (2)

Table 9 General questions (coding is in parentheses)

Section 2: Research questions

	Label	*(1) Strongly disagree*	*(2) Disagree*	*(3) Somewhat disagree*	*(4) Neither agree or disagree*	*(5) Somewhat agree*	*(6) Agree*	*(7) Strongly agree*
Personal innovativeness	Agarwal & Karahanna, 2000							
Personal innovativeness is defined as an individual trait reflecting one's willingness to try out any new technology.								
If I heard about new information technology, I would look for ways to experiment with it	PI_1	0	0	0	0	0	0	0
In general, I am hesitant to try out new information technology	PI_2	0	0	0	0	0	0	0
Among my peers, I am usually the first to try out new information technologies	PI_3	0	0	0	0	0	0	0
I like to experiment with new information technologies	PI_4	0	0	0	0	0	0	0
Computer self-efficacy	Compeau & Higgins, 1995							
Computer self-efficacy can be considered the belief that one has the capability to perform a particular behavior.								
I could complete any particular job using the software if there was no one around to tell me what to do as I go	CSE_1	0	0	0	0	0	0	0
I could complete any particular job using the software if I had never used a package like it before	CSE_2	0	0	0	0	0	0	0
I could complete any particular job using the software if I had only the software manuals for reference	CSE_3	0	0	0	0	0	0	0
I could complete any particular job using the software if I had seen someone else using it before trying it myself	CSE_4	0	0	0	0	0	0	0
I could complete any particular job using the software if I could call someone for help if I got stuck	CSE_5	0	0	0	0	0	0	0
I could complete any particular job using the software if someone else had helped me get started	CSE_6	0	0	0	0	0	0	0
I could complete any particular job using the software if I had a lot of time to complete the	CSE_7	0	0	0	0	0	0	0

	Label	(1) Strongly disagree	(2) Disagree	(3) Somewhat disagree	(4) Neither agree or disagree	(5) Somewhat agree	(6) Agree	(7) Strongly agree
job for which the software was provided								
I could complete any particular job using the software if I had just the built-in help facility for assistance	CSE_8	0	0	0	0	0	0	0
I could complete any particular job using the software if someone showed me how to do it first	CSE_9	0	0	0	0	0	0	0
I could complete any particular job using the software if I had used similar packages before this one to do the same job	CSE_10	0	0	0	0	0	0	0
Facilitating conditions	Adapted from Venkatesh et al., 2003							
The extent to which a person believes that there is an organizational and technical infrastructure to support his or her use of a system. As in this case, the EMR. It is used to represent the external support one can get from the working environment.								
Guidance was available to me for the use of the EMR system	FC_1	0	0	0	0	0	0	0
Specialized instruction concerning the EMR system was available to me	FC_2	0	0	0	0	0	0	0
A specific person (or group) is available for assistance with EMR difficulties	FC_3	0	0	0	0	0	0	0
There is an instruction note for extending or modifying the system	FC_4	0	0	0	0	0	0	0
Behavioral EMR adaptation	Wu et al., 2017; Barki et al., 2007							
Concerns the degree to which users change the functions of the EMR system and task procedures to fit personal preferences.								
I spent efforts (in time and energy)on changing functions of the EMR system to fit my work	BHA_1	0	0	0	0	0	0	0
I spent efforts (in time and energy) on changing my tasks so that they better fit the EMR system	BHA_2	0	0	0	0	0	0	0
I spent efforts (in time and energy) so that the EMR and my tasks would be in harmony with each other	BHA_3	0	0	0	0	0	0	0
Overall, I spent efforts in recommending changes to the EMR system	BHA_4	0	0	0	0	0	0	0

	Label	(1) Strongly disagree	(2) Disagree	(3) Somewhat disagree	(4) Neither agree or disagree	(5) Somewhat agree	(6) Agree	(7) Strongly agree
I'm using the EMR in a different way than when I began using the EMR	BHA_5	0	0	0	0	0	0	0
Decision-making effectiveness	Adapted from Cao et al., 2019							
To adapt the functions in the EMR-system and task procedures on personal preferences can improve the effectiveness of the decision-making process.								
I am more capable than my colleagues in responding quickly to change in the status of a patient by consulting the EMR	DME_1	0	0	0	0	0	0	0
I am more capable than my colleagues in making the correct decisions based on real-time data in the EMR	DME_2	0	0	0	0	0	0	0
I am more capable than my colleagues in understanding patients in their treatment	DME_3	0	0	0	0	0	0	0

Table 10 Research questions (coding in parentheses)

Appendix C: Indicator item loadings

Construct & Items	Item loadings	Mean	Standard Deviation
Behavioral EMR adaptation			
BEA_1	0.804	4.556	1.736
BEA_2	0.758	4.015	1.690
BEA_3	0.809	4.684	1.605
BEA_4	0.801	4.556	1.624
BEA_5	0.703	4.752	1.652
Computer self-efficacy			
CSE_1	-0.496	5.218	1.553
CSE_2	-0.638	4.120	1.645
CSE_3	-0.043	4.586	1.452
CSE_4	0.737	5.376	1.180
CSE_5	0.622	5.782	0.976
CSE_6	0.742	5.248	1.253
CSE_7	0.370	5.278	1.178
CSE_8	0.015	4.992	1.265
CSE_9	0.821	5.466	1.167
CSE_10	0.506	5.376	1.128
Decision-making effectiveness			
DME_1	0.890	4.474	1.549
DME_2	0.929	4.789	1.344
DME_3	0.747	4.699	1.487
Facilitating conditions			
FC_1	0.901	5.338	1.481
FC_2	0.906	5.135	1.481
FC_3	0.769	5.737	1.195
FC_4	0.735	5.090	1.390
Personal innovativeness			
PI_1	0.825	5.068	1.287
PI_2	0.695	4.752	1.633
PI_3	0.826	4.173	1.620
PI_4	0.879	4.256	1.639

Table 11 Items and descriptive statistics

Appendix D: Outer loadings

	BEA	CSE	DME	FC	PI
BEA_1	0.802				
BEA_2	0.762				
BEA_3	0.813				
BEA_4	0.796				
BEA_5	0.705				
CSE_10		0.667			
CSE_4		0.833			
CSE_5		0.752			
CSE_6		0.834			
CSE_7		0.495			
CSE_9		0.851			
DME_1			0.892		
DME_2			0.934		
DME_3			0.723		
FC_1				0.901	
FC_2				0.907	
FC_3				0.768	
FC_4				0.735	
PI_1					0.825
PI_2					0.695
PI_3					0.826
PI_4					0.879

Table 12 Outer loadings after removal 4 items in CSE

Appendix E: CTA-PLS

Tetrads	Std Beta	Std Error	t-value	p-value	CI
Behavioral EMR adaptation					
1: BEA_1,BEA_2,BEA_3,BEA_4	0.928	0.424	2.220	0.026*	[-0.033, 1.939]
2: BEA_1,BEA_2,BEA_4,BEA_3	0.178	0.551	0.322	0.747(ns)	[-1105, 1.460]
4: BEA_1,BEA_2,BEA_3,BEA_5	0.900	0.406	2.248	0.025*	[-0.018, 1.873]
6: BEA_1,BEA_3,BEA_5,BEA_2	-0.494	0.258	1.968	0.049*	[-1120, 0.080]
10: BEA_1,BEA_3,BEA_4,BEA_5	-0.862	0.393	2.230	0.026*	[-1805, 0.024]
Computer self-efficacy					
1: CSE_10,CSE_4,CSE_5,CSE_6	0.109	0.064	1.736	0.083*	[-0.049, 0.277]
2: CSE_10,CSE_4,CSE_6,CSE_5	0.081	0.082	0.974	0.330(ns)	[-0.130, 0.287]
4: CSE_10,CSE_4,CSE_5,CSE_7	0.113	0.056	2.082	0.037*	[-0.023, 0.261]
6: CSE_10,CSE_5,CSE_7,CSE_4	-0.091	0.074	1.296	0.195(ns)	[-0.287, 0.087]
7: CSE_10,CSE_4,CSE_5,CSE_9	0.010	0.056	0.219	0.826(ns)	[-0.128, 0.158]
10: CSE_10,CSE_4,CSE_6,CSE_7	0.075	0.071	1.071	0.284(ns)	[-0.103, 0.258]
16: CSE_10,CSE_4,CSE_7,CSE_9	-0.022	0.101	0.224	0.823(ns)	[-0.279, 0.234]
22: CSE_10,CSE_5,CSE_6,CSE_9	-0.001	0.060	0.048	0.962(ns)	[-0.158, 0.148]
26: CSE_10,CSE_5,CSE_9,CSE_7	-0.052	0.060	0.890	0.373(ns)	[-0.208, 0.098]
Facilitating conditions					
1: FC_1,FC_2,FC_3,FC_4	0.733	0.319	2.331	0.020*	[0.130, 1.382]
2: FC_1,FC_2,FC_4,FC_3	0.842	0.315	2.717	0.007**	[0.253, 1.489]
Personal innovativeness					
1: PI_1,PI_2rev,PI_3,PI_4	0.584	0.317	1.900	0.057*	[-0.001, 1.241]
2: PI_1,PI_2rev,PI_4,PI_3	0.923	0.305	3.108	0.002**	[0.375, 1.571]

*** p<0.001 ** p<0.01, *p<0.1, (ns) not significant

Table 13 CTA-PLS

Appendix F: Multigroup Analysis for gender

Relationship	Gender	Std Beta	Std Error	t-value	p-value
BEA -> DME	Female	0.088	0.122	0.704	0.482(ns)
	Male	0.173	0.204	0.853	0.394(ns)
	Parametric test			0.380	0.705(ns)
CSE -> BEA	Female	0.086	0.124	0.730	0.466(ns)
	Male	-0.184	0.224	1.236	0.217(ns)
	Parametric test			1.523	0.130(ns)
CSE -> DME	Female	0.397	0.115	3.208	0.001***
	Male	-0.129	0.274	0.570	0.569(ns)
	Parametric test			2.111	0.037*
FC -> BEA	Female	0.163	0.100	1.942	0.053*
	Male	0.045	0.194	0.019	0.985(ns)
	Parametric test			0.954	0.342(ns)
Moderating Effect FC*CSE -> BEA	Female	0.043	0.179	0.489	0.625(ns)
	Male	-0.127	0.173	0.653	0.514(ns)
	Parametric test			0.656	0.513(ns)
Moderating Effect FC*PI -> BEA	Female	-0.029	0.127	0.915	0.360(ns)
	Male	0.126	0.108	0.860	0.390(ns)
	Parametric test			0.975	0.332(ns)
PI -> BEA	Female	0.240	0.104	2.422	0.016*
	Male	0.153	0.208	0.853	0.394(ns)
	Parametric test			0.357	0.722(ns)
PI -> DME	Female	0.092	0.128	0.688	0.492(ns)
	Male	0.102	0.243	0.433	0.665(ns)
	Parametric test			0.067	0.947(ns)

*** p<0.001 ** p<0.01, *p<0.1, (ns) not significant
Sample size: female = 96; male = 37

Table 14 Multigroup analysis for gender

Appendix G: Multigroup Analysis for occupation

Relationship	Occupation	Std Beta	Std Error	t-value	p-value
BEA -> DME	Nurse	0.124	0.120	0.978	0.329(ns)
	Medical professional	0.188	0.192	0.917	0.360(ns)
	Parametric test			0.274	0.784(ns)
CSE -> BEA	Nurse	-0.041	0.137	0.340	0.734(ns)
	Medical professional	0.092	0.168	0.821	0.412(ns)
	Parametric test			0.838	0.404(ns)
CSE -> DME	Nurse	0.342	0.139	2.372	0.018*
	Medical professional	-0.200	0.329	0.943	0.346(ns)
	Parametric test			2.095	0.038*
FC -> BEA	Nurse	0.156	0.100	1.749	0.081*
	Medical professional	0.102	0.165	0.782	0.434(ns)
	Parametric test			0.255	0.799(ns)
Moderating Effect FC*CSE -> BEA	Nurse	-0.076	0.163	0.899	0.369(ns)
	Medical professional	-0.056	0.356	1.018	0.309(ns)
	Parametric test			1.492	0.138(ns)
Moderating Effect FC*PI -> BEA	Nurse	-0.038	0.121	1.039	0.299(ns)
	Medical professional	0.118	0.097	0.981	0.327(ns)
	Parametric test			1.258	0.211(ns)
PI -> BEA	Nurse	0.131	0.132	1.019	0.309(ns)
	Medical professional	0.452	0.177	3.499	0.001***
	Parametric test			2.212	0.029*
PI -> DME	Nurse	0.070	0.169	0.181	0.856(ns)
	Medical professional	-0.079	0.218	0.236	0.814(ns)
	Parametric test			0.297	0.767(ns)

*** p<0.001 ** p<0.01, *p<0.05
Sample size: nurse = 85; medical professional = 48

Table 15 Multigroup analysis for occupation

Appendix H: Reflective essay

For the past ten months, I have been writing and mostly rewriting my thesis. This journey has given me new insights into how to conduct research and has updated my existing knowledge. In this reflective essay, I would like to contemplate what I have learned, what part of my research project could go better, and what segment went well.

The questionnaire and the main model were already given by the supervisor. The basis of the thesis is already constructed on a strong foundation. Instead, the effort by me could be put into selecting relevant literature and to gain a better understanding of the field of technology acceptance. My search was therefore more focused.

One aspect of my research project did not go well and that is finding respondents through e-mail. I made an e-mail list containing the e-mail addresses of 1068 nurses and doctors. The intention was to send this through Mailchimp, which at my current work is commonly used. Most of the e-mails got bounced or ended up in the spam filter. Normally a response of 8% would be expected. Instead, this approach has led to almost none additional respondents. I discovered that the days of finding respondents through e-mail and forums are over and instead this has changed to social media. By using Facebook and LinkedIn Premium most of my respondents could be collected. On Facebook, there are community groups that mostly include nurses. By joining and posting the survey in these groups, has led to additional responses. The most effective method is writing a private message through InMail to nurses and ask them to help fill in the questionnaire and sent it further to their coworkers. The downside is that LinkedIn Premium only allows 15 private messages and you need to have a link with them (for example if you went to the same university or worked at the same workplace). Asking nurses to connect on LinkedIn for you to send the questionnaire to them has proven zero results.

The biggest adjustment I made to my research practice was changing the approach from an exploratory approach to an affirmative approach. After the data was collected from the survey, I analyzed the survey responses in SPSS by checking the reliability and the number of factors by applying exploratory factor analysis (EFA). I was testing if the assumptions, which were made a priori of this research, were correct. However, the factors chosen a priori were based on prior research and thus this approach was not necessary. Instead administering the model in SmartPLS to test the reliability, then the AVE, and lastly the discriminant reliability would be a more fitting procedure. Furthermore, Hair et al. (2017) mention that cluster analysis and EFA is a first-generation technique and that PLS-SEM has been developed to overcome the weaknesses of these first-generation methods. PLS-SEM is a second-generation technique (Hair, et al., 2017, p3/4).

By using SmartPLS to analyze the answers of the respondents, I could improve my knowledge of statistics. Concepts like model fit and effect size were new to me. SmartPLS proved to be an intuitive tool that was easy to use. Furthermore, videos by James Gaskin and others that explain how to perform certain tests in SmartPLS were a valuable resource. This is a new way of learning for me and it opens possibilities to go deeper into the data. I could, for example, figure out how to do the CTA-PLS test or calculate the q^2 from the Q^2.

Further, adjustments that I could have made was to do the data collection at an earlier time. Especially in my network people work in the Thorax department at the Erasmus MC (specialized in the part of the human body between the neck and the abdomen). These doctors and nurses were extremely busy preparing for the influx of patients due to Covid-19.

What I would do the same in the event of another research project is how the theoretical framework was done. The first step was to find related articles and to review the quality of the journals that published those articles. The next step would be, to inspect the theories in those papers and theorize which would fit into my research. In this thesis, I chose coping theory as an important theory to base my work on, instead of TAM or UTAUT models, which are common in research on the acceptance of technology. Due to this thesis using personal traits of nurses and doctors to explain how the EMR is being used in daily work routines, coping theory which comes from psychology proved to be a better fit.

All in all, my learning experience from this research project has been positive. One of my main goals of joining this university was to refresh my knowledge of the statistical field and discover what new methods have been developed. I have learned how to use the internet effectively to do better research and reach out to respondents. New skills were acquired regarding PLS. It was interesting to see how computer sciences also started to look into the importance of the human factor in handling the software. Companies can build a great EMR, but if the people for who it is designed are using it differently or even rejecting it, this can have strong results on the effectiveness of the EMR.