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Universitair Medisch Centrum Utrecht

Master thesis for Master and Science Degree.

The Healthcare No-show Reduction Method

Universitair Medisch Centrum Utrecht

NO-SHOW Patients

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Abstract

This research presents the method that supports the healthcare sector in reducing the number of no-show patients. The method is applicable for hospitals, clinics or other medical care centers that are willing to reduce their no-show rate, by following these phases: Select dataset, analyze demographic factors, analyze environmental factors, analyze patients' behaviors and analyze doctors. Based on the gathered knowledge from the prior phases, a plan to reduce the number of no-show patients can be created and suitable interventions can be employed to tackle the no-show patients.

First the patients' demographic factors, environmental factors and patients' behavior are examined through literature research. Next, several methods, models, techniques and technologies to mitigate no-show are described. Some of them are well known in the healthcare sector and provide a basis into reducing the number of no-show patients, while the other one are new or related to reduce the number of no-show patients.

The method is evaluated and validated by conducting qualitative semi-structured interviews, utilizing NVIVO. As a result, the method is successfully evaluated and validated on the following criteria: completeness, consistency, efficiency and applicability. By applying the method an appropriate strategy to reduce the number of no-show patients in hospitals, clinics or other medical care centers can be built.

Furthermore, data analysis on a large no-show dataset consisting on average 900 thousand patients has taken place. Moderators have been analyzed between patients' demographic factors variables and environmental factors variables to no-show. Finally, The method has been tested, based on the data analysis results as a recommendation on how to reduce the number of no-show patients.

Keywords: *no-show, non-attendance, healthcare, methods, models, techniques*

Preface

This thesis is the final part of my Master program of Business Informatics at Utrecht University. I started this research on 4th December 2013 and it was carried out at University Medical Center Utrecht (UMCU), a nationally and internationally renowned institute in Utrecht. I chose this subject for two reasons, one because of my interest in data analysis, on the other hand because with this thesis and its results, hospitals, clinics or other medical care centers can benefit from. This research was challenging but also very educational.

I would like to express my gratitude to some special people, without whom I would not have accomplished this research. First of all, I would like to thank my teachers from Master in Business Informatics at Utrecht University, for offering me invaluable knowledge and a lot of inspiration. I am truly thankful to my first supervisor dr. Marco R. Spruit, for providing me with useful advice and feedback for carrying out this project, finalizing this thesis and writing the scientific papers. I would also like to thank dr. Ronald Batenburg, my second supervisor in this thesis for providing me with ideas and feedback. In addition, I would like to thank dr. Ad Feelders, a lecturer in the Advanced Data Mining course, who gave me feedback on the selection of data mining techniques for the data analysis. Finally, I would especially like to express my gratitude to a master student in Youth Studies, Rachel Croes, for giving me feedback on my writing for this thesis.
My thankfulness also goes to UMCU, for providing me with facilities and important data, which were necessary for this research. I would like to thank Hans van Belleghem, the head care group administration and information at UMCU, who offered me this internship, and invested time to give me interesting insights in this project.

Last but not least, I would like to thank my family and friends for the support and understanding me while I was writing this thesis.

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1 Introduction

The healthcare sector is currently experiencing certain fundamental changes. Healthcare organizations are reorganizing their processes to reduce costs, be more competitive, and provide better and more personalized customer care. This new business strategy requires healthcare organizations to implement new technologies, such as Internet applications, enterprise systems, mobile technologies and data mining in order to achieve their desired business goals (Siau, 2003).

No-show at hospitals is an important national problem the healthcare sector is trying to cope with within the last decade (Hamilton, Round, & Sharp, 2002). A no-show in the healthcare sector is an appointment, where the patient or client did not show-up or try to call the hospital to cancel the appointment or reschedule the appointment (Detman & Gorzka, n.d.). These no-shows reduce scheduling capacity, contribute to inefficiency, lower the quality of care, and negatively affect the working environment for providers and staff (Ulmer & Troxler, 1999). Moreover, with medical care costs rising, efforts should be made to examine areas where a possible waste of resources might take place (Hurtado, Greenlick, & Colombo, 1973). No-show is not a phenomenon that only evolved in a day and therefore it cannot be resolved overnight. It is a phenomenon that is happening more and more often all over the world, it occurs among all age groups and people from various different social, cultural and ethnic backgrounds; it affects all specialties and does not seem to be restricted to a particular healthcare sector (Hardy, O'Brien, & Furlong, 2001). In some clinics and hospitals, up to 42% of scheduled patients failed to show up for their pre-booked appointments (Muthuraman & Lawley, 2008).
Lin, Muthuraman, and Lawley (2011) reported patient no-show rates from 22% to more than 50%, especially prevalent in mental health, pediatrics and dentistry. This does not only occur in the healthcare sector, but also, for example, in the aviation industry, in hotels and on cruise lines.

To describe how no-show affects the healthcare sector and how the healthcare sector is coping with this phenomenon, information needs to be conducted and recent activities that have already been undertaken to reduce missed patient appointments, need to be looked into too. According to Pesata, Pallija, and Webb (1999), no-show patients deprive themselves of professional services, disrupt client-care provider relationships and reduce the opportunity for other patients to receive timely care. Daggy et al. (2011) state that a patient waiting for his/her appointment costs the organization €0.25 per minute on average, based on their descriptive study of no-show patients. Furthermore, the healthcare sector suffers a tremendous loss of €443 million on a yearly basis due to administrative costs and other related costs as a consequence of the no-shows (Mitchell & Selmes, 2007).

Henceforth, further in-depth understanding of the reasons and factors why patients are unable to keep their appointments can be very useful and helpful in developing changes and policies to address unmet patient needs, reduce the healthcare sector's costs, and provide an effective delivery on medical care services by developing a method. This method needs to capture these aspects by focusing on different factors, such as the patients' demographic factors, environmental factors and patients' behavior.

In different previous studies of patients, hospitals often encounter the following three subjects, namely: the arrival rate, the cancellation rate and the no-show rate of a patient. In this research, we focus on the latter, the no-show rate of patients.

As shown in Figure 1, no-show in the healthcare sector is mainly centralized in the following group factors of determinants: social factors, demographic factors, environmental factors, medical factors, and the organization of health services (Dove & Schneider, 1981). The focus of this research is especially on the demographic and environmental factors that influence patients in a way that it leads to no-show. The research focuses on these factors, because these are responsible for the healthcare sector's highest costs due to no-show and are also known to lead to the most popular predictions of no-show. The demographic factors include patients' characteristics and patients' behavior. The environmental factors regarding to no-show include factors, such as travel distance and transportation of a particular patient (Anderson, 1973).

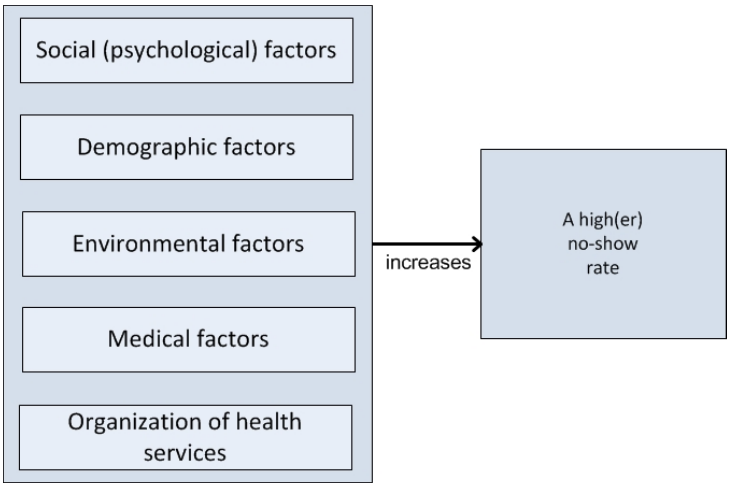


Figure 1. No-show centralized factors, retrieved from (Dove & Schneider, 1981).

1.1 Problem statement

No-show is not a new problem, however, it is a problem that affects all medical specialties. As Garuda, Javalgi, and Talluri (1998) explained, one of the most important reasons for the current failure to effectively resolve the no-show issue, lies in the surprisingly sparse number of studies attempting to match specific causes of no-show with cause-specific solutions to these problems. There are certainly scientific researches (Daggy et al., 2011; Hamilton et al., 2002; Kruse, Rohland, & Wu, 2002; Lacy, Paulman, Reuter, & Lovejoy, 2004; Parikh et al., 2010; Satiani, Miller, & Patel, 2009) that studied why or for what reasons no-show patients occur in the healthcare sector, however, no method has been created that provides an *insight into the process* of reducing the number of no-show patients in hospitals. Therefore, this research attempts to create a method to reduce no-show in the healthcare sector by studying patients' demographic factors, their environmental factors, their behavior and the relation between these factors that lead to no-show. In addition, literature studies on interventions to prevent no-show, such as models and techniques, are also studied and taken into consideration in this research.

1.2 Research Question

The problem statement resulted in the following research question:

"How can a method be created that supports the healthcare sector in reducing the number of no-show patients, based on studies on patients' demographic factors, environmental factors, behavior of patients and the use of technology?"

In order to answer the main research question a drill-down is required. This drill-down consists of two steps. First, a systematic literature study is performed to collect scientific knowledge of studies on patients' factors and behaviors. Second, qualitative structured interviews are held and a data analysis is performed to gain more knowledge on the subject. In order to answer the research question the following five sub-questions are created:

Sub-question 1: What are the patients' demographic factors and how do these factors influence patients towards no-show?

Sub-question 2: What are the environmental factors that influence patients towards no-show and how are these factors related to the patients' demographic factors?

Sub-question 3: How can a patient's behavior have an influence towards no-show and how is this related to the patients' demographic factors and the environmental factors?

Sub-question 4: What are the previously used methods, models and techniques in the healthcare sector with regard to no-show and how can these best support the healthcare sector in its battle against no-show?

Sub-question 5: How can Information Technology support healthcare to reduce no-show?

1.3 Scope & Goal

The scope of this research is not limited exclusively to hospitals; it also includes clinics and other medical care centers in the healthcare sector. There are numerous demographic and environmental factors that influence patients into not attending their appointment, which leads to a rapid increase of expenditures (Anderson, 1973). If hospitals can reduce their costs, they can focus more on customer care and provide better electronic devices and technologies for their staff members, which can help them do their work more efficiently and on time.

In conclusion, understanding the relation between patients' demographic factors, environmental factors and patients' behavior that are potentially related to no-show should improve the rate of kept appointments and ultimately help preserve staff and financial resources. Therefore the goal of this research is to develop a method to obtain an insight into the process of reducing no-show. This method provides a schematic overview on how to approach and reduce the number of no-show patients for hospitals, clinics and other medical care centers. These healthcare institutions can henceforth use this method as a tool or guide, which allows them to make profound decisions on how to confront no-show patients.

To develop such a method that gives an insight into the process of reducing the number of no-show patients, this research is set out to collect literature studies on patients' demographic factors, environmental factors and patients' behavior towards no-show and information on how technologies, such as smart phone, social networks and web forms can help prevent no-show patients.

1.4 Relevance

Hospitals, clinics and other medical care centers globally are trying to reduce their costs as much as possible due to no-show patients (Hamilton et al., 2002). This research benefits the healthcare sector by providing an insight into how to reduce the no-show rate, which eventually will lead to reduced costs.

1.4.1 Scientific contribution

The research is scientifically relevant because there currently is no similar method to reduce the number of no-show patients in the healthcare sector. It is interesting for the researchers to see how information about patients' demographic factors, environmental factors, patients' behavior, technology and interventions with regard to no-show can be combined, and further be developed to create a method to support the healthcare sector. This research is also significant for other researchers, because it is the first step towards reducing no-show and serves as the basis for other research on this subject. Furthermore, this research creates the source of information to perform future research.

1.4.2 Societal contribution

The societal contributions of this research include the results and therefore the method that is developed, which provides new insights and a schematic overview that may serve to reduce no-show patients in the healthcare sector. Next to that, the results from this research may help hospitals, clinics and other medical care centers to understand the factors associated with no-show. Ultimately, hospitals can utilize the method to give presentations in order to transfer knowledge to their staff members regarding the reduction of the number of no-show patients. This knowledge helps to improve the communication between the staff and their patients and creates a better understanding of the patients.

1.5 Explanation of concepts & definitions

In this research, several concepts are used that either have multiple or unclear definitions. Therefore, this section provides an overview of definitions of concepts that are frequently used and are fundamental to this research.

Definition of concepts	
Data mining	"Data mining is the process of searching and analyzing data in order to find implicit, but potentially useful, information. It involves selecting, exploring and modeling large amounts of data to uncover previously unknown patterns, and ultimately comprehensible information, from large databases."

	(Berry & Linoff, 1997)
Data analysis	Analysis of data is a process of inspecting, cleaning, transforming, and modeling data with the goal of highlighting useful information, suggesting conclusions, and supporting decision making (Field, 2009).
Pattern	"A pattern is a local structure, in a possibly vast search space, describing data with an anomalously high density compare with that expected in a baseline model. Patterns are usually embedded in a mass of irrelevant data." (Hand, 2007)
Regression	Regression shows the relationships between variables for the purpose of predicting future values (Field, 2009).
Clustering	"A common descriptive task where one seeks to identify a finite set of categories or clusters to describe the data." (Fayyad, Piatetsky-shapiro, & Smyth, 1996)
Correlation	Correlation shows the statistical measure that indicates the extent to which two or more variables fluctuate together. A positive correlation indicates the extent to which those variables increase or decrease in parallel, whereas a negative correlation indicates the extent to which one variable increases as the other decreases (Field, 2009).
Classification	"A function that maps (classifies) a data item into one of several predefined classes." (Fayyad et al., 1996)
Dependency modeling	"Consists of finding a model that describes significant dependencies between variables." (Fayyad et al., 1996)
Direct factors	Factor A influences Factor B.
Moderator factor	"A moderator is a qualitative (e.g., sex, race, class) or quantitative (e.g., level of reward) variable that affects the direction and/or strength of the relation between an independent or predictor variable and a dependent or criterion variable." (Baron & Kenny, 1986)
Database	"Database is a set of tables containing data fitted into predefined categories. Each table contains one or more data categories in columns. Each row contains a unique instance of data for the categories defined by the columns. Users

	can access or reassemble the data in different ways without having to reorganize the database tables." (Leavitt, 2010)
Dataset	"Dataset is a stable, aggregated collection of data described by objects or object classes and used by a data flow." (Brinkkemper, Saeki, & Harmsen, 1999)
SQL Query	Structured Query Language (SQL) query "is the programming language for querying and updating relation databases." (Leavitt, 2010)
Data warehouse	A data warehouse is defined as a "subject-oriented integrated, time-variant, and non volatile collection of data in support of management's decision-making process." (Baars & Kemper, 2008)
eHealth	"The use of Internet or Web technology in healthcare is called eHealth." (Van de Belt, Engelen, Berben, & Schoonhoven, 2010)
mHealth	"Emerging mobile communications and network technologies for healthcare systems." (Istepanian, Laxminarayan, & Pattichis, 2006)
Web 2.0	"A set of economic, social, and technology trends that collectively form the basis for the next generation of the Internet, a more mature, distinctive medium characterized by user participation, openness, and network effects." (Reilly, 2007)

Table 1. Research definition and concepts.

1.6 Thesis overview

The rest of this research is organized as follows. Chapter 2 describes the research approach, how this thesis is organized with its threats of validity and the interview and data analysis method. Chapter 3 provides a thorough literature study on no-show patients including the relation between patients' demographic factors, environmental factors and their behavior with regard to no-show. In addition, chapter 3 gives an overview of several interventions and discusses how Information Technology can be utilized to reduce the number of no-show patients. Finally, based on the conducted literature research in chapter 3, the method to reduce no-show is created, which consists of a PDD and a flowchart, as shown in chapter 4. In chapter 5, several semi-structured expert interviews are described and analyzed in order to collect more knowledge on no-show patients and to evaluate and improve the discussed method. In addition, chapter 5 uses several data analysis techniques on the large data set conducted from UMCU to gain more knowledge on what influences UMCU's no-show patients, and, more importantly, to evaluate the method in practice. Last, in chapter 6 the conclusion of this research is drawn.

2 Research approach

In order perform a research a systematic and detailed research, a framework concerning this research, created by Hevner, March, Park, and Ram (2004) was used. The framework has been adapted for the purpose of this research, as shown in Figure 2. The proposed conceptual framework combines two of the main paradigms used in the research, namely behavioral science and design science. The behavioral-science paradigm's main purpose is to develop and justify theories that refer to human and organizational behavior. On the other hand, design-science paradigms try to solve problems by creating artifacts that are not based on natural laws or behavioral theories (Hevner, March, Park, & Ram, 2004).

The framework consists of three main parts, namely environment (i), research (ii) and knowledge base (iii). The environment combines people, organizations and technology in order to fully define the area of the interest. The business needs are the goals, tasks, problems, and opportunities as they are perceived by people within the organization (Hevner et al., 2004). The second part is presented by two complimentary phases. The direction that the behavioral science gives in the research is a development and justification of theories, while the design science emphasizes on the building and evaluation of artifacts. The final knowledge base part provides the building blocks, foundations and methodologies that support this research.

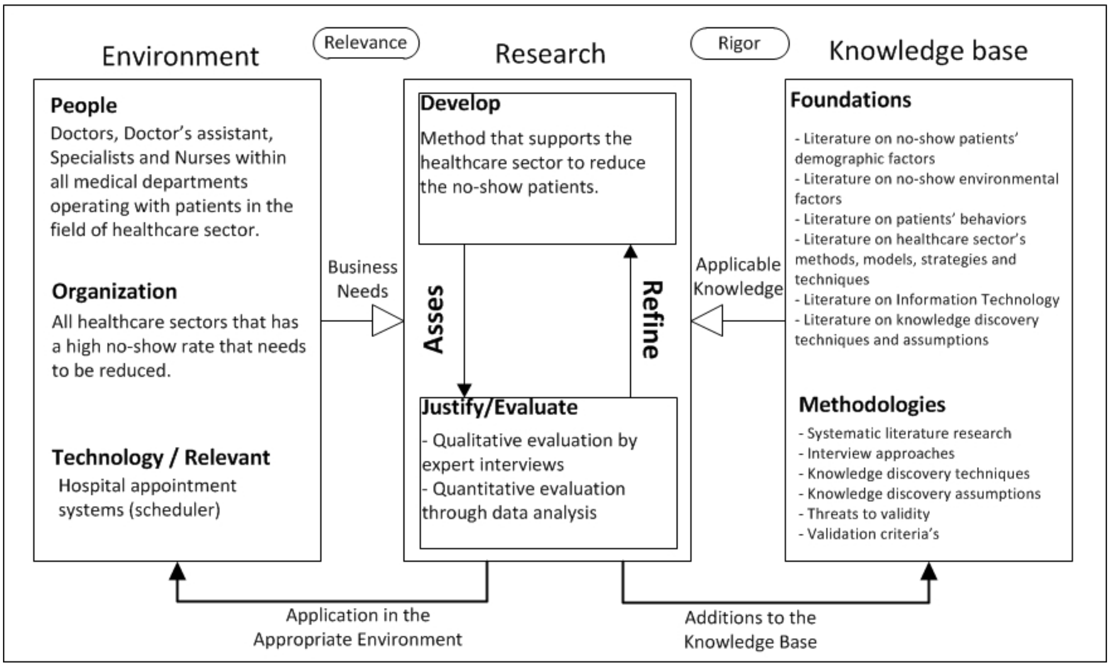


Figure 2. Research methodology approach

Hevner et al. (2004) defined seven main principals for conducting and evaluating a design science research. The seven main principals are listed and explained below:

1. **Design as an artifact:**
   Creation of a method supporting the healthcare sector to reduce the number of no-show patients.

2. **Problem relevance:**
   The method aims to be relevant for all departments within hospitals, clinics and other medical care centers that have a high no-show rate.

3. **Design evaluation:**
   The method is conducted by studying literature research and also by acquiring relevant knowledge from expert interviews. Ultimately, a no-show dataset from UMCU is acquired.

4. **Research contribution:**
   This research investigates the main factors that influence patients towards no-show and attempts to find out the reasons for no-shows. In this research these factors are the patients' demographic factors, environmental factors and the patients' behavior. It contributes to the body of science and healthcare research by providing a guide/tool to reduce the number of no-show patients.

5. **Research rigor:**
   The method is developed acquiring knowledge by studying previous literature studies on healthcare and extracting knowledge from experts. The evaluation is checked with literature studies and also by experts.

6. **Design as a search process:**
   This research contains, in total, seven phases, more on these phases can be read in section 2.1.

7. **Communication of research:**
   The research results are presented in a thesis for a master's degree in Business Informatics. Both the research process and the end results are presented in several presentations.

2.1 Research process

In addition, the research process and the expected deliverables are visualized with a Process Deliverable Diagram (PDD) as described by Van de Weerd and Brinkkemper (2009).

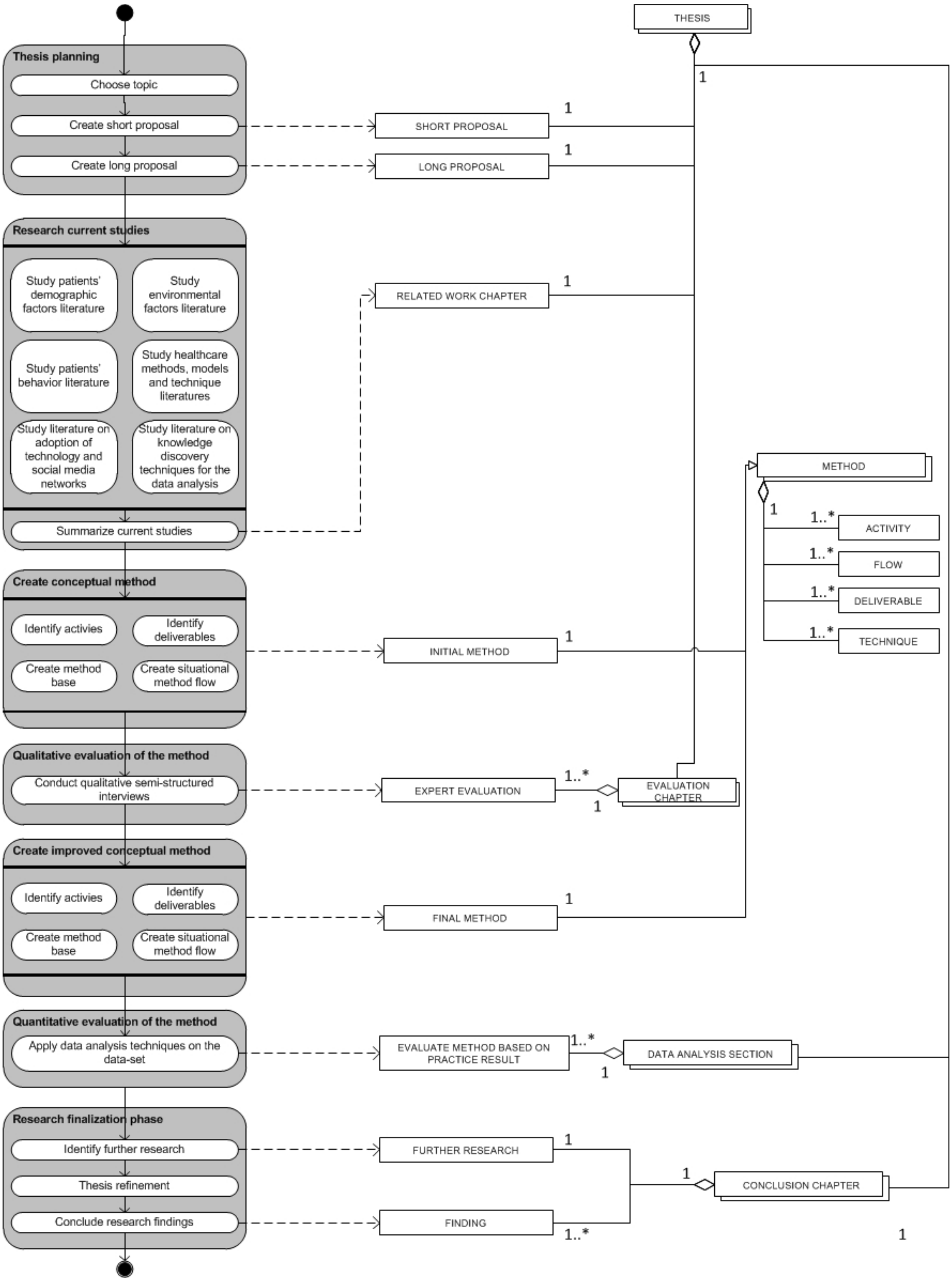


Figure 3. Thesis research process

As depicted in Figure 3, this research consists of seven phases, namely: thesis planning, research of current studies, create conceptual method, qualitative evaluation of the method, create improved conceptual method, quantitative evaluation of the method and research finalization phase.

The 'research of current studies' comprises all literature studies, meaning all relevant knowledge that needs to be collected in order to 'create the conceptual method', hereby to get an overview of the following points:

- Why patients are not attending their appointments;
- The reasons why patients are not attending their appointments;
- The association between patients' demographic factors, environmental factors and patients' behavior with regard to no-show;
- The adoption of Information Technology to support the healthcare sector;
- Interventions to reduce no-show

The conceptual method gives a schematic overview of knowledge on no-show patients utilizing a PDD and a flowchart. In the qualitative evaluation of the method semi-structured interviews with experts have taken place to evaluate the conceptual method to consequently create the improved conceptual method. These experts have sufficient knowledge regarding to *'the why and how'* of no-show patients. The qualitative semi-structured interviews are henceforth conducted to evaluate and to receive feedback on the proposed method and to collect more information on why no-shows occur.

Next, the quantitative evaluation of the method's data analysis on the no-show dataset is acquired from UMCU. This dataset contains valuable information on no-show patients. Once all non-relevant variables have been filtered out, removed and or transformed, a data analysis is performed to search for associations, correlations and trends. In addition, to validate whether the method serves its purpose to reduce the number of no-show patients, the method is evaluated based on the data analysis results.

The research finalization phase entails the identification of further research, and aims to refine this research based on the supervisor's feedback. Last, the conclusion of this research is written.

2.2 Literature study

The search engines used for the literature retrieval were Google Scholar, Omega and PubMed. Combinations of one keyword from each category (A, B and C) depicted in Table 2 were queried between double quotation marks using the above-mentioned search engines. In the case of Omega and PubMed the available advanced search options were used. The three categories were chosen to collect a total overview on no-show patients' demographic factors, environmental factors, patients' behavioral features and the technology in the healthcare sector. The research papers that are consulted are limited to English and Dutch papers. Furthermore, the literatures were selected based on relevance by reading the title, abstract, conclusion and discussion. This resulted in 119 relevant papers. The literature study was considered complete as soon as no new concepts related to the previously mentioned subjects could be found.

The above-mentioned search engines and keywords were chosen to improve the chances to find the most relevant and most cited information about no-show patient's demographic factors, environmental factor, behaviors and technology for this research.

An example of how the keywords are queried is shown below. The 'x' can be replaced with an alphabet letter that is depicted in Table 2. The [AND] and [OR] display the advanced search options.

1. A1.x	[AND]	B1.x	[AND]	C1
2. A1.x	[OR]	B1.x	[OR]	C1
3. A2	[AND]	B1.x	[AND]	C1
4. A2	[OR]	B1.x	[OR]	C1
5. …				
6. …				
7. A1.x	[AND]	A2		
8. A1.x	[OR]	A2		
9. A1.x	[AND]	A3		
10. A1.x	[OR]	A3		
11. …				
12. …				
13. B1.x	[AND]	B2.x		
14. B1.x	[OR]	B2.x		
15. B1.x	[AND]	B3.x		
16. B1.x	[OR]	B2.x		
17. …				
18. …				
19. C1	[AND]	C2		
20. C1	[OR]	C2		

(A) The no-show patients	(B) No-show interventions	(C) Theories
1. Patients a. Missed appointment b. No-show c. No-show prediction d. Non-attendance 2. Demographic factors 3. Environmental factors 4. Ecological factors 5. Behavior a. Patient behavior b. Patient predicted behavior c. Patient satisfaction	1. Technology a. Productive technology in the healthcare b. Medical Information technology c. Information technology d. Social media networks e. Smart phone f. Web 2.0 g. eHealth h. mHealth 2. Method a. Appointment scheduling method b. No-show method 3. Model a. Appointment scheduling model b. No-show model 4. No-show strategy 5. No-show techniques	1. Technology Acceptance Model 2. Theory on no-show patients 3. Social Influence Theory 4. Behavior theory

Table 2. Literature keyword analysis.

2.3 *Interviews*

The results gathered in the 'research of current studies' and the conceptual version of the method serve as an input to perform a set of qualitative semi-structured interviews. The list of the interviewees is adapted and may even be extended.

The interview questions are designed based on:

- What influences patients (i.e., factors and behaviors) not attending their appointments;
- Already used interventions (e.g., methods, techniques, models) to reduce the number of no-show patients;
- Previous experiences with no-show patients;
- Other improvements of no-show patients that should be taken into consideration

The semi-structured interviews are conducted in person (face-to-face). In the case of collecting data over the Internet, surveys are held. This does not invalidate the data findings, because the same questions are asked when conducting this in person. Furthermore, the questions are asked in the same order (sequence).

The qualitative semi-structured interviews contain 28 questions related to the four above-mentioned subjects. The goal of the interviews is to gain an insight on the above-mentioned subjects, and also to define new (if any) knowledge on why patients are not attending their appointments. This knowledge may consist of new associations or the expanding of associations, new factors and behaviors that could be utilized for the improvement of the conceptual version of the method.

The list of interviewees may include doctors, doctor assistants, specialists and patients. These experts are the ones who most likely know why patients are not attending and who can provide valuable information on how to reduce the number of no-show patients.

2.3.1 The influence on patients towards no-show

The goal of the questions regarding the influence of patients not attending their appointment, is to find out if the literature findings about the patients' demographic factors, environmental factors and behavior factors match with what the expert interviewees have to say about no-show patients, and also to receive feedback to improve the developed method. It is possible that new knowledge associations about no-show are derived from the structured interviews.

2.3.2 Methods, models, strategies and techniques

The goal of the questions regarding the methods, models, strategies and techniques is to help categorize these interventions in line with the conceptual method aspects, such as the patients' demographic factors, environmental factors and patients' behaviors with regard to the reduction of no-show (see Figure 4). This may be applicable, however, only if UMCU uses any of the above-mentioned interventions, if not only knowledge gathered in the literature study can be used.

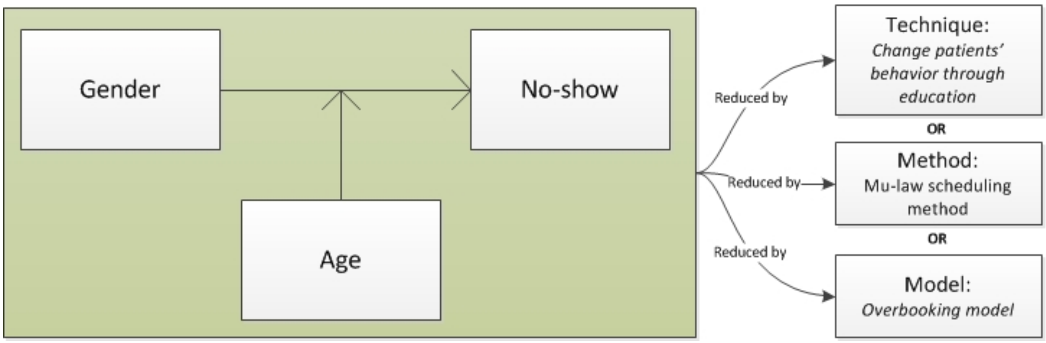


Figure 4. Example: goal of methods, models and technique questions

2.3.3 *Experience with no-show*

The goal of the questions regarding the current experiences with no-show is to help the researcher gain more information on this matter, such as information the researcher did not encounter during his literature study that may help him answer his research questions. These questions are open questions.

2.3.4 *Other improvements*

The goal of the questions regarding other improvements can be compared to the questions asked in section 2.3.3.

2.4 *Interview analysis*

The results of the interviews were transcribed. These transcriptions were loaded into a software package suited for qualitative data analyses called Nvivo. Because all interviews were semi-structured, this software package was suitable.

Using Nvivo, the data is coded line by line. Data coding in the context of grounded theory research means adding a label to each bit of data, linking the data to a concept. The Grounded Theory Analysis describes multiple rounds of coding and data gathering to collect as much information possible concerning the methods, models and techniques that are currently being utilized in the hospitals to reduce no-show. Coding each statement to an individual interviewee is the way to capture the overall evaluation of the method. Basically, it helps to understand what the interviewees are talking about when defining concepts and associations. These concepts are either combined or linked together and main concepts are identified. The created concepts and associations can assist the researcher with his final version of the method.

2.5 *Data analysis*

A UMCU no-show dataset is acquired in order to collect even more knowledge on no-show patients. This dataset is first transformed from unstructured to a structured dataset and afterwards filtered and analyzed. The method that is used during the data analysis is called the Three-phases method (3PM), as shown in Figure 5. The 3PM is the method of choice, because two parties are involved. The first party is the case company, which provides data to perform the data analysis. The other party is the researcher, who performs the actual data analysis. In addition, the 3PM accurately describes the data mining process and has a clear distinctive distribution of roles for each activity within the method (Vleugel, Spruit, & Van Daal, 2009). The activities are distributed between the case company and the researcher. In this research case, the first party is UMCU, which provides the no-show dataset and also initiated this research. The second party is the author (researcher) who performs the data analysis

(Vleugel et al., 2009).

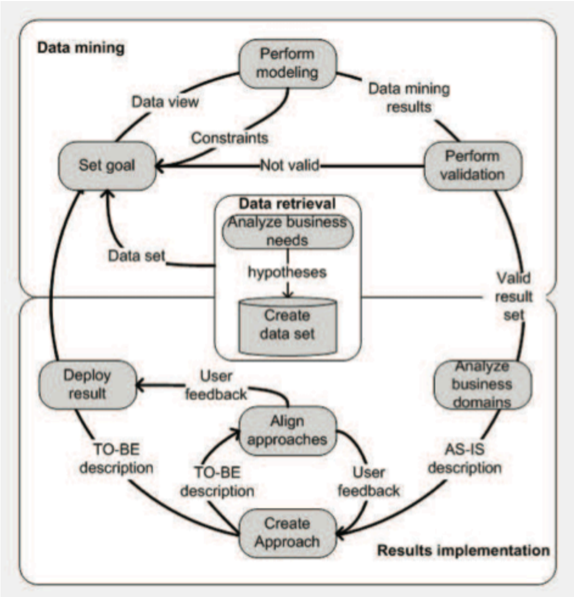


Figure 5. Three-phases model, retrieved from (Vleugel et al., 2009)**.**

2.6 Threats to validity

The four types of threats to be analyzed are: internal validity, external validity, construct validity and statistical conclusion validity. These are analyzed because there are several pitfalls that could harm the validity of this research. These four types of threats were deducted from the study of Barker, Pistrang, and Elliott (1979).

2.6.1 Internal validity

Internal validity refers to the degree to which causality can be inferred in a study (Barker, Pistrang, & Elliott, 1979). In the context of this research, internal validity is mainly concerned with data collection and data credibility (trustworthy). Which means that, for example, only relying on the data gathered from a literature study is not sufficient to create the method. This is why semi-structured interview and data mining are also performed in order to collect even more data on no-show patients.

Another possible problem is data collector bias during the semi-structured interviews. The researcher can unconsciously distort data during the collection process. For example, when the researcher is asking questions in a way that the interviewees are forced to answer a question in a positive way, which may not be according to the truth. Using a qualitative semi-structured interview template helps to mitigate this problem.

2.6.2 External validity

External validity refers to the degree to which the results of a study may be generalized over time (Barker et al., 1979). In the context of this research, it concerns whether the method is applicable to all hospitals, clinics or other medical care centers, or whether it solely applies to UMCU. Therefore, the question to ask here is: What are the differences between hospitals? Each hospital differs strongly in terms of patients, staff members, doctors, nurses, costs, customer care, customer service and so on. The only thing the hospitals have in common is that they are hospitals and that they have a no-show problem. Therefore, the method created will prove to be successful at hospitals with a no-show problem.

2.6.3 Construct validity

Construct validity refers to whether we measure what we believe we measure. This solely relates to the quantitative part of the research (Barker et al., 1979). As explained by Barker et al. (1979); other factors (out of our scope) may affect the outcome of the study, which were previously unidentified. In order to mitigate this problem; semi-structured interviews with experts are held in order to cover the unidentified factors.

2.6.4 (Statistical) Conclusion validity

Conclusion validity concerns the appropriateness of the statistical methods (Barker et al., 1979), thus how reasonable the conclusions are based on the collected data; because some might ask, if the conclusions are credible. In order to mitigate this problem, several qualitative semi-structured interviews are held to eliminate Type I and Type II errors. Conclusion validity mostly concerns the case study analysis, where we test if there is a difference between the collected information from the literature studies about no-show patients and what the experts have to say about no-show patients. To mitigate the risk of making a Type I error, the alpha level is kept low (0.05); so that there is a low chance of rejecting the hypothesis while there is no actual relationship.

A Type I error rejects a relationship between two variables or factors when we conclude that there is a relationship between the two variables. Type II is the vice versa of Type I error, where we conclude that there is no relationship while in fact there is a relationship (Barker et al., 1979).

As for this research, the author goes from deductive reasoning to inductive reasoning. Deductive reasoning starts with the general and then works towards the specific facts, whereas inductive reasoning starts with specific facts and then end with the general, which is not generally accepted in science (Barker et al., 1979). In the case of this research, we start with literature studies (general) ending with a case study at UMCU (specific). The case study's semi-structured interviews are based on the knowledge collected from the literature studies.

3 Related work

This chapter focuses on studies on no-show patients. First, general information about the healthcare costs in hospitals due to no-show is given. Second, knowledge is collected on why and for what reason no-show occurs in the healthcare sector by researching the influence between patients' demographic factors, environmental factors and patients' behavior with regard to no-show. In addition, information on how Information Technology can support the healthcare sectors to reduce no-show is also collected. All this information is collected to function as an input for this research and the method that is created.

Non-attendance is claimed to waste substantial healthcare resources (Bech, 2005). Over the last decade, the rising price of medical care in both urgent and primary settings has gone up due to no-shows (Ulmer & Troxler, 1999). The range of no-show varies from 5% to 39%, this depends on the departments within the hospitals (Satiani et al., 2009).

As the no-show rate increases, the waiting time and operational costs for all patients also increase. In 1996, a children's hospital located in a Midwestern state in the USA documented a total of 14,000 appointments that were not kept, resulting in an estimated loss of €764526.00 (Pesata, Pallija, & Webb, 1999). The researchers of another study found that, within one year, 31.1% of the appointments were either cancelled or missed. Even if all X amount of no-show patients were replaced by the same X amount of walk-in patients, there would still be a loss, as explained by Moore, Wilson-Witherspoon, and Probst (2001). This is because the charge for no-show patients is not as high as for walk-in patients; because walk-in patients usually have minor problems they want to discuss.

Figure 6 depicts the correlation between no-show rates and revenue of a vascular Laboratory at a large teaching hospital. As can be seen, a 12% no-show rate in the outpatient population represented a gross annual loss of €67725.95. Reducing the no-show rate to 5% would reduce the gross annual loss to €39347.13. The calculation is gathered under the assumption listed in the study of (Satiani et al., 2009) who studied the financial effects of no-show by outpatients during a 9 month period.

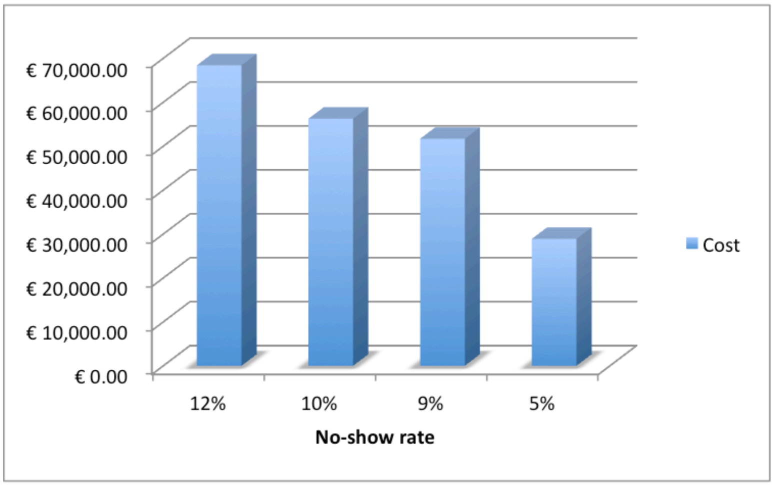


Figure 6. Chart correlates the no-show rate with revenue, retrieved from (Satiani et al., 2009)**.**

No-show is argued to be a problem that only has consequences for the costs of healthcare, however, no show also results in poorer access to healthcare services for those in need with subsequent poorer clinical outcomes. Bech (2005) describes that social costs also need to be taken into consideration. Social costs due to no-show are the lost value of unused or misused resources, such as personnel time and ward capacity, resulting in lower productivity and lost benefits. An additional potential social cost related to no-show patients, is the problem of patients spending too much time in waiting rooms (Bech, 2005). The costs related to this is what is referred to as overbooking. Given that a health service provider expects a number of no-show in the course of the day, the provider may overbook to counteract the problem of unused resources. The consequence of overbooking will result in patients spending too much time in waiting rooms to see their doctor. This waiting time is associated with lost production. Muthuraman and Lawley (2008) have shown the contrary: overbooking is not only cost related, it is also an important strategy to improve patients' access and stabilizing revenue when there is a significant chance that some scheduled patients will not show up.

According to the health accounts of "CBS - Health and Welfare" (2011) in 2011, 90 billion euros were spent on healthcare and welfare in the Netherlands. Depicted in Figure 7, one can see that the costs of hospitals ranged from 10 billion euros (in 2000) to around 30 billion euros (in 2011). No-show patients were not accounted for in the whole expenditure, although it consists a big part of it. Other healthcare sectors such as general practitioners and Eldercare were smaller in cost than hospitals. It is possible to reduce the above-mentioned expenses by targeting efforts at those patients that are most likely not to show up. However, this requires an understanding of the patients' factors underlying no-shows, including hospital factors (Hamilton et al., 2002). More on the patients' factors can be read in section 3.1 to section 3.3.

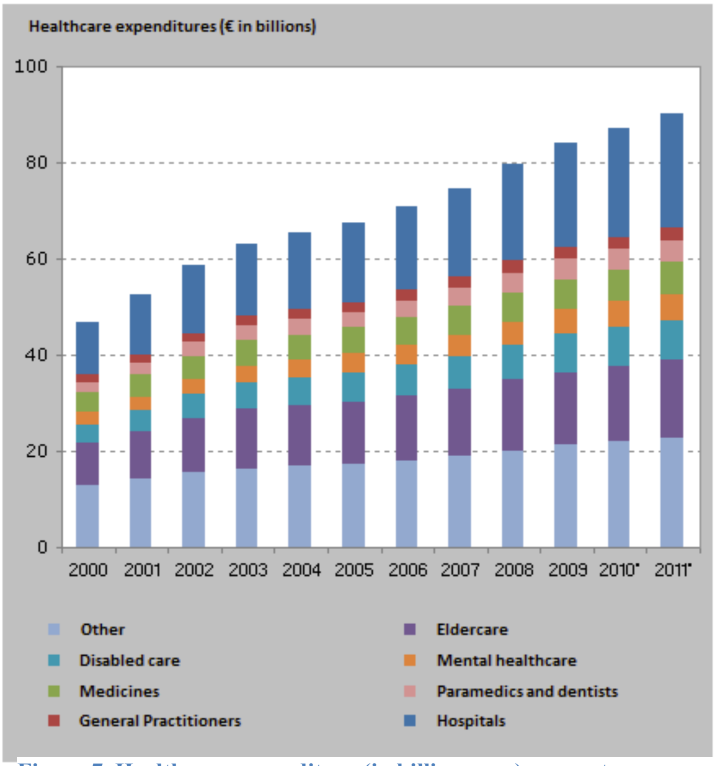


Figure 7. Healthcare expenditure (in billion euro) per sector, retrieved from ("CBS - Health and Welfare," 2011)

3.1 Demographic factors

The influence of demographic factors towards no-show

The purpose of this section is to gather valuable information about demographic factors that cause patients to become no-show patients. Furthermore, this section also aims to gather information on the categories within the demographic factors, the reasons related to demographic factors that lead to no-show, and also aims to acquire information on how to reduce no-shows.

This section aims to give an answer to sub-question number 1:
SQ-1: *"What are the patients' demographic factors and how do these factors influence patients towards no-show?"*

This question is answered reviewing different papers on the phenomenon no-show. By illustrating the barriers for each demographic factor and investigating how these barriers can be overcome, the researcher can create the method more accurately.

3.1.1 Introduction

Demographic factors are factors relating to an individual's personal characteristics, environmental factors and behaviors that can influence the individual to undertake a certain action, which afterwards can lead to performing the next action (Glanz, Rimer, & Viswanath, 2008). Demographic factors have a significant influence on the healthcare sector with regard to why patients are not attending their appointments. Despite the great amount of energy, time, resources and attention devoted to no-shows, however, the problem has continued to persist and grow, eating away at both general health status of the population as well as the bottom-line of healthcare organizations (Mba, Javalgi, & Vijay, 1998). Identifying the most influencing demographic factors is one of the most important first steps in order to reduce the number of no-show patients, the second step is to apply methods, models, strategies and techniques to further tackle this problem. It is not only to identify patient's demographic factors, but also to know the main reason why this occurs. As Mba, Javalgi, and Vijay (1998) explained, one seeks not to simply correlate different factors to no-show behaviors, but rather to determine the underlying reasons behind the phenomenon. For example, certain demographic factors, such as age, are known factors to be more likely to increase the no-show rate. The doctor, however, cannot do anything about such factors. It is therefore far more interesting to find out why younger- or older patients have a higher probability of no-show. Using this approach does not only allow one to focus on the true causes of no-show, it also facilitates the development strategies to address the problem.

3.1.2 Age

Tremendous costs in the healthcare sector are made due to the phenomenon age. It is one of the demographic factors that is most consistently associated with no-show (Kruse et al., 2002). In order to get to the bottom of why age is a problem with regard to no-show, several previous studies have been taken into consideration (Bennett & Baxley, 2009; Daggy et al., 2011; George & Rubin, 2003; Hamilton et al., 2002; Kruse et al., 2002; Norris et al., 2012; Parikh et al., 2010). Daggy et al. (2011) established a call-in process, which consists of 400 clinics days using two different scheduling approaches compared among a total of 3.484 patients. Their results showed that patients ≤ 50 years had a no-show rate of 31.4%, whereas patients above 50 years, namely 51-60, 61-70 and >70 had a no-show rate of 17.2%, 9.4% and 5.3%, respectively. Similar results have been observed in the studies of Norris et al. (2012) and Parikh et al. (2010), which explain that age is a significant predictor of no-show. One can almost predict that a certain patient will not show up for their appointment due to the patient's age. The researchers devided the patients into four sub-groups (i.e., 18-44, 45-56, 57-68 and 69-100). The no-show rate among patients aged 18 to 44 years was between 33% and 37%, while the no-show rate of patients between 45-56, 57-68, and 69-100 was 25%, 21% and 16%, respectively.

Based on various studies it can be concluded that no-show patients tend to be younger, have a lower socioeconomic status and have a large unstable family (Barron, 1980; Lacy et al., 2004). The reason that younger patients have a higher no-show rate is because they are less likely to understand the purpose of their appointment, government-provided health benefits and (or) psychosocial problems. According to Verbrugge and Steiner (1981), patients in their adulthood, between the age of 30 and 60 tend to attend their appointments more often, because the physicians do more extensive workup and offer more services to them. Other group factors such as the environmental factors could also be associated with age. These environmental factors include transportation from and to the hospital, which has more effect on younger- and older patients (≤18-, or ≥74 years). This effect has been proven in the studies of Bennett and Baxley (2009), and Norris et al. (2012) and is shown in Figure 8.

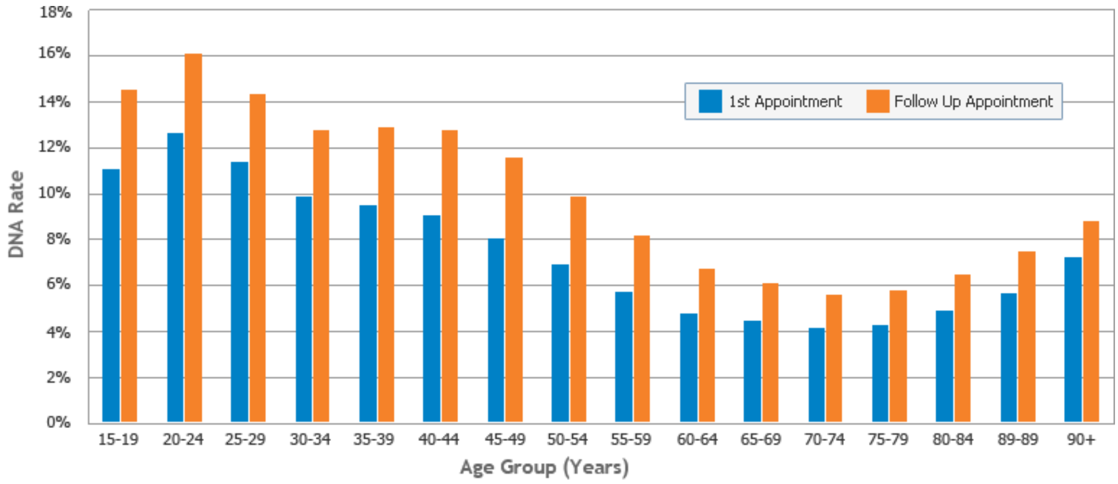


Figure 8. No-show rate by age group for appointment in 2007/8, retrieved from (Dr Foster Research Limited, 2007)**.**

Figure 8 reveals the estimated no-show rate of the Health and Social Care Information Centre (Dr Foster Research Limited, 2007). It shows that the highest no-show rates occur among younger age groups, as explained above. As patients' age increases, there is less likelihood of them missing an appointment. The increase of no-shows in the older age groups is due to other existing health issues or transportation difficulties (i.e. association with environmental factor) from care homes to hospitals. The color blue in Figure 8 depicts the patient's first appointment grouped by a specific age, while the color orange depicts the follow up appointment for the same age group.

3.1.3 Gender

The demographic factor gender also influences the no-show rate of patients, as shown in several previous studies. Males particularly have been associated with no-shows (Hamilton et al., 2002). The researchers of this study examined in a cohort of

1.972 referrals from 26 general practitioners, with a complete follow-up of a total of 2.708 patients. Their results revealed that the male group between the age of 16 to 35; and those with a longer interval between referral and appointment and with a higher Jarman score (index of social and medical deprivation), were all most likely to not attend their appointment. The no-show rates between these ages were 21%. However, Carpenter, Morrow, Del Guadio, and Ritzler (1981), and Potamitis, Chell, Jones, and Murray (1994) contradict this. They did not find any association between gender and no-shows with the experiment they conducted. This highly depends on the type of patients the hospital receives and on other environmental conditions, such as transportation difficulties.

Why male patients are associated with no-show more often than female patients, is perhaps the most important issue in this section. According to Deyo and Thomas (1980), female patients account for higher appointment keeping rates. A myriad of factors explains why female patients attend to their appointments more often than male patients. It has to be said that not many studies have been performed on this subject, although Verbrugge and Steiner (1981) studied the difference between male and female visits. In addition, the researchers investigated whether no-show differs by gender after considering medically relevant factors such as the patient's age, seriousness of the problem and prior visit status. They explained that people often assert that physicians are "sex biased", which is not the case. Doctors often offer different diagnoses and care to men and women who have the same problems due to gender. Overall, the researcher found that men and women are usually treated similarly for their complaints, however, when significant sex differences appear in treatment, the physicians will provide more services and follow-up care for women. This means men receive less service, which is probably the reason why men are more likely to not show up. Similar results have been found in the study of Wallen, Waitzkin, and Stoeckle (1979). Here the researchers performed 336 tape-recorded conversations between a stratified random sample of physicians and a sample of their patients. The researchers came to the conclusion that women receive more explanations from their physicians than men. The reason behind this, is that women ask for more information about their problems than men. Furthermore Willems, De Maesschalck, Deveugele, Derese, and De Maeseneer (2005) pointed out that *"doctors' communicative style is influenced by the way patients communicate"*. However, no research has been done to generalize the results of this study.

Educating patients about their diseases or other helpful medical explanations can lead to patients attending their appointments on a regular basis. More about the methods, models and techniques to reduce no-show is written in section 3.4.

3.1.4 Elapsing calendar days

The following demographic factor, which is also associated with no-show, is the amount of days patients have to wait from the day the appointment has been made (patient call-in) until the actual day that patients gets to see the doctor. The impact of a long waiting time has an influence on the rate of kept appointments, which causes the no-show rate to increase. The longer a patient has to wait for his appointment (e.g., 1 day, 2 days, 1 week, 2 weeks and so on), the higher the chance is that the patient will not show up for the appointment. This has been proven in several studies (Athenahealth, 2012; Benjamin-Bauman, Reiss, & Bailey, 1984; Gallucci, Swartz, & Hackerman, 2005; Parikh et al., 2010). Gallucci, Swartz, and Hackerman (2005) did a study on the impact of the amount of days that a patient has to wait for an initial appointment at a medical health center called the Johns Hopkins Bayview Medical Center. This research has been done by conducting a sample consisting of 5.901 consecutive patients who were referred to or sought out for an initial appointment. They came to the conclusion, by performing several multivariate logistic regressions between several selected predictors, that for each consecutive day of delay for an appointment, the odds ratio increases with 1.12% that a patient will not show up. There also was a direct association between gender and age, as they explained further on in their study. Similar results have been gathered in the study of Anderson (1973). The researchers explained that hospital admission rates and the average length of stay are the lowest for children and then rise with age. Their results indicated that the no-show rate rose to 42% among the 241 patients whose appointment was delayed for seven days or more. Other similar results have been conducted by Athenahealth (2012). Athenahealth (2012) studied the difference between initial date scheduled and actual date seen of a patient (see Figure 9).

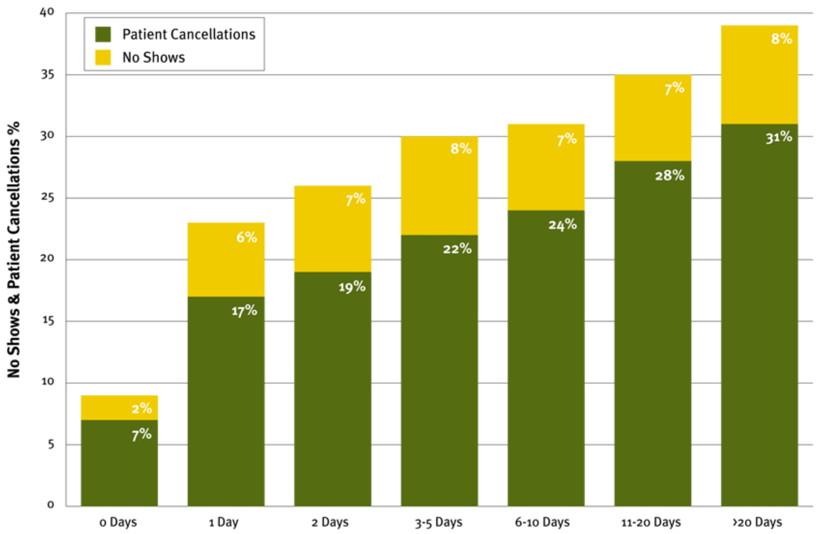


Figure 9. Difference between date scheduled and date seen, retrieved from (Athenahealth, 2012)**.**

Figure 9 shows that the length of time a patient has to wait for an appointment greatly affects the cancellation and no-show rate. According to Athenahealth (2012), 40% of the appointments scheduled for more than 20 days after the call-in or the initial appointment get cancelled or become no-shows. The longer the wait, the more likely the patient is not to show up at his appointment (Parikh et al., 2010). Therefore, to stop this from happening and to attain new patients, practices, clinics and hospitals must be able to grant appointments relatively quick (i.e. provide better access time) by introducing reminders, either mailed, by SMS or delivered by phone. This has been proven to improve appointment "keeping" rates by 30% to 70%. Although it is not experimentally verified. Benjamin-Bauman, Reiss, and Bailey (1984) examined the effects of reducing the interval between a patient's call for an appointment and the appointment itself. They suggest that when verification appointments were scheduled between 1 to 2 days away; the incidence of no-shows decreased to less than 5%, whereas if the verification appointment was scheduled 3 or more days away (Benjamin-Bauman et al., 1984). The same study (Benjamin-Bauman et al., 1984) did two experiments to prove this, namely, experiment 1 and experiment 2.

In experiment 1, patients were assigned to either an appointment for the next day (next-day group) or to an appointment in two weeks from the initial call date (two-week group). In experiment 2, which was also about the waiting time between scheduling an appointment and the day that a patient actually sees the doctor, also were divided two patient groups: the one-week group and the three-week group, where the patients had a waiting time of approximately 1 week and 3 weeks. The results of these two experiments are depicted in Figure 10 and Figure 11 respectively. What the experiments shows, is that when the patients were scheduled for an appointment close to the date of them actually seeing their doctor, the show-rates were significantly higher.

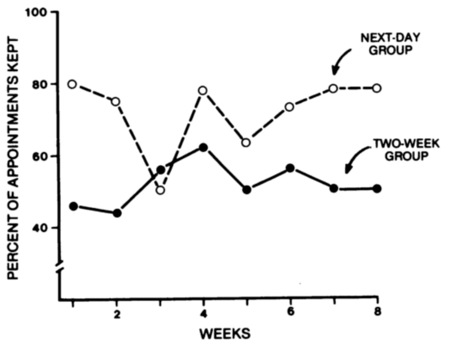


Figure 10. Percentage of appointments kept per week by patients in the next-day and two-week interval groups, retrieved from (Benjamin-Bauman et al., 1984)**.**

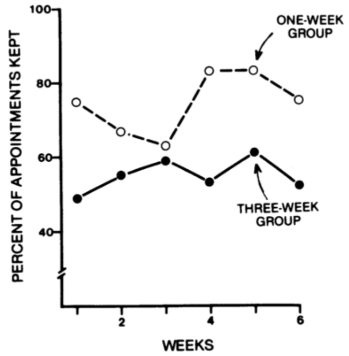


Figure 11. Percentage of appointments kept per week by patients in the one-week group and three-week group interval groups, retrieved from (Benjamin-Bauman et al., 1984)**.**

3.1.5 Low socioeconomic patients

Socioeconomic status is a measure of an individual's or family's economic and social position based on education, income, and occupation (Winkleby, Jatulis, Frank, & Fortmann, 1992). Low socioeconomic patients, or also called low socio-demographic patients, are patients who are more likely to miss their appointments. Research has indicated that these patients have a low yearly income, have less than a high school education, a negative personal history (e.g., childhood low socioeconomic status and living conditions), unequal distribution of risk factors in the population and so on (Grossman, Humbert, & Powell, 1996). Pesata et al. (1999) indicated that families who fall into the lower socioeconomic groups and who are headed by young adults with small children have a higher incidence of missed appointments. These above-mentioned factors have been associated with lower attendance of appointments (Barron, 1980; Deyo & Thomas, 1980; George & Rubin, 2003; Mitchell & Selmes, 2007; Moore, Wilson-Witherspoon, & Probst, 2001; Quattlebaum, Darden, & Sperry, 1991). Because of their low socioeconomic status patients are unable to pay for their expenses, such as for their received medicines and appointments. Therefore, they will not attend their appointments nor worry too much about their own health.

Furthermore, these patients may or may not have insurance, telephone, mobile phones or other means of communications, which they can use to call their doctor or called by their hospital to keep in-touch with them, and to remind them of their upcoming appointment(s).

Communication between patients and their doctors is very important. As Ong, de Haes, Hoos, and Lammes (1995) stated, *"communication can be seen as the main ingredient in the healthcare sector"*. For this reason, further research on the communication between low socioeconomic patients with their doctors was collected in order to possibly find the reasons why this group is less likely to attend their appointments. Willems et al. (2005), revealed that patients with low SES received less information, less directions, and less emotional and partnership building expressions from their doctors.

As depicted in Figure 12, it is clear that almost everyone with a low SES has a poor health in every way compared to the health of people with a high SES (Hoeymans, Melse, van Oers, & Polder, 2006). The immigrants are often vulnerable when it comes to health. This theory is supported by the mortality rate among immigrants. Low SES is very often associated with the neighborhood, the poor quality housing, and the less favorable conditions that low SES people live in. Individuals with better prospects and a high SES move away from these neighborhoods. In the Netherlands the low educated men and women's lifespan is on average 19.2 and 20.6 years, respectively, shorter in perceived good health than the lifespan in perceived good health of higher educated men and women. Also the life expectancy for less educated is lower, 7.3 and 6.4 years respectively (Mulder, 2010). The prevention index, which is also depicted in Figure 12, shows the care assessment for preventive medical services provided in the Netherlands. This has no direct association with both the health of people and their SES.

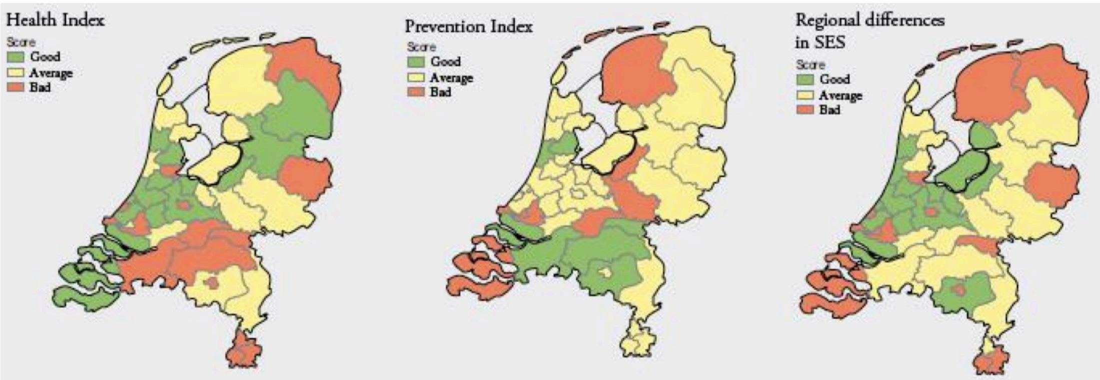


Figure 12. A geographical view on health, prevention and SES, retrieved from (Hoeymans et al., 2006)

3.1.6 Health insurance

Patients who have lost their health insurance or patients who have changed their health insurance plan are most likely to delay seeking care. This leads to a decline of their health and an increase of the no-show rate. Demographic factors, such as low SES, the condition of the patient, age and urgency were most likely associated with patients with health insurance issues (Hoeymans et al., 2006; Mulder, 2010). A major challenge for the healthcare sector is to give a more transparent picture of the quality of care for government, parties and citizens. The performance of healthcare institutions can henceforth in many ways be mapped to improve this for their patients, such as in the form of ratios and performance indicators. These will offer an insight into the quality of care and other aspects of the functioning of healthcare, such as accessibility and affordability (Hoeymans et al., 2006).

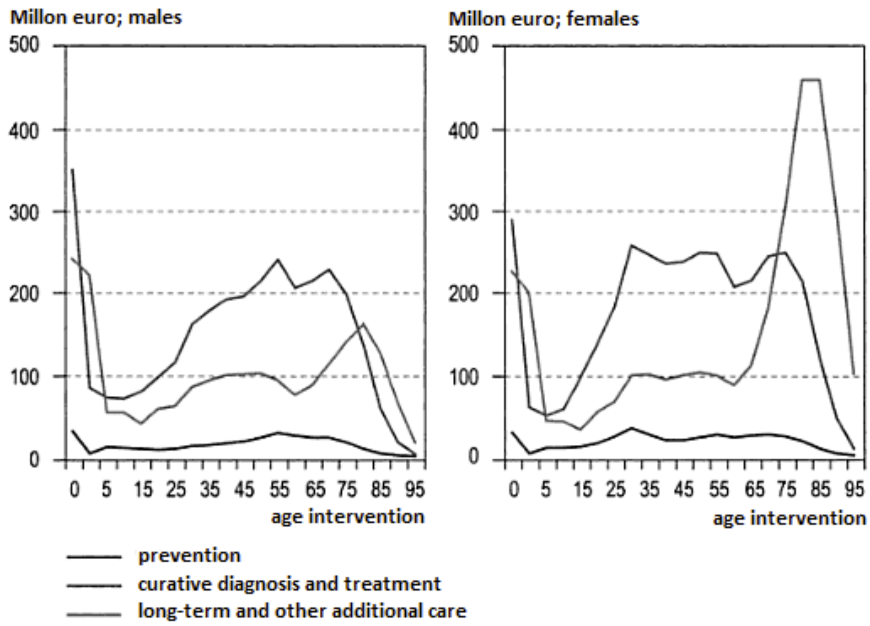


Figure 13. Cost of the Dutch healthcare to care function, age and gender in 2003 (in million euro), retrieved from (Hoeymans et al., 2006)**.**

Figure 13 depicts how much money is spent on healthcare insurances in the Netherlands. This is grouped by gender and age (0-95). In 2003, 57.5 billion euros were spent on healthcare in the Netherlands. Over the period of 1999 to 2003 this rose by almost 10% on a yearly basis, more than half of this was due to price increase, whereas 4% was due to volume growth. Only a quarter of the volume growth (1%) was related to demographic developments.

Twenty-seven percent of the hospitals and over 21% of elderly care (nursing, care and home care) in the Netherlands have the largest share in the health expenditure. After this there are the medicines and medical devices. They account for somewhat more than 10% of the expenditures. The allocation of costs of disease and care sectors is in line with other countries such as Germany, Australia and France, with the exception of the expenditure on long-term care in the Netherlands, which is considerably higher (Hoeymans et al., 2006).

3.1.7 Ethnicity

A patient's race or also called the ethnicity of a patient has been significantly associated with no-show in the following studies (Anderson, 1973; Bennett & Baxley, 2009; Kopach et al., 2007a; Kruse et al., 2002; Weisman & Teitelbaum, 1985). The reason that a patient's race has an influence on the no-show is due to the (i) poor communication between patient and doctor, (ii) cultural barriers and (iii) language difficulties (Anderson, 1973). Other studies refer to this as social distance. Social distance refers to the number of importance of dissimilarities between a doctor and his patient (Glanz et al., 2008).

Available data collected by Anderson (1973) indicates that non-Caucasians do not utilize health services as frequently as Caucasians. Feldstein and German (1965) performed a regression coefficient to predict patient days per thousand populations for this variable. These researchers found out that as the percentage of non-Caucasians increased, the amount of days that patients have to wait to see their doctor declined

(Feldstein & German, 1965). This has a direct association with the above-mentioned demographic factor; elapsing calendar days.

Ethnicity differences have been cited to cause important cultural barriers in the patient-physician communication. It has been studied that non-Caucasian patients receive less patient-centered communication than Caucasian patients, which is exactly what Johnson, Roter, Powe, and Cooper (2004) investigated. Their objective was to examine the association between a patient's ethnicity and the patient's physician during medical visits. This has been recorded over three years (from 1998 untill 2002). The results they collected indicated that physicians were 23% more verbally dominant and engaged in 33% less patient-centered communication with non-Caucasians patients than with Caucasian patients. Similar results have been conducted by Yergan, Flood, LoGerfo, and Diehr (1987), who revealed, based on their results (hospitals, n=17), that non- Caucasian patients receive fewer hospital services than expected on the basis of their health characteristics, and that their hospital lengths of stay may be longer than expected, especially in the E.R.

Previous studies have shown that both verbal dominance and patient centeredness are sensitive markers to indicate whether the patient is going to attend the appointment or not. Some studies say that non-Caucasian patients often have language difficulties with their doctors, which is the reason why the communication between patient and doctors is difficult. If the doctor cannot fully understand the patient's problem, he cannot help the patient as well as he could when he understood the problem. The main goal of the study of Van Wieringen, Harmsen, and Bruijnzeels (2002) was to explore the influence of communication and patients' beliefs on understanding and the compliance of native-born and ethnic-minority patients. The study was carried out with 8 general practitioners, working in seven general practices with a mixed ethnic population in Rotterdam. The study lasted for a total of 5 weeks (patients, n=142). In 24% of all consultations there was no mutual understanding about the health problem between the patient and the doctor. These findings may be explained by the fact that the physicians and patients often hold different views of health and illness, due to the patient having different cultural orientations (Van Wieringen, Harmsen, & Bruijnzeels, 2002).

In order to tackle the communication problem and language difficulties between patients and their doctors, Cooper-patrick et al. (1999) suggests that non-Caucasian patients should rather visit a doctor of their own race. This allows them to communicate more effectively and to feel more comfortable. Improving cross-cultural communication between patients and doctors may lead to more patient involvement in care, and also to a higher level of patient satisfaction and better health outcomes. As a consequence, this may lead to a decrease of the no-show rate in the healthcare sector.

3.1.8 Non-chronic patients

Non-chronic patients have a high no-show rate, whereas patients with chronic diseases break fewer appointments (Deyo & Thomas, 1980; George & Rubin, 2003; Hermoni, Mankuta, & Reis, 1990). Chronic illness is a human health condition or disease that is persistent or otherwise long lasting in its effects. Chronic illness is when the course of the disease lasts, on average, more than three months. Common chronic diseases include, for example, arthritis, asthma, cancer, COPD, diabetes and HIV/AIDS.

Patients with chronic diseases receive more medical attention, especially the older the patients. Older patients with chronic diseases are given more return appointments than younger ones (Verbrugge & Steiner, 1981). The more serious the problem, the more services and dispositions (in appointments) for follow-up care the patient will receive from the doctors. Hurtado, Greenlick, and Colombo (1973), who gathered some related results, explain that notably chronic treatable disease patients had a lower failure rate, possibly because they have a greater dependence on medical care and a greater motivation from their doctors to keep their appointments. In addition, they explained that the lowest rates of no-show were among pregnant women and those who required hospitalization due to their diseases, and also among the patients who had a greater tendency for symptoms and a greater likelihood to seek physician attention early.

The patients with chronic prevalent diseases in the Netherlands are the ones who have heart problems, cancer, mental disorders, infection diseases, musculoskeletal, injuries and poisonings. These patients are most likely associated with the age of 45 and up, as depicted in Figure 14. There is no significant association found in previous studies, between gender, age and patients who have chronic diseases and the increase of the no-show rate in the healthcare sector. Further studies on this subject are therefore necessary.

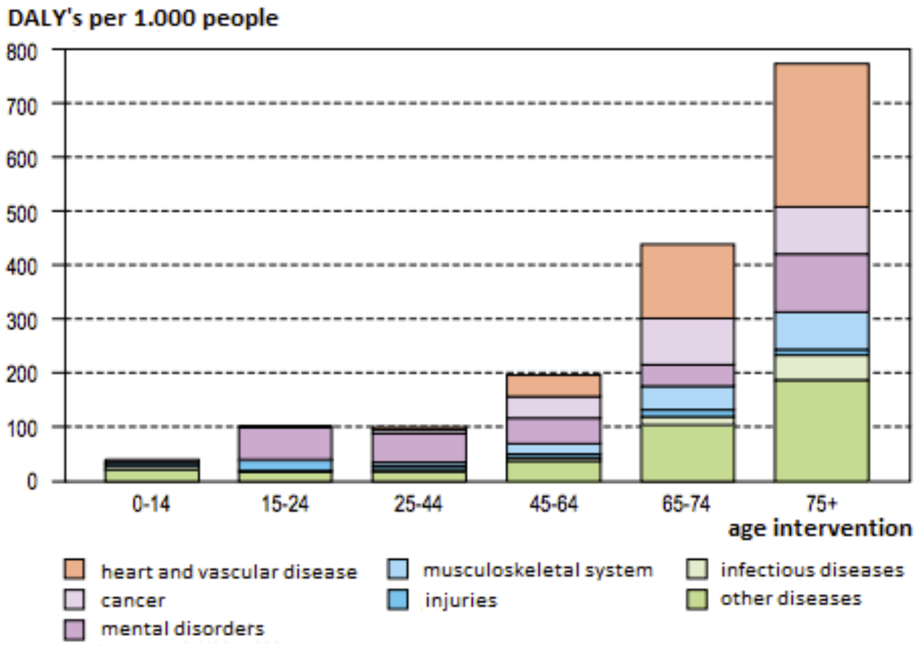


Figure 14. disease burden (DALY's per 1.000 people) by age and disease, retrieved from (Hoeymans et al., 2006)**.**

3.1.9 Conclusion

Some valuable information about patients' demographic factors was collected from several literature studies that lead to no-show in the healthcare sector. These are: age (i), gender (ii), elapsing calendar days (iii), low socioeconomic status (iv), health insurance (v), ethnicity (vi) and non-chronic patients (vii). In Table 3, the groups of patients that are affected by this are shown, corresponding with the reason why this occurs. By knowing the reasons why no-shows occur, we can later employ different interventions in order to confront this problem.

Demographic factor	*Group*	*Reasons*
Age	- Young patients (≤ 25) - Old patients (≥ 75)	- Don't understand the purpose of the appointment. - Previous failed appointment. - Health benefits. - Psychosocial problem. - Transport problem. - Emotional problem (fear)
Gender	- Male	- Receive less service. - Receive less follow up care. - Communicative style; men ask less information on their health than women.
Elapsing calendar days	- All patients	- When a doctors' appointment is created too early (≥ 3 days). Patients tend to forget about their appointment.
Low-socio economic status	- Young adults with children	- Unable to pay. - No health insurance. - No communication medium. - Communication difficulties between doctor and patient were poor.
Health insurance	✖	✖
Ethnicity	- Immigrants - Non-whites	- Cultural barriers. - Language barriers. - Social distance. - Fewer hospital services
Non-chronic patients	- Patients of 45+	- Not interested

Table 3. Patients' demographic factors with their corresponding reasons that leads to no-show in the healthcare sector.

✖ = No information found

3.2 Environmental factors

So far, we have discussed the key patients' demographic factors in relation to no-show. These demographic factors may also be moderated by any numbers of environmental factors that influence patients to not show up. A moderator is a qualitative or quantitative variable that affects the direction or strength of the relationship between an independent variable and a dependent variable (Glanz et al., 2008). This chapter aims to explore the related environmental factors that influence no-show patients and to understand these factors by researching why and when these factors have an influence on patients. As we know, patients' demographic factors influence to not attend their appointment, moreover, environmental factors could have a negative influence on these demographic factors, which may increase the chance of patients not to show up.

This section aims to give an answer to sub-question number two, namely:
SQ-2: *"What are the environmental factors that influence patients towards no-show and how are these factors related to the patients' demographic factors?"*

3.2.1 Introduction

Previous literature studies of hospitals and clinical patients revealed environmental factors, such as lack of transportation, inconvenient hours, day of the week and the distance between the patient's home and the hospital that must be traveled, to be reasons for no-show (Dove & Schneider, 1981; George & Rubin, 2003; Pesata et al., 1999). Therefore, in the following sub-sections we did a literature study on these environmental factors in order to find out the reasons why these factors have an influence on patients with regard to no-show.

The term environmental factor is derived from biological science and refers to the interrelations between organisms (in our case, patients) and their environments. Environmental models, as evolved in behavioral sciences and public health, focus on the nature of people's transactions with their physical and sociocultural surroundings, which is their environment (Glanz et al., 2008). The environmental levels of influence distinguish environmental models from behavioral models and theories that emphasize individual characteristics, skills and proximal social influences such as family and friends. However, these levels of influence do not explicitly concern the broader community, organizational and policy influences on health behaviors. Every day of a person's life is marked by wide fluctuations in almost every discriminable attribute of his behavior; the speed with which he moves, emotions he expresses, goals he pursues, humor, energy and so on (Glanz et al., 2008). Environmental factors are thus moderators of the demographic factors, because these factors moderate the actual ethical decision making process of a person. Activity choices, for instance, are believed to be altered mainly due to the environmental factors (Humpel, Owen, & Leslie, 2002; Simpson, Banerjee, & Simpson, 1994). However, of the factors associated with an individuals' activity, environmental factors are among the least understood.

In the healthcare sector, environmental factors play a big role in whether a patient attends the appointment or not. This is explained in the following sub-sections. As we explained earlier, the patients' demographic factors were the patient's characteristics, such as age, gender, SES and so on. In this section, we discuss the influence of environmental factors on patients with regard to no-show.

A multilevel environmental model was developed by Sallis et al. (2006), as depicted in Figure 15. The figure depicts the roles of numerous disciplines that can play in research on active living. The model consists of four domains of active living, each with multiple levels of influences specific to each domain, such as (i) perceived environment, (ii) behavior: active living domains, (iii) behavior settings: access & characteristics and (iv) policy environment. The researchers synthesized these findings and concepts from the fields of health, behavioral science, transportation and city planning, policy studies and economics and leisure sciences to create the *multiple environmental model*. As can be seen, the model has an "onion" structure to represent the multiple levels of influence on people of their environment. For each domain several examples are given.

Considering our subject, the no-show, we are interested in most of the activities within the (iii) *access and characteristic behavior settings of the patient towards his environment*, marked in orange in Figure 15. As explained by Sallis et al. (2006), behavior represents the interaction of the person with the environment. Furthermore, behavior settings are the places where physical activity may occur, and it is useful to consider both access to settings and their specific characteristics.

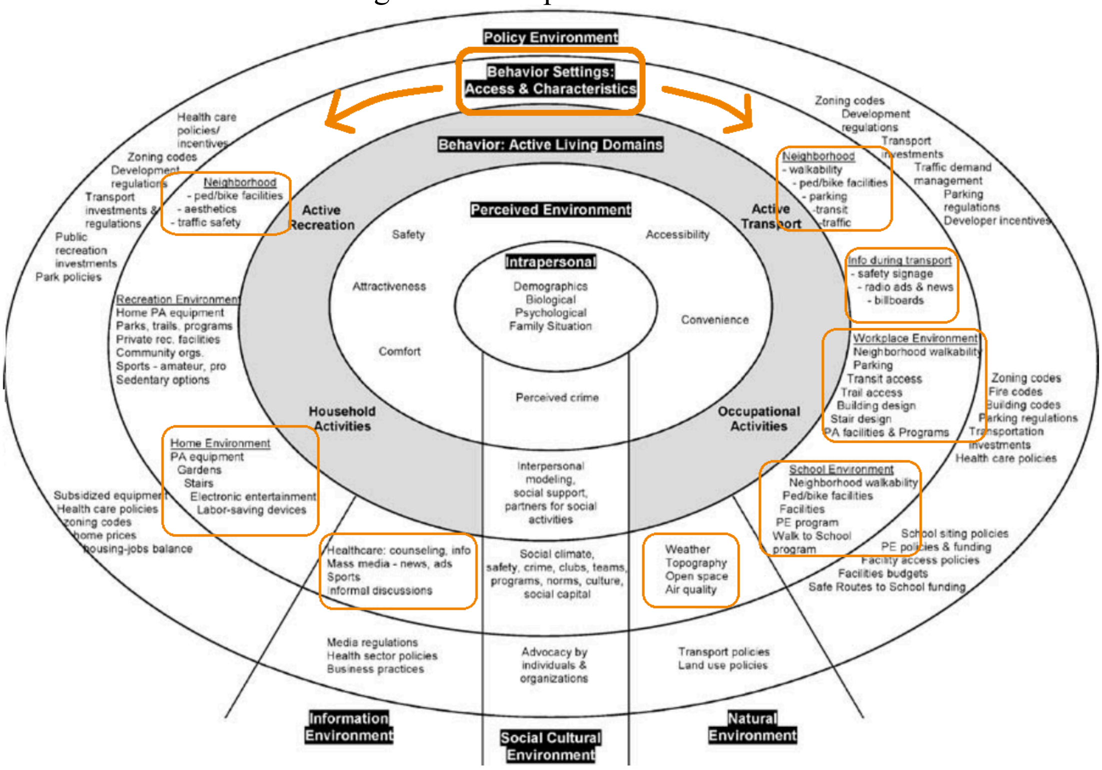


Figure 15. Multilevel environmental model of four domains of active living, retrieved from (Sallis et al., 2006).

3.2.2 Transportation

Transportation is one of the environmental factors that has an influence on why patients are not attending their appointments, especially in rural residents (Arcury, Preisser, Gesler, & Powers, 2005). Many families have cited transportation difficulties as one of the primary reason for no-show is that the patient does not have a car or has difficulties arranging transport to the hospital (Cosgrove, 1990; Dove & Schneider, 1981; Jackson, Booth, McGuire, & Salmon, 2006; Norris et al., 2012; Pesata et al., 1999; Satiani et al., 2009). Other researchers such as Miller, Hill, Kottke,

and Ockene (1997), explain that transportation does not always need to be a barrier to stop patients attending their appointments, and that it is rather the lack to take time off from work to keep their appointments that results in no-shows.
As explained by Pesata et al. (1999), the SES of a patient is moderated by its transportation, due to the fact that these patients have no car, or have difficulties buying a car. This negatively influences the patient's attendence rate. Transportation is also associated with a long waiting time. An example of this, is when parents do not know where to leave their children before attending an appointment. Henceforth, their children become frustrated due to the long waiting time. The consequence of this is that regarding the next appointment parents may decide not to show up (Deyo & Thomas, 1980).

A patients' age is also moderated by its transportation. As explained by Carpenter et al. (1981) and Potamitis et al. (1994), no-show highly depends on the type of patients the hospital is receiving or other ambient conditions, such as transportation difficulties. This has also been proven significantly in the studies of Bennett and Baxley (2009), and Norris et al. (2012). These researchers concluded that transportation difficulties have more effects on younger and older patients. Young patients of the age of 25 or younger and old patients 75 and up are most likely to be without a driver's license or a car, because they are either too young or too old. In this case, transport has a negative influence on whether these patients attend their appointments or not.

The relation between the patients' demographic factors: low SES and age with its moderator transport, is depicted in Figure 16.

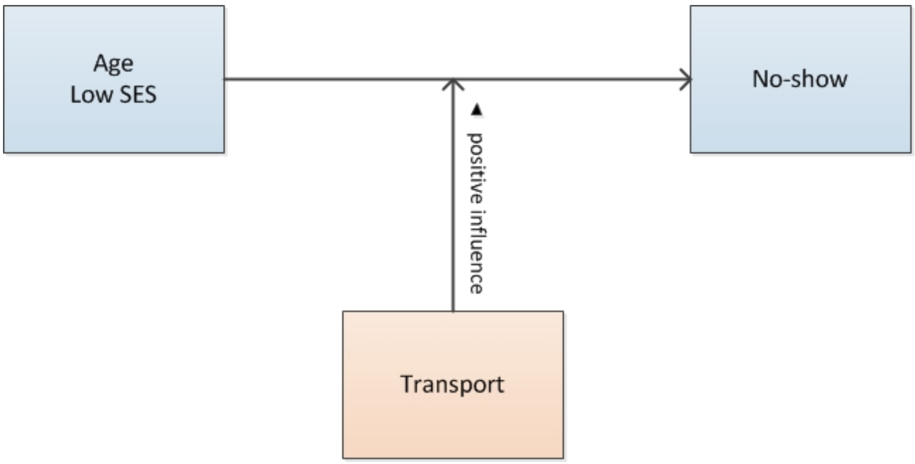


Figure 16. Relation between the patients' demographic factor: age and low SES to no-show, with its moderator, transport.

In order to reduce the no-show rates caused by transportation difficulties, Smith and Yawn (1994) came with a solution, namely providing transportation from the patient's home to the hospital. Providing this service could double the regular visits in a year (Arcury et al., 2005). This could be very useful for patients who do not have a driver license, low SES or other patients who are, for example, blind or experience other difficulties.

3.2.3 Geographic distance

The location of healthcare facilities is an increasingly complex problem, not only for the patient seeking care, but also for the provider of the services as well.

Researchers from studies conducted at several medical care centers came to the conclusion that patients who lived closer to the hospital, attend their appointments on a more regular basis than patients living further away (Booth & Bennett, 2004; Dove & Schneider, 1981; Jackson et al., 2006; Weiss & Greenlick, 1970), which associates with an increase of no-shows (Dove & Schneider, 1981). Patients who have to travel a fair distance may be deterred from attendance due to the costs, time complexity or inconvenience of transport. This relates to patients with low SES, who have transport difficulties (Pesata et al., 1999), which is also explained in section 3.2.2.

Mobley and Frech (2000) explain that patient travel distance depends on three factors: (i) patients' characteristics, which affects perceived travel costs and benefits; (think of patients with low SES, who cannot afford to pay their traveling costs), (ii) hospital characteristics that affect the gains from travel and (iii) environmental factors that may complicate the travel itself, such as transportation difficulties. In the Netherlands the average travel time between a patient's home to the hospital is 12.3 minutes, as shown in Table 4. This has been almost constant since 2008 to 2012. Although, 12.3 minutes does not seem much, this is equivalent to ±11 kilometers of traveling distance.

The effects of the long distances patients have to travel is explained in the study of Weiss, Greenlick, and Jones (1971). The goal of this study was to determine the impact of spatial factors in a medical care utilization. Weiss et al. (1971) found that distances and directions traveled depend upon the kind of services that the patient sought. So, the longer the patient has to travel the more specialist services they were seeking, while shorter trips were made for not so important services, such as services provided by general practitioners. Thus, here we can see a travel pattern that depends on the service type the patient requires. If patients do not understand the reasons for their appointments, and the distance between their home and the hospital, they are most likely to not attend their appointment in contrary to patients who know the reasons for their appointments and also have a great distance to travel.

The study conducted by Booth and Bennett (2004) aimed to identify the variables associated with attendance and therefore divided the patients in four bands. Band 1 meaning the closest distance that has to be traveled to the clinic, whereas Band 4 meaning the furthest away from the clinic. Their results revealed that patients living the furthest away did not respond to the reminder calls left by the hospital, and thus they are less likely to attend their appointments. Similar results were conducted by Jackson, Booth, McGuire and Salmon (2006), who divided their patients into two groups, namely Band 1 and Band 2. Band 1 are patients living approximately 5.31 km away from the hospital, whereas Band 2 are patients living further away. The patients that belonged to Band 1 attended their appointments on a more regular basis than patients that belonged to Band 2.

According to O'Neill (2004), the effect of insurance status could also have an effect on the traveling time. This study by O'Neill (2004) revealed, by collecting information on 85,586 Medicare inpatient discharges, that Medicare beneficiaries traveled up to ±10.2 minutes farther to receive their care. Medicare beneficiaries are most likely to be patients who are young, male and have a low SES. Furthermore, apart from the patients' insurance status, they came upon the fact that young and older patients tend to travel less (O'Neill, 2004). Similar results have been conducted in a prior research by Basu and Cooper (2000), who found that the patients' age is moderated to long distance travel, which is also explained in the studies in section 3.2.2.

The relation between the patients' demographic factors: low SES, gender and age to no-show with its moderator; geographic distance is depicted in Figure 17. Geographic distance is moderated by transport due to the distance that has to be traveled. Low SES patients with transport difficulties are affected by this distance (Carpenter et al., 1981; Pesata et al., 1999; Potamitis et al., 1994).

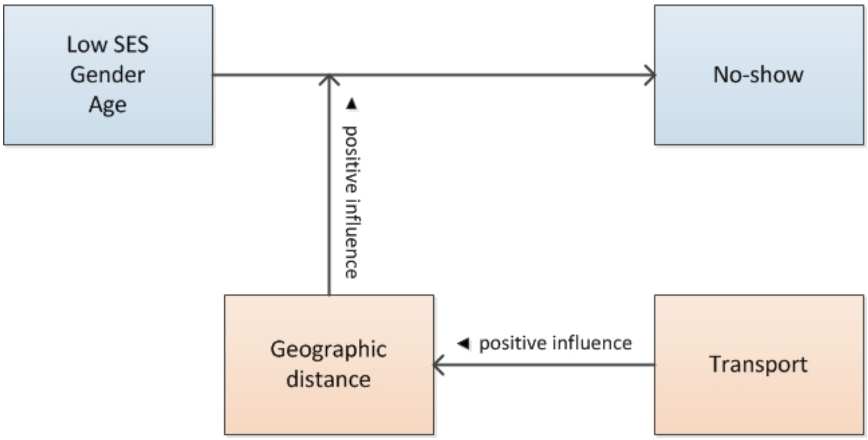


Figure 17. Relation between the patients' demographic factor: low SES, gender and age to no-show, with its moderators.

The healthcare sector can prevent long distance travel by implementing several techniques, such as making initial contact with patients, reminding them why it is important to attend their appointments or by sending them SMS and e-mails 24 hours before their appointments. More on these techniques is later further elaborated in section 3.4.

Primary care	2008	2010	2011	
General practice	1,32	1,41	1,37	
Physiotherapy Practice	1,5	1,5	-	
Pharmacy	1,2	1,2	1,3	
Midwifery Practice	6,7	6,3	6,3	

Secondary care	2008/2009	2010	2011	2012
Hospital	12,2	12,3	12,3	12,3
Nursing or care	3,1	-	-	-

Table 4. Average travel time (in minutes) to the nearest healthcare facility, 2008-2012, retrieved from ("Gemiddelde reistijd naar dichtstbijzijnde zorgvoorziening - Zorgbalans," 2012).

3.2.4 Day of the week

Failure to attend is less likely on Mondays than on Fridays according to the researchers George and Rubin (2003), and more likely if the appointments are booked one or more weeks in advance. The environmental factor 'elapsing calendar days' act as a moderator on the environmental factor 'day of the week'. Due to the fact that 'elapsing calendar days' has a negative influence on the direct relation between 'day of the week' and no-show the no-show rate could be increased. The same result was gathered by Goldman, Freidin, Cook, Eigner, and Grich (1982) who performed a research to predict no-show in a primary care center. These researchers analyzed a total of 376 patients during a twelve-month period. Their results showed that 18% of the patients whose appointment was made too far in advance committed no-show, while 82% kept their appointment. This does not only have something to do with the elapsing calendar days, but also with the patient's age and ethnicity. To prevent no-shows, hospitals must be able to grant appointments relatively quickly, within 2 or 3 days (Benjamin-Bauman et al., 1984). This result cannot be generalized because this depends on the geographic location of the hospitals.

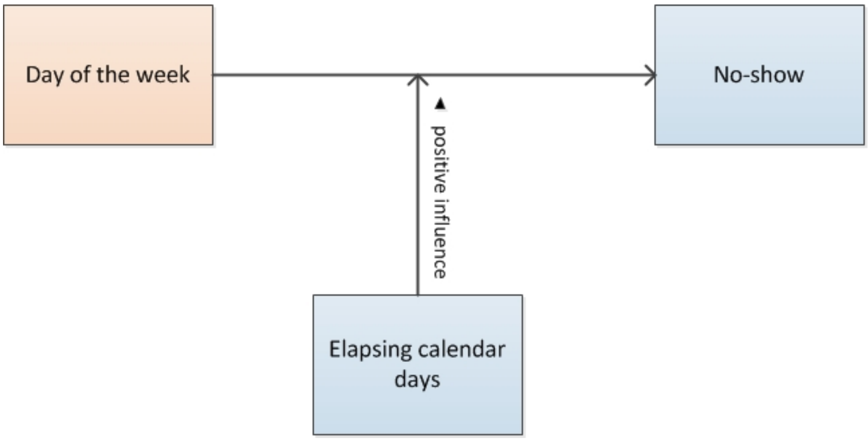


Figure 18. Relation between Environmental: Day of the week and patients' demographic factors: Elapsing calendar days to no-show.

3.2.5 Conclusion

This chapter performed a literature study on the environmental factors, which act as a moderator on the patients' demographic factors. These factors positively influence patients toward no-show. These factors were: (i) transportation, (ii) geographic distance and (iii) day of the week, as shown in Table 5. The literature studies also provided different reasons for this positive influence. With these reasons and associations between the patients' demographic factors and environmental factors we can employ different interventions to reduce no-show rates.

Environmental factors	Relation with *demographic factor*	*Reasons of no-show*
Transportation	- Age - Low socioeconomic status	- Time to get off work - Child care
Geographic distance	- Low socioeconomic status - Gender - Age	- Travel cost - Hospital characteristics, such as what kind of services they offer - Appointment importance - Health insurance status
Day of the week	- Elapsing calendar days	- Appointment created too far in advance

Table 5. Relation between Environmental and patients' demographic factors.

✖ = No information found

3.3 Related patient's behavior models

The influence of patient's behavior with regard to no-show

In the previous sections, we have discussed the key patients' demographic factors and key environmental factors that act as a moderator on the demographic factors with regard to no-show. In this section, we study previous literature on theories and models that explain an individuals' behavior. As Ulmer and Troxler (1999) explained, patients' behavior can also contribute to a lower quality of care. Doctors may have a negative attitude towards no-show patients, and some may even choose not to accept patients who resemble stereotypical no-show patients. These negative attitudes towards potential no-show patients may result in a disrupted patient-doctor relationship that leads to a decrease of communication lack of empathy, decreased quality of care and a higher no-show rate.

These theories and models serve to improve our knowledge of no-show patients, only this time from a different perspective, namely studying the behavior of the individual itself. By using the Theory of Planned Behavior and the Theory of Social Influence along with the gained knowledge of, for example the patient's behavior or attitude, we can predict that this patient will most likely not attend his (following) appointment. With this knowledge we can learn how to reduce the no-show rate in the healthcare sector. As explained by Ajzen (1991) "*many studies performed in recent years have demonstrated the workings of the aggregation principle by showing that general attitudes and personality traits do in fact predict behavioral aggregates much better than they predict specific behaviors.*"

This section aims to give an answer to sub-question number three, namely:
SQ-3: *"How can a patient's behavior have an influence towards no-show and how is this related to the patients' demographic factors and the environmental factors?"*

This question is answered by reviewing different theories and models about patients' behavior. Studying these theories and models help to show that a no-show does not only happen due to patients' demographic factors and their environmental factors. It also occurs because of an individual's own behavior. In this section, we also demonstrate how these two factors are related to a patient's behavior when discussing no-shows.

3.3.1 Theory of Planned Behavior

The Theory of Planned Behavior (TPB) is a theory about the link between attitudes and behavior. This theory was developed by Icek Ajzen (1991) to improve the predictive power of the theory of reasoned action by including perceived behavioral control. This theory has been applied to studies on the relations between beliefs, attitudes, behavioral intentions and behaviors in various fields, also in the field of healthcare. TPB consists of 4 factors, namely (i) attitude toward the behavior, (ii) subjective norm, (iii) perceived behavioral control and (iv) intention, which all leads to the individual's behavior (Ajzen, 1991), as depicted in Figure 19.

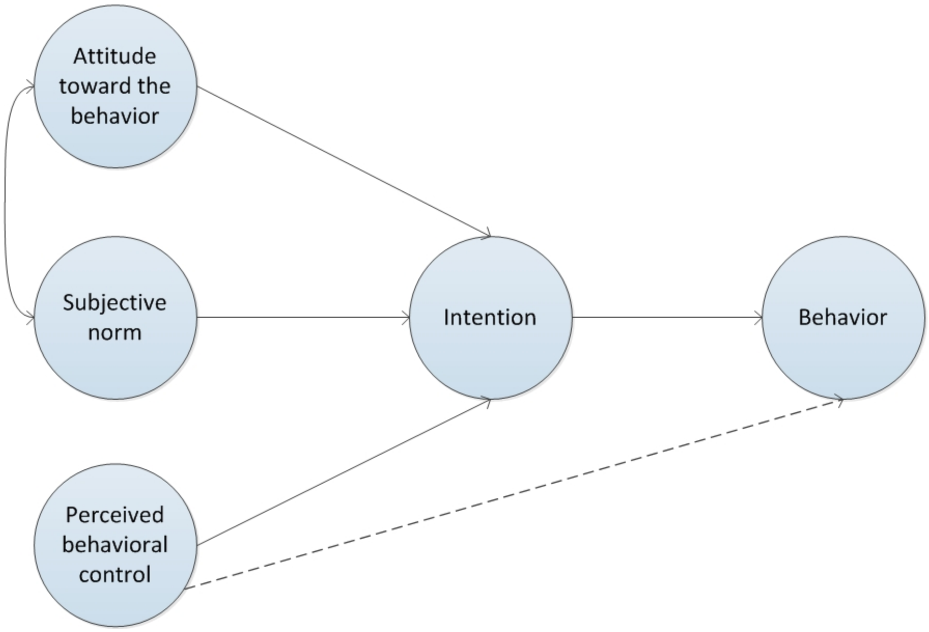


Figure 19. Theory of Planned Behavior, retrieved from (Ajzen, 1991)**.**

- ***Intention***
  With intention the individual's intention to perform a given behavior is meant. Intentions are indications of how hard people are willing to try, or the effort they are willingly to put into something in order to perform a behavior. The stronger the intention, the more likely the behavior takes place. In the case of no-show patients, their intention is associated (dependent on) with the amount of money they have, the time they have to attend their appointments and the communication between the patient and doctor.

- ***Perceived behavioral control***
  Perceived behavioral control is the importance of actual behavior or the expectancy of success of the behavior and the motive henceforth. The perceived behavioral control is determined by control beliefs concerning the presence or absence of barriers and facilitators to behavioral performance (Glanz et al., 2008). It is assumed to reflect past experiences as well as anticipated impediments and obstacles (Ajzen, 1991). In the case of no-show patients; if patients know the reason for attending their appointment or if they acknowledge that the appointment is important and if they do not have to wait a long time to see their doctor, they are most likely to attend.

  According to the TPB, perceived behavioral control, together with behavioral intention, can be used to predict an individual's behavioral achievement (Ajzen, 1991). In other words 'Intention' is the mediator of 'Perceived behavioral control', weighted by their perceived power or the impact of this (Glanz et al., 2008). If 'Perceived behavioral control' has a positive influence on 'Intention', than patients most likely attend their appointments.

- ***Subjective norm & Attitude toward the behavior***
  Subjective norm refers to the perceived social pressure to perform or not to

perform a behavior (Ajzen, 1991). In other words, subjective norm is determined by an individual's normative beliefs and weighted by his own motivation to comply. For example, if a person believes that he should perform a certain behavior for his own benefit, he will perform this to meet his own expectations. In our no-show patients' case; if doctors explain to each of their patients (young or old, low or high socioeconomic status, ethnicity is not an issue) the benefits of showing up at appointments (e.g., cure a disease by taking this type of medicine) patients are more likely to attend.

'Attitude toward the behavior' refers to the degree to which a person has a favorable or unfavorable evaluation or appraisal of the behavior in question. Many theorists have described attitude as composed of effective and cognitive dimensions (Glanz et al., 2008). Attitude toward a behavior is an individual's emotional response to the idea of performing a recommended behavior. Individuals who show a negative emotional response to a certain behavior are least likely to perform this behavior. The more positive an individual attitude and subjective norm is with respect to his behavior the most likely that he will perform the behavior. When discussing no-show patients, they do not attend their appointments due to fear or anxiety prior to seeing their doctor, often because of what the doctor might say to them (Lacy et al., 2004; Mitchell & Selmes, 2007; Ong, de Haes, Hoos, & Lammes,1995).

By conducting different literature studies on TPB and on no-show patients, we can conclude that a patients' attitude toward his behavior, his subjective norm and his perceived behavioral control have a positive influence on his own behavior intention (moderator) to increase the possibility of attending appointments (Ajzen, 1991; Glanz et al., 2008). If one or more of these factors have a negative influence on his behavior intention, the chance is most likely that he does not attend his appointment.

3.3.2 Social Influence Theory

The Social Influence Theory (SIT) states that *"behavior is intentionally or unintentionally influenced by others"* (Schmitz & Fulk, 1991). In other words, SIT occurs when one's opinions, intentions or behaviors are affected by others. The SIT is based on the media richness theory and adds the construct of social influence ((Schmitz & Fulk, 1991). This theory assumes that the social context affects the behavior and attitude of an individual regarding communication media. SIT can be divided into three different processes of influence, namely (Kelman, 1958):

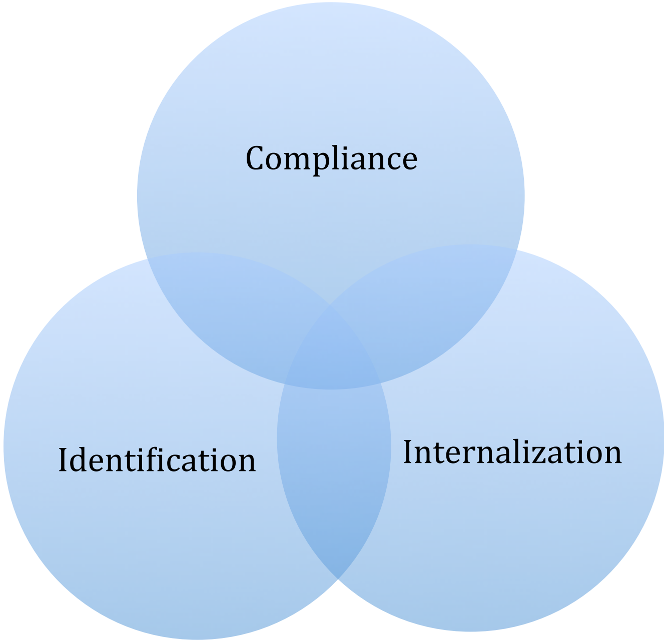


Figure 20. Social Influence Theory (SIT), retrieved from (Kelman, 1958)**.**

- ***Compliance***
  Can be said to occur when an individual accepts influence from another person, because he knows to receive or achieve some benefits or a favorable reaction in return (Kelman, 1958).

- ***Identification***
  When an individual adopts an induced behavior, because it is associated with the desired relationship (Kelman, 1958). In other words, when an individual is influenced by another individual he is closely connected with, such as a family-member or friend.

- ***Internalization***
  This is when an individual accepts an influence, because of the content of the induced behavior, such as the ideas and actions of which it is composed is intrinsically rewarding (Kelman, 1958).

Social Influence Theory also has an influence on patients within the healthcare sector. For example, a recent retrospective cohort study conducted at different General Practitioners (GP) explains that a family plays an important role in whether a family member should consult or not consult a physician (Cardol et al., 2005). If a family member (e.g., a parent) is often sick and therefore often goes to his GP and comes back with good results or positive feedback, there is a greater chance that his family members also go to their GP or attend their appointments. This correlation has been proven significantly in the studies by Cardol et al. (2005) and Dove and Schneider (1981). Moreover, this influence is greater between mothers and their children than between fathers and their children (Dijk, 2007).

3.3.3 Patient's explanation for no-show

The top six patient's explanations found to be related to no-show, is depicted in Table 6. Many patients seem to forget about their appointments. This is because they tend to have a busy work schedule, because their appointments were set at a different time during the day or because they overslept or because they have memory problems due to an illness or disease; especially in the case of older patients.

Patients who have a full-time job are a predictor of the increase of no-show rates. They often are seen as the homogeneous no-show patients, due to the fact that they almost never attend their appointments. Such patients who are ill call their doctors, however, as soon as their illness (or disease) is gone they conclude that they do not need to attend to their appointments anymore. They then stay away without informing their doctors. Other patients who have other explanations, such as a 'situation arose', refer to the following situations: (i) transportation problems, (ii) child-care, (iii) weather issues or the (iv) distance that they have to travel from their home to the hospital.

Patients' explanation	Studies / References
Forget	(Booth & Bennett, 2004; Detman & Gorzka, n.d.; Garuda, Javalgi, & Talluri, 1998; Hamilton et al., 2002; Hardy et al., 2001; Lacy et al., 2004; Maxwell et al., 2001; Mitchell & Selmes, 2007; Moore et al., 2001; Sparr, Moffitt, & Ward, 1993)
No need to come	(Carpenter, Morrow, Del Guadio, & Ritzler, 1981; Detman & Gorzka, n.d.; Lacy et al., 2004; Maxwell et al., 2001)
Work	(Detman & Gorzka, n.d.; Deyo & Thomas, 1980; Hamilton et al., 2002; Lacy et al., 2004; Maxwell et al., 2001; Weisman & Teitelbaum, 1985)
Didn't know about visit	(Maxwell et al., 2001; van Wieringen et al., 2002)
Situation arose	(Detman & Gorzka, n.d.; Lacy et al., 2004; Maxwell et al., 2001)
Thought it was a different time	(Detman & Gorzka, n.d.; Maxwell et al., 2001)

Table 6. Patient's explanation no-show, based on previous studies.

3.3.4 Conclusion

This chapter consisted of a literature study on several theories in order to gain knowledge on how the behavior of an individual can influence the individual to perform a certain action. Theories found that were relevant on this matter were: the Theory of planned behavior (i) and the Social Influence Theory (ii). What we can conclude by following the TPB and the SIT is that the no-show patients are not only influenced by demographic- and environmental factors, but also by their own behavior, and in this case also by other individuals that surround them. Previous bad experiences affect a patient negatively when it comes to attending an appointment, as explained in the previous sections in this chapter.

Figure 21 illustrates the relation between demographic-, environmental factors and the patient's behavior. As explained in section 3.2, the environmental factors act as a positive or negative influence on the patient's demographic factors (moderator effect). A patient's own behavior can also have an influence towards no-show, as explained in this section. By understanding the relation between these three factors, one can create a strategy to reduce the number of no-show patients. In this section, we gained knowledge on the patient's behavior. Now we know that by informing a patient more often that he has an appointment he most likely will attend this appointment. It is also very important that doctors inform their patients of the valuable reasons to attend the appointment, such as what the doctor is actually going to perform during the appointment (i.e., medical tests, medical procedures) and what kind of result he is going to extract. The communication between the patient and the doctor is therefore important.

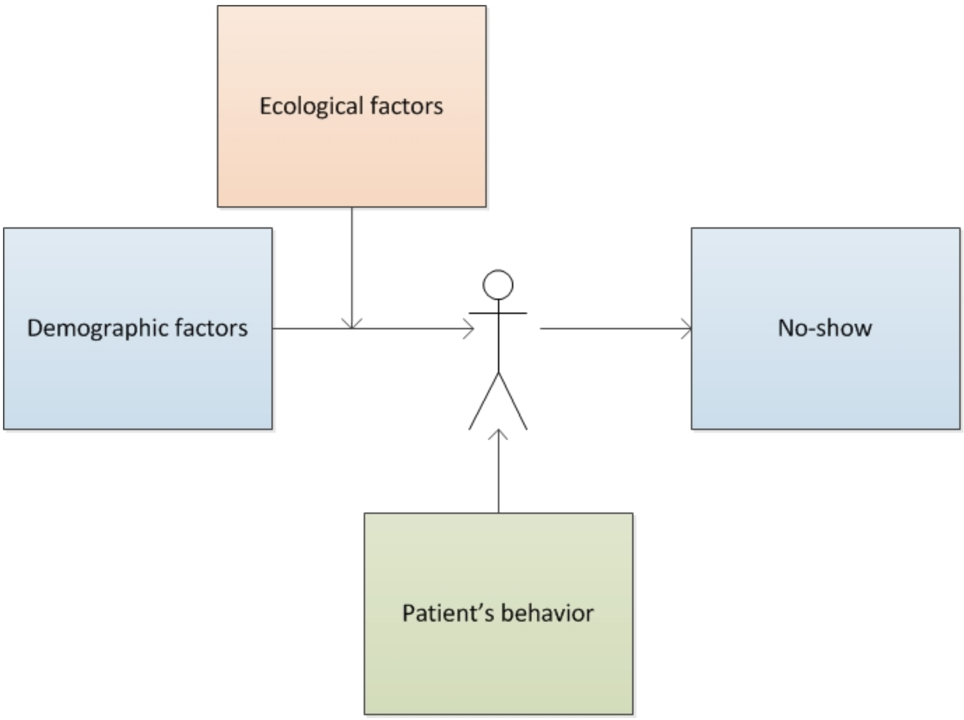


Figure 21. The relation between a patients' demographic, environmental and its own behavior towards no show

3.4 Interventions to reduce the number of no-show patients

Methods, models and techniques to reduce no-show

3.4.1 Introduction

Due to the above-mentioned financial costs, stress and frustration of the staff and the physicians and the negative effects on the health of patients, there have been a variety of discussions and attempts to reduce the no-show rates in the healthcare sector. Interventions to reduce the number of no-show patients recently became a popular topic in the US, Europe and also in other countries, such as Israel (Glanz et al., 2008). As explained earlier, no-show created a problem for doctors, patients, and clinics all around the world. This section explains various interventions that have previously been conducted in studies and also been performed as experiments in hospitals, clinics or other medical care centers.

This section aims to give an answer to sub-question number four:
SQ-4: *"What are the previously used methods, models and techniques in the healthcare sector with regard to no-show and how can these best support the healthcare sector in its battle against no-show?"*

Previously used methods, models and techniques were consulted based on how many times they were mentioned in previous literature studies. These were then categorized in three categories, as depicted in Table 7: methods (i), models (ii) and techniques (iii). Each intervention is explained to gain knowledge on how to reduce the number of no-show patients in the healthcare sector.

Various interventions (Benjamin-Bauman et al., 1984; Daggy et al., 2011; Lacy et al., 2004; Parikh et al., 2010; Satiani et al., 2009) have been previously utilized to maximize the patient flow (hence increasing the profitability) without incurring additional costs (Journals, 2012), however most of them have only been used in studies. The most apparent reason for this, is that too few hospital and clinics in the healthcare sector are aware of these interventions and thus they are not often used (Daggy et al., 2011). Some interventions, that have been experimentally applied and evaluated, effectively reduced the no-show rate in the healthcare sector. These interventions often use several input variables in order to function properly, such as no-show rates, walk-in rates, appointment scheduling intervals, physician service times, interruptions and so on (Journals, 2012).

Methods	Models	Techniques
1. (Modified)Wave scheduling method 2. Mu-law scheduling method 3. Short lead-time scheduling method	1. Overbooking	1. Reminder letters/ card 2. Telephone reminders 3. Automated telephone reminder 4. Establishing a separate cancellation phone line 5. Charge a fine on no-show patients

	6. Change patient behavior through educations 7. Positive financial incentives

Table 7. interventions regarding to reduce the number of no-show patients in the healthcare sector.

3.4.2 Methods

When patients fail to show up for their scheduled appointments, the hospital's capacity is reduced to under its maximum number of allowed patients (Laganga & Lawrence, 2007). To mitigate this loss, hospitals and healthcare clinicians have experimented with a number of alternative appointment scheduling policies. Some clinics overbook appointments by double-booking patients into common appointment times and relying on no-shows to allow the schedule to catch up (Chung, 2002). Others have experimented with methods, such as the wave scheduling method, mu-law scheduling method and short lead-time scheduling method.

3.4.2.1 Wave scheduling method

Wave scheduling is a known method previously used in several hospitals, clinics and primary cares (Ferenchick, Simpson, Blackman, DaRosa, & Dunnington, 1997; Satiani et al., 2009). It involves having several patients arrive at the same time followed by another "wave" during the next hour. Without decreasing the volume of patients seen in a day; different doctors or specialists see two or more patients simultaneously in the same time-slot. Here, you can think of making an appointment for patients with similar diseases in order to boost the productivity of the hospital's staff and to prevent overworking hours (Laganga & Lawrence, 2007). Imagine three patients who have been addressed for the same time-slot (e.g. 11:00am) on the same day. One of them does not attend his appointment, this gap is then filled with the next patient waiting in line; leaving no wasted time for the doctors by following the "*first-come and first-served*" basis.

While wave scheduling is good for productivity, it has its disadvantages; this method did not take into account the long waiting time, especially when it gets crowded at the doctor's office, which could worsen the no-show rates (Daggy et al., 2011). Therefore, this method was unpopular among the patients, because some had to wait several hours to be seen, despite having arrived on time for their appointments. Therefore a modified wave scheduling was developed. This method schedules more patients at the beginning of each hour and less towards the end of the hour, allowing the specialists to absorb unexpected delays and return back to schedule at the end of each hour in order to catch up (Laganga & Lawrence, 2007).

3.4.2.2 Mu-law scheduling method

Mu-law scheduling method is a stochastic mathematical overbooking method that builds the schedule sequentially through a call-in process (Daggy et al., 2011). This method was developed by Muthuraman and Lawley (2008), which explains the name 'Mu-law' scheduling method. This method considers a number of patient types with several no-show probabilities where weights are assigned to each defined patient type. Afterwards the call-in sequence is generated based on these weights (Daggy et al., 2011; Muthuraman & Lawley, 2008).

For example, if five patient types with no-show probabilities of 0.15, 0.34, 0.60, 0.75 and 0.80, and weights of 0.35, 0.25, 0.18, 0.15 and 0.07 are considered, the average no-show probability rate is 0.33% (0.15 x 0.35 + 0.34 x 0.25 + 0.60 x 0.18 + 0.45 x 0.15 + 0.21 x 0.07 = 0.33%). For that example, 35% of the time the patient has a no-show probability of 0.15, 25% of the time the patient has a no-show probability of 0.34 and 60% of the time the patient has a no-show probability of 0.60.

The Mu-law scheduling method uses the following input variables to create an optimally balanced patient waiting time, clinic overtime and patient revenue, these variables are: (i) no-show, (ii) service time, (iii) slot length information, (iv) patient waiting costs, (v) overtime costs and (vi) patient revenue (Daggy et al., 2011; Muthuraman & Lawley, 2008). It is logical that these inputs should be adjusted to their appropriate values for the given hospital, clinic or other organization.

Figure 22 acquired from Daggy et al. (2011), provides an example of a daily schedule of 30 patients labeled according to the order that they called in for an appointment using a one patient per slot method and afterwards using the Mu-law method. This study used information on scheduled outpatient appointments collected over a three-year period at a Veterans Affairs medical center in USA.

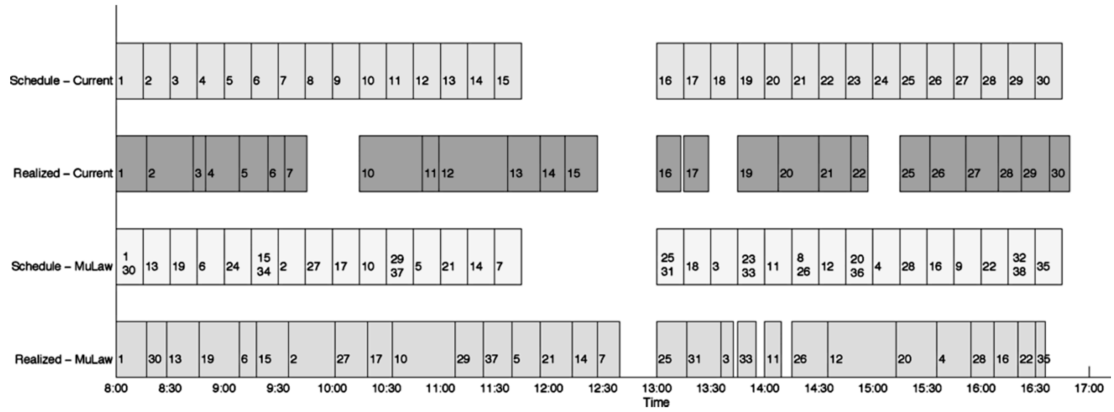


Figure 22. Mu-law scheduling method, retrieved from (Daggy et al., 2011).

The 'schedule-current' and 'realized-current' rows represent the one patient per slot method where all patients received the same amount of time interval (e.g., 15 minutes) for their appointments. The 'realized-current' row shows how it really went; the gaps represent the no-shows during the day. Due to that not every patient received the same amount of time interval for their appointment and also due to the no-show gaps between the appointments, there was an overtime of ±15 minutes.

In the following two rows; the Mu-law scheduling method was employed and thus a call-in sequence was applied. As can be seen, two patients are scheduled in the same time-slot, which ensures fewer gaps if no-shows occur. Patients with a high no-show probability were scheduled in with patients with a low no-show probability. Doing this decreased the gaps and prevented overtime during the day.

The advantages of utilizing the Mu-law scheduling method versus the one patient per slot method according to the experiment performed in Daggy et al. (2011) is depicted in Figure 23, which is the increase of physician utilization (panel A), decrease of the physician overtime (panel B) and the increase of the patients served (panel C), while the disadvantage, same with the Wave scheduling method, is the long waiting time (panel D) due to the patients' crowdedness.

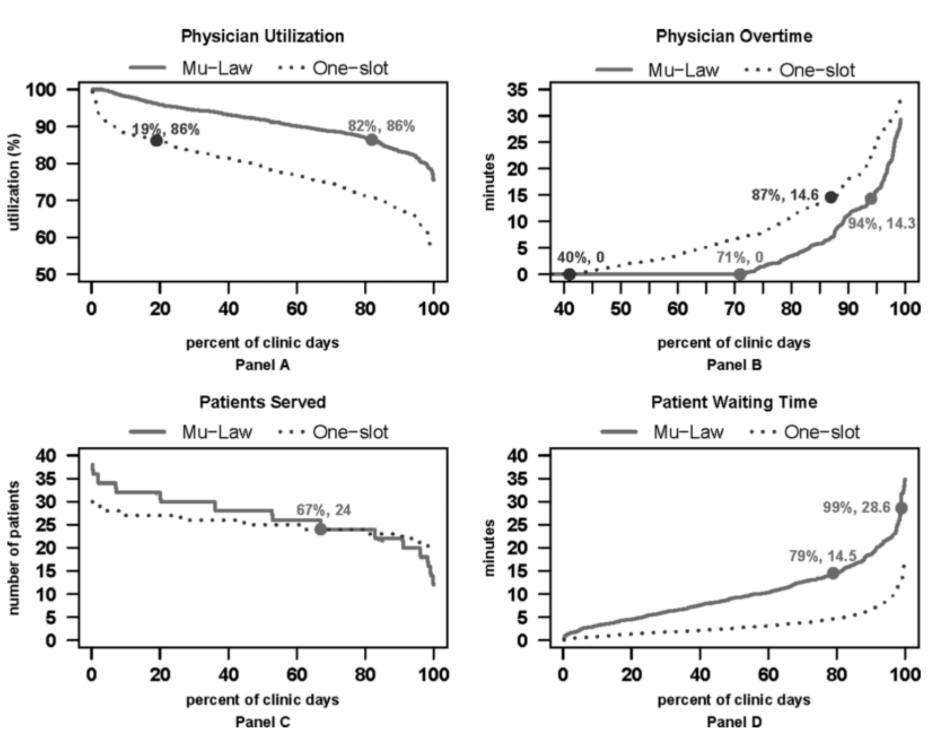


Figure 23. Mu-law scheduling method statistics, retrieved from (Daggy et al., 2011).

3.4.2.3 *Short lead-time scheduling method*

The short lead-time scheduling method, or also called open access scheduling (Kopach et al., 2007b), allows patients to see their doctor within a day or two of scheduling the appointment (Daggy et al., 2011) rather than booking a patient several weeks or months in advance. If the appointment slots are not available within the next day or two, the patient may be asked to call back later. In theory, short lead-time scheduling method should reduce the rate of no-shows and should increase access to healthcare (Daggy et al., 2011). Despite its appeal, this method can fail if not configured for the individual clinic's capacity and environment (Kopach et al., 2007b). See appendix, Figure 53 for the configuration. The variables that should be considered for this method are: (i) patient continuity of care, (ii) clinic's patient demographics, (iii) patients' location, (iv) patients' public transport and (v) patients' no-show history. All these factors should be taken into consideration when making the schedule.

Researchers of six case studies performed at primary care practices in the Boston metropolitan area from October 2003 to June 2006 reported that this method works for some clinics in their system, however, not for others (Mehrotra, Keehl-Markowitz, & Ayanian, 2008). This depends on the staff's and patients' satisfaction.

Kopach et al. (2007b) explain that by using the short lead-time scheduling method and by shortening appointment lead times for long term scheduling, clinics can serve more patients. However, if a clinic schedules in too many patients to see their doctor within a day or two of scheduling the appointment, the continuity of care will significantly be compromised, which will result into long waiting times, and also in higher treatment costs, physicians' overtime hours and patients' dissatisfaction. In order to prevent this from happening, staff members require to be educated to work with this method, refinement assimilation by the patient population and timely implementations (Kopach et al., 2007b).

3.4.3 Models

3.4.3.1 Overbooking model

To reduce the negative impact of no-show patients, doctor assistants and clinic schedulers also use a model called overbooking (Daggy et al., 2011; Zeng, Turkcan, Lin, & Lawley, 2009) Overbooking involves scheduling an additional fixed number of patients each day based on the no-show rate of the organization. This is meant to compensate revenue lost due to no-show, and also to reduce the negative impact of no-show patients either on clinics' operations or the hospitals and their performance (Zeng et al., 2009). This method, however, can only be effective if the effects of no-show are well balanced with those of over-show. This is achievable by estimating the probability that patients will not attend by regressing patient demographics and conditions, appointment characteristics, and other type of information on patient no-show data. An ideal overbooking model depends according to Zeng et al. (2009) on four characteristics, namely: (i) a valid patient no-show description that captures the real pattern of patient behavior, (ii) an underlying service model, (iii) performance of the organization and (iv) efficient algorithm that can generate schedules of desired quality in a timely fashion.

A disadvantage of this model is that it is associated with an increased waiting time for patients, which could increase the no-show rates and also increase the working time, which again could negatively affect the revenue of the hospital. Several studies performed on how to improve the performance have been conducted (Journals, 2012; Rising, Baron, & Averill, 1973; Smith & Warner, 1971). All of these studies have shown positive conclusions when an arrival pattern of patients is used. The research by Smith and Warner (1971), compared patients arriving according to a uniformly scheduled arrival pattern versus patients arriving in a highly variable manner. They show that the uniformly scheduled arrival pattern can decrease the average length of waiting for the appointment at the clinic or hospital by over 40%. Furthermore, this is accomplished due to the more predictable use of resources when patient's arrivals are uniformly spaced. Similarly, as studied by Rising, Baron, and Averill (1973), the researchers used mathematical-computer models to develop operating policies for a university-health-service outpatient clinic. They explained that if you increase the number of appointment slots during those days that had the least number of patients would smooth the demand of the staff members, resulting in a 13.4% increase in patient performance and less clinic overtime. This then has as a result a reduced average patient waiting time which leads to reducing the no-show rate. Although, overbooking seems to increase the patient performance as explained by Satiani, Miller, and Patel (2009), overbooking is more advantageous when a clinic or facility serves large numbers of patients, when the no-show rates are high, and the service variability is lower.

3.4.4 Techniques

Various techniques (Bech, 2005; Benjamin-Bauman et al., 1984; Daggy et al., 2011; Lacy et al., 2004; Maxwell et al., 2001; Parikh et al., 2010; Satiani et al., 2009) have been performed that have resulted in a reduction of the number of no-show patients, though, these techniques tend to be expensive. Such approaches are: reminder letters, telephone reminders, SMS-reminders, providing patients with the right information, focusing on changing the patients' behavior through communication, charging a no-show fee and using the effects of positive financial incentives (e.g., cash reward, gifts, vouchers and lottery tickets) and so on, prior to or after the appointment. In the following sub-sections more on these techniques is explained in coherence with studies done on these techniques.

3.4.4.1 Reminders

Automatic telephone reminder systems are used to decrease no-show rates. These systems allow for a reduction in staff requirements and provide a standardized, uniform reminder to the patient. Automatic telephone reminders have their benefits, because if no contact is made, a message is left on the patient's answering machine or voice mail. Some automatic telephone reminders try to reach the patient each night for three nights before their appointment. If no contact was made, the patient remains registered in the system for the appointment. Although, reminders seem to be a good technique to reduce the number of no-show patients, one has to know when to remind which patients. A conducted research by Hardy, O'brien, and Furlong (2001) performed at a clinic (patients, n = 1661) explains that calling patients one week before their appointments can reduce the no-show rate by 1%.

A clinical research study was performed at an academic outpatient practice from March 2007 to July 2007 (Parikh et al., 2010). The researchers studied patient acceptance and no-show rates among three groups: (i) patients receiving a clinic staff reminder (STAFF), (ii) an automated appointment reminder (AUTO), (iii) and a no reminder (NONE). The patients scheduled for appointments were assigned randomly to one of the three groups: STAFF (n = 3266), AUTO (n =3219), or NONE (n = 3350). The patients that fell into the STAFF group were reminded of their appointment(s) three days in advance by front desk personnel, whereas patients in the AUTO group were reminded of their appointments three days in advance by an automated (robot) fixed message. The researchers (Parikh et al., 2010) used surveys in order to evaluate the patients who arrived at the clinic. Furthermore, the patients were distributed into quartiles by age: 18 to 44, 45 to 56, 57 to 68 and 69 to 100 years. The results of this study was interesting; the no-show rate decreased for every increase in age quartile (+1 year, -2.4% no-show rate), also the no-show rate in the AUTO group tended to be lower than in the STAFF group. As we know, new patients tend to have a higher no-show rate; this was also the case in this study where the no-show rate of new patients was significantly higher than of established patients (17.7% vs. 15.9%). This remained true for both the STAFF and the AUTO group. Next to that, the no-show rates for patients who received a STAFF, AUTO and NONE was 13.6%, 17.3% and 23.1%, respectively (see Figure 24).

The cancellation rates were not statistically different between the AUTO (17.6%) and STAFF (16.9%) groups. Cancellation rates were a bit higher in the AUTO and STAFF groups when compared to the NONE group (14.5%) ($P = .0001$ and $P = .003$, respectively). The reschedule rates were also not statistically different between the NONE, STAFF and AUTO groups (2.09%, 2.63% and 2.02%, respectively).

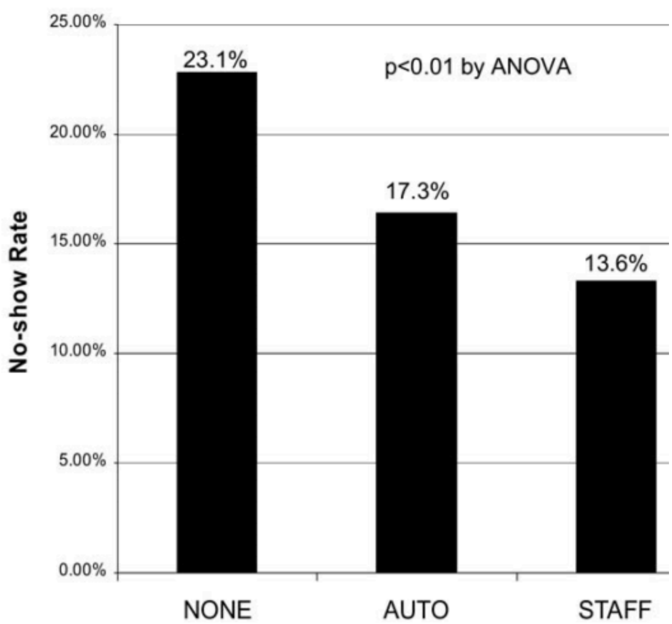


Figure 24. No-show rates grouped by call group: none, auto and staff, retrieved from (Parikh et al., 2010)**.**

It can be concluded from the research by Parikh et al. (2010) that patients who received a reminder (i.e., STAFF or AUTO reminder) tend to attend their appointments more often than patients who did not receive any reminders at all, in this case the NONE group. This was also the case in the study by Bech (2005) which proved that mailings and telephone reminders reduced non-attendance rates by 47-68% and 27-75%, respectively. As mails and telephone reminders seem to reduce the no-show rate, one also has to keep in mind that this may also improve the ease of rescheduling, identifying vacant appointments in advance or cancelling appointments. This was the case in the research by Parikh et al. (2010) where the researchers reported that there was an association between higher cancellation rates and the presence of an auto reminder system. Therefore, receiving a reminder from live clinic staff members seems to be more effective, because by using an automatic reminder system patients can already predict what the automatic reminder is going to tell them, which thus leads to the patient not answering the phone or just cancelling the appointment at that moment. In order to prevent this from happening, Livianos-Aldana, Vila-Gomez, Rojo-Moreno, and Luengo-Lopez (1999) explain, a shorter time interval between the appointment reminders and the appointment is necessary, because this could prevent 40% of non-attendance.

Garuda et al. (1998) concluded that despite the widespread use of postcards and telephone reminders, the problem of no-show still remains in some cases, because these techniques only addresses one of the many causes of no-show, namely, forgetfulness. They suggest that other techniques should be implemented, such as ‘charge a fine’, ‘contracting patients’ and ‘improve patient’s education through communication’. These techniques are explained in the following sub-sections of this research based on the relevant literature.

3.4.4.2 Charge a fine (fee) on no-show patients

Some clinics and hospitals charge a no-show fee for patients who do not show up for their appointments. The purpose of charging a no-show fee is to optimize the no-show rate and the healthcare resources and to secure the appropriate use of healthcare funding (Bech, 2005). Although this is a solution for the hospitals, clinics and other medical care centers to reduce the no-show rate, it is a less desirable solution for the patients, because this approach can limit access to care for patients with a restricted income (Daggy et al., 2011). For this reason, the possibility of charging a fine has been debated in a number of countries, such as Denmark and United Kingdom, by asking the obvious questions whether this intervention is effective when it comes to reducing the rate of no-shows and administrative costs associated with the intervention (Bech, 2005).

Two studies who compared the pre-intervention and post-intervention by introducing the no-show fee to those patients who do not show up for their appointments, revealed that the introduction of a fine on non-attendees reduces the no-show rate (Lesaca, 1995; Mäntyjärvi, 1994), which contradicts what Daggy et al. (2011) said about patients with a restricted income. These results are consistent with the results of Mäntyjärvi (1994). Mäntyjärvi (1994) reported that the no-show rate decreased from 6.4% to 5.5% after the introduction of the no-show fee. They suggested, in order to reduce the no-show rate even further, that "*it is important to inform the patient well about his disease and the significance of the examinations and follow-up visits*". Lesaca (1995) found that the no-show rate in fact decreased from 20.1% pre-intervention to 9.27% post-intervention for their total sample.

What can be concluded from these two studies is that charging a no-show fee seems to reduce the no-show rate depending on the group (set) of patients that the hospital is expecting. If the hospital's average patient has a low income or consists mainly of elderly or insured patients, than a patient fee is not the solution. However, as seen in previous studies, this technique does reduce the no-show rate.

3.4.4.3 Positive financial incentives

Another approach is called the positive financial incentives to enhance patient compliance. Financial incentives are defined as money, cash, or vouchers redeemable for other goods, such as clothes, food, gifts and so on (Giuffrida & Torgerson, 1997), and compliance can be defined as the extent to which a patient's behavior coincides with medical advice. This includes medical appointments failure rates. A study (Giuffrida & Torgerson, 1997) performed to determine whether financial incentives increase patients' compliance with healthcare treatments, concluded based on 11 other studies that financial incentives tend to be more effective than other methods. This method can also be more cost effective than alternative interventions and also tends to achieve greater compliance at lower costs. Financial incentives have according to Giuffrida and Torgerson (1997) a greater effect among low income patients.

3.4.4.4 Change patient behavior through communication

Giving patients valuable information by informing them about their forthcoming appointment has significant effects on no-show rates. Valuable information such as, the name of the hospital, location of the hospital and its available parking lots, the doctor's name, day and time of the appointment, and most importantly what the patient should bring, could make a positive difference. Some researchers state that the rise of broken appointments is due to the breakdown of communication on the part of health centers (Guse, Richardson, Carle, & Schmidt, 1997). As explained by Hardy et al. (2001), it is also significant to exactly describe what is going to happen to the patient during the appointment; from greeting the nurse to taking a blood test and the patient's departure. Effective communication between patients and their physicians improves the healthcare quality, which also decreases the patient's stress and increases the patient's satisfaction with going to the hospital to attend the appointments (Liederman, Lee, Baquero, & Seites, 2005a). Apart from that, information regarding what to do after the appointment, such as who the patient would see next in five weeks' time and when and where this is going to take place, also is beneficial.

Several previously conducted studies on changing patients' behaviors through communication have come with some interesting results (Bech, 2005; Guse et al., 1997; Hardy et al., 2001).

The research by Hardy et al. (2001) was performed at a diabetes clinic in a district general hospital. Information was collected from 1.336 historical controls three years before the study. Two weeks before the patient's appointment the researchers sent an information pack telling the patients when and where to come, where to park and so on. One week before the appointment the patients receive a supplementary phone call. In total 325 patients received only the information pack and 147 patients received the information pack plus the follow-up telephone call and 178 patients received the information pack without the telephone call. They concluded that by telling the patients what to expect the no-show rate was reduced from 15% to 4.6% (-10.4%).

So, if the patients are told what to expect before the actual appointment takes place this reduces the no-show rate by around 10%. Similar conclusions have been drawn by Deyo and Thomas (1980), who points out that a patient's knowledge and educational efforts can improve appointment keeping and broken appointment rates. This was also the case in the study by Guse et al. (1997) that held exit-interviews with patients (n= 443) during a one year period. In this study, the patients received the standard clinic information pamphlet, which describes the services provided at the clinic and also what to expect at their first visit, about the scheduling and rescheduling of their appointments and so on. Their results were significant; the overall no-show rate reduced the odds of no-show rate by 5.2%, from 21.7% to 16.5%.

The disadvantage of changing a patient's behavior by educating them is that the effects will fade away (decay) over-time, also it will take time to educate each patient. Henceforth, technology will come in handy. The benefits of using technology is explained in section 3.5.

3.4.5 Conclusion

This section discussed literature studies on the different methods, models and techniques to reduce no-show. Most of these methods and models only focus on the appointment-scheduling problems in order to reduce no-show, whereas the techniques apparently are more oriented towards how to confront the patients when they do not show up. As we have learnt in this section and previous sections in this chapter, no-show did not only occur because of the patients fault, it was also based on other factors, amongst other, due to the long waiting times.

To answer the sub-question of this section two tables are depicted (Table 8 and Table 9). The tables summarize the advantages and disadvantages of each intervention, based on this literature study. The advantage column shows how the methods, models and techniques support the healthcare to reduce no-show, and the disadvantage column shows where the interventions fall short. Table 8 focuses on the hospitals, clinics or other medical care centers and Table 9 focuses on the patients.

Hospitals, clinics or other medical care centers' perspective		
Methods, models and techniques	**Advantages**	**Disadvantages**
Wave scheduling method	- Boost the productivity of	- Doctor's could not keep

	the hospital's staff members - Prevent overworking time - Follow the "first-come and first-serve basis"	up with patients when it gets crowded
Modified Wave scheduling method	- Absorb unexpected delays	
Mu-law scheduling method	- Prevent overworking time - Boost the productivity of the hospital's staff members - Increase of patient served - Less unexpected no-show gaps	- Doctor's could not keep up with patients when it get crowded
Short lead-time scheduling method	- Reduce the no-show rate and increase access to healthcare	- Overworking time - The continuity of care will be significantly compromised
Overbooking model	- Increase hospitals revenue - Boost the productivity of the hospital's staff members - Increase of patient served	- Model is associated with increased waiting time for patients - Overworking time
(Automatic) Reminders	- Reduce staff overload	
Charge a fine on no-show patients	- Force no-show patients to attend their appointments	
Positive financial incentives		- Costs associated with this intervention
Change patients behavior through communication	- Increased communication between patient and doctor	

Table 8. Hospital, clinics and other medical care centers' perspective: Advantages and disadvantages of the methods, models and techniques to reduce the number of no-show patients.

Patients' perspective		
Methods, models and techniques	**Advantages**	**Disadvantages**
Wave scheduling method	- Follow the "first-come and first serve basis"	- Long waiting lines at the doctor's office when it gets crowded
Modified Wave scheduling method	- No unexpected long waiting lines	- Long waiting lines at the doctor's office when it gets crowded

Mu-law scheduling method	- Fixed patient slot-time - See the doctor quicker	- Long waiting lines at the doctor's office when it gets crowded
Short lead-time scheduling method	- See the doctor within 2 or 3 days of making the appointment	- Higher treatment cost
Overbooking model		- Long waiting lines at the doctor's office when it gets crowded
(Automatic) Reminders	- Provide a standardized, uniform reminder - Patient are less likely to forget about their appointments	
Charge a fine on no-show patients		- Could lead to patient dissatisfaction
Positive financial incentives	- Enhance patient compliance	
Change patients behavior through communication	- Increased communication between patient and doctor	

Table 9. Patients' perspective: Advantages and disadvantages of the methods, models and techniques to reduce the number of no-show patients

3.5 eHealth

The use of Internet or Web technology in healthcare (Van de Belt et al., 2010).

3.5.1 Introduction

With the enormous investment in Information Technology (IT) within the healthcare sector, it is the question whether this have payoff or not (Devaraj & Kohli, 2000). It is interesting to study if the impact outcomes have increased the patients' satisfaction with regard to no-shows or not. In this chapter, we do not discuss how hospitals can decrease their costs by using software technologies, such as (i) BPR and (ii) DSS (Devaraj & Kohli, 2000). The goal of this chapter is to collect literature studies on how web technologies, such as social networks, mobile communication and telecommunication can be utilized to support the healthcare in reducing the number of no-show patients. Social networks (SN) are for example Facebook and Twitter. Telecommunication is, for example, Skype and VoIP, and Mobile communication is the utilization of smartphones to reduce the number of no-show patients. Some studies merged these three technologies into one by calling them: Information Technologies (Falahah & Rosmala, 2012), which can be used as a synonym.

- Facebook is a social networking website launched in February 2004 that is operated and privately owned by Facebook.
- Twitter is an online social networking service and micro blogging service that enables its users to send and read text-based messages of up to 140 characters, known as "tweets".
- VoIP stands for Voice over IP. This is a methodology and broad range of technologies for the delivery of voice communications and multimedia sessions over Internet Protocol (IP) networks, such as the Internet.

SN is defined as "a group of Internet-based applications that build on the ideological and technological foundations of Web 2.0, and they allow the creation and exchange of user-generated content" (Van de Belt, Berben, Samsom, Engelen, & Schoonhoven, 2012). This is a new trend in almost all organizations today. SN had an impact on the productivity of employees by making communication easier and faster between co-workers and also between departments (Chan & Chan, 2012). SN has thus proved its ability to boost the communication between people. For this reason many organizations attempt to use the power of social media. In the healthcare sector, active use of SN could speed up communication by supplying valuable information, such as medical information and health guides to patients, thus increasing the service quality even more (Van de Belt et al., 2012).

In section 3.4 we explained how methods, models and techniques can support the healthcare in reducing the number of no-show patients. Though, it has to be taken into consideration that there are various reasons for no-shows, such as illness, accidents, car breakdowns or very late cancellations (Chan & Chan, 2012). These situations give rise to a level of no-shows, which cannot be completely resolved by these above-mentioned interventions alone.

This section aims to give an answer to sub-questions number five, namely:
SQ-5: *"How can information technology support healthcare towards no-show?"*

3.5.2 *Social networks as an effective communication tool*

In the healthcare, patients increasingly use SN to communicate and share information. The researchers Van de Belt, Berben, Samsom, Engelen, and Schoonhoven (2012), who did a longitudinal study on the exploration of the use of social media by hospitals in 12 Western European countries, found that all hospitals (n=873) in all countries use social media. Sixty-four percent of their respondents of an online questionnaire among patients indicated that they performed a search to analyze their condition before calling their doctor.

A reason why hospitals should embrace social media is that it may contribute to quality improvement; active use of social networks does not only speed up communication and improve information provision for patients, it also allows doctors to engage patients in the delivery of care. Thus allowing patients to receive answers to their questions more quickly and collaboratively, which could also improve the relationship between the patients and their doctors (Van de Belt et al., 2012). It therefore can help hospitals with reducing the waiting time or their rate of no-show.

Communicating last-minute availabilities to prospective patients is the initial and fundamental step which social networks help with. Social networks reduce the workload on staff members and facilitate networking (Beach, 2011). Furthermore, answers given on social networks can be read by multiple patients, which reduces the amount of calls per day. Facebook and Twitter announcements provide the most effective platforms for doing so, initiating a process in which patients can directly interact with the hospital (Chan & Chan, 2012). This may appeal to new patients and also to existing patients, those hoping to get appointments on the same day, walk-in patients and those without prior bookings. The social networks are also useful when an established appointment is cancelled, because with the use of these networks it is often easier to find a 'new replacement' patient than to reschedule other established appointments (Chan & Chan, 2012).

In the Netherlands, only 15% (n=13) of hospitals use Facebook, which is a relatively low percentage compared to other European countries, as depicted in Figure 25. All 15 hospitals have a group on Facebook, ten of them also have a Facebook link somewhere on their website, though, none of the hospitals have a Facebook profile (Van de Belt et al., 2012).

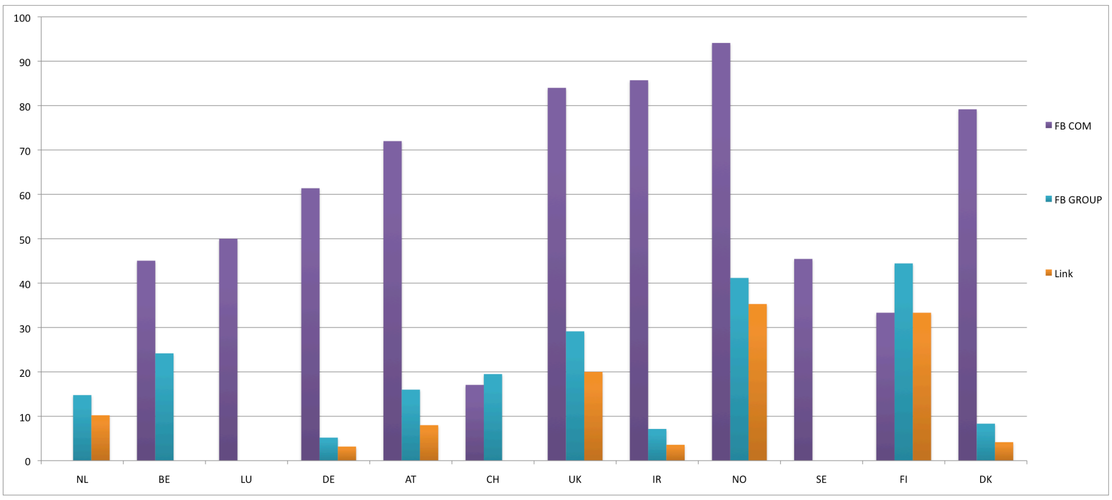


Figure 25. Percentage of Facebook profiles, group pages and link to a Facebook account on hospital websites (April to July 2011), retrieved from (Van de Belt et al., 2012)**. NL = the Netherlands, BE = Belgium, LU = Luxembourg, DE = Germany, AT = Austria, CH = Switzerland, UK = United Kingdom, IR = Ireland,**

NO = Norway, SE = Sweden, FI = Finland, DK = Denmark. FB COM = Facebook profile, FB GROUP = Facebook group, Link = Facebook link on hospital website.

3.5.2.1 Difference of traditional reminder systems and the use of social networks

A typical reminder process is depicted in Figure 26. It can be clearly seen by following the process that reminders cannot address no-show patients of a last minute nature. This is the reason why SN can help fill in this gap. According to Chan and Chan (2012) zero non-attendance is achievable through the new technology of SN, as can be seen in Figure 27.

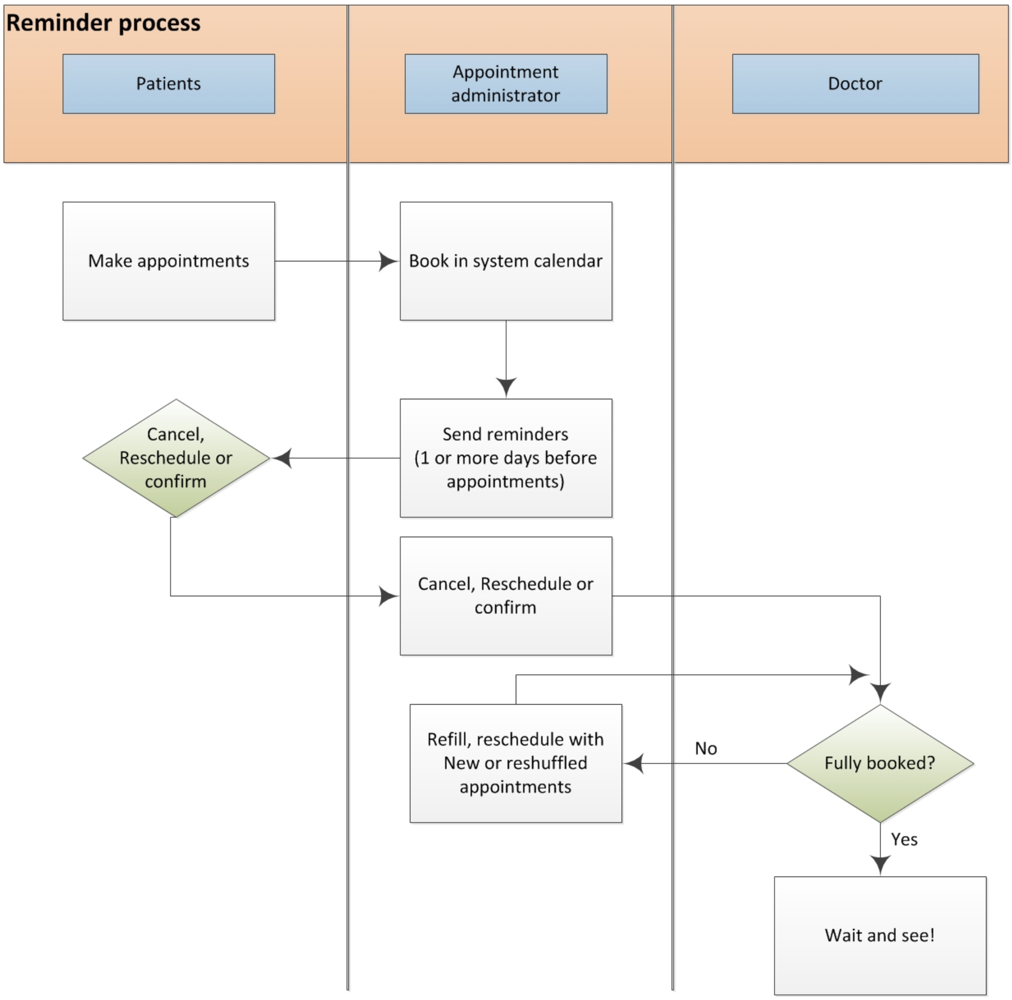


Figure 26. Traditional reminder process, retrieved from (Chan & Chan, 2012)**.**

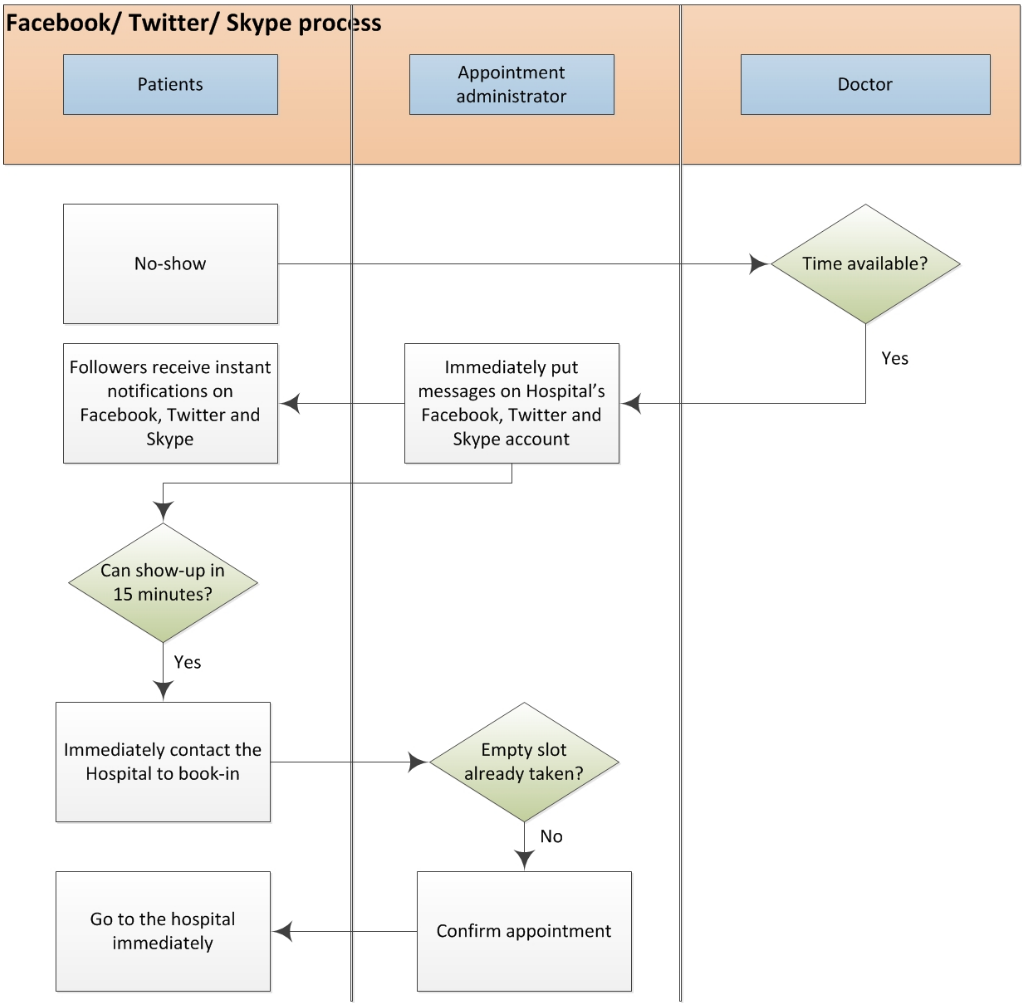


Figure 27. Social network process, retrieved from (Chan & Chan, 2012).

3.5.3 Telecommunications as an effective communication tool

As explained in the introduction of chapter 3, millions of euros are wasted each year on no-show patients. With the political and financial demands on services, innovative ways to reform services and promote effective practices are required (McMullen, 2012). As explained in section 3.2.3, long distances (between the patients' homes and the hospital) cause patients to not attend their appointments. With telecommunication or also called teleconsultation, such as Skype and VoIP, patients do not have to travel long distances. Telecommunication holds the potential for appointments at short notices, as it involves no travel-time and as it is ideal for situations in which physical presence is not directly necessary (Chan & Chan, 2012). Patients who are sick, patients who cannot leave their homes, just had an accident or live at a distance that it is not suitable to attend their appointment can make use of telecommunication options. The disadvantage of utilizing telecommunication is its privacy and poor Internet security concerns, which may result in the compromising a patient's confidentiality (Chan & Chan, 2012).

3.5.4 The web as an effective communication tool

Other technology possibilities, which are used in the healthcare sector, are called web forms, or as the following researchers call it: structured forms (Liederman, Lee, Baquero, & Seites, 2005b). These structured forms can save a lot of time for both the doctors and the patients by reducing the patients' waiting time to see the doctor or receive treatment. Structured forms can elicit the information requested by patients online, such as headache or other types of disease, to be delivered automatically to the right doctor. Doctors can then contact the patients via electronic communications, such as e-mail and blogs, by telling them which procedure they should follow in order to confront their illness. Some have estimated that online patient consultations, such as the structured forms, could trim the healthcare costs by 20%, saving patients an estimate of €5 billion (Bowman, 2002). Furthermore, hospitals' staff members could benefit from fewer telephone calls, lower administrative costs, increased patient recruitment and less crowdedness at the doctor's office (Physicians, 2003).

InterSystems Healthcare and InterSystems Ensemble are also popular technologies used in the healthcare, though these are out of scope of this research, due to the fact that they focus more on the improvement of the internal business sections of hospitals rather than that they have a direct connection with patients (INTERSYSTEMS Benelux, 2013). Internal business sections are, for example, the Business Analyst department, where Business Analysts conduct data analysis on the hospital patients' data to gain valuable knowledge. In the case of a high no-show rate, Business Analysts can create a strategy, based on their gained knowledge, to reduce the hospitals' no-show rate.

3.5.5 Mobile (smartphones) as an effective communication tool

Emerging Mobile Health Systems presents a new and innovative source of information that explores the present and future trends of the applications of current emerging wireless communication technologies for different healthcare scenarios (Istepanian et al., 2006). It is clear that the potential for mobile communication to transform healthcare and clinical intervention in the community is tremendous (Blaya, Fraser, & Holt, 2010). Several previous studies have evaluated the use of mobile phones to support healthcare and public health interventions, notably in the collection and collation of data for healthcare research, and have come to the conclusion that (Blaya et al., 2010), mobile phones can be of enormous value in providing support to healthcare in multiple settings. Mobile phones can, for example, support the hospitals' staff members performing clinician duties when there are no doctors and mobile phones can help keep track of patients. Furthermore, mobile communication improves the communication between institutions, assist in ordering and managing medications, and helps to monitor and detect patients who are late or who cancelled their appointment (Blaya et al., 2010). With the help of smartphones, the gap between appointments can be filled in more accurately and in time, which can lead to the reduction of no-show rate.

Mobile communication is not only beneficiary to doctors it is also helpful for patients. The following iPhone application: 'InfantRisk Center Healthcare Professional Mobile', available on Apple's online application store, is another example of how mobile phones can improve the quality of healthcare for the patient. This application gives these patients valuable information, amongst other, which Vitamins and (non) prescription drugs to take and so on, which can lead them not to travel long distances to see their doctor, reduce the long waiting lines at the doctors' office, which may lead to the reduction of the no-show rate.

3.5.6 Computer systems as an effective tool

Computer systems, such as the Electronic Healthcare Records (EHR), can be used to track no-show patients. EHR is a repository of patient data in digital form, stored and exchanged securely, and accessible by multiple authorized users. Its primary purpose is to improve the quality of care (Häyrinen, Saranto, & Nykänen, 2008). Tracking no-show patients can be used, for example, where no-show probabilities can be added to each no-show patient. By doing this, the Mu-law scheduling method can be employed.

3.5.7 Benefits of adopting technologies

Adopting technologies within the healthcare sector does have its benefits for patients, doctors and staff members. In the previous sections, we explained the SN and technologies. In this sub-section, we summarize the benefits of implementing or using these technologies in the healthcare sector. The reason for this is different and it is useful to explain and classify these reasons in order to develop a better strategy to reduce the number of no-show patients.

Using technology, such as the electronic communication, can lead to a situation in which patients and their doctors are not required to be available at the same time. This has the potential to free both parties from restrictions associated with traditional communication methods, such as telephone calls (reminders) and face-to-face visits (Liederman et al., 2005b). E-mail for example, does not require patients and doctors to be available concurrently. Furthermore, by using technology patients do not have to travel long distances, worry to take time off their work to attend their appointments, nor wait in long lines to see their doctor. Other advantages of patients and doctors using technology, is that e-mails are less likely to get lost and do not require transcriptions (Liederman et al., 2005a). Liederman, Lee, Baquero, and Seites (2005a), whose objective was to examine how commercial web messaging systems affect patients, providers and the staff satisfaction, revealed that out of 5.971 patients surveyed with 267 providers, 52.6% of patients who sent a message got a response within 4 business hours. Any patient; young, old, different ethnicity and non-chronic patients with only a little knowledge of how to work with a computer can benefit from this technology. To the staff members, the amount of telephone call volume reduced. Equivalent results has been conducted by Liederman, Lee, Baquero, and Seites (2005b) who experienced an 18% drop in telephone volume, which have safed them an amount of time, which also prevents overworking and more time to focus on their patients (Liederman et al., 2005a).

3.5.8 Conclusion

The discussed studies show different ways SN and other technologies can be used in the healthcare sector to reduce the number of no-show patients' rates and to reduce the workload on doctors or other staff members. Reducing the workload also reduces the amount of errors on a daily basis.

It is well established that the traditional reminder system does its job for patients that scheduled their appointments with their doctor(s) one or more days before the actual appointment. Whilst, this is effective for doctors, it is not effective for patients who experience, for example, a last minute car breakdown, accident, meeting or something else that could increase the no-show ratio. These are situations in which social media networks can be really effective by not only reducing the number of no-show patients, but also by filling gaps between appointments.

4 The method to reduce the number of no-show patients

4.1 Introduction

In the previous chapters we have discussed several key patients' demographic factors; the relation between the demographic factors and the environmental factors; the influence of a patients' behavior on no-show and how Information Technology supports the healthcare to reduce the number of no-show patients' rates. Next to that, we also presented several methods, models and techniques to reduce no-show. All of the above-mentioned literature studies, described in chapter 3, acted as an input for the method developed in this study. The method consists of two parts, namely a Process Delivery Diagram (i) and a flowchart (ii) (both are elaborately explained in section 4.3).

A system approach process was utilized as a guideline for the creation of the method. The idea behind the system approach process was developed and described by Garuda et al. (1998), who revealed that in order to systematically reduce the number of no-show patients, it is important to follow the six steps shown in Figure 28. The process is a modification of a marketing approach, adapted and expanded in specific regards to the healthcare setting and the particular problem of no-show (Garuda et al., 1998). With the first three steps of the system approach process, the Business Analyst extracts valuable knowledge from the no-show patients' dataset. In the last three steps the Business Specialist selects the suitable strategies, techniques, methods or models (interventions) to reduce the number of no-show patients. More on the six steps of the system approach process on addressing no-show patient is elaborated in section 4.2.

4.2 The system approach process of addressing no-show patients

As depicted in Figure 28, the system approach process consists of six steps. The first three steps involve gaining knowledge about the no-show patients. The latter two steps involve the creation of a plan based on the gained knowledge to reduce the number of no-show patients.

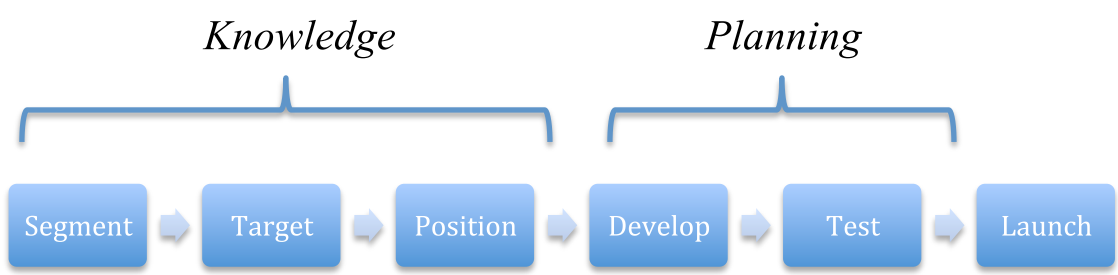


Figure 28. The systematic approach process, retrieved from (Garuda et al., 1998).

- *Segment*

  Segment involves dividing the no-show patients' population into distinct groups of patients. Doing this, allows one to get a top-down overview (per segment) on the current problems. It allows one to focus on patient segments with, for example, a specific demographic factor problem or a relation between a patients' demographic and environmental factors problem. Also, in order to use the Mu-law scheduling method (explained in chapter 3.4.2.2), the segmentation step can be utilized to measure, for example, only patients with a certain no-show rate in an interval of one week or month.

In order to identify meaningful segmentation criteria for a particular organization such as a hospital, a dataset is needed. This dataset can be retrieved from a hospital's large patient database that has enough information about the patients' demographic factors, appointments, the date of the appointment, reason for not showing up and so on. Therefore this step is by far the most important step in this process; it also will involve the most time, effort and patience. Once the most important criteria have been identified, it is important to categorize the no-show patients based on these criteria (e.g., if transportation was the problem, all patients with this problem should be categorized). As explained above, identifying meaningful segmentation criteria allows one to have a top-down overview of the problem regarding no-show patients. It is recommended by Garuda et al. (1998) not to have more than 4 or 5 segmentation criteria, though as datasets are growing each year by thousands of Gigabytes and therefore more knowledge can be extracted from these datasets, more criteria's may be needed.

- *Target*

Target entails to develop a targeting strategy for each segment criteria created in the former step. There are according to Garuda et al. (1998), several advantages to a targeting strategy. First, it addresses cost-limitations. If the financial situation is a problem for the hospital, than only the segment criteria that falls within the budget should be focused on or the criteria which will be the most beneficial. Furthermore, some segment criteria cost a lot to create but will only reduce the number of no-show patients by 5%, other criteria may be cheap to create, though will reduce the number of no-show patients by 15%. Henceforth, the targeting step is the step during which such classifications should be made.

In this step, the size of the segment and its rate of growth or decline within the hospital and also the 'solvability' should be taken into consideration. If the segment criterion is cheap to create, though unsolvable, it may consume too much time to work on (therefore losing money). Therefore it should be temporarily ignored. Targeting the most efficient criteria with the highest priorities that would reduce the number of no-show patients must be first executed.

- *Position*

The ultimate goal is to thoroughly and completely understand each targeting segment. With this understanding, the understanding of the segments' characteristics and their needs are meant. It is important to understand each segment, because this information in turn, will allow a clear and understandable picture of the problem to be obtained, and more importantly, it will provide the possibility of designing a solution (strategies) to reduce no-show patient rates. To understand each targeting segment, data mining can be performed; with data mining valuable knowledge can be extracted from the targeting segment. Another possibility is to collect interviews with experts or with patients to gain more information on no-shows in order to reduce this phenomenon. As Garuda et al.

(1998) described it: *"how else does one get to 'know' their segments, as much as such is possible? Direct contact with such people is the most valuable tool."*

- *Develop*

During the developing stage of the method, one must begin to develop the strategies the hospital can utilize to address each of the target problems. The strategies may consist of many interventions. Once the intervention list has been created, the Business Specialist has to make the decision which intervention is going to be used and which target problem is going to be confronted first. This may depend on the evaluated costs and feasibility of the targeting problem. In the case of no-show patients, methods, models and techniques and Information Technology are used in order to reduce the no-show patient rates. These interventions are used, depending on the type of demographic factor problem or environmental factors problem the hospital faces or the division faces within the hospital. In the developing phase it is also important to include all stakeholders (i.e., patients, physicians, nurses, managers, team-leaders and employers) in the process when developing potential solutions.

- *Test*

The testing stage is also important. A pilot study with a small subset of each targeted segment should be performed with the selected interventions; also information on compliance behavior before and after the testing phase should be collected and revised in order to see if the selected intervention was fruitful. This can be compared with other interventions during a later stage.

- *Launch*

In this phase the hospital, clinic or another medical-care center can launch its plan to reduce the number of no-show patients. It is really important to start the process with care, to minimize the risk and learn from mistakes. Finally, it is important to inform divisions and stakeholders of what is happening, so they know how in-depth Business Specialists have researched, understood, and adapted to the patient's needs.

4.3 The healthcare no-show reduction method

A Process Delivery Diagram with its Flowchart

In this sub-section the method (*Healthcare No-show Reduction Method)* is described. The first part of the method is created using the meta-modeling technique proposed by Van de Weerd and Brinkkemper (2009): the Process Delivery Diagram (PDD). This technique entails a method analysis, method comparison and method adaptation, which results in a PDD. A PDD is a twofold diagram that reflects the main activities based on a UML activity diagram on the left side and the deliverable view based on a UML class diagram on the right side (Van de Weerd & Brinkkemper, 2009). The deliverable view constitutes different types of concepts. These concepts are explained as follows:

- Standard concepts contain no further sub-concept(s);
- Open concepts contain further sub-concept(s);
- Closed concepts are concepts that are not further elaborated, since it is not known or not relevant to the context (topic).

Furthermore, Van de Weerd and Brinkkemper (2009) proposed two descriptive tables: activity table (i) and a concept table (ii). These two tables give additional information about the activities and concepts illustrated in the PDD, which is further explained in sub-section 4.3.1.1. Either the Business Analyst or Business Specialist performs all the activities and sub-activities, as depicted in Figure 29. Last, the PDD is divided into six main phases, which are discussed extensively in section 4.3.1.

4.3.1 How to read and use the healthcare reduction method

As explained, the method consists of two parts: the PDD and flowchart. The conceptual PDD consists of six phases, namely: Select dataset, Analyze demographic factors, Analyze environmental factors, Analyze patient behavior, Create a plan to reduce the number of no-show patients and Select suitable interventions.

The first four phases of the PDD are created for Business Analysts to gain knowledge on no-show patients by performing different data analysis techniques on the patients' demographic factors, environmental factors and patients' behaviors. After the Business Analysts gained valuable knowledge on the no-show patients, the Business Specialists should take over the two last phases. The last two phases of the PDD focus on the development of a plan and the selection of suitable interventions to reduce no-show rates.

The link between the PDD and the flowchart (Figure 30) is as follows: the last phase of the PDD is extracted and drawn as a flowchart. This is to make it easier for Business Specialists when creating a plan and selecting the suitable intervention(s) to reduce no-show rates. The flowchart can therefore only be used after the first five phases of the PDD have been concluded. In addition, information about the patients' behavior and interventions collected from the literature studies (section 3.4) are also included in the flowchart.

The flowchart depicts the sequence of instructions (linked by arrows) that needs to be carried out to reduce no-show for each demographic factors and environmental factors. For example, if Age is the demographic factor and Transportation is the environmental factor that influences patients to no-show; the sequence of instructions connected to both the Age and Transportation must be followed. After following the method, Business Analysts and Business Specialists should have a plan, and should thus have enough knowledge to reduce the no-show rate.

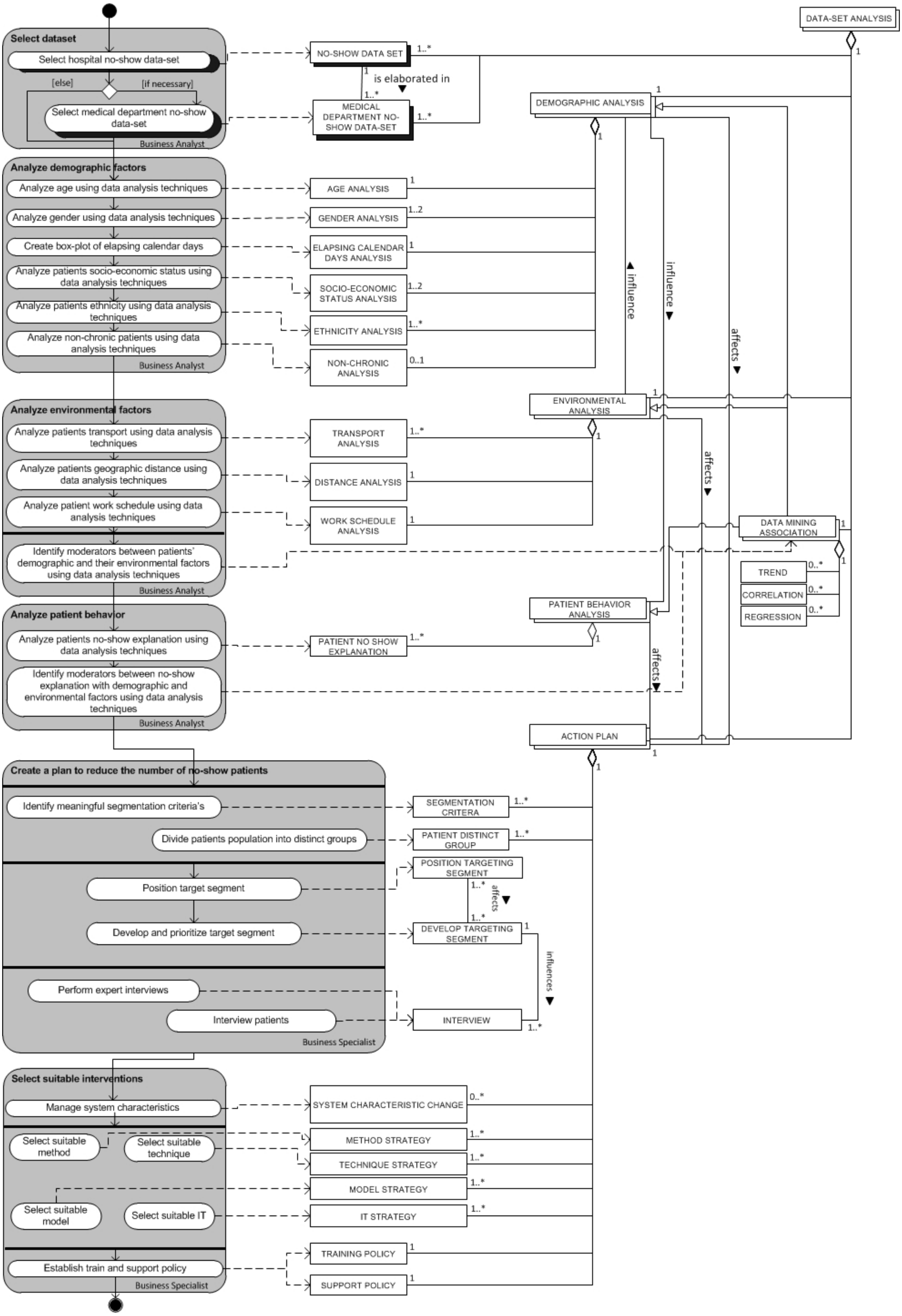


Figure 29. Conceptual: Process Delivery Diagram to reduce the number of no-show patients

4.3.1.1 Phase 1. Select dataset

The first phase of the proposed method is “Select dataset”. As described in section 4.2, in order to even begin to understand what the problem is or for what reason patients do not show up and to identify meaningful segmentation criteria for a hospital, a no-show dataset is needed (Garuda et al., 1998). This necessary dataset is selected and is focused on a particular department in the hospital.

The activity is determined to be the first phase of the method, because in order to identify meaningful patient segmentation criteria for a hospital data on no-show patients has to be collected. As Garuda et al. (1998) described, the most effective way to identify institution-specific segmentation criteria is through computer database searches.

The activities for all six phases of the PDD resulted in different concepts, which are part of the DATASET ANALYSIS. This report summarizes all the findings and issues that are considered important and relevant to be utilized as a tool or guide to make profound decisions to reduce the number of no-show patients in the healthcare sector.

The outcome (concept) of the mentioned closed activities of this phase is DATA ANALYSIS, which is divided into two closed concepts, namely NO-SHOW DATASET (i) and MEDICAL DEPARTMENT NO-SHOW DATASET (ii).

The activity table below presents the activities, sub-activities and a description of these activities.

Activity	Sub-Activity	Description
Select dataset	Select hospital no-show dataset	Select a NO-SHOW DATASET to go about identifying meaningful segmentation criteria.
	Select medical department no-show dataset	If necessary, select MEDICAL DEPARTMENT NO-SHOW DATASET to go about identifying meaningful segmentation criteria. This is a zoomed-in version of the NO-SHOW DATASET.

Table 10. Activity table phase 1

Concept	Description
DATASET ANALYSIS	The DATASET ANALYSIS is a collection of related sets of information that is composed of separate elements but can be manipulated as a unit by a computer (IBM CORPORATION, 2010). The DATASET ANALYSIS will be used by Business Analysts and Business Specialists to gather all relevant results to create a strategy to

	reduce the number of no-show patients.
NO-SHOW DATASET	NO-SHOW DATASET shows all the patients information regarding to no-show.
MEDICAL DEPARTMENT NO-SHOW DATASET	MEDICAL DEPARTMENT NO-SHOW DATASET shows all the patients information regarding to no-show within a selected medical department.

Table 11. Concept table phase 1

4.3.1.2 Phase 2. Analyze patients demographic factors

Phase two of the method is mostly inspired by the collected literature studies in section 3.1. The main purpose of this phase is for Business Analysts to gain knowledge on which patients' demographic factors lead to high no-show rates.

The first sub-activity: "Analyze age using data analysis techniques" is a part of the method, because many researchers (Bennett & Baxley, 2009; Daggy et al., 2011; George & Rubin, 2003; Hamilton et al., 2002; Kruse et al., 2002; Norris et al., 2012; Parikh et al., 2010) have noticed that age has an impact on no-show rates. It is important to analyze age using different data analysis techniques to discover which age groups (e.g., children, youth, adults or seniors) are the predictors of no-show within the hospital. Age can also be related with other variables within the dataset, such as the distance between the patient's home and the hospital. It has been concluded that the reason that younger patients have a higher no-show rate is because they are less likely to understand the purpose of their own appointment, psychosocial problem or government-provided health benefits (Verbrugge & Steiner, 1981).

The next sub-activity "Analyze gender using data analysis techniques" aims to find out if gender has any kind of influence on no-show rates. According to Deyo and Thomas (1980), female patients accounted for higher appointment keeping rates. The reason for this is that females ask more questions about their health than males. This leads to males receiving less service, which is probably the reason why they are less likely to keep their appointments (Wallen, Waitzkin, and Stoeckle, 1979). Therefore, it is important to analyze the variable gender within the hospital's dataset to gain knowledge on the reason why males cause a higher rate of no-show than females.

The third sub-activity is "Create box-plot of elapsing calendar days". This sub-activity is important when analyzing whether creating an appointment too far in advance has an effect on the no-show rate within the hospital. The percentiles (e.g., quartile 1, median, quartile 3 and quartile 4) of the waiting days, can be depicted using a box-plot. The longer a patient has to wait for his appointment (e.g., 1 day, 2 days, 1 week, 2 weeks, 1 month or more), the higher the chance the patient will not show up for the appointment. This has been proven significantly in the studies by Athenahealth (2012), Benjamin-Bauman et al. (1984), Gallucci et al. (2005) and Parikh et al. (2010). Forty percent of appointments scheduled more than 20 days away from the call-in date get cancelled or result in no-show (Athenahealth, 2012).

The next sub-activity: "Analyze patients SES using data analysis techniques", aims to study the influence of either a low or high SES on the no-show rates at the hospital. Because low SES patients are unable to pay for their expenses, such as for their received medicines and appointments, they sometimes not attend their appointments nor even worry too much about their own health. This and other reasons, such as the poor communication between these patients and their doctors, are good reasons for Business Analysts to study the influence of SES towards no-show.

"Analyze patients' ethnicity using data analysis techniques"; the fifth sub-activity of the method is important, because studies refer this as social distance. As described in section 3.1, social distance refers to the number of important dissimilarities between doctors and patients. For example, non-Caucasians receive less patient-centered communication than Caucasians. If the doctor cannot fully understand what the patient's problem is, he cannot help the patient to his potential. This study by Jackson et al. (2006) suggests that non-Caucasians rather visit a doctor of their own race; this allows them to communicate more effectively and to feel more comfortable. This variable is therefore important to analyze to gather information on this matter.

The goal of the final sub-activity "Analyze non-chronic patients using data analysis techniques" is to analyze if non-chronic patients commit no-show. As the researchers Deyo and Thomas (1980), George and Rubin (2003), Hermoni, Mankuta, and Reis (1990) describe (chapter 3.1), non-chronic patients have a higher no-show rate, while patients with chronic diseases break fewer appointments. The reason why chronic patients attend their appointments more often is because they have a greater dependence on medical care and are highly motivated by their doctors to keep their appointments (Hurtado et al., 1973). This is in contrast to non-chronic patients, who receive less medical attention, especially the younger the patient is.

All of the above-mentioned sub-activities of this phase resulted in the DEMOGRAPHIC ANALYSIS. Different data analysis techniques may be used for the execution of this phase, namely the Descriptive and Chi-square analysis. It is up to the Business Analyst of the hospital to decide which technique to use to collect valuable information on the no-show patients.

Activity	Sub-activity	Description
Analyze demographic factors	Analyze age using data analysis techniques	Categorize the age variable into: Children, Youth, Adults and Seniors. Afterwards, analyze this variable using descriptive or chi-square analysis and store the results in the AGE ANALYSIS.
	Analyze gender using data analysis techniques	Categorize the gender variable into: Male and Female. Afterwards, analyze this variable using descriptive or chi-square analysis and store the results in the GENDER ANALYSIS.
	Create box-plot of elapsing calendar days	Gather information on the actual day that the appointment was made for a patient, and the date to which the patient actually saw his doctor. Calculate this for all patients, afterwards create a box-plot and store the results in the ELAPSING CALENDAR DAYS ANALYSIS.
	Analyze patients socioeconomic status	Categorize the socioeconomic variable into: low socioeconomic and high

	using data analysis techniques	socioeconomic status. Afterwards, analyze this variable using descriptive or chi-square analysis and store the results in the SOCIOECONOMIC STATUS ANALYSIS.
	Analyze patients ethnicity using data analysis techniques	Categorize the ethnicity variable into for example: Dutch and Canadians. This depends on the ethnic of the patients. Afterwards, analyze this variable using descriptive or chi-square analysis and store the results in the ETHNICITY ANALYSIS.
	Analyze non-chronic patients using data analysis techniques	Categorize the patients into: chronic and non-chronic. Afterwards analyze this variable using descriptive or chi-square analysis and store the results in the NON-CHRONIC ANALYSIS.

Table 12. Activity table phase 2

Concept	Description
DEMOGRAPHIC ANALYSIS	DEMOGRAPHIC ANALYSIS consists of the conducted data analyses on all patients' demographic factors. Information regarding to the patients' demographic factors related to no-show can be found in the DEMOGRAPHIC ANALYSIS (Glanz et al., 2008).
AGE ANALYSIS	AGE ANALYSIS consists of the conducted data analysis on the variable age within the NO-SHOW DATASET (Kruse et al., 2002).
GENDER ANALYSIS	GENDER ANALYSIS consists of the conducted data analysis on the variable gender within the NO-SHOW DATASET (Hamilton et al., 2002).
ELAPSING CALENDAR DAYS ANALYSIS	ELAPSING CALENDAR DAYS ANALYSIS consists of the conducted data analysis on the variable elapsing_calendar_days within the NO-SHOW DATASET (Gallucci et al., 2005).
SOCIO-ECONIMIC STATUS ANALYSIS	SOCIO-ECONIMIC STATUS ANALYSIS consists of the conducted data analysis on the variable socio_economic_status within the NO-SHOW DATASET (Pesata et al., 1999).
ETHNICITY ANALYSIS	ETHNICITY ANALYSIS consists of the conducted data analysis on the variable ethnicity within the NO-SHOW DATASET (Feldstein & German, 1965).
NON-CHRONIC ANALYSIS	NON-CHRONIC ANALYSIS consists of the conducted data analysis on the variable chronic within the NO-SHOW DATASET (George & Rubin, 2003)

Table 13. Concept table phase 2

4.3.1.3 Phase 3. Analyze environmental factors.

Phase 3 is named “Analyze environmental factors”. The main purpose of this phase is not only for the Business Analyst to analyze which environmental factors lead to no-show, but also to analyze which environmental factors are a moderator on the relation between the patients’ demographic factors and no-show. This phase is inspired by the collected literature studies on the relation between patients’ demographic and environmental factors as described in section 3.2. Many researchers revealed that demographic factors could be moderated by any number of environmental factors, as depicted in Table 5.

The following three sub-activities of this phase, namely: identify patients’ transport using data analysis techniques (i), identify patients’ geographic distance using data analysis techniques (ii) and identify patients’ work schedule using data analysis techniques (iii) should all be conducted, because as many researchers revealed these three sub-activities could act as a moderator with the patients’ demographic factors, which may increase the no-show rate. Other environmental factors could also be included, such as day of the week, month of the year, season and so on. This depends on which variables are available in the NO-SHOW DATASET. Identifying the patient’s geographic distance can be done utilizing the zip code of the patient’s home and the zip code of the patient’s hospital. Afterwards, using Google Geographic API, Business Analysts can calculate the distance between a patient and the hospital.

All of the above-mentioned sub-activities of this phase resulted in the ENVIRONMENTAL ANALYSIS. Different data analysis techniques may be used for the execution of this phase, namely Descriptive, Chi-square and Multivariate analysis. The Multivariate analysis is a must in order to analyze which environmental factors is a moderator on the relation between the patients’ demographic factors and no-show. It is up to the Business Analyst to decide which technique to use to collect valuable information on the no-show patients.

Activity	Sub-activity	Description
Analyze environmental factors	Analyze patients transport using data analysis techniques	Categorize the transport variable into: Public transport and Private transport. Afterwards analyze this variable using descriptive or chi-square analysis and store the results into the TRANSPORT ANALYSIS.
	Analyze patients geographic distance using data analysis techniques	Categorize the distance variable into groups of interval of 50 KM. Afterwards analyze this variable using descriptive analysis and store the results into the DISTANCE ANALYSIS.
	Analyze patients work schedule using data analysis techniques	Categorize the day_of_the_week (work schedule) variable into: Monday, Tuesday, Wednesday, Thursday, Friday, Saturday and Sunday. Afterwards analyze this

		variable using descriptive or chi-square analysis and store the results into the WORK SCHEDULE ANALYSIS.
	Identify moderators between patients' demographic and their environmental factors using data analysis techniques	Identify which environmental factors is a moderator on the relation between the patients' demographic factors and no-show, by using multivariate analysis. Afterwards, store the results into DATA MINING ASSOCIATION.

Table 14. Activity table phase 3.

Concept	Description
ENVIRONMENTAL ANALYSIS	ENVIRONMENTAL ANALYSIS consists of the conducted data analyses on all environmental factors, including the moderators. Information regarding to the patients' environmental factors related to no-show can be found in the ENVIRONMENTAL ANALYSIS.
TRANSPORT ANALYSIS	TRANSPORT ANALYSIS consists of the conducted data analysis on the variable transport within the NO-SHOW DATASET (Miller, Hill, Kottke, and Oekene, 1997).
DISTANCE ANALYSIS	DISTANCE ANALYSIS consists of the conducted data analysis on the variable distance within the NO-SHOW DATASET (Mobley & Frech, 2000).
WORK SCHEDULE ANALYSIS	WORK SCHEDULE ANALYSIS consists of the conducted data analysis on the variable day_of_the_week within the NO-SHOW DATASET (George & Rubin, 2003).
DATA MINING ASSOCIATION	DATA MINING ASSOCIATION shows which environmental factors is a moderator on the relation between the patients' demographic factors and no-show by conducting multivariate analysis. TREND shows the general direction in which something is developing or changing. The most commonly seen trend is the simple trend, which is a straight line fitted to the data; *straight line best fit* (Field, 2009). CORRELATION shows the statistical measure that indicates the extent to which two or more variables fluctuate together. A positive correlation indicates the extent to which those variables increase or decrease in parallel, whereas a negative correlation indicates the extent to which one variable increases as the other

		decreases (Field, 2009). REGRESSION shows the relationships between variables for the purpose of predicting future values (Field, 2009).

Table 15. Concept table phase 3

4.3.1.4 *Phase 4. Analyze patients' behavior.*

Phase 4 is named "Analyze patients' behavior". According to Glanz et al. (2008) and Ajzen (1991), a patients' attitude toward his behavior, his subjective norm and his perceived behavioral control from the TPB (Theory of Planned Behavior) have to have a positive influence on the patients' behavior intention, increasing the possibility of attending the appointments. Also, according to the SIF (Social Influence Theory) a patients' behavior can be influenced by other persons (Cardol et al., 2005; Cosgrove, 1990). Therefore, the focus of this phase is based on the literature studies collected in section 3.3.

According to Lacy, Paulman, Reuter, and Lovejoy (2004), Mitchell and Selmes (2007) and Ong et al. (1995) some patients will not attend their appointments due to emotional problems, such as fear, which increases the no-show rate. In order to gain knowledge on why patients do not attend their appointments, Business Analyst are recommended to gather information on the sub-activity "Analyze patients no-show explanation using data analysis techniques". This information is useful to develop a strategy to reduce no-show rates. An association between the patients' no-show explanation and their demographic factors and environmental factors is also possible, which explains the focus of the sub-activity named "Identify moderators between no-show explanation with demographic and environmental factors using data analysis techniques". As depicted in Figure 21 the association between patients' demographic factors, environmental factors and patients' behavior has a positive or negative influence on patients to attend their appointment.

All of the above-mentioned sub-activities of this phase resulted in the PATIENT BEHAVIOR ANALYSIS. Different data analysis techniques may be used for the execution of this phase, namely Descriptive, Chi-square and Multivariate analysis. It is up to the Business Analyst to decide which technique to use to collect valuable information on the no-show patients.

Activity	Sub-activity	Description
Analyze patients' behavior	Analyze patients' no-show explanation using data analysis techniques	Categorize the explanation variable into: Forget, Didn't know about the visit, Situation arose and Thought it was a different time. More categories are possible. Afterwards, analyze this variable using descriptive or chi-square analysis and store the results in the PATIENT NO-SHOW EXPLANATION.
	Identify moderators between no-show explanation with demographic factors	Identify which environmental factors and PATIENT NO-SHOW EXPLANATION are moderators on the relation between the patients' demographic factors and no-show,

	and environmental factors using data analysis techniques	by using multivariate analysis. Afterwards, store the results into DATA MINING ASSOCIATION.

Table 16. Activity table phase 4

Concept	Description
PATIENT BEHAVIOR ANALYSIS	PATIENT BEHAVIOR ANALYSIS consists of the conducted data analysis on all PATIENT NO-SHOW EXPLANATION analysis. Information regarding to the patients' behavior related to no-show can be found in the PATIENT BEHAVIOR ANALYSIS.
PATIENT NO-SHOW EXPLANATION	The PATIENT NO-SHOW EXPLANATION gathers data analysis on the patients' behavior towards no-show. Behavior regarding towards the TPB and the SIF (Glanz et al., 2008), (Ajzen, 1991), (Cardol et al., 2005).
DATA MINING ASSOCIATION	DATA MINING ASSOCIATION shows which environmental factors is a moderator on the relation between the patients' demographic factors and no-show by conducting multivariate analysis. TREND shows the general direction in which something is developing or changing. The most commonly seen trend is the simple trend, which is a straight line fitted to the data; *straight line best fit* (Field, 2009). CORRELATION shows the statistical measure that indicates the extent to which two or more variables fluctuate together. A positive correlation indicates the extent to which those variables increase or decrease in parallel, whereas a negative correlation indicates the extent to which one variable increases as the other decreases (Field, 2009). REGRESSION shows the relationships between variables for the purpose of predicting future values (Field, 2009).

Table 17. Concept table phase 4

4.3.1.5 Phase 5. Create a plan to reduce the number of no-show patients.

The penultimate phase, namely phase 5, is named "Create a plan to reduce the number of no-show patients". To begin this phase, the first four phases have to be completed, as explained by Garuda et al. (1998), in section 4.2.

Based on the gained knowledge conducted by the Business Analyst in the previous four phases, the Business Specialist can afterwards create a plan to reduce no-show rates. Garuda et al. (1998) describe this as follows: “Identify meaningful segmentation criteria”, “Divide patients population into distinct groups”, “Position target segment”, “Develop and prioritize target segment”, “Perform expert interviews” and “Interview patients”.

In order to develop strategies, segmentation criteria must first be known. These segmentation criteria are developed based on the knowledge gained from the data analysis techniques performed in the previous four phases.

The second sub-activity is named “Divide patient population into distinct groups”. As Garuda et al. (1998) described, the segmentation also involves dividing the no-show patients population into distinct groups of patients. Doing this allows Business Specialists to get a top-down overview of each segment, to see what the current problems are. This allows one to structurally position himself to target the segmentation criteria created earlier.

In order to further strengthen the strategies, the following two sub-activities are recommended, namely: “Position target segment” and “Develop and prioritize target segment”. The sequence in which these are performed is important. Positioning allows Business Specialists to thoroughly and completely understand each targeting segment, because the information, in turn, will allow a clear and understandable picture of the problem to be obtained, and more importantly, it will provide the possibility to develop a solution to reduce the number of no-show patients (Garuda et al., 1998).

Information gained from the hospital’s dataset may not contain all the information necessary for Business Specialists to develop strategies for each segmentation, therefore interviews need to be held with experts and patients to completely understand the no-show issue (Garuda et al., 1998). For this reason, the following two sub-activities are performed, namely: “Perform expert interviews” and “Interview patients”.

All of the above-mentioned sub-activities of this phase resulted in the first part of the ACTION PLAN. Different data analysis techniques may be used for the execution of this phase, such as surveys or semi-structured interviews.

Activity	Sub-activity	Description
Create a plan to reduce the number of no-show patients	Identify meaningful segmentation criteria	Identify Meaningful SEGMENTATION CRITERIA based on the conducted data analysis techniques gathered from the previous four phases.
	Divide patients population into distinct groups	Utilize the earlier identified SEGMENTATION CRITERIA to divide the patients into distinct groups (demographic and environmental factors). Put the results in PATIENT DISTINCT GROUP.
	Position target segment	Allow Business Specialists to thoroughly and completely understand each targeting segment. The segment

		can be saved in POSITION TARGET SEGMENT.
	Develop and prioritize targeting strategy	Develop and prioritize the target segments defined earlier. This allows Business Specialists to prioritize for which segment a strategy will be developed.
	Perform expert interviews	PERFORM EXPERT INTERVIEWS with staff members of the hospital, think of doctors, specialists and so on. This will allow the Business Specialist to get a total perspective to comprehend the target segments.
	Interview patients	Perform INTERVIEWs with patients of the hospital. This will allow the Business Specialist to get a total perspective to comprehend the target segments.

Table 18. Activity table phase 5

Concept	Description
ACTION PLAN	Part 1 of the ACTION PLAN includes all meaningful segmentation criteria, group of patients and strategies developed for each group of patients (segment) reduce the number of no-show patients (Garuda et al., 1998).
SEGMENTATION CRITERIA	SEGMENTATION CRITERIA consists of the criteria on which the segments will be created on (Garuda et al., 1998).
PATIENT DISTINCT GROUP	A PATIENT DISTINCT GROUP involves dividing the no-show patients SEGMENTATION CRITERIA population into distinct groups of patients (Garuda et al., 1998). Dividing the patient into distinct group allows Business Specialists to receive a top-down overview of the problem (no-show) within the hospital.
ESTABLISH TARGETING STRATEGY	ESTABLISHING TARGETING STRATEGY allows the business analysis to calculate which of the segmentation is the most important, also the most beneficial that's going to reduce the no-show the most and the cost behind the strategy (Garuda et al., 1998). Without a proper targeting strategy the organization may end up with higher costs than expected, also without any significant results. In this concept a list with

	targeting strategy is created.
POSITIONING TARGETING SEGMENT	POSITIONING TARGETING SEGMENT will not only focus on the efforts the organization will present, it will provide a basis for future planning and strategy formulation, as well (Garuda et al., 1998). The Business Specialist makes sure he thoroughly and completely understand and comprehend the no-show issue of each particular group (Garuda et al., 1998).
DEVELOP TARGETING SEGMENT	During the developing stage one must begin to develop the strategies that the hospital can utilize to address each of the *target segment* problem. Here a list consisting of several interventions for each segment are gathered. The results can be saved in DEVELOP TARGET SEGMENT (Garuda et al., 1998).
INTERVIEW	INTERVIEW shows the information collected from the expert interviews, as well from the interview conducted on the patients.

Table 19. Concept table phase 5

4.3.1.6 Phase 6. Select suitable interventions.

The last phase named "Select suitable interventions" is all about selecting the right intervention, which aims to support Business Specialists to reduce no-show rates.

The first sub-activity is meant to manage the system characteristics. The goal of this sub-activity is to inform all staff members and stakeholders (e.g., patients, physicians, nurses and managers) of a particular division, department within a hospital, clinic or other medical care centers about the needs of the target groups. Here, all of the previous phases' results referring to reducing the no-show rate should be taken into consideration.

The final three stages described by Garuda et al. (1998) is about creating a good plan to reduce no-show rates. Once the intervention list is created and each item has been evaluated in terms of cost, feasibility and so on, it is the task of the Business Specialist to make the final decision. For this reason the following four sub-activities have been created, namely: "Select suitable method", "Select suitable technique", "Select suitable model" and "Select suitable IT".

After the above-mentioned suitable strategies have been selected, the testing and launching phase will take place; this is where the following sub-activity will take place "Establish train and support policy".

Activity	Sub-activity	Description
Select suitable interventions	Manage system characteristics	Offer SYSTEM CHARACTERISTIC CHANGE in order to customize the system to ensure better results of the performed strategies. The SYSTEM CHARACTERISTIC CHANGE is part 2 of the ACTION PLAN. The ACTION PLAN is created based on the DEMOGRAPHIC ANALYSIS, ENVIRONMENTAL ANALYSIS and PATIENT BEHAVIOR ANALYSIS. All of the results will be saved into the DATASET ANALYSIS.
	Select suitable method	A list of selected method strategies for a particular group of no-show patient.
	Select suitable technique	A list of selected technique strategies for a particular group of no-show patient.
	Select suitable model	A list of selected model strategies for a particular group of no-show patient.
	Select suitable IT	A list of selected Information Technology strategies for a particular group of no-show patient.
	Establish train and support policy	TRAINING POLICY and SUPPORT POLICY, which are part of the ACTION PLAN.

Table 20. Activity table phase 6

Concept	Description
ACTION PLAN	Plan on how to reduce the number of no-show patients, based on the selected strategies, expert interviews, patient's interviews and the findings in the previous deliverables.
SYSTEM CHARACTERISTIC CHANGE	SYSTEM CHARACTERISTIC CHANGE is referring to physicians, employers and doctors know about what you are going to do, and how in-depth you have researched, understood, and adapted to your patient's need. A good product is only useful if others are aware of it (Garuda et al., 1998).
METHOD STRATEGY	The list of methods to be implemented to reduce the number of no-show patients (Garuda et al., 1998).
TECHNIQUE STRATEGY	The list of techniques to be implemented to reduce the number of no-show patients (Garuda et al., 1998).
MODEL STRATEGY	The list of models to be implemented to reduce the number of no-show patients (Garuda et al., 1998).

IT STRATEGY	The list of IT strategies to be implemented to reduce the number of no-show patients, such as E-mail, SMS and Patient Portal (Garuda et al., 1998).
TRAINING POLICY	TRAINING POLICY is the plan to train the staff members with the new strategy to reduce the number of no-show patients.
SUPPORT POLICY	SUPPORT POLICY is the plan to support the staff members with the new strategy to reduce the number of no-show patients.

Table 21. Concept table phase 6

4.3.2 *Flowchart*

As explained in section 4.3.1, the last phase of the PDD is extracted and drawn as a flowchart (Figure 30). This is to make it easier for Business Specialists when creating a plan and selecting the suitable interventions to reduce the number of no-show patients.

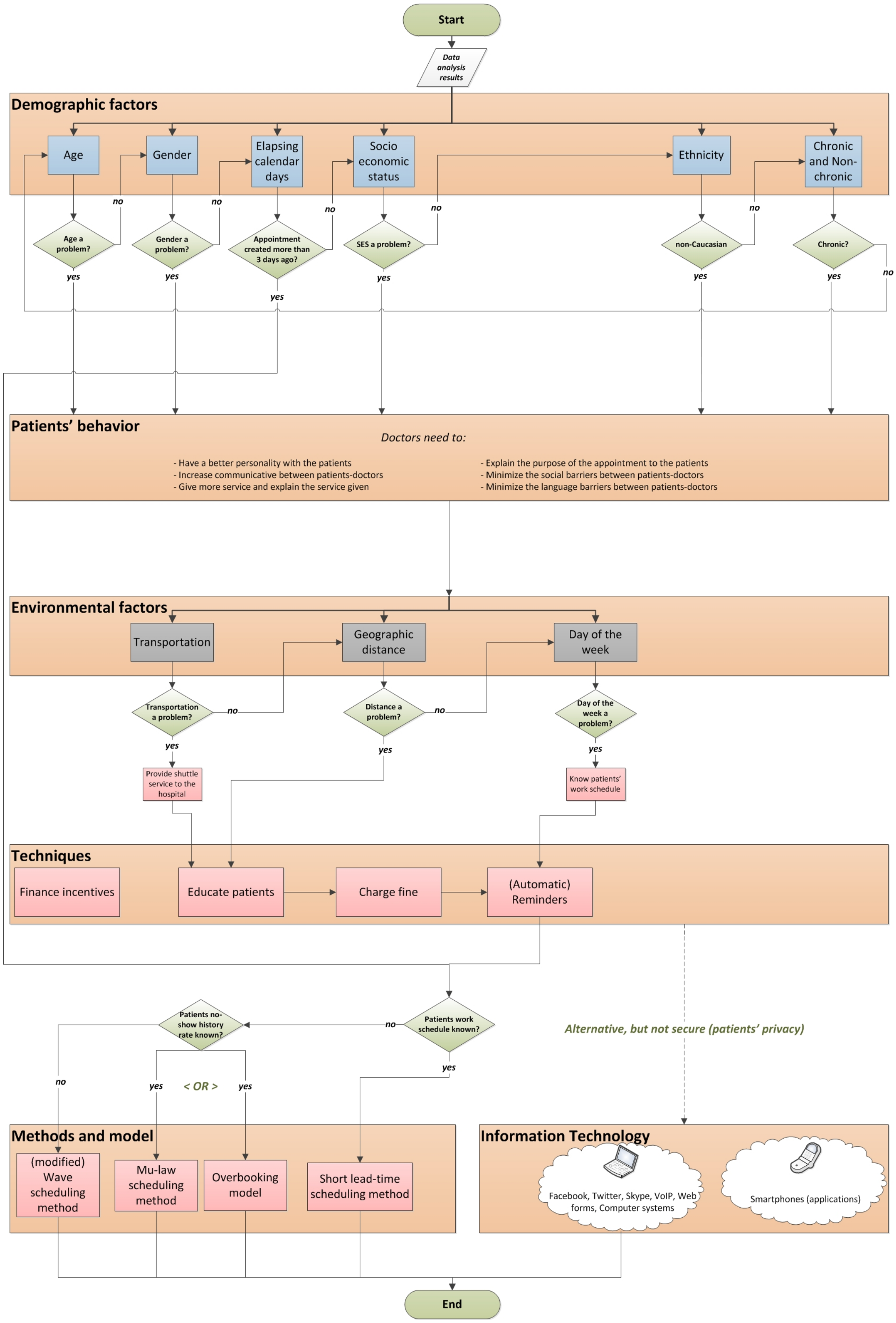


Figure 30. Flowchart – Select suitable intervention procedure

5 Qualitative & Quantitative evaluations

This chapter is divided into two sections. In the first section (5.1) a qualitative evaluation of *the healthcare reduction method*, which was created in chapter 4, is conducted. The evaluation consists of semi-structured interviews with 5 experts working at UMCU. In addition, for testing the quality of the method a number of criteria proposed by Brinkkemper, Saeki, and Harmsen (1999) are used. The outcome of this section is the final version of the method.

In the second section (5.2) of this chapter a quantitative evaluation of UMCU's no-show dataset is conducted. Here, several data analysis techniques are used to gain knowledge on the reasons of no-show at UMCU and also to test the method in practice, based on the data analysis results.

5.1 Qualitative evaluation through expert interviews

No-show: UMCU case study

5.1.1 Introduction

The method developed to reduce the number of no-show patients in the healthcare sector is based on previous literature studies on this subject. In addition to the method's theoretical background a number of expert interviews were performed at UMCU. The expert interviews were conducted for two reasons. First, to gain knowledge on why there is a no-show problem at UMCU and also to gain knowledge on the interventions that are used at UMCU. Second, to evaluate the proposed method to further shape it, so it can reach the research target. The researcher of this thesis can thus improve the proposed method based on the knowledge and feedback from the expert interviews.

The semi-structured expert interviews were conducted in a face-to-face conversation. Because English is not the native language of the experts, the questions were translated to Dutch. Each interview started with the researcher briefly explaining the goal of the interview. Second, the researcher explained what he had already done in the last couple of months to know more to reduce no-show. Last, before the interview started, both parts of the method were explained in detail. Each interview lasted between 50 to 70 minutes. The interviews were recorded with the permission of the interviewees. Personal information, such as the interviewees first and last name, are kept private and thus are not mentioned in this research.

5.1.2 Data gathering

NVIVO version 10 was used for the data gathering of the expert interviews. First, all interviews were transcribed. These transcriptions were afterwards imported into NVIVO using data coding and concepts. Data coding, in the context of grounded theory research, means a label is added to each bit of data, this way linking the data to a concept. Afterwards, these concepts were combined or linked together and the main concepts were identified. The concepts were identified by creating nodes. These nodes were named based on what the interviewees talked about.

In this research many quotes are used from the interview transcripts. The pre-coding that was developed before utilizing NVIVO is depicted in Appendix section 7.3. This pre-coding helped the researcher to create the nodes needed for NVIVO. All of the created nodes for the conducted expert interviews are depicted in Appendix section 7.4 and the results of the expert interviews are shown in sub-section 5.1.6.

5.1.3 Quality criteria

For testing the quality of the proposed method a number of criteria were used. Brinkkemper et al. (1999) suggest five main criteria for the quality of assembled methods: completeness, consistency, efficiency, reliability and applicability. The authors regard the first two as most important for all issues related to the internal or situation independent quality, whereas the authors distinguished the last three on the internal quality of the method.

- *Completeness*
  The situational method contains all of the method fragments that are referred to by other fragments in the situational method (Brinkkemper et al., 1999). In other words, check if there are no missing fragments in the method.

- *Consistency*
  All activities, products, tools and people plus their mutual relationships in a situational method do not contain any contradictions and are thus mutually consistent (Brinkkemper et al., 1999).

- *Efficiency*
  The method can be performed at a minimal cost and effort (Brinkkemper et al., 1999). In other words, the method performs the way it was meant for a minimal amount of effort and costs.

- *Reliability*
  The method is semantically correct and meaningful (Brinkkemper et al., 1999).

- *Applicability*
  The developers are able to apply the situational method (Brinkkemper et al., 1999). In other words, the method is easy to understand by any Business Analyst and Business Specialist that is going to work with it.

Some other quality criteria required that the interviewees were questioned in the same way, and also with the same attitude. No hints were given into which direction the interviewees should answer the questions. All of the questions were asked tailored to improve the proposed method.

5.1.4 Interview structure

This sub-section presents the questions of the semi-structured interviews. The questions were grouped into five categories. The first category consisted of general questions, which aimed to collect more information about the experts, their role and their background at UMCU. In addition, questions on how did they first heard about no-show patients were also asked.

The second category of questions focused on the reasons of origin of no-show and solutions for the no-show problem. The aim of this category was as follows:

- To understand why there is a no-show problem at UMCU;
- Where this problem starts;
- What kind of solutions the staff members have already tried (based on the problem) to reduce the no-show rates

The third category focused on the interventions (methods, models and techniques) that UMCU has been using to reduce the number of no-show patients. Information extracted by these questions can improve the researcher's knowledge about the intervention that works best to reduce no-show. The following two categories were grouped according to their relevance to the quality criteria. The main purpose of the interviews was to find out the professional opinion of the experts about the method, its structure and usability. The full list of the predefined questions along with questions asked about the quality criteria for the method is presented in Appendix 7.2.

5.1.5 Experts

The experts were selected based on their knowledge and connection to the domain of no-show. They were contacted via the mail with the help of the researcher's daily supervisor and were asked to cooperate with the evaluation process. After they agreed, several interview appointments were made. The table below gives more information about the experts and their experience.

Expert nr.	Division	Department	Years experience	Duration of interview	Interview protocol followed
1	Surgical specialist	Ophthalmology	± 24	50 min.	✔
2	Information provision and finance	Health information system	1	55 min.	✔
3	Heart & Lungs	Cardiology	± 32	60 min.	✔
4	Internal Medicine and Dermatology	Dermatology, allergy, rheumatology and sexually transmitted diseases	± 19	50 min.	✔
5	Internal Medicine and Dermatology	Acute Medicine and Infectious Diseases	± 2.5	70 min.	✔

Table 22. Interviewees expert information

5.1.6 Interview results

In the first category general questions were asked. When asked the following question: "*5. How did you notice that no-show was becoming a problem?*"

Experts 1 and 2 said they heard about this problem from other divisions. Experts 3 and 5 said they noticed that the doctors were less busy than before. Expert 4 indicated noticing no-show as a problem when booking and preparing the appointments for patients who did subsequently not show up. The staff members are as a consequence of no-shows left without any duties to carry out due to the gaps in between appointments, which is a situation that frustrates the staff members..

When asked: "*6. How is your work influenced by the no-show of patients?*"

One expert indicated that no-show causes delay in his job-process. This is logical, given the resulting gaps between the appointments. Two experts seek out a solution to this problem, while the other two experts did not experience any effects of no-show patients on their jobs.

When asked the next question: "*4. In which year did you notice that the no-show of patients was becoming a problem?*"

Three experts, namely expert 1, 3 and 4, indicated that the no-show problem began 10 to 20 years ago; however, they also indicated that it was not until recently that UMCU began seeking for a solution. UMCU began searching solutions because the problem was becoming more serious. The other two experts indicated that the no-show problem began less than 10 years ago. The answers depended, of course, on the division in which the interviewees work. Some divisions experience less no-show problems than other divisions.

With regard to the first category of questions, it becomes clear that the no-show of patients at UMCU is not a recent problem, it is a problem that has been there for the last 10 to 20 years. This problem leads, according to the experts, to a delay in the daily job-processes and to staff members without duties to carry out due to the gap between the appointments.

In the second category questions were asked about the reasons of no-show and also about the carried out solutions to reduce no-show. The aim of this category was to gain knowledge from each division on the internal and external reasons why patients are not attending their appointments. Internal reasons are according to Glanz et al. (2008): poor communication between doctors and patients and mistakes that staff members make during working-hours. External reasons are when the patient does not show up due to the influence of demographic factors, environmental factors or his own behavior to no-show (Anderson, 1973; Glanz et al., 2008; Smith & Yawn, 1994). It was also aimed to gain knowledge on the relations between the patients' demographic and their environmental factors.

When asked this question: "*8. What are according to you the internal reason(s) or causes why patients don't attend their appointments(s)? How would you solve these reasons or causes to reduce no-show?*"

Experts 1, 2, 4 and 5 indicated that unnecessary appointments are being made due to weak or bad communication between doctors and patients. Appointments are, for example, being made without the patients knowing about them, which leads to an appointment created at an undesirable date or time for the patient. Doctors do not communicate well enough with their patients, leaving their patients with an array of questions unanswered about their health and following appointment. Experts 2 and 5 also stated that the appointments are being made three or more months in advance. Expert 3 mentioned that they do not make use of any reminders such as SMS or email to remind the patients about their appointments, which leads to patients forgetting about their appointments. Expert 3 also indicated that these reminders could be used as a solution. The other experts did not know any solution for the reduction of the number of no-show patients when focusing on the internal issues.

In Figure 31 and Figure 32 two schematic representations are depicted showing the internal reasons or causes why patients do not attend their appointments based on the transcription of the expert interviews. Figure 31 shows where ‘Weak or bad communication’ leads, according to the experts, to three actions that can increase the no-show rate: ‘Don’t call’, ‘Forgotten’ and ‘Undesirable date or time’. The citations of the experts leading to this graph are as follows:

Expert 1: *“…when the communication between doctors and patients is weak or when a doctor mistakenly created an appointment without the patient knowing about this, this leads to patients not showing up due to their busy work schedule…”*

Expert 4: *“…bad communication leads to forgetting about the appointment. These patients do not experience any consequences due to not showing up, anyway.”*

Expert 5: “…weak communication leads to patients creating other appointments somewhere else on the date they supposedly have an appointment with the doctor. As a consequence patients do not call to cancel their appointments.”

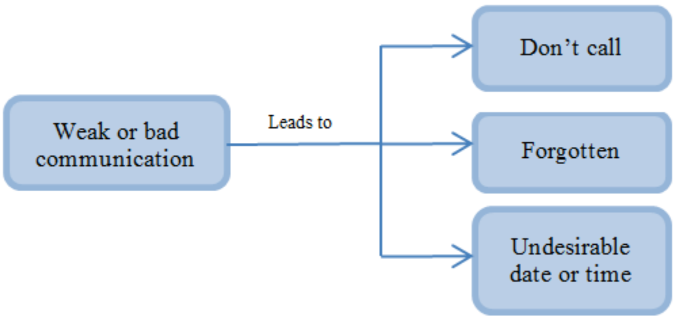


Figure 31. Redrawn NVIVO graph 'weak or bad communication'

Figure 32 shows that ‘Create unnecessary appointments’ leads to three actions, which can increase the no-show rate: ‘Don’t call’, ‘No complaints anymore’ and ‘Undesirable date and time’. The citations of the experts leading to this graph are as follows:

Expert 1: *“…when appointments are made too far in advance, or when unnecessary appointments are made, patients may not have the same complaints,* *after 3 months for example, or even not have any complaints at all. This in most cases also leads to patients not cancelling their appointments…"*

Expert 5: *"...several internal reasons exist. One example is when appointments are moved to another date or time, or when an extra appointment is made without the patient knowing about this. This leads to patients not showing up for their appointments due to the undesirable date or time of the created appointment."*

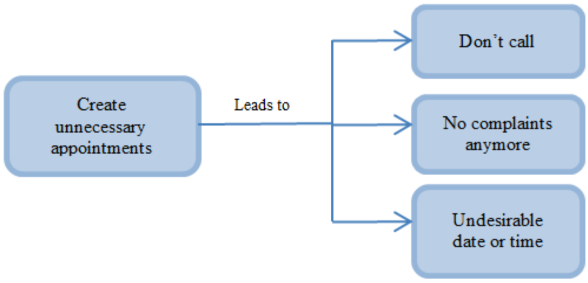


Figure 32. Redrawn NVIVO graph 'create unnecessary appointments'

When asked the following question: "*9. What are according to you the external reason(s) or causes why patients don't attend their appointment(s)? How would you solve these reasons or causes to reduce no-show?*"

All experts indicated that patients tend to forget about their appointments. Only one of the five experts has a solution for this problem, which is to send patients an SMS, e-mail or a reminder. The other experts did not know how this problem could be tackled. Experts 1 and 5 indicated that some patients do not call to cancel their appointment, because they went to another hospital closer to their home. This has a direct relation with the distance between the patients' homes and the hospital (Mobley & Frech, 2000). Other experts have indicated that the appointments are made on undesirable dates and times or too many days in advance which leads to patients not showing up for their appointments.

The following two questions, 10 and 11, were about the patients' demographic and environmental factors. The aim of these two questions was to gain knowledge on which patients' demographic factors at UMCU have an influence on no-show and which environmental factors correlate with the patients' demographic factors to cause no-show. The experts were also asked: "*How would you resolve these factors towards the reduction of no-show?*" The solution to this question was mainly asked in order to improve the flowchart (part 2 of the method).

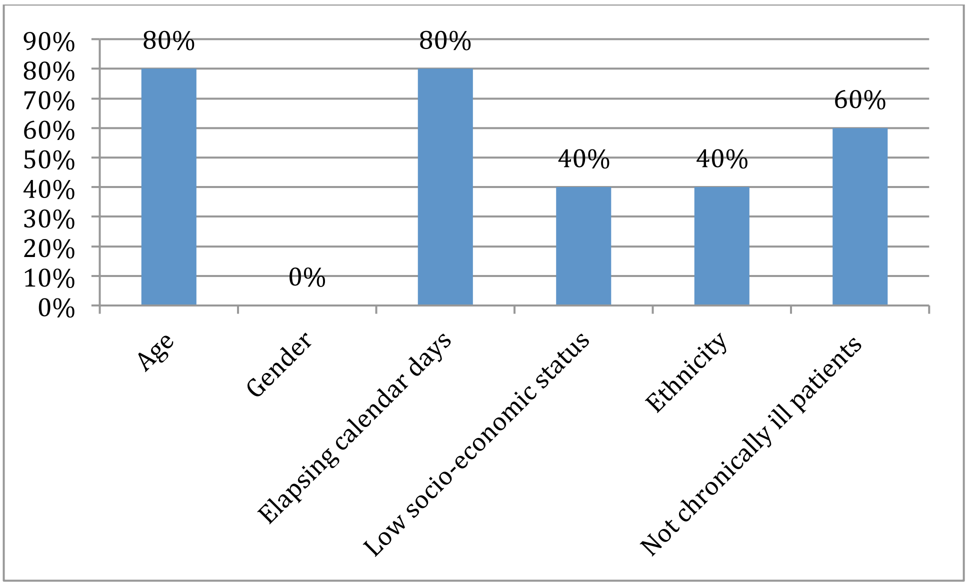


Figure 33. Patient demographic factors which leads to no-show according to the experts.

As depicted in Figure 33, experts think that mostly ‘Age’ and ‘Elapsing calendar days’ affect patients to not show up. Creating appointments too early in advance leads to no-shows, as explained by (Goldman, Freidin, Cook, Eigner, & Grich, 1982). The solutions the experts provided during the interviews were SMS, e-mail and, the most interesting provided solution, an online portal (web form) where patients can login and see when and where they have an appointment with their doctor. Expert 4 does not recommend to send an appointment letter as a reminder, because this can lead to writing errors or mistakes, which afterwards can lead to miscommunications. Due to age and elapsing calendar days being the most common no-show predictors, the experts indicated that appointment letters are not a good solution for the no-show problem, since patients tend to throw away the appointment letters or forget about them.

In Table 23 the Pearson’s correlation coefficient of the relation between the patients’ demographic and environmental factors is depicted. This was transcribed utilizing Nvivo. The Pearson’s correlation coefficient from the Node Cluster Analysis in Nvivo tells the researcher how well the nodes are correlated to one another. It shows the linear relationship between the two nodes. The results of the Pearson correlation coefficient can have a value between -1 and 1. Negative 1 means there is a perfect negative correlation between the two nodes, whereas positive 1 means there is a perfect positive correlation between the two nodes. It is, for example, depicted in Table 23 that according to the transcribing results ‘Elapsing calendar days’ and ‘Age’ have a strong relation with each other with regard to no-show. The Pearson’s correlation coefficient is 1, which means that these two variables are perfectly correlated with one another. The Pearson’s correlation coefficient for ‘Non-chronically ill patients’ and ‘Low socioeconomic status’ is 0.67, which means they are strongly correlated.

Correlations between demographic factors

Demographic factors		R
Non chronically ill patients	Low Socioeconomic status	0.17
Ethnicity	Low Socioeconomic status	0.67
Elapsing calendar days	Age	1.00

Correlations between environmental factors		
Environmental factors		R
Transport	Day of the week	0.41

Correlations between demographic and environmental factors		
Demographic factors	Environmental factors	R
Elapsing Calendar days	Transport	0.61
Non chronically ill patients	Transport	0.17
Age	Transport	0.61
Age	Day of the week	0.25
Low Socioeconomic status	Day of the week	0.61
Non chronically ill patients	Day of the week	0.41
Elapsing calendar days	Day of the week	0.25

Table 23. Pearson's correlation coefficient of the relation between patients' demographic factors to no-show, environmental factors to no-show and the relation between demographic factors and environmental factors to no-show (NVIVO) according to the experts.

In the third category, questions were asked about previously used methods, techniques and models in order to reduce the no-show rates at the UMCU. When asked: "12. *What does the UMCU do to reduce the number of no-show patients? Think of methods, models, techniques and technologies. What else can be done to reduce the number of no-show?*"

Experts 1, 2, 3 and 4 answered that not all divisions within the hospital use modern interventions, such as reminders, appointment letters and e-mail. Some doctors call their patients ± 24 hours prior to their appointment. The results of these modern interventions are, according to the experts, 'fruitful', because they remind the patients that they have an upcoming appointment. Some patients cancel their appointment immediately after receiving the reminder; others replied that they did not know about the appointment. Experts 3 and 5 confront their patients the next time they do show up for their appointment. This is done by asking them why they did not attend their last appointment. Furthermore, Expert 5 said they have discussed using a 'structured functionality policy', however did not launch it yet. This is a checklist that patients must fill in. The checklist consists of different ways patients wish to receive a reminder, for example, via SMS, e-mail or the telephone.

The following questions are about social-media, smart-phone applications and web applications. All experts indicated that 'social-media' is not a plan they want to go into, because there are many privacy issues here that need to be taken into consideration. Instead, the experts suggested the following idea: to incorporate a (web application) 'Patient portal', where patients can login and view their settings; from the date and time when they have their following appointments, to seeing if their Doctors are sick on a particular day or not. All experts indicated that smart-phone applications could help by bringing forth reminder notifications about their upcoming appointments. Smart-phone applications could also display the route within UMCU. Old patients tend to get lost in the building, which is also a reason why they do not show up for their appointment.

It was concluded by the researcher based on the interview results that UMCU currently uses no methods or models to help reduce the number of no-show patients.

The experts are, however, using some techniques to counteract the no-show problem, such as reminders and folders.

5.1.6.1 Method completeness

The experts were also asked to answer questions about the completeness of the method. Expert 1 indicated the following about the PDD: “The PDD is good, I like it – It’s logical, because these particular issues depicted are relevant to why patients are not showing up for their appointments.” Expert 1 further explained, that it is difficult to conclude which part of the method can be improved, since it first has to be tested in practice, though he also indicated that “from what I can see, it does look very good”. Expert 1 agreed that studying the patients’ demographic factors and patients’ behavior is important in order to reduce the number of no-show patients.

Expert 2 found that all the method activities were relevant for the no-show situation. Expert 2 said the PDD is “Very clear - well first you have to know your patients, know the reasons of no-showing, afterwards you can select and implement your method, strategy and models to reduce the number of no-show patients.” The most important part of the PDD, according to expert 2, is to analyze the patients’ demographic factors, because “it always depends on the demographic factors of the patients if they are attending or not, after analyzing this, it should be sufficient to know which strategy to apply”. Expert 2 noticed that the activity “Analyze Doctors” should be included, because no-show is not always the patients’ fault.

Another expert explains that “it looks professional, because you first analyze the patients within a particular department, and afterwards you create a plan – excellent.” Expert 3 explained that in order for the PDD to be complete, you “do not only analyze the patients and afterwards create a plan to reduce the no-show rate, you also have to analyze the doctors. This way you can send a particular patient to a particular doctor.”

Expert 4 agreed that all activities of the PDD are well thought out. The ‘create a plan to reduce the number of no-show patients’ activity according to expert 4 is the most important one and also the most interesting one, because it is during this activity that Business Specialists have to ‘brainstorm’ about all the different strategies to reduce the number of no-show patients. Expert 4 further explained, “It does look like a lot of work.”

The last expert concluded that, “analyzing the patients’ demographic factors and environmental factors is a must. I think analyzing the patients’ behavior is also good, because not every patient is the same, some do not like going to the hospital”.

About the flowchart, expert 1 concluded, “you can directly follow a solution process per patient’s demographic and environmental factors.” Expert 1 explained that in order for the flowchart to be complete, a solution has to be added per department. In a hospital, for example, you have the children’s division but also a division especially for adults. Each division has its own set of no-show problems.

Expert 2 found the flowchart very good – “per type of patient you can seek a solution, this is ideal”

Expert 3 sees the flowchart as an “interesting information giver with which in practice you can solve a lot of issues by simply following the processes – Yet, this flowchart has to be tested in practice first”. Furthermore, he found that the steps in the flowchart are logical, and the decisions and the sequence are correctly depicted.

Experts 4 and 5 found the flowchart clear and structured. Expert 4 concluded that the only downside was that there are no explanations of how the chosen methods, strategies and technologies work (A description on how they work).

In the end, all the experts found the PDD and flowchart useful for reducing the number of no-show patients' at the hospital. Two experts found that the PDD should also include the activity: 'analyze the doctors', in order to send a particular patient to a particular doctor, and because not attending an appointment is not always the patients' fault.

5.1.6.2 Method consistency

Expert 1 sees the following two activities: 'Create a plan to reduce the number of no-show patients' and 'Select suitable interventions' as two of the most important activities in the PDD, because developing or creating a plan to form a barrier against the no-show patients is critical. A plan either reduces the no-show rate or it does not. That is why the former activities (i.e., analyze demographic factors, analyze environmental factors and analyze patients' behavior) are also important. Analyzing the patients' demographic, environmental factors and behavior can therefore be determined as the key activities; without analyzing these activities no plan or suitable interventions can be created and selected. Expert 1 also found the sequence of the (sub-) activities relevant and consistent.

Expert 2 sees the activities 'Analyze demographic factors' and 'Analyze environmental factors' as the key activities in the PDD. He believes that "these are the factors that have a direct relation with no-show". A remark expert 2 made was about the naming of the last activity in the PDD, which should, according to this expert, be changed to 'Create and develop a flowchart process plan to reduce the number of no-show patients'. According to expert 2, the sequence of the PDD is correct. No further changes have to be made, however, the following activity 'Analyze doctors' has to be added due to the fact that it is not always a patient's fault that they do not show up.

Expert 3 also regards the following two activities: 'Create a plan to reduce the number of no-show patients' and 'Select suitable interventions' as two of the most important activities in the PDD. The prior activities, according to expert 3, are also important, however, these two are the activities that are going to be the most time consuming, especially for the Business Specialist when creating a good plan to reduce the number of no-show patients. Expert 3 thinks that the sub-activity 'Divide patients population into distinct groups' should form a great part of the activity 'Create a plan to reduce the number of no-show patients'. As expert 3 described, "this allows Business Specialists to separate the patients into distinct groups in order to create a plan to reduce the number of no-show patients – Awesome!".

Experts 4 and 5 stress that the name of the last activity should be altered, though they do not know exactly to which name it should be changed. They further explained that the consistencies of the activities are well and thoroughly created. No further changes have to be made.

Three of the five experts explained that the name of the last activity should be altered, because the name has overlap with the 'Create a plan to reduce the number of no-show patients' activity. This feedback is ignored, due to the feedback that the researcher received at a later date from his supervisor which overruled the feedback received from the experts. Furthermore, the experts think that the activities are consistent with one another and that the sequence of the activities is excellent. All five experts indicated that the identification of the proposed factors is a key part of the PDD.

About the flowchart, expert 1 regards the segmentations, such as the demographic factors, environmental factors, techniques, methods and models, as a perfect and easy way for Business Specialists to select the suitable interventions to reduce the number of no-show patients. Expert 1 said, the processes are consistent and in the right sequence. Next to that, he explained that the process called 'Doctor' is an important process. The only process that is missing is the solution per department within a hospital, which he further explains, "there are many departments (divisions), so that poses a challenge."

Expert 2 and 3 think that the link between the PDD and flowchart is excellent; one can really follow what is going on and there is a solution for each problem. Furthermore, the sequence of the processes within the flowchart is good and consistent.

Expert 4 made the following remark about the interventions as given in the flowchart: "In order for Business specialists to know how the intervention works, a description has to be created for each one of them" Expert 5 also explained that the consistency and sequence of the flowchart process is good. The only remark he had, was to take the "treatment times for the appointments" into consideration. What he meant with this, is to not only focus on the demographic and environmental factors, but also on the length of the appointments.

5.1.6.3 Method efficiency and applicability

All of the experts found that the method is clear, well put together and user-friendly. Expert 1 thinks that the PDD can prepare the healthcare sector by giving Business Analysts an idea on how no-patients can be analyzed and how to put a plan together to reduce the number of no-show patients, whereas the flowchart can help Business Specialists by following the processes and applying the suitable interventions to tackle the problem.

The experts do not see any critical limitations for conducting and executing the method. They think it is applicable and that it can be executed in practice. Expert 3 also adds that the flowchart process is a really good way to depict a solution for the factors by applying methods and techniques, "we never thought that no-show can be reduced in such a structured way".

5.1.7 Conclusion

In conclusion, the five experts found the PDD and flowchart well structured, useful and applicable in practice. They also considered the PDD to be complete and consistent, though they did offer small corrections in the naming of activities and their number. Two of five experts found that the naming of the last activity in the PDD should be altered. Two experts think that it is a great idea to not only analyze the patients but to also analyze the doctors. A more structured view on what was proposed, is shown in Table 24. The evaluation of the method based on the quality criteria proposed by Brinkkemper et al. (1999) is shown in Table 25.

Expert 1
• The flowchart needs to be updated with a solution per department
Expert 2
• A sub-activity called 'Analyze doctors' should be included in the PDD; • The name of the last activity in the PDD should be changed to 'Create and develop a flowchart process plan to reduce the number of no-show patients'.

This is to remove doubts between the naming of the other activities.
Expert 3
• Add a new sub-activity to analyze the doctors
Expert 4
• A description on how the interventions in the flowchart work.
Expert 5
• The name of the last activity in the PDD should be altered to remove any doubts.

Table 24. Expert proposals for change in the proposed methods

Experts	Completeness	Consistency	Efficiency	Applicability
#1	+/-	++	++	++
#2	+/-	+/-	++	++
#3	+/-	++	++	++
#4	++	+/-	++	++
#5	++	+/-	++	++

Table 25. Experts method evaluation on the quality criteria proposed by (Brinkkemper et al., 1999)**.**

++ = positive feedback
+/- = positive feedback, minor changes
-- = negative feedback

5.1.8 Improvements of the method that support the healthcare sector in reducing the number of no-show patients

A new version of the method is proposed after the conducted expert interviews at UMCU. The improvements are made, because it is assumed that they will clarify some parts of the method and complete the method. The new version of the method is presented in the PDD below, together with the new activities and concept tables. The major changes are marked with yellow rectangles so that the changes are easier to spot.

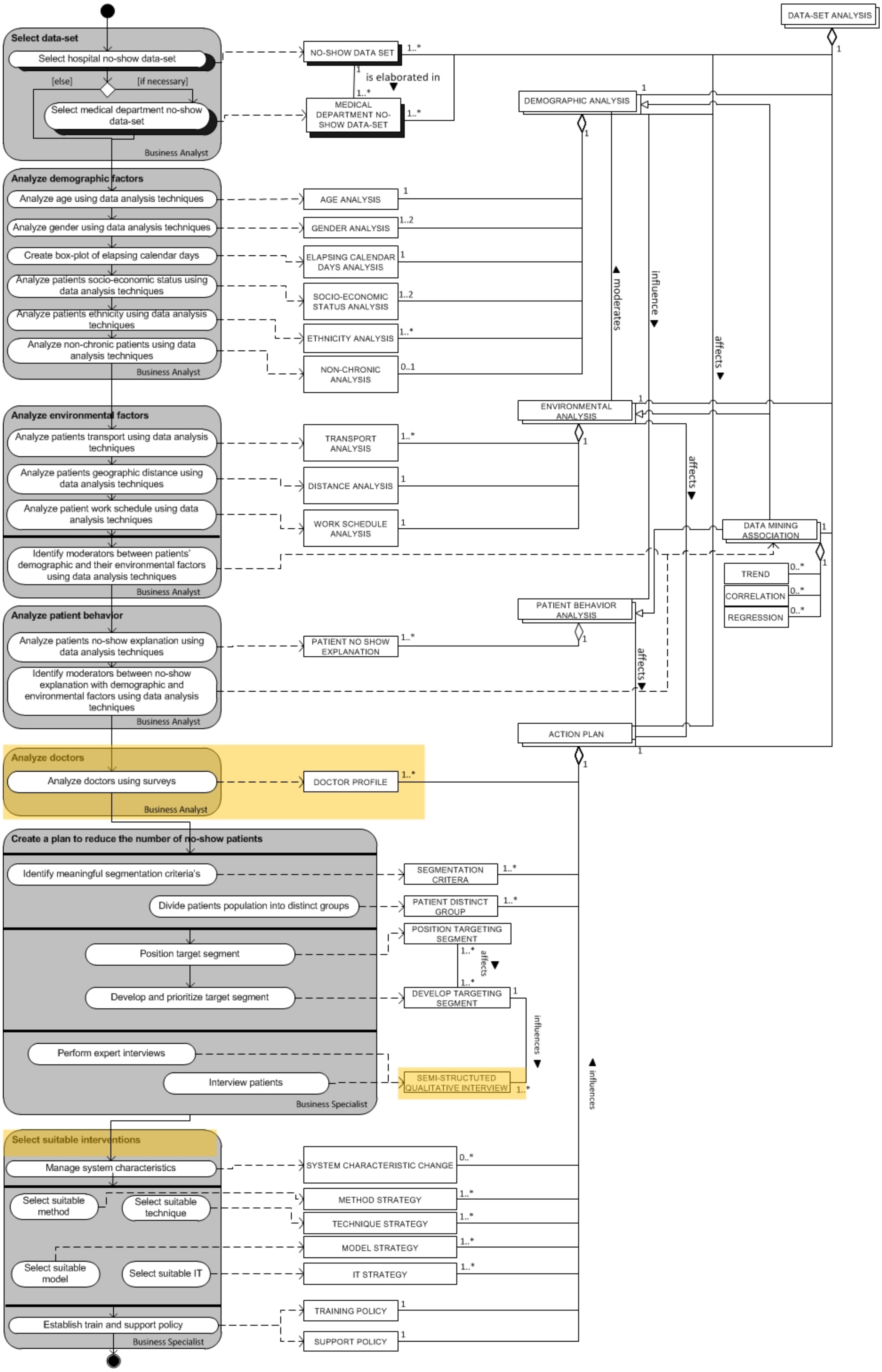


Figure 34. Final version: Process Delivery Diagram to reduce the number of no-show patients.

Several new phases, activities and concept tables were created based on the received feedbacks from the experts and the researcher's first supervisor. The following phase, namely 'Analyze doctors' is created because no-show is not always the patients' fault, it can also be the doctor's fault. By analyzing the doctors more knowledge can be gained on the reduction of the number of no-show patients.

Activity	Sub-activity	Description
Analyze doctors	Analyze doctors using surveys	ANALYZE DOCTORS USING SURVEYS is to gain knowledge on: - How far in advanced the appointments are being made; - How the communication is between doctors and patents. - Other factors which may lead to no-show Put all the results in the DOCTOR PROFILE.

Table 26. Activity table phase 5.

Concept	Description
DOCTOR PROFILE	DOCTOR PROFILE consists of surveys conducted on the doctors to gain knowledge where the problem lies that lead to patients committing no-show (Potamitis et al., 1994).

Table 27. Concept table phase 5.

There is one minor but important change in the 'Create a plan to reduce the number of no-show patients' phase, which is the change of the concept name from INTERVIEW to SEMI-STRUCTURED INTERVIEW. It is only a minor transformation, which aims to make the method clearer, more precise and remove doubts about the used interview strategy. The activity table shown below stayed the same. Changes in the concept table are marked in yellow.

Activity	Sub-activity	Description
Create a plan to reduce the number of no-show patients	Identify meaningful segmentation criteria	Identify Meaningful SEGMENTATION CRITERIA based on the conducted data analysis techniques gathered from the previous four phases.
	Divide patients population into distinct groups	Utilize the earlier identified SEGMENTATION CRITERIA to divide the patients into distinct groups (demographic and environmental factors). Put the results in PATIENT DISTINCT GROUP.
	Position target segment	Allow Business Specialists to

		thoroughly and completely understand each targeting segment. The segment can be saved in POSITION TARGET SEGMENT.
	Develop and prioritize targeting strategy	Develop and prioritize the target segments defined earlier. This allows Business Specialists to prioritize for which segment a strategy will be developed.
	Perform expert interviews	PERFORM EXPERT INTERVIEWS with staff members of the hospital, think of doctors, specialists and so on. This will allow the Business Specialist to get a total perspective to comprehend the target segments.
	Interview patients	Perform INTERVIEWs with patients of the hospital. This will allow the Business Specialist to get a total perspective to comprehend the target segments.

Table 28. Activity table phase 5

Concept	Description
ACTION PLAN	Part 1 of the ACTION PLAN includes all meaningful segmentation criteria, group of patients and strategies developed for each group of patients (segment) reduce the number of no-show patients (Garuda et al., 1998).
SEGMENTATION CRITERIA	SEGMENTATION CRITERIA consists of the criteria on which the segments will be created on (Garuda et al., 1998).
PATIENT DISTINCT GROUP	A PATIENT DISTINCT GROUP involves dividing the no-show patients SEGMENTATION CRITERIA population into distinct groups of patients (Garuda et al., 1998). Dividing the patient into distinct group allows Business Specialists to receive a top-down overview of the problem (no-show) within the hospital.
ESTABLISH TARGETING STRATEGY	ESTABLISHING TARGETING STRATEGY allows the business analysis to calculate which of the segmentation is the most important, also the most beneficial that's going to reduce the no-show the most and the cost behind the strategy (Garuda et al., 1998). Without a proper targeting strategy the organization may end up with higher costs than

	expected, also without any significant results. In this concept a list with targeting strategy is created.
POSITIONING TARGETING SEGMENT	POSITIONING TARGETING SEGMENT will not only focus on the efforts the organization will present, it will provide a basis for future planning and strategy formulation, as well (Garuda et al., 1998). The Business Specialist makes sure he thoroughly and completely understand and comprehend the no-show issue of each particular group (Garuda et al., 1998).
DEVELOP TARGETING SEGMENT	During the developing stage one must begin to develop the strategies that the hospital can utilize to address each of the *target segment* problem. Here a list consisting of several interventions for each segment are gathered. The results can be saved in DEVELOP TARGET SEGMENT (Garuda et al., 1998).
SEMI-STRUCTURED QUALITATIVE INTERVIEW	SEMI-STRUCTURED QUALITATIVE INTERVIEW shows the information collected from the expert interviews, as well from the interview conducted on the patients.

Table 29. Concept table phase 5

The last phase of the method stays the same. This phase, as well the previous phases, was determined as well put together and structured. The most important issues regarding the actual naming of the activity are marked in yellow.

Activity	Sub-activity	Description
Select suitable interventions	Manage system characteristics	Offer SYSTEM CHARACTERISTIC CHANGE in order to customize the system to ensure better results of the performed strategies. The SYSTEM CHARACTERISTIC CHANGE is part 2 of the ACTION PLAN. The ACTION PLAN is created based on the DEMOGRAPHIC ANALYSIS, ENVIRONMENTAL ANALYSIS and PATIENT BEHAVIOR ANALYSIS. All of the results will be saved into the DATASET ANALYSIS.
	Select suitable	A list of selected method strategies for a

	method	particular group of no-show patient.
	Select suitable technique	A list of selected technique strategies for a particular group of no-show patient.
	Select suitable model	A list of selected model strategies for a particular group of no-show patient.
	Select suitable IT	A list of selected Information Technology strategies for a particular group of no-show patient.
	Establish train and support policy	TRAINING POLICY and SUPPORT POLICY, which are part of the ACTION PLAN.

Table 30. Activity table phase 6

Concept	Description
ACTION PLAN	Plan on how to reduce the number of no-show patients, based on the selected strategies, expert interviews, patient's interviews and the findings in the previous deliverables.
SYSTEM CHARACTERISTIC CHANGE	SYSTEM CHARACTERISTIC CHANGE is referring to physicians, employers and doctors know about what you are going to do, and how in-depth you have researched, understood, and adapted to your patient's need. A good product is only useful if others are aware of it (Garuda et al., 1998).
METHOD STRATEGY	The list of methods to be implemented to reduce the number of no-show patients (Garuda et al., 1998).
TECHNIQUE STRATEGY	The list of techniques to be implemented to reduce the number of no-show patients (Garuda et al., 1998).
MODEL STRATEGY	The list of models to be implemented to reduce the number of no-show patients (Garuda et al., 1998).
IT STRATEGY	The list of IT strategies to be implemented to reduce the number of no-show patients, such as E-mail, SMS and Patient Portal (Garuda et al., 1998).
TRAINING POLICY	TRAINING POLICY is the plan to train the staff members with the new strategy to reduce the number of no-show patients.
SUPPORT POLICY	SUPPORT POLICY is the plan to support the staff members with the new strategy to reduce the number of no-show patients.

Table 31. Concept table phase 6

5.1.9 Conclusion

The evaluation of the proposed method that supports the healthcare sector into reducing no-show was evaluated by five experts at UMCU. The experts were asked a total of 28 questions, where 12 questions were to examine if the method is complete, consistent, efficient and applicable. The results showed that the proposed method is well-structured and logical. All of the phases, activities and concepts are relevant.

5.2 *Quantitative evaluation through data analyses*

No-show at UMCU: case study

In this section, several data analysis techniques were used to gain knowledge on the reason for no-shows at UMCU. After this, to validate whether the Healthcare reduction method serves its purpose to reduce the number of no-show patients, the researcher applied this to the data analysis results. For a clear presentation, the results of the conducted data analyses are divided into sections to give an appropriate flow.

5.2.1 *Data analysis method*

The statistical analytics software SPSS version 20 was utilized to extract valuable knowledge from the no-show dataset. SPSS is a quantitative statistical application with which researchers can predict with confidence what will happen next so that smarter decisions, problem solutions and improved outcomes can be accomplished. According to Duffin, Rae, Prakash, Somers, and Easterbrook (n.d.), SPSS is widely used for a variety of disciplines, such as:

- Manage, analyze, manipulate and display data;
- Quickly and accurately perform an enormous number of statistical functions;
- Present results in a range of formats including graphically;

5.2.1.1 Dataset

The dataset gathered from UMCU has an approximate size of 367.40 MB. It consists of appointments made during 2012; from 01-Jan to 31-Dec. The dataset consisted of 43 variables. In the following sub-section, the most interesting variables and their measurements within the dataset are shown.

5.2.1.2 Role of the Three-phases method (3PM)

Before the actual data analysis of the dataset, this had to be transformed into a structured, usable and measurable dataset, so that valuable information of the no-show patients could be gathered. Numerous methods exist in this domain that supports data analyses. In this research the 3PM created by Vleugel, Spruit, and Van Daal (2009) was utilized. The 3PM consists of three-phases, namely: data-retrieval, data-mining and results implementation. Each phase of the 3PM tailored to this case study is explained below.

Data-retrievable phase

UMCU's needs were analyzed by performing several face-to-face conversations with the researcher's daily supervisor. Based on the conducted conversations a goal was defined. This was to pin point ("red flag") by utilizing SPSS and the no-show dataset, why or for what reasons there is a no-show problem at UMCU. Hypotheses were used to achieve this goal. These were created, based on the knowledge gained from literature studies and the available patients' demographic factors, environmental factors and patients' behavior variables. No (database) tables were created, based on the entities and attributes from the constructed hypotheses, contrary to what Vleugel et al. (2009) suggested. The reason for this is that the dataset itself was used when new variables were created, computed or transformed. The hypotheses to reach the goal are shown in the sub-section 5.2.2.

Data mining

For this specific goal, the predictive data mining technique was chosen and afterwards employed on the no-show dataset. The option to use a time-variable, such as ‘date’ was not conducted, as explained by Vleugel et al. (2009). In other words, no forecast future events models were compared with known past events models. Regression analyses were performed because the dependent variable is dichotomous (show vs. no-show). Furthermore, the researcher wants to predict the reasons for no-show by testing the relation between the patients’ demographic factors with their environmental factors to no-show. A more elaborated explanation of this can be found in sub-section 5.2.3.

Result implementation

UMCU preference regarding the solution was stated very clear; UMCU wanted a report containing the results. For this reason, the researcher simply needed to present a report, based on the data analyses result. In addition, in this phase, the Healthcare reduction method will be put to the test.

5.2.1.3 Variables and measurements

Table 32 depicts the group size and the measurement for each variable. Some of the variables have the name ‘coded’ at the end. This means that these variables were transformed, computed and recoded to a numeric format to create a categorical variable (e.g., ordinal and nominal), so that afterwards data analyses could be performed.

#	Variables	Size of group	Measurement	Variable not included with original dataset
1	Patientnummer	n/a	Scale	
2	Postcodecijfers	n/a	Nominal	
	Provincie	7+	Nominal	✔
	Provincie_coded	7+	Nominal	✔
3	Sociostatus	n/a	Scale	✔
4	Sociostatus_coded	2	Dichotomous	✔
5	Woonplaats	7+	Nominal	
6	Woonplaats_coded	7+	Nominal	✔
	distancekm_to_umcu	n/a	Scale	✔
7	Geslacht	2	Dichotomous	
8	Geslacht_coded	2	Dichotomous	✔
9	Leeftijd	n/a	Ratio	
10	Leeftijd_coded	4	Ordinal	✔
11	Afspraaknummer	n/a	Scale	
12	Ziekhuislocatie	2	Dichotomous	
13	Ziekenhuislocatie_coded	2	Dichotomous	✔
14	Agendacode	7+	Nominal	
15	Agenda	7+	Nominal	
16	Agenda_coded	7+	Scale	✔
17	Subagendacode	7+	Nominal	
18	Subagenda	n/a	Scale	
	Subagenda_coded	7+	Scale	✔

19	Behandelaar	7+	Nominal	
20	Behandelaar_coded	7+	Scale	✔
21	Specialismecode	7+	Nominal	
22	Specialisme	7+	Nominal	
23	Specialisme_coded	7+	Scale	✔
24	Consulttypegroep	2	Dichotomous	
25	Consulttypegroep_coded	2	Dichotomous	✔
26	Consulttype	7+	Nominal	
27	Consulttype_coded	7+	Nominal	✔
28	Afspraak	7+	Nominal	
29	Afspraak_coded	7+	Nominal	✔
30	Noshow	2	Dichotomous	
31	Noshow_coded	2	Dichotomous	✔
34	Afspraakdatum	n/a	Scale	
35	Toegangsdagen	n/a	Scale	✔
36	Consultdatum	n/a	Scale	
37	Consultdatum_dagVandeWeek	7	Nominal	✔
38	Consultdatum_dvdweek_coded	7	Nominal	✔
39	ConsultdatumSeizoen_coded	4	Nominal	✔
40	Jaar	n/a	Interval	
41	Kwartaal	4	Nominal	✔
42	Maand	7+	Nominal	✔
43	Weekeinde	2	Dichotomous	
44	Feestdag	2	Dichotomous	
45	Dagdeel	4	Nominal	
46	Dagdeel_coded	4	Nominal	✔
47	Consulttijd	n/a	Ratio	
48	Consultduur	n/a	Ratio	

Table 32. No-show dataset's variables and measurements

5.2.2 Hypotheses

The collected literature study offered several theories, which indicated that no-show patients are influenced by the patients' demographic factors, patients' behavior and their environmental factors. The dataset conducted from UMCU provides the opportunity to perform data analyses to test these above-mentioned theories.

The theory about patients' behavior could not be measured nor included in the data analysis, because the dataset did not contain the variables necessary to measure the patients' behavior. The hypotheses for this study are therefore only made for the following variables:

- Patients' demographic factors
    - Gender, age, socioeconomic status and elapsing calendar days
- Environmental factors
    - Distance (in KM), day of the week, week or weekend, month of the year, season of the year and part of the day

We are firstly interested in whether a single demographic and a single environmental factor are directly related to no-show (see Figure 38). Therefore, the first two hypotheses are:

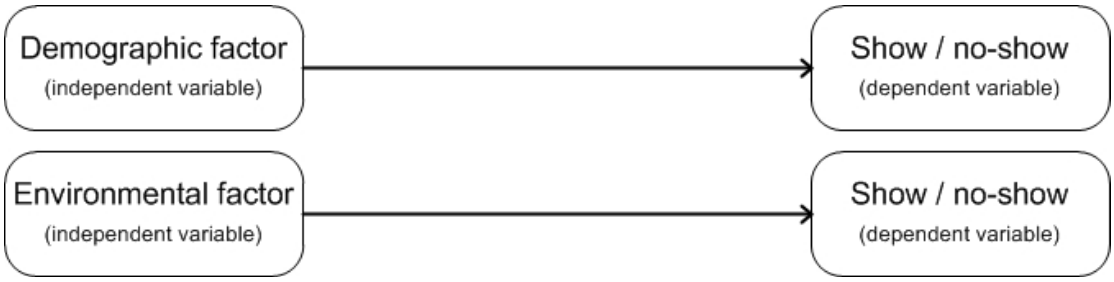


Figure 35. Single demographic and single environmental factors directly related to no-show.

Hypothesis 1) The demographic factors 'age', 'socioeconomic status' and 'elapsing calendar days' are directly related to no-show.

Hypothesis 2) The environmental factors 'distance', 'day of the week', 'week or weekend', 'month', 'season' and 'part of the day' are directly related to no-show.

We are secondly interested in whether the direct relations between a single demographic factor and no-show are being positively moderated by controlling the effects of a single environmental factor (moderator) in one model (see Figure 36). This leads to hypotheses three to six:

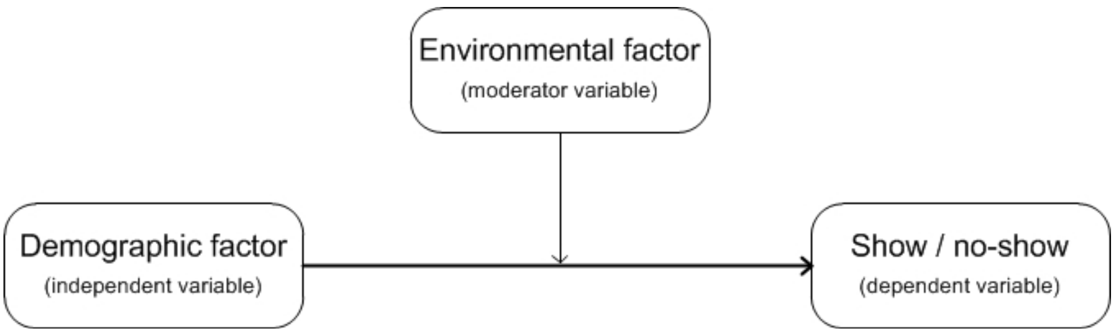


Figure 36. Direct relations between single demographic factor and no-show are being moderated by single environmental factors.

Hypothesis 3) The direct relation between the demographic factor 'gender' and no show is positively moderated by a single environmental factor.

Hypothesis 4) The direct relation between the demographic factor 'age' and no-show is positively moderated by a single environmental factor.

Hypothesis 5) The direct relation between the demographic factor 'socioeconomic status' and no-show is positively moderated by a single environmental factor.

Hypothesis 6) The direct relation between the demographic factor 'elapsing calendar days' and no-show is positively moderated by a single environmental *factor.*

We are lastly interested in whether the direct relations between a single demographic factor and no-show are positively moderated by controlling the effects of all environmental factors (moderators) in one model (see Figure 37). This leads to hypotheses seven to ten:

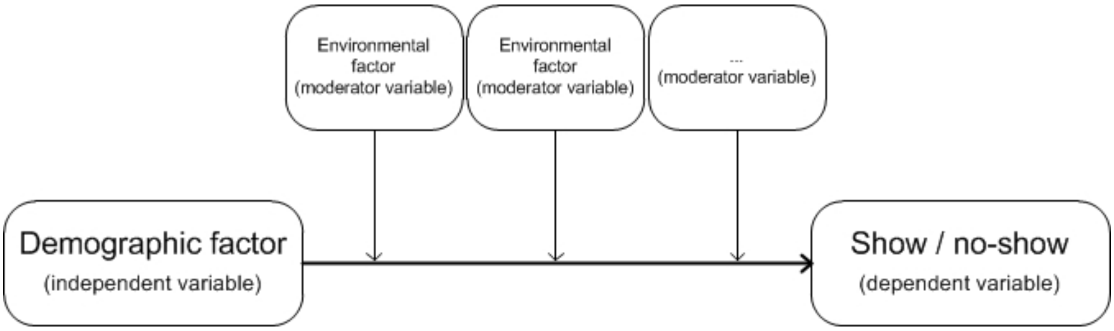


Figure 37. Direct relations between single demographic factor and no-show are being moderated by multiple environmental factors.

Hypothesis 7) The direct relation between the demographic factor 'gender' and no show is positively moderated by environmental factors.

Hypothesis 8) The direct relation between the demographic factor 'age' and no-show is positively moderated by environmental factors.

Hypothesis 9) The direct relation between the demographic factor 'socioeconomic status' and no-show is positively moderated by environmental factors.

Hypothesis 10) The direct relation between the demographic factor 'elapsing calendar days' and no-show is positively moderated by environmental factors.

5.2.3 Data analysis plan

Before performing the data analysis, three actions were performed to provide for an accurate and reliable outcome of the results. First, patients with missing values were not deleted, because these patients also had other variables that were important, which were utilized when applying other data analysis techniques. Secondly, each variable within the dataset was given a measurement (e.g., nominal, ordinal, scale or ratio), an example of this is shown in Table 32. Last, new variables were created, based on the transformation or computing of the old variables; think of 'Strings' transformed to 'Numeric'.

The data was first analyzed using descriptive statistics through cross-tables and graphs. The cross-tables were used to create a statistical process to summarize the categorical data (Field, 2009). Afterwards, Chi-square tests (χ^2 test) were performed to test Hypotheses one and two. This analysis was performed to determine whether the independent variables (demographic and environmental factors) are associated with the dependent variable 'no-show'. As Glanz, Rimer, and Viswanath (2008) explained, demographic factors are factors related to an individual's environmental factors that can influence the individual leading to no-show. The strength of these relations was determined by the Cramer's V (φc) value. According to (Field, 2009), the Cramer's V value must be read as follows:

- value of 0.1 indicates a weak relation;
- value of 0.3 indicates a moderate relation;
- value of 0.5 indicates a strong relation

Subsequently, variables that were significantly related to no-show were further analyzed using Multivariate logistic regression analysis. This analysis was performed for two reasons. First, the dependent variable is dichotomous ('show' vs. 'no-show') and second, relations between two or more variables were analyzed. In this case, the relation between the independent (demographic) variables and dependent variable were analyzed, while controlling for moderator (environmental) variables. As explained by Humpel, Owen, and Leslie (2002), and Simpson, Banerjee, and Simpson (1994), environmental factors are associated with demographic factors because these factors moderate the actual ethical decision making process of a person; activity choices are believed to be altered depending on the individual's environmental factors. This analysis tested Hypotheses three to six.

Hypotheses seven to ten were tested using backward (conditional)-multivariate logistic regression analysis. This analysis analyzes the relations between the independent variables and no-show, while controlling the effects of all moderators variables at once. As Field (2009) explained, this analysis shows the suppressor effects that can occur when an independent variable has significant effects, though only when another variable is held constant. This implies removing the most insignificant variable in the model and iterating the logistic regression until only significant independent variables appear in the regression model.

The multivariate analysis and the backward (conditional)-multivariate logistic regression were performed utilizing categorical features *(indicator(first))* of the logistic regression analysis.

5.2.3.1 Assumptions

Two assumptions were conducted before performing the logistic regressions. The first assumption is called 'independence of error'. Independence of error means that the cases or data are not related and that thus all observations must be independent (Field, 2009). The dataset acquired from UMCU meets this assumption given that all patients' details and information were automatically saved into the database.

The second assumption concerns the absence of 'multicollinearity', which means there should be no perfect linear relationship between two or more of the independent variables. Thus, the independent variables should not correlate too highly (Field, 2009). If there is a perfect collinearity between independent variables it becomes impossible to obtain unique estimates of the regression coefficients, because there is an infinite number of combinations of coefficients that would work equally well (Field, 2009). This assumption was tested with the Variance Inflation Factor (VIF) statistics. The VIF value indicates whether an independent variable has a strong linear relationship with other independent variables. In order to meet this assumption the VIF has to have a value of ≤ 10 (Field, 2009). The assumption of 'multicollinearity' is met; given that the VIF values were ≤ 1.4.

5.2.4 Results

5.2.4.1 Descriptive

The no-show rate of UMCU in 2012 was 2.95%. This was calculated by dividing the number of no-show patients with the total number of patients scheduled, times 100% (26,432/894,554)*100 = 2.95%. The ratio of show to no-show was 434,061 to 13,216. In other words, for every 434,061 shows UMCU received, 13,216 were no-shows. In total there were 894,554 appointments registered in the dataset, of which 46.5% is registered under male patients and 53,5% was registered under female patients. Of all patient appointments, 26.4% had a low SES and 72.4% had a high SES. The SES of the genders is depicted in Table 33.

Socioeconomic status	Male	Female
Low	44.85%	55.15%
High	47.03%	52.97%

Table 33. Descriptive: Socioeconomic status looking at the gender's perspective

As depicted in Figure 38, the top three provinces where patients of UMCU live, are Utrecht (59.5%), Gelderland (15.0%) and South Holland (6.4%). Furthermore, a majority of 18.4% of patients lives in the residence of Utrecht, whereas 4.0% is from Amersfoort and 3.6% is from Zeist. The provinces with the most number of no-show are Utrecht (64.7%), followed by Gelderland (12.4%) and South Holland (5.9%).

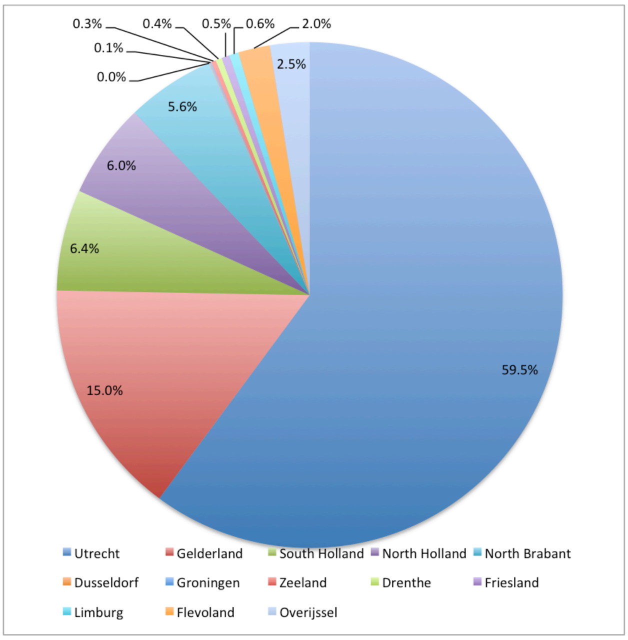


Figure 38. Descriptive patients and the province where they live.

The variable 'Age' was categorized in four groups, namely: children (17.2%), youth (8.8%), adults (52.6%) and seniors (21.4%). As depicted in Figure 39, more than 50% of each of the above-mentioned groups lives less than 50 KM away from UMCU. By only looking at the variable no-show, the group that commits the most number of no-shows was adults (54.4%), followed by seniors (15.3%), children (16.0%) and youth (14.3%).

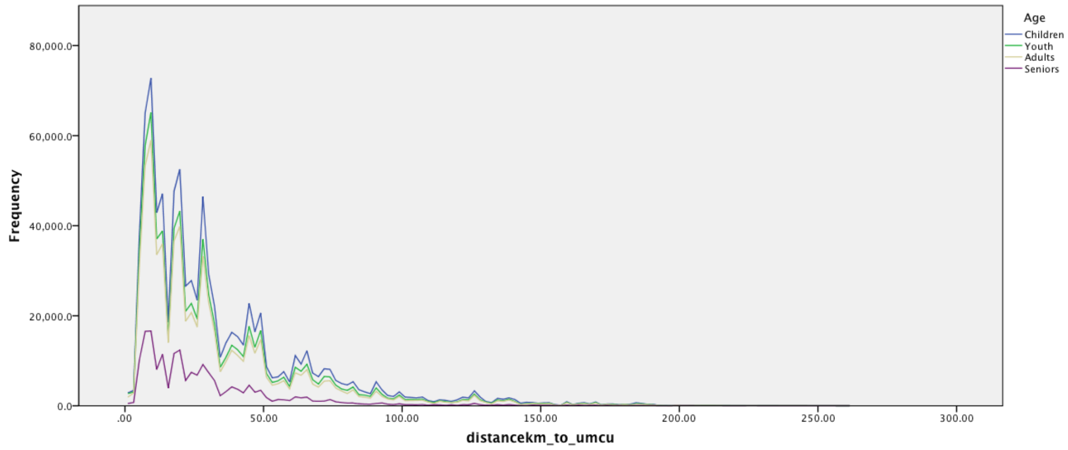


Figure 39. Descriptive Age and distance. Children = Dark blue, Youth = Green, Adults = Yellow, Seniors = Purple

The variable 'part of the day' was categorized in four groups, namely: morning (51.9%), noon (46.8%), night (0.7%) and evening (0.6%). By only looking at the variable no-show, the most number of no-show occurred in the morning (54,7%), followed by noon (45.0%), night (0.3%) and evening (0.003783%). Depicted in Figure 40, we can see that adults account for the most no-shows in the morning and in the noon.

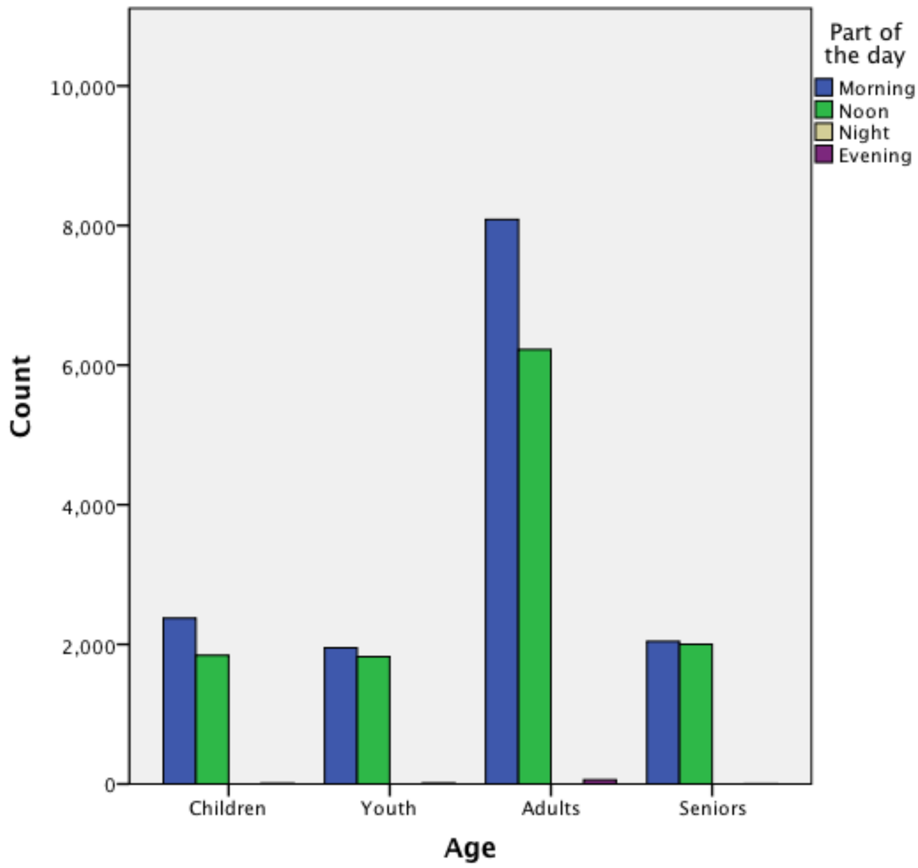


Figure 40. Descriptive Age and Part of the day by looking only at no-show.

A box-plot (Figure 41) is depicted showing the minimal, first quartile, median, third quartile and maximal amount of days that no-show patients (split in age groups) had to wait to see their doctors. As can be seen the minimal amount of days of the four groups is 0 days. For the first quartile, children had to wait 15 days, youth 11 days, adults and seniors 13 days. For the second quartile (median), children had to wait 42 days, youth 29 days, adults 32 days and seniors 40 days. For the third quartile, children had to wait 82 days, youth 70 days, adults 77 days and seniors 92 days. The maximal amount of days for children is 385 days, youth 430 days, adults 420 days and seniors 463 days.

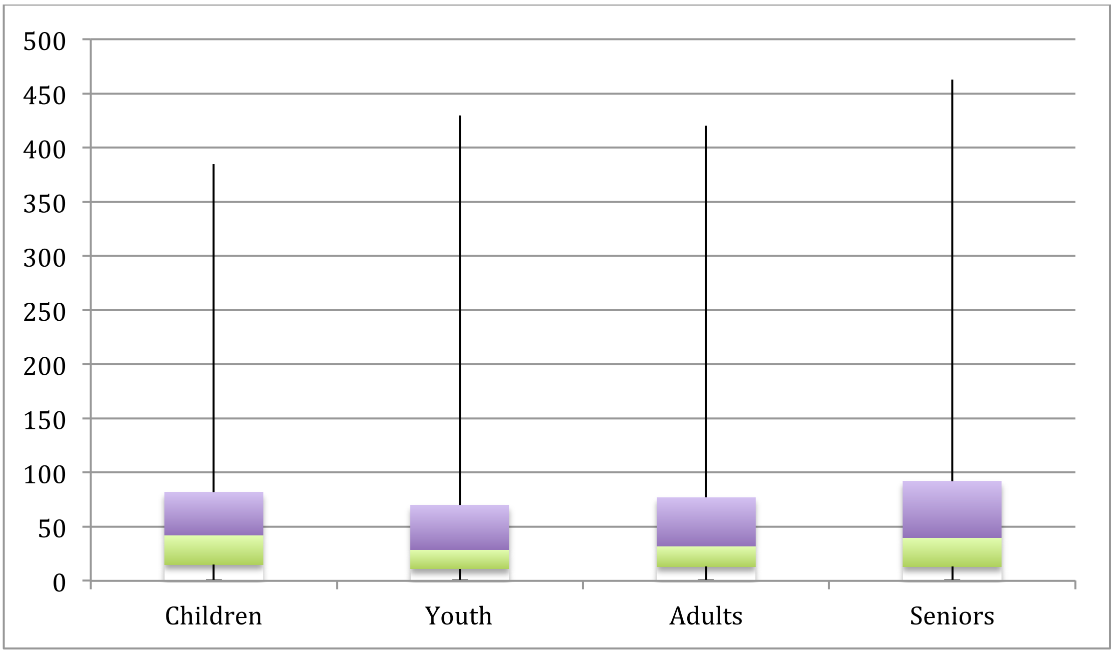


Figure 41. Box-plot. No-show patients split in age groups

A majority of 99.3% of the appointments was made for the week (Monday through Friday), while only 0.7% of the appointments were made for the weekend (Saturday and Sunday). The least amount of appointments was made on Friday. As depicted in Figure 42, the day during the week with the most amount of no-show was Monday (23.20%), whereas the day during the week with the least amount of no-show was Friday (15.70%).

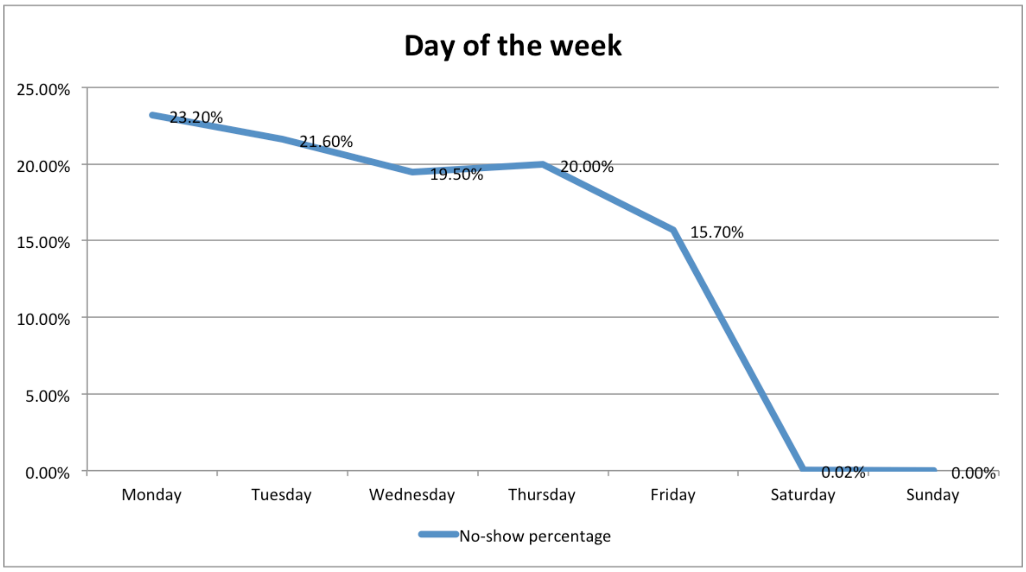


Figure 42. Descriptive day of the week and no-show.

The variable 'season' was categorized into four groups, namely: spring (25.9%), summer (24.5%), autumn (24.0%) and winter (25.6%). By looking only at the variable no-show, the group with the most amounts of no-show was spring (27.3%), followed by summer (26.0%), autumn (23.4%) and winter (23.3%). The variable 'distance' and 'Socioeconomic status' depicted from the seasons' perspective is shown in Figure 43.

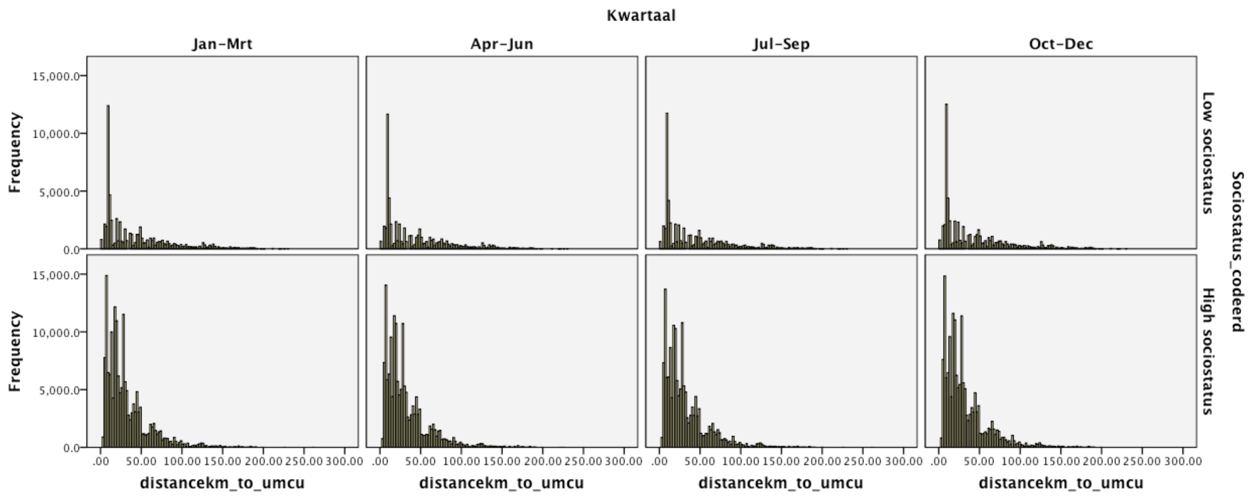


Figure 43. Descriptive Distance (KM), Season and Socioeconomic status.

5.2.4.2 Chi-square tests

The Chi-square test analysis was performed in order to test hypotheses one and two. Hypotheses one and two test whether individual demographic factors and individual environmental factors are directly related to no-show. The results of the chi-square analysis are divided into the subsections ‘demographic factors’ and ‘environmental factors’.

5.2.4.2.1 Results hypothesis one

The first Chi-square analysis tested whether a single demographic factor: gender, age, socioeconomic status and elapsing calendar days, is directly related with patients not showing up for their appointment. As shown in Table 34, all of the demographic factors are significantly related to no-show, however, this relation is weak in strength. These results are consistent with hypothesis one, since there is a significant relationship between the demographic factors and no-show. For a complete overview of this Chi-square test, see Appendix 7.6.1.

	χ^2	*Φc (strength)*
Gender	239.22***	.02 (weak)
Age	1450.58***	.04 (weak)
Socioeconomic status	729.84***	.03 (weak)
Elapsing calendar days	7008.65***	.09 (weak)

Table 34. Chi-square analysis of the demographic factors in relationship with no-show.

Note: χ^2= Chi-square; Φc =Cramer’s V, * p < .05. ** p < .01, en *** p < .001

5.2.4.2.2 Results hypothesis two

The second Chi-square analysis tested whether a single environmental factor, namely: day of the week, week or weekend, month, season and part of the day are directly related to no-show. As shown in Table 35, all of the environmental factors are significantly related to no-show. This means that they are significant predictors for patients not showing up for their appointments. The Cramer’s V results show, however, that the relationships are weak in strength. These results are consistent with hypothesis two, since there is a significant relationship between the environmental factors and no-show. For a complete overview of this Chi-square test, see Appendix 7.6.2.

	χ^2	*Φc (strength)*
Days of the week	266.42***	.02 (weak)
Week or weekend	173.19***	.01 (weak)
Month	134.47***	.01 (weak)
Season	97.83***	.01 (weak)
Part of the day	276.07***	.02 (weak)

Table 35. Chi-square analysis of the environmental factors in relationship with no-show.

Note: χ^2= Chi-square; Φc =Cramer’s V, * p < .05. ** p < .01, en *** p < .001

5.2.4.3 Multivariate logistic analysis

A multivariate logistic analysis was performed to test hypotheses three to six. Hypotheses three to six state that environmental factors positively moderate the relation between demographic factors and no-show. Multivariate logistic analysis tests whether there is an interaction between each independent variable and the moderator variable, in relation to the dependent variable in a model. A significant interaction (p <.05) means that the direct relation is moderated by the environmental factor, whereas the Odds Ratio (OR) indicate the likelihood of no-show occurring.

5.2.4.3.1 Results hypothesis three

Results show that there is a significant and positive relation between the direct relation gender and no-show. Male patients, as opposed to female patients, increase the likelihood of no-show by approximately 1.22 times. As depicted in Figure 38, the results show, in contrary to hypothesis one, that the relation between the demographic factor 'gender' and the dependent variable 'no-show' is not moderated by any of the environmental factors: Distance (p=.832), day of the week (p=.098), week or weekend (p=.101), month (p=.625), season (p=.148) and part of the day (p=.122). In other words, no environmental factor influences the probability that a male or female patient would not show-up for their appointment. A complete overview of the results can be seen in Appendix 7.7.1.

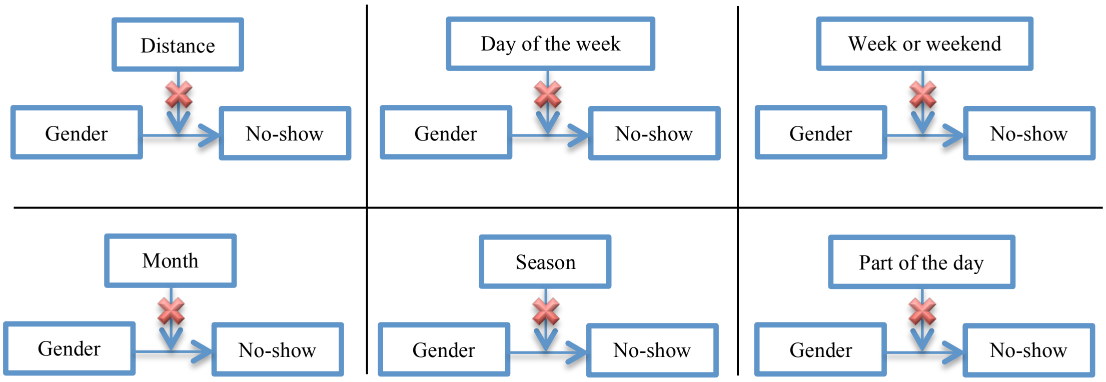


Figure 44. Results hypothesis 3. Multivariate analysis.

5.2.4.3.2 Results hypothesis four

According to hypotheses four, five of the six environmental factors moderate the direct relation between the demographic factor 'age' and the dependent variable 'no-show'. The five significant moderators are: distance (p = .001), day of the week (p < .001), month (p = .001), season (p < .001) and part of the day (< .001). Only two of five moderators positively predict no-show, namely: day of the week and part of the day. As depicted in Figure 45 (top middle section), the likelihood of no-show is significantly increased 1.29 times by youth, 1.20 times by adults and 1.30 times by seniors when the appointment is made on a Wednesday. The likelihood of no-show is on the other hand increased: 1.14 times by adults and 1.26 times by seniors with an appointment scheduled during the noon. A complete overview of the results can be seen in Appendix 7.7.2.

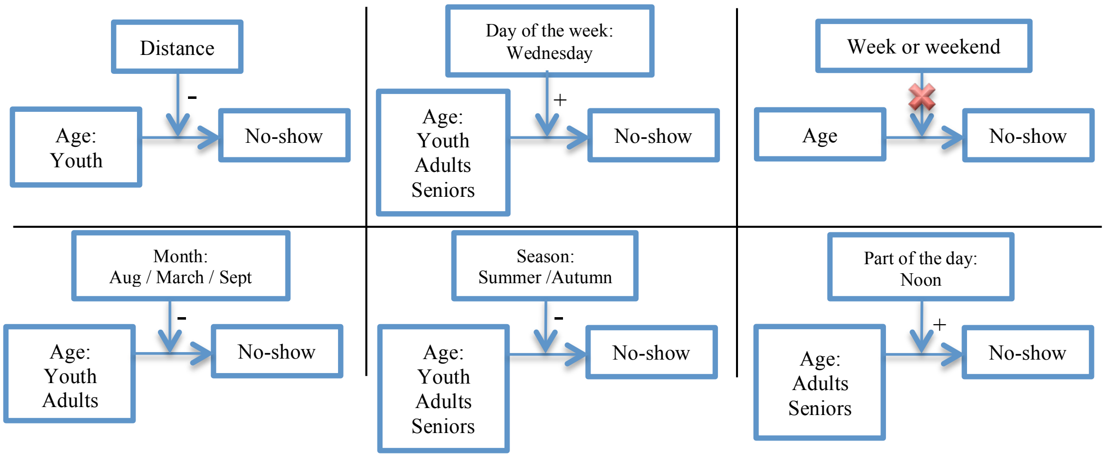


Figure 45. Results hypothesis 4. Multivariate analysis.

5.2.4.3.3 Results hypothesis five

Results show that two of the six environmental factors significantly moderate the direct relation between the demographic factor ‘socioeconomic status’ (SES) and the dependent variable ‘no-show’ (see Figure 46). These two moderators are: Distance ($P<.001$) and month ($p<.05$), though only distance positively predicts no-show. The probability of patients with a high socioeconomic status not showing up for their appointment is increased by 1.00 times due to distance. A complete overview of the results can be seen in Appendix 7.7.3.

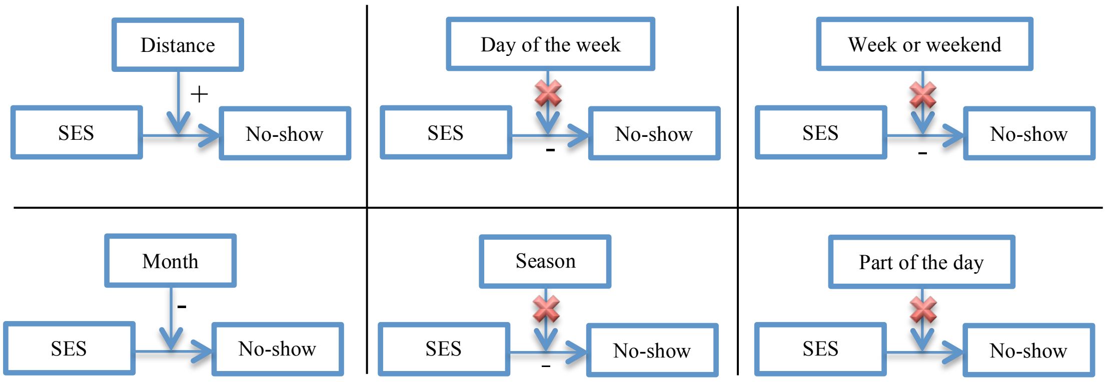


Figure 46. Results hypothesis 5. Multivariate analysis.

5.2.4.3.4 Results hypothesis six

Results show that the direct relation between ‘elapsing calendar days’ (ECD) and the dependent variable ‘no-show’ is moderated by three of the six environmental factors (see Figure 47), namely: month ($p = .007$), season ($p = .007$) and part of the day ($p = .05$). These three environmental factors positively predict no-show. The probability of patients not showing up for their appointment is increased by 1.12 times when patients have to wait between 31 to 120 days to see their doctors and when the appointment is scheduled in summer. The likelihood of no-show is also increased when an appointment is made during the month of April or August and when patients have to wait an amount of days for the appointment. A complete overview of the results can be seen in Appendix 7.7.4.

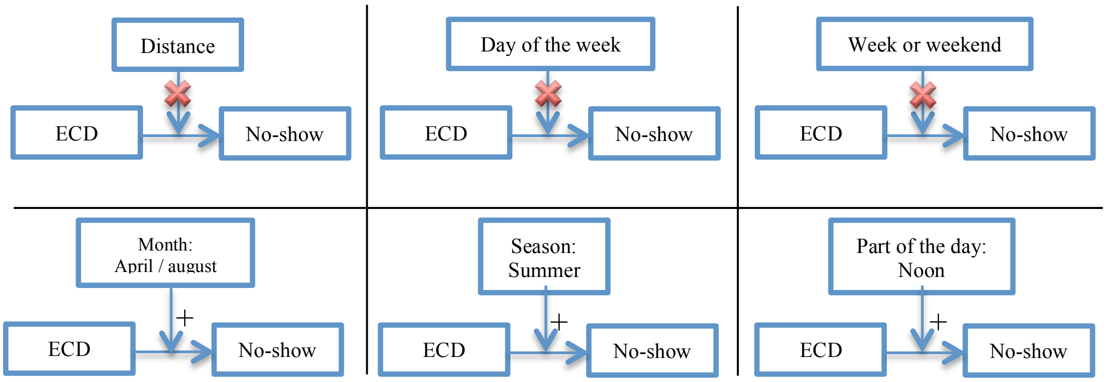


Figure 47. Results hypothesis 6. Multivariate analysis.

5.2.4.4 Backward (conditional) Multivariate logistic analysis

Hypotheses three to six were also tested, this time using backward (conditional) multivariate logistic analysis. This analysis analyzes the relation between each demographic factor and no-show, while controlling for the effects of all environmental factors (moderators) in one model. This is in contrast with the first multivariate logistic analysis performed in sub-section 5.2.4.3, which tested all environmental factors separately.

5.2.4.4.1 Results of hypothesis seven

The results of the backward multivariate analysis show, in comparison with the results of the multivariate analysis, that the relation between the demographic factors ‘gender’ and ‘no-show’ is only negatively moderated by one environmental factor, namely ‘day of the week’ (p=.019). Appointments scheduled on Thursdays increase the likelihood that male patients show up for their appointment by 0.91 times. Thus in other words, this moderator does not positively predict no-show. For a complete overview of the results see Appendix 7.8.1.

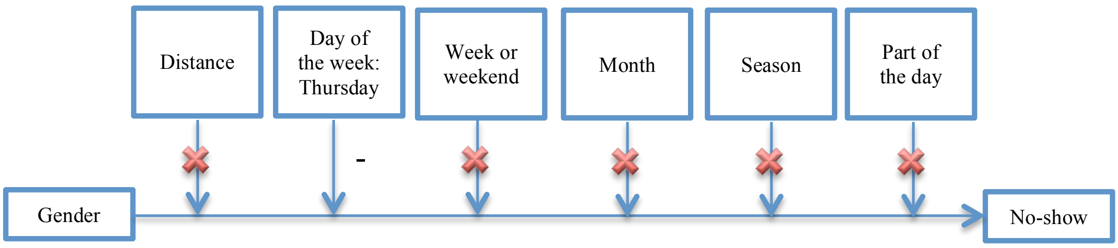


Figure 48. Results hypothesis 7. Backward (conditional) multivariate analysis.

5.2.4.4.2 Results of hypothesis eight

The results of the backward multivariate analysis show, in comparison with the results of the multivariate analysis that the relation between ‘age’ and no-show is moderated by four environmental factors (see Figure 49), namely: distance (p= .001), day of the week (p= .001), month (p <.001) and part of the day (p= .003). Only the moderators ‘day of the week’ and ‘part of the day’ positively predict no-show. The likelihood of no-show is increased 1.10 times by ‘youth’, 1.66 times by ‘adults’ and 1.27 times by ‘seniors’ with an appointment scheduled on Tuesdays. The likelihood of no-show when an appointment is scheduled during noon is increased 1.05 times by adults and 1.41 times by seniors. The model had a R^2 of .013. For a complete overview of the results, see Appendix 7.8.2.

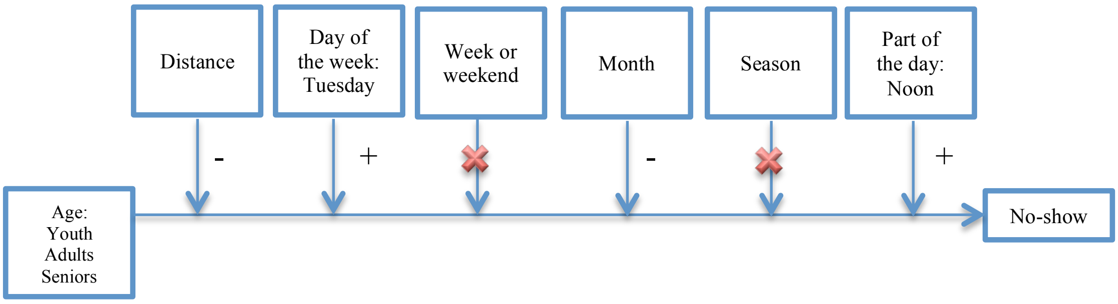


Figure 49. Results hypothesis 8. Backward (conditional) multivariate analysis.

5.2.4.4.3 Results of hypothesis nine

The results of the backward multivariate analysis show, in comparison with the results of the multivariate analysis, that the relation between the demographic factor ‘socioeconomic status’ and the dependent variable ‘no-show’ is only positively moderated by the environmental factor ‘Distance’ ($p<.001$), as shown in Figure 50. The model had a R^2 of .01. The likelihood of patients not showing up due to the distance they have to travel is 1.002 times greater for patients with a high SES than for patients with a low SES. For a complete overview of the results, see Appendix 7.8.3.

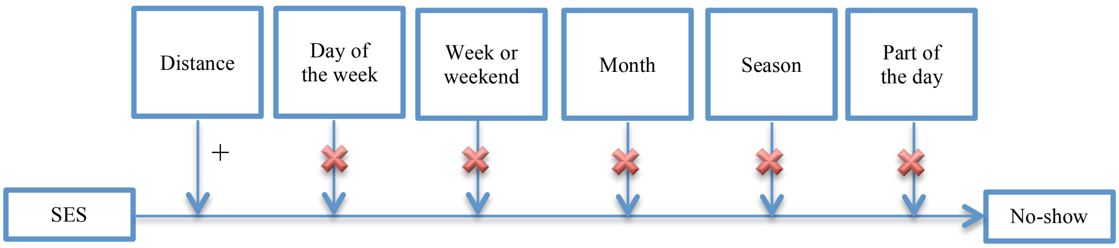


Figure 50. Results hypothesis 9. Backwards (conditional) multivariate analysis.

5.2.4.4.4 Results of hypothesis ten

The results of the backward multivariate analysis show, in comparison with the results of the multivariate analysis, that the direct relation between ‘elapsing calendar days’ and ‘no-show’ is only positively moderated by one environmental factor (see Figure 46), namely: month ($p=.006$). The likelihood of no-show is increased by 1.26 times in the month of February when patients have to wait between 91 to 120 days to see their doctors. For a complete overview of the results, see Appendix 7.8.4.

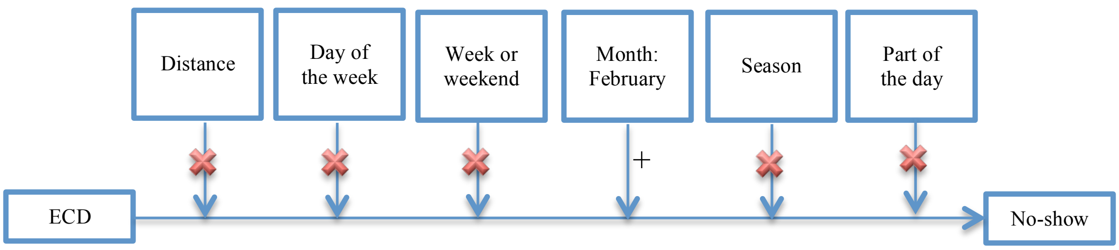


Figure 51. Results of hypotheses 10. Backwards (conditional) multivariate analysis.

5.2.5 *Summarized*

Chi-square, Multivariate and Backwards (conditional) multivariate analyses have been conducted utilizing the patients' demographic and their environmental variables to create the prediction models shown in sub-section 5.2.4. and Appendix 7.6 to 7.8. The created models provided the following knowledge: 'for what reason patients are unable to keep their appointment' or in other words 'what influences patients into committing no-show'. With this knowledge Business Specialists can create a plan and select suitable interventions to reduce UMCU's no-show patients.

5.2.5.1 *Hypotheses testing*

Based on the data analysis results, ten hypotheses were tested. For the Chi-square analysis both hypothesis were accepted, namely: Hypothesis 1 and 2. For the Multivariate analysis, three hypotheses were accepted, namely: Hypothesis 4, 5 and 6, while hypothesis 3 was rejected. Lastly, for the Backwards (conditional) multivariate analysis three hypotheses were accepted, namely: Hypothesis 8, 9 and 10, while hypothesis 7 was rejected.

The outcomes of the Backwards (conditional) multivariate analyses were for two reasons more reliable and correct than the Multivariate analyses. First, this analysis controls for the effect of more than one moderator and also the R^2 outcome of this analysis was higher than the R^2 outcome of the Multivariate analysis. Henceforth, this data analysis was selected to test *the healthcare reduction method* in practice.

5.2.6 *Healthcare no-show reduction method in practice*

In this subsection the Healthcare no-show reduction method was validated with regard to whether it served its purposes to reduce the number of no-show patients, based on the data analysis result. The following sections explain how the researcher used the phases of the method to gain knowledge and therefore to reduce the number of UMCU's no-show patients.

Two of the seven phases of the method were not conducted, namely: phase 4 and 5. Phase 4 had to be skipped for the reason that the variables necessary to analyze patients' behavior were not present in the dataset. Next, phase 5, the doctors were not analyzed, due to their busy working schedules

5.2.6.1 *Phase 1: Select dataset*

In the first phase, a no-show dataset was acquired from UMCU. It was not necessary to select a specific no-show dataset within a medical department, because the hospital had already gathered all information with a focus on the no-show of patients.

5.2.6.2 *Phase 2 and 3: Analyze demographic and environmental factors*

In the second and third phase, three data analysis techniques were conducted on the patients' demographic and environmental variables, namely: Chi-square, Multivariate and Backwards (conditional) multivariate logistic regression.

For both phases, Chi-square analyses were conducted to gather knowledge on which demographic and environmental factors have a direct relation with the phenomenon no-show. Afterwards, moderators were identified, as indicated in the final sub-activity in phase 3: "IDENTIFY MODERATORS BETWEEN PATIENTS' DEMOGRAPHIC AND THEIR ENVIRONMENTAL FACTORS USING DATA

ANALYSIS TECHNIQUES". This was conducted using two data analysis techniques: Multivariate and Backwards (conditional) Multivariate logistic regression.

All of the results of the demographic factor were saved in the DEMOGRAPHIC ANALYSIS, and the results of the environmental factor were saved in the ENVIRONMENTAL ANALYSIS.

5.2.6.3 Phase 6: Create a plan to reduce the number of no-show patients

The results of the conducted Backwards (conditional) multivariate data analyses technique provided the researcher with enough knowledge to identify meaningful segmentation criteria. These criteria were afterwards divided into distinct groups of no-show patients.

The criteria to create a plan to reduce the number of UMCU's no-show patients were: age, socioeconomic status, elapsing calendar days, day of the week, part of the day, distance and month. These criteria were afterwards divided into three distinct groups of no-show patients, as shown in Figure 52.

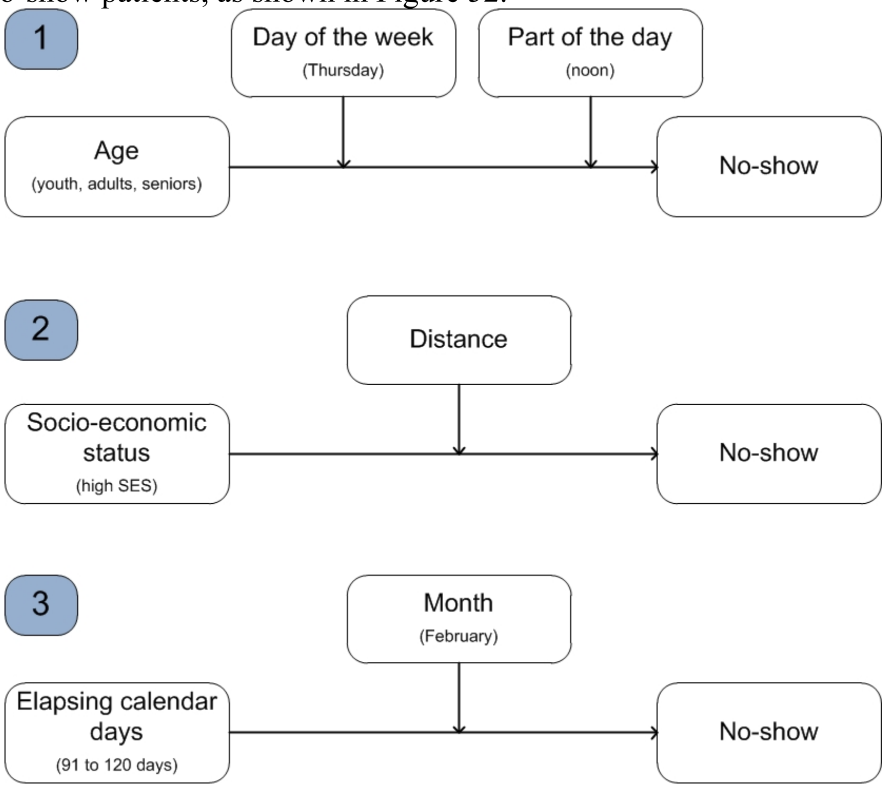


Figure 52. Distinct groups of patients

For the purpose of this research, all three groups received a high priority status. If this was not a case study, the hospital's budget has to be taken into consideration to only focus on the criteria which results will be most beneficial for the hospital.

Only one of the two following interviews was conducted, namely: PERFORM EXPERT INTERVIEWS. The reason for this lies in the fact that the researcher had to wait a total of 4 months to receive UMCU's no-show dataset, because of this the SEMI-STRUCTURED QUALITATIVE INTERVIEWs were conducted before the actual data analysis (see section 5.1). Patients of UMCU were not interviewed due to UMCU's privacy policies with regard to its patients.

5.2.6.4 Phase 7: Select suitable interventions

As explained in sub-section 4.3.1, the last phase of the PDD is drawn, which results in a flowchart (Figure 30). This flowchart is created to make it easier for Business Specialists to select the most suitable intervention to reduce the number of no-show patients. It is a matter of following the sequence of instructions that is linked from the demographic factor section to the environmental factor section, which leads to the interventions (techniques, methods, models, Information Technology) section to reduce no-show.

Based on the Backwards (conditional) multivariate data analysis results, the sequence of instructions depicted in Figure 30 starting from Age, Socioeconomic status and Elapsing calendar days must be followed.

6 Conclusion

In this research, two research areas were merged. First, a literature study was conducted. The literature studies elaborated on the influence between patients' demographic factors, environmental factors and patients' behavior to no-show. In addition, information on how Information Technology, methods, models and technique can support the healthcare sectors to reduce the number of no-show patients was also collected.

Second, a case study took place at UMCU. Here, expert interviews were held for the evaluation of and feedback on the developed method, and also to improve the method and to collect knowledge on why there is a no-show problem at UMCU. Moreover, several data analysis techniques had been conducted on UMCU's no-show dataset. The created method was tested based on the data analysis results.

The following main research question was posed in chapter 1:

"How can a method be created that supports the healthcare sector into reducing the number of no-show patients, based on studies on patients' demographic factors, environmental factors, behavior of patients and the use of technology?"

The stated main research question was divided into five sub-questions. The answers to these sub-questions are provided below.

6.1 SQ-1

"What are the patients' demographic factors and how do these factors influence patients towards no-show?"

A literature research study was conducted about the influence of patients' demographic factor towards no-show. The observations of the current research in the mentioned fields show that age, gender, elapsing calendar days, patients with a low SES, different types of health insurance, patients' ethnicity and non-chronic patients are demographic factors that have a high influence on the no-show rate. By understanding how these demographic factors influence patients towards no-show, doctors can understand their patients, which afterwards allow them to intervene and to reduce no-show. Furthermore, when conducting expert interviews, four of the five experts answered that age and elapsing calendar days are the main problems with regard to no-show.

Patients that are 25 years and younger or 75 years and older are most likely to commit no-show because they may not understand the purpose of the appointment, have experienced previous failed appointments, have psychosocial problems and most importantly have transport problems and emotional problems.

Males receive less service and less follow-up care from their doctor due to the fact that they do not ask as much questions as females do about their own health.

Elapsing calendar days also influence patients towards no-show, because, according to the literature, appointments were created too far in advance. Due to this patients tend to forget about their appointments. It also happens that appointments were scheduled at undesirable dates or at an inconvenient time.

Young adults with children have according to the literature a low SES. Having a low SES leads to patients not attending their appointments, because they are unable to pay their medical services, have no health insurance and they most likely have communication difficulties and transport problem.

Patients with another ethnicity than the ethnicity of their doctor experience cultural barriers, language barriers and social distance problems. Due to this, they receive less hospital services because their doctor does not understand fully what their health problem is. Non-chronic patents (45+) are just not interested in going to the appointment.

6.2 SQ-2

"What are the environmental factors that influence patients towards no-show and how are these factors related to the patients' demographic factors?"

The multilevel environmental model developed by Sallis et al. (2006) specifies several domains that influence a person on an environmental level. The observation of the current research in the mentioned field shows that lack of transportation, geographic distance between a patients' home to the hospital and day of the week have a great influence towards no-show. These factors form a moderate effect between the relations of a patients' demographic factor to no-show. According to the literature studies, transportation is associated with young and old patients, because they have difficulties driving a car or do not have a driver license, furthermore, chronic patients and patients who have a low SES are also associated with transportation.

Geographic distance is associated with low SES, age and gender. This could be explained by the travel costs and the importance of the appointment, however also by the hospital's characteristics, such as what kind of services they offer. UMCU experts pointed out that patients who live further away are most likely to go to another hospital (or clinic) for the same (or better) service than driving a far distance to a hospital. Day of the week is mainly associated with elapsing calendar days. A sought explanation of this is; if appointments are made too far in advance, patients tend to forget about their appointments.

In the case of the data analysis results, the direct relation between 'age' and no-show was positively moderated by 'day of the week' and 'part of the day', which increases the prediction towards no-show, especially for patients who are in their youth and adults and seniors. Furthermore, contrary to the literature studies, patients with a high SES were significant more likely not to show up, instead of patients with a low SES.

6.3 SQ-3

"How can a patient's behavior have an influence towards no-show and how is this related to the patients' demographic factors and the environmental factors"

A patient's behavior can be an influenced towards no-show by several factors. Ajzen (1991) who created the Theory of Planned Behavior pointed out four factors on which these factors depend, namely the intention of the patient, their perceived behavior control,which acts as a moderator towards the patients behavior, their subjective norms and their attitude toward the behavior. All these factors have a positive influence on the patient's behavior.

A patient's behavior could also be influenced by another person's behavior, or as stated by Schmitz and Fulk (1991), who created the Social Influence Theory, "behavior is intentionally or unintentionally influenced by others". A patient can adopt the influence of others (e.g., family members) for the reason of the content of the induced behavior, such as if the ideas and actions of which they are composed are intrinsically rewarding.

No previously conducted research has been found that relates patients' behavior to their environmental factors, nor to their demographic factors. A patient's behavior is directly dependent on the patient himself.

6.4 SQ-4

"What are the previously used methods, models and techniques in the healthcare sector with regard to no-show and how can these best support the healthcare sector in its battle against no-show?"

Several methods and models exist, such as the (modified) Wave scheduling method, Mu-law scheduling method, Short lead-time scheduling method and the overbooking model, that are developed to reduce the long waiting time at hospitals which causes patients to not show up for their appointments. The Mu-law is a mathematical overbooking method, which focuses on combining the ratio of a no-show patient with another patient who has a high show-ratio. Here patients with a high no-show ratio receive a shorter slot-time in contrast to the high show ratio patient. This way the method reduces gaps if no-show occurred during the day, furthermore it also reduces the waiting time.

The short lead-time scheduling method is straightforward and effective. It allows patients to see their doctor within a day or two of scheduling the appointment, rather than booking a patient several weeks in advance. In theory short lead-time scheduling method reduces the rate of no-shows and increases the accessibility of healthcare.

The overbooking model involves scheduling a fixed number of patients each day, based on the no-show rate of the hospital. This model is only effective if the effects of no-show are well balanced with those of show.

Techniques that are effective in theory to reduce the number of no-show patients are: reminder letters, telephone reminders, automatic reminders, SMS-reminders, giving patients valuable information, changing the behavior of the patients through education, charging a no-show fee, and positive financial incentives. Automatic reminders are effective, because using this method allows for a reduction in staff members and provides a standardized, uniform reminder to the patients. According to the literature study, these techniques will optimize the no-show rate and the healthcare resources, and also secure the appropriate use of healthcare funding.

Last, changing a patient's behavior through communication is a popular technique. It involves sending the patients valuable information or calling them a week before their appointment to make sure they attend their appointments.

6.5 SQ-5

"How can Information Technology support healthcare towards no-show?"

Adopting technologies within the healthcare sector has its benefits for patients, doctors and staff members. By making use of social networks, such as Facebook and Twitter, doctors and patients do not have to be available at the same time. Patients can leave important questions on one of these networks and doctors can then later answer these questions. This has the potential to free both parties from restrictions associated with traditional communication methods, such as telephone calls (reminders) and face-to-face visits.

By utilizing Facebook, Twitter and or Skype, the healthcare sector can fill no-show gaps immediately. This can be done by posting a message on one of these networks. This way, any patient: young, adults, seniors, different ethnicity, low SES, high SES and non-chronic patients with little knowledge of how to work with a computer or mobile phone can benefit from this technology. However, according to several expert interviewees, social networks do have a downside, which involves security and privacy concerns.

6.6 Discussion

This research aims to create a method to reduce the number of no-show patients in the healthcare sector by uncovering what influences patients to commit no-show by studying patients' demographic factors, their environmental factors and their behavior with regard to no-show. Not forgetting about the interventions, such as social networks, technology and previously used appointment methods and models or other strategies to reduce the number of no-show patients.

Literature studies and expert interviews show that no-show is associated with gender, age and socioeconomic status, a patients' ethnicity and non-chronic patients as described by Bennett and Baxley (2009), Daggy et al. (2011), George and Rubin (2003), Hamilton et al. (2002), Kruse et al. (2002), Norris et al. (2012) and Parikh et al. (2010), while the data analysis results show that no-show is associated with age, socioeconomic status and elapsing calendar days and moderated by day of the week, part of the day, distance and month. Age is the most predictable variable that causes no-show based on the dataset. Next come a patient's Socioeconomic-status and Elapsing calendar days that one has to wait to see the doctor. Looking back at the literature studies, data analysis and the interview results to draw a conclusion about reducing no-show, several recommendations can be made; Doctors and other staff member need to start learn more about their patients, know their (work) schedule and most importantly not make appointments too far in advance.

Although research Vankatesh, Morris, Davis, and Davis (2003) recommended technology to reduce the number of no-show patients, physicians fear that e-messaging (i.e., SMS, e-mail) with patients would make them less productive, would cause them to come home later, and reduce their incomes (Liederman et al., 2005b). And on top of that, not all patients use the Internet, especially the older ones.

The Interventions mentioned in this research have an enormous potential of reducing the number of no-show patients. However, although this is true, one still has to take into account that utilizing an intervention, such as a method, model or technique requires the hospital staff to learn how to work with it, as described in this research. This learning phase carries some risks. Mistakes can for example be made during this phase that could affect the patients' waiting time to see their doctor.

A final remark to consider is that it is likely that the experts who answered the questions related to no-show patients, answered in a socially desired manner.

6.7 Limitations

Although this research was carefully prepared, the author is still aware of its research limitations and shortcomings. First, a summarization of the research is outlined, afterwards the points of improvements for further research are outlined.

In this research several steps were conducted. First, a literature research was conducted. Second, expert interviews were held at UMCU to evaluate and receive feedback on the method, to improve the method and to collect knowledge on why there is a no-show problem at UMCU. Third, a large dataset containing almost 900 thousands patients was acquired in order to discover why patients are not attending their appointments at UMCU.

A point of limitation is that the acquired dataset was from the year 2012. This indicates that the dataset is already 6 months old when this research is written. The second point of limitation, according to UMCU's Business Analysts, is that not all data within the dataset were correctly saved by the system; the dataset may consist of false positive information, which thus means that the results are not as reliable, which can be of influence to the results of this research. Last, the variables necessary were not presented in the dataset, which were needed to analyze the patients' behavior towards no-show. Therefore, it is recommended that further research sheds a light on the patients' behavior towards no-show.

Furthermore, due to the privacy-protective behavior of UMCU with regard to the information of its patients, the dataset was handed over to the author 4 months late. For this reason and the time limit of this research, no other data analysis software tools were used to conduct further data analyses. Though, SPSS was already found good enough to extract knowledge on why or for what reason patients of UMCU commit no-show.

6.8 Future research

Having a positive view on the limitations, it can be said that these also provide opportunities for future research. First, the same statistical analysis conducted in this research should be conducted for the dataset of 2013.

Second, if healthcare sectors want a more accurate result, data analysis should be conducted on at least 25% of the hospitals in the Netherlands. Taking this sample would increase the reliability and the validity of the data analysis results on no-show patients.

Last, although this research came with interesting results, for future researches it is also interesting to collect statistical analyses between environmental factors themselves. It may be possible that some environmental factors interact with one another and influence no-show.

Bibliography

Ajzen, I. (1991). The Theory of Planned Behavior. *Organizational Behavior and Human Decision Processes*, *50*(1), 179–211.

Anderson, J. G. (1973). Demographic factors affecting health services utilization: a causal model. *Medical care*, *11*(2), 104–120. Retrieved from http://www.ncbi.nlm.nih.gov/pubmed/4688477

Arcury, T. a, Preisser, J. S., Gesler, W. M., & Powers, J. M. (2005). Access to transportation and health care utilization in a rural region. *The Journal of rural health : official journal of the American Rural Health Association and the National Rural Health Care Association*, *21*(1), 31–8. Retrieved from http://www.ncbi.nlm.nih.gov/pubmed/15667007

Athenahealth. (2012). Electronic Health Records (EHR), Medical Billing, and Practice Management. Retrieved December 13, 2012, from http://www.athenahealth.com/

Baars, H., & Kemper, H.-G. (2008). Management Support with Structured and Unstructured Data—An Integrated Business Intelligence Framework. *Information Systems Management*, *25*(2), 132–148. doi:10.1080/10580530801941058

Barker, C., Pistrang, N., & Elliott, R. (1979). RESEARCH METHODS in CLINICAL PSYCHOLOGY. *John Wiley & Sons, Ltd.*, *2*, 1–299.

Baron, R. M., & Kenny, D. A. (1986). The Moderator-Mediator Variable Distinction in Social Psychological Research: Conceptual, Strategic, and Statistical Considerations. *Journal of personality and social psychology*, *51*(6), 1173–1182.

Barron, W. M. (1980). Failed appointments. Who misses them, why they are missed, and what can be done. *Primary care*, *7*(4), 563–74. Retrieved from http://www.ncbi.nlm.nih.gov/pubmed/7010402

Basu, J., & Cooper, J. (2000). Out-of-Area Travel From Rural and Urban Countries: A Study of Ambulatory Care Sensitive Hospitalizations for New York State Residents. *Journal of Rural health*, 129–138.

Beach, C. (2011). Using Social Media to Engage Patients. *ARAMARK Healthcare*, 66–71.

Bech, M. (2005). The economics of non-attendance and the expected effect of charging a fine on non-attendees. *Health policy (Amsterdam, Netherlands)*, *74*(2), 181–91. doi:10.1016/j.healthpol.2005.01.001

Benjamin-Bauman, J., Reiss, M., & Bailey, J. (1984). INCREASING APPOINTMENT KEEPING BY REDUCING THE CALL-APPOINTMENT INTERVAL. *Journal of Applied Behavior Analysis*, *3*(3), 295–301.

Bennett, K. J., & Baxley, E. G. (2009). The effect of a carve-out advanced access scheduling system on no-show rates. *Family medicine*, *41*(1), 51–6. Retrieved from http://www.ncbi.nlm.nih.gov/pubmed/19132573

Berry, M. J., & Linoff, G. (1997). Data Mining Techniques: For Marketing, Sales, and Customer Support. *John Wiley & Sons, Inc.*, 1–444. Retrieved from http://dl.acm.org/citation.cfm?id=560675

Blaya, J. a, Fraser, H. S. F., & Holt, B. (2010). E-health technologies show promise in developing countries. *Health affairs (Project Hope)*, *29*(2), 244–51. doi:10.1377/hlthaff.2009.0894

Booth, P. G., & Bennett, H. E. (2004). Factors associated with attendance for first appointments at an alcohol clinic and the effects of telephone prompting. *Journal of Substance Use*, *9*(6), 269–279. doi:10.1080/14659890410001711715

Bowman, B. (2002). Beyond the Telephone: Electronic Tools for Patient-provider Communication. *Group Pract. J*, *51*(1), 11–14.

Brinkkemper, S., Saeki, M., & Harmsen, F. (1999). META-MODELLING BASED ASSEMBLY TECHNIQUES FOR SITUATIONAL METHOD ENGINEERING. *Elsevier*, *24*(03), 209–228.

Cardol, M., Groenewegen, P., Bakker, D. De, Spreeuwenberg, P., Dijk, L. Van, & Bosch, W. Van Den. (2005). Gezinsgelijkenis in contactfrequentie met de huisartsenpraktijk : een retrospectief cohortonderzoek, *48*(10), 490–494.

Carpenter, P., Morrow, G., Del Guadio, A., & Ritzler, B. (1981). Who Keeps the First Outpatient Appointment?, *138*(1), 102–105.

CBS - Health and Welfare. (2011). Retrieved July 17, 2013, from http://www.cbs.nl/en-GB/menu/themas/gezondheid-welzijn/publicaties/artikelen/archief/2011/default.htm

Chan, K. C., & Chan, D. B. (2012). Targeting Zero Non-Attendance in Healthcare Clinics. *Open Access by IOS Press*, *1*(1), 52–57. doi:10.3233/978-1-61499-152-6-52

Chung, M. K. (2002). Tuning up your patient schedule. *Family practice management*, *9*(1), 41–5. Retrieved from http://europepmc.org/abstract/MED/11828685/reload=0

Cooper-patrick, L., Gallo, J. J., Gonzales, J. J., Hong Thi, V., Powe, N. R., Nelson, C., & Ford, D. E. (1999). Race, Gender, and Partnership in the Patient-Physician Relationship. *THE PATIENT-PHYSICIAN RELATIONSHIP*, *282*(6), 583–589.

Cosgrove, M. P. (1990). Defaulters in general practice: reasons for default and patterns of attendance. *British Journal of General Practice*, *40*(February), 50–52.

Daggy, J., Lawley, M., Willis, D., Thayer, D., Suelzer, C., Turkcan, A., … Sands, L. (2011). Using no-show modeling to improve clinic performance. *Health Informatics*, *16*(4), 246–259. doi:10.1177/1460458210380521

Detman, L., & Gorzka, P. (n.d.). A STUDY OF MISSED APPOINTMENTS IN A FLORIDA. *PUBLIC HEALTH DEPARTMENT*, *1*(1), 1–22.

Devaraj, S., & Kohli, R. (2000). Information Technology Payoff in the Health-Care Industry : A Longitudinal Study. *Journal of Management Information Systems*, *16*(4), 41–67.

Deyo, R., & Thomas, S. (1980). Dropouts and Broken Appointments: A Literature Review and Agenda for Future Research, *18*(11), 1146–1157.

Dijk, L. van. (2007). Ziek omdat je moeder het zegt. *Facta*, *17*(3), 2–7. Retrieved from http://www.narcis.nl/publication/RecordID/publicat:2947

Dove, H. G., & Schneider, K. C. (1981). The usefulness of patients' individual characteristics in predicting no-shows in outpatient clinics. *Medical care*, *19*(7), 734–40. Retrieved from http://www.ncbi.nlm.nih.gov/pubmed/7266121

Dr Foster Research Limited. (2007). Feature: Outpatient appointment no-shows cost hospitals £600m a year. Retrieved July 03, 2013, from http://www.drfosterhealth.co.uk/features/outpatient-appointment-no-shows.aspx

Falahah, & Rosmala, D. (2012). Study of Social Networking usage in Higher Education Environment. *Procedia - Social and Behavioral Sciences*, *67*(November 2011), 156–166. doi:10.1016/j.sbspro.2012.11.316

Fayyad, U., Piatetsky-shapiro, G., & Smyth, P. (1996). From Data Mining to Knowledge Discovery in Databases. *Al Magazine*, *17*(3), 37–54.

Feldstein, P., & German, J. (1965). Predicting hospital utilization: An evaluation of three approaches, *2*(1), 13–36.

Ferenchick, G., Simpson, D., Blackman, J., DaRosa, D., & Dunnington, G. (1997, April). Strategies for efficient and effective teaching in the ambulatory care setting. *Academic medicine : journal of the Association of American Medical Colleges*. Retrieved from http://www.ncbi.nlm.nih.gov/pubmed/9125942

Field, A. (2009). *Discovering Statistics Using SPSS* (3rd ed., pp. 1–822). Asia: SAGE Publications.

Gallucci, G., Swartz, W., & Hackerman, F. (2005). Impact of the wait for an initial appointment on the rate of kept appointments at a mental health center. *Psychiatric services (Washington, D.C.)*, *56*(3), 344–6. doi:10.1176/appi.ps.56.3.344

Garuda, S. R., Javalgi, R. G., & Talluri, V. S. (1998). Tackling No-Show Behavior: A Market-Driven Approach. *Health Marketing Quarterly*, *15*(4), 25–44.

Gemiddelde reistijd naar dichtstbijzijnde zorgvoorziening - Zorgbalans. (2012). Retrieved January 07, 2013, from http://www.gezondheidszorgbalans.nl/toegankelijkheid/geografische-toegankelijkheid/gemiddelde-reistijd-naar-dichtstbijzijnde-zorgvoorziening/

George, a., & Rubin, G. (2003). Non-attendance in general practice: a systematic review and its implications for access to primary health care. *Family Practice*, *20*(2), 178–184. doi:10.1093/fampra/20.2.178

Giuffrida, A., & Torgerson, D. J. (1997). Should we pay the patient? Review of financial incentives to enhance patient compliance. *BMJ*, *315*(September).

Glanz, K., Rimer, B. K., & Viswanath, K. (2008). *HEALTH BEHAVIOR AND HEALTH EDUCATION* (4th ed., pp. 1–590). Jossey-Bass. doi:10.1016Soo33-3506(49)

Goldman, L., Freidin, R., Cook, F., Eigner, J., & Grich, P. (1982). A Multivariate Approach to the Prediction of No-show Behavior in a Primary Care Center. *JAMA Internal Medicine*, *142*(3), 563–567. doi:10.1001/archinte.1982.00340160143026

Grossman, L. K., Humbert, A. J., & Powell, M. (1996). Continuity of Care Between Obstetrical and Pediatric Preventive Care: Indicators of Nonattendance at the First Well-Child Appointment. *Clinical Pediatrics*, *35*(11), 563–569. doi:10.1177/000992289603501102

Guse, C. E., Richardson, L., Carle, M., & Schmidt, K. (1997). The effect of exit-interview patient education on no-show rates at a family practice residency clinic. *The Journal of the American Board of Family Practice / American Board of Family Practice*, *16*(5), 399–404. Retrieved from http://www.ncbi.nlm.nih.gov/pubmed/14645330

Hamilton, W., Round, A., & Sharp, D. (2002). Patient, hospital, and general practitioner characteristics associated with non-attendance: a cohort study. *The British journal of general practice : the journal of the Royal College of General Practitioners*, *52*(477), 317–9. Retrieved from http://www.pubmedcentral.nih.gov/articlerender.fcgi?artid=1314275&tool=pmcentrez&rendertype=abstract

Hand, D. J. (2007). Principles of data mining. *Drug safety : an international journal of medical toxicology and drug experience*, *30*(7), 621–622. Retrieved from http://www.ncbi.nlm.nih.gov/pubmed/17604416

Hardy, K. J., O'Brien, S. V, & Furlong, N. J. (2001). Information given to patients before appointments and its effect on nonattendance rate. *BMJ*, *323*(1), 1298–1300.

Häyrinen, K., Saranto, K., & Nykänen, P. (2008). Definition, structure, content, use and impacts of electronic health records: a review of the research literature.

International journal of medical informatics, *77*(5), 291–304. doi:10.1016/j.ijmedinf.2007.09.001

Hermoni, D., Mankuta, D., & Reis, S. (1990). Failure to Keep Appointments at a Community Health Centre. *Scand J Prim Health Care*, *8*(1), 107–111.

Hevner, B. A. R., March, S. T., Park, J., & Ram, S. (2004). DESIGN SCIENCE IN INFORMATION SYSTEM RESEARCH. *Design Science in IS Research*, *28*(1), 75–105.

Hoeymans, N., Melse, J., van Oers, J., & Polder, J. (2006). *Zorg voor gezondheid: volksgezondheid toekomst verkenning 2006* (pp. 01–348). Bohn Stafleu van Loghum. Retrieved from http://books.google.com/books?hl=en&lr=&id=oAAL-zHo2IQC&pgis=1

Humpel, N., Owen, N., & Leslie, E. (2002). Environmental factors associated with adults' participation in physical activity: a review. *American journal of preventive medicine*, *22*(3), 188–199. Retrieved from http://www.ncbi.nlm.nih.gov/pubmed/11897464

Hurtado, A. V, Greenlick, M. R., & Colombo, T. J. (1973). Determinants of Medical Care Utilization: Failure to Keep Appointments. *Lippincott Williams & Wilkins*, *11*(3), 189–198.

IBM CORPORATION. (2010). What is a data set? Retrieved July 10, 2013, from http://publib.boulder.ibm.com/infocenter/zos/basics/index.jsp?topic=/com.ibm.zos.zconcepts/zconc_datasetintro.htm

INTERSYSTEMS Benelux. (2013). Innoverende IT technologie voor de gezondheidszorg - Intersystems. Retrieved January 17, 2013, from http://www.intersystemsbenelux.com/page/nl/gezondheidszorg.html

Istepanian, R., Laxminarayan, S., & Pattichis, C. S. (2006). *M-Health: Emerging Mobile Health Systems* (p. 624).

Jackson, K. R., Booth, P. G., McGuire, J., & Salmon, P. (2006). Predictors of starting and remaining in treatment at a specialist alcohol clinic. *Journal of Substance Use*, *11*(2), 89–100. doi:10.1080/14659890500143614

Johnson, R. L., Roter, D., Powe, N. R., & Cooper, L. a. (2004). Patient race/ethnicity and quality of patient-physician communication during medical visits. *American journal of public health*, *94*(12), 2084–90. Retrieved from http://www.pubmedcentral.nih.gov/articlerender.fcgi?artid=1448596&tool=pmcentrez&rendertype=abstract

Journals, P. M. (2012). Application of discrete-event simulation in health care clinics : A survey, *50*(2), 109–123.

Kelman, H. C. (1958). Compliance, identification, and internalization three processes of attitude change. *Sage Publications, Inc*, *2*(1), 51–60.

Kopach, R., DeLaurentis, P.-C., Lawley, M., Muthuraman, K., Ozsen, L., Rardin, R., … Willis, D. (2007a). Effects of clinical characteristics on successful open access scheduling. *Health Care Management Science*, *10*(2), 111–124. doi:10.1007/s10729-007-9008-9

Kopach, R., DeLaurentis, P.-C., Lawley, M., Muthuraman, K., Ozsen, L., Rardin, R., … Willis, D. (2007b). Effects of clinical characteristics on successful open access scheduling. *Health Care Management Science*, *10*(2), 111–124. doi:10.1007/s10729-007-9008-9

Kruse, G. R., Rohland, B. M., & Wu, X. (2002). Factors associated with missed first appointments at a psychiatric clinic. *Psychiatric services (Washington, D.C.)*, *53*(9), 1173–6. Retrieved from http://www.ncbi.nlm.nih.gov/pubmed/12221319

Lacy, N. L., Paulman, A., Reuter, M. D., & Lovejoy, B. (2004). Why We Don ' t Come : Patient Perceptions on No-Shows. *Annals of Family Medicine*, *2*(6), 541–545. doi:10.1370/afm.123.INTRODUCTION

Laganga, L. R., & Lawrence, S. R. (2007). APPOINTMENT SCHEDULING WITH OVERBOOKING TO MITIGATE PRODUCTIVITY LOSS FROM NO-SHOWS. *Decision Sciences*, *38*(2), 1–29.

Leavitt, N. (2010). Will NoSQL Database Live Up to Their Promise? *IEEE Computer Society*, *43*(2), 12–14.

Lesaca, T. (1995). ASSESSING THE INFLUENCE OF A NO-SHOW FEE ON PATIENT COMPLIANCE AT A CMHC, *22*(6), 629–631.

Liederman, E. M., Lee, J. C., Baquero, V. H., & Seites, P. G. (2005a). Patient-physician web messaging. The impact on message volume and satisfaction. *Journal of general internal medicine*, *20*(1), 52–7. doi:10.1111/j.1525-1497.2005.40009.x

Liederman, E. M., Lee, J. C., Baquero, V. H., & Seites, P. G. (2005b). The impact of patient-physician Web messaging on provider productivity. *Journal of healthcare information management : JHIM*, *19*(2), 81–6. Retrieved from http://www.ncbi.nlm.nih.gov/pubmed/15869217

Lin, J., Muthuraman, K., & Lawley, M. (2011). Optimal and approximate algorithms for sequential clinical scheduling with no-shows. *IIE Transactions on Healthcare Systems Engineering*, *1*(1), 20–36. doi:10.1080/19488300.2010.549927

Livianos-Aldana, L., Vila-Gomez, M., Rojo-Moreno, L., & Luengo-Lopez, M. a. (1999). Patients Who Miss Initial Appointments in Community Psychiatry? a Spanish Community Analysis. *International Journal of Social Psychiatry*, *45*(3), 198–206. doi:10.1177/002076409904500307

Mäntyjärvi, M. (1994). No-show patients in an ophthalmological out-patient department. *Acta ophthalmologica*, *72*(3), 284–9. Retrieved from http://www.ncbi.nlm.nih.gov/pubmed/7976256

Maxwell, S., Maljanian, R., Horowitz, S., Pianka, M. A., Cabrera, Y., & Greene, J. (2001). Effectiveness of Reminder Systems on Appointment Adherence Rates. *Journal of Health Care for the Poor and Underserved*, *12*(4), 504–514. doi:10.1353/hpu.2010.0766

Mba, S. R. G., Javalgi, R. G., & Vijay, T. (1998). Tackling No-Show Behavior : A Market-Driven Approach. *Health Marketing Quarterly*, *15*(4), 37–41.

McMullen, E. (2012). Use of audiovisual equipment (SKYPE) for the treatment of hand injuries for remote consultations. *Hand Therapy*, *17*(2), 42–46. doi:10.1258/ht.2012.012003

Mehrotra, A., Keehl-Markowitz, L., & Ayanian, J. (2008). Implementation of Open Access Scheduling in Primary Care: A Cautionary Tale. *NIH Public Access*, *148*(12), 915–922.

Miller, N. H., Hill, M., Kottke, T., & Ockene, I. S. (1997). The Multilevel Compliance Challenge: Recommendations for a Call to Action: A Statement for Healthcare ProfessiMiller, N. H., Hill, M., Kottke, T., & Ockene, I. S. (1997). The Multilevel Compliance Challenge: Recommendations for a Call to Action: Miller, N. *Circulation*, *95*(4), 1085–1090. doi:10.1161/01.CIR.95.4.1085

Mitchell, a. J., & Selmes, T. (2007). Why don't patients attend their appointments? Maintaining engagement with psychiatric services. *Advances in Psychiatric Treatment*, *13*(6), 423–434. doi:10.1192/apt.bp.106.003202

Mobley, L. R., & Frech, H. . (2000). Managed Care, Distance, Traveled, and Hospital Market Definition. *Excellus Healthplan, Inc*, *37*(1), 91–107.

Moore, C. G., Wilson-Witherspoon, P., & Probst, J. C. (2001). Time and money: effects of no-shows at a family practice residency clinic. *Family medicine*, *33*(7), 522–7. Retrieved from http://www.ncbi.nlm.nih.gov/pubmed/11456244

Mulder, M. (2010). Sociaaleconomische status 2010 - Nationale Atlas Volksgezondheid. Retrieved January 07, 2013, from http://zorgatlas.nl/beinvloedende-factoren/sociale-omgeving/ses/sociaaleconomische-status/#breadcrumb

Muthuraman, K., & Lawley, M. (2008). A stochastic overbooking model for outpatient clinical scheduling with no-shows. *IIE Transactions*, *40*(9), 820–837. doi:10.1080/07408170802165823

Nicole Duffin, S. R. (n.d.). Library guides. Computing software support resources. SPSS. Retrieved from http://libraryguides.griffith.edu.au/content.php?pid=265213&sid=2301505

Norris, J. B., Kumar, C., Chand, S., Moskowitz, H., Shade, S. a., & Willis, D. R. (2012). An empirical investigation into factors affecting patient cancellations and no-shows at outpatient clinics. *Decision Support Systems*, *1*(1), 1–16. doi:10.1016/j.dss.2012.10.048

O'Neill, L. (2004). The effect of insurance status on travel time for rural Medicare patients. *Medical care research and review*, *61*(2), 187–202. doi:10.1177/1077558704263798

Ong, L. M., de Haes, J. C., Hoos, a M., & Lammes, F. B. (1995). Doctor-patient communication: a review of the literature. *Social science & medicine (1982)*, *40*(7), 903–18. Retrieved from http://www.ncbi.nlm.nih.gov/pubmed/18666041

Parikh, A., Gupta, K., Wilson, A. C., Fields, K., Cosgrove, N. M., & Kostis, J. B. (2010). The effectiveness of outpatient appointment reminder systems in reducing no-show rates. *The American journal of medicine*, *123*(6), 542–8. doi:10.1016/j.amjmed.2009.11.022

Pesata, V., Pallija, G., & Webb, a a. (1999). A descriptive study of missed appointments: families' perceptions of barriers to care. *Journal of pediatric health care : official publication of National Association of Pediatric Nurse Associates & Practitioners*, *13*(4), 178–82. doi:10.1016/S0891-5245(99)90037-8

Physicians, A. C. of. (2003). The changing face of ambulatory medicine-reimbursing physicians for computer-based care. *Medical Service Committee.*, *1*(1).

Potamitis, T., Chell, P. B., Jones, H. S., & Murray, P. I. (1994). Non-attendance at ophthalmology outpatient clinics. *Journal of the Royal Society of Medicine*, *87*(10), 591–3. Retrieved from http://www.pubmedcentral.nih.gov/articlerender.fcgi?artid=1294847&tool=pmcentrez&rendertype=abstract

Quattlebaum, T. G., Darden, P. M., & Sperry, J. B. (1991, October). Effectiveness of computer-generated appointment reminders. *Pediatrics*. Retrieved from http://www.ncbi.nlm.nih.gov/pubmed/18339112

Reilly, T. O. (2007). What Is Web 2.0: Design Patterns and Business Models for the Next Generation of Software. *O'Reilly Media*, *1*(65), 17–37.

Rising, E., Baron, R., & B, A. (1973). A system analysis of a university-health service outpatient clinic. *Operations Research*, *21*(5), 1030–1047.

Sallis, J. F., Cervero, R. B., Ascher, W., Henderson, K. a, Kraft, M. K., & Kerr, J. (2006). An ecological approach to creating active living communities. *Annual review of public health*, *27*, 297–322. doi:10.1146/annurev.publhealth.27.021405.102100

Satiani, B., Miller, S., & Patel, D. (2009). No-show rates in the vascular laboratory: analysis and possible solutions. *Journal of vascular and interventional radiology : JVIR*, *20*(1), 87–91. doi:10.1016/j.jvir.2008.09.027

Schmitz, J., & Fulk, J. (1991). Organizational Colleagues, Media Richness, and Electronic Mail: A Test of the Social Influence Model of Technology Use. *Communication Research*, *18*(4), 487–523. doi:10.1177/009365091018004003

Siau, K. (2003). Health care informatics. *IEEE Transactions on Information Technology in Biomedicine*, *7*(1), 1–7. doi:10.1109/TITB.2002.805449

Simpson, P. M., Banerjee, D., & Simpson, C. L. (1994). Softlifting: A model of motivating factors. *Journal of Business Ethics*, *13*(6), 431–438. doi:10.1007/BF00881451

Smith, C. M., & Yawn, B. P. (1994). Factors associated with appointment keeping in a family practice residency clinic. *The Journal of Family Practice*, *38*(1), 25–29.

Smith, E., & Warner, H. (1971). Simulation of a multiphasic screening procedure for hospital admission. *Simulation*, 57–64.

Sparr, L., Moffitt, M., & Ward, M. (1993). Missed Psychiatric Appointments: Who Returns and Who Stays Away. *Am J Psychiatry*, *150*(5), 801–805.

Ulmer, T., & Troxler, C. (1999). The Economic Cost of Missed Appointments and the Open Access System, *1*(1), 1–21.

Van de Belt, T. H., Berben, S. A., Samsom, M., Engelen, L. J., & Schoonhoven, L. (2012). Use of Social Media by Western European Hospitals: Longitudinal Study. *Journal of Medical Internet Research*, *14*(3), 1–15. doi:10.2196/jmir.1992

Van de Belt, T. H., Engelen, L. J., Berben, S. A., & Schoonhoven, L. (2010). Definition of Health 2.0 and Medicine 2.0: A systematic Review. *Journal of Medical Internet Research*, *12*(2), 1–15. doi:10.2196/jmir.1350

Van de Weerd, I., & Brinkkemper, S. (2009). Meta-modeling for Situational Analysis and Design Methods. *Information Science Reference*, 35–54.

Van Wieringen, J. C. M., Harmsen, J. a M., & Bruijnzeels, M. a. (2002). Intercultural communication in general practice. *European journal of public health*, *12*(1), 63–8. Retrieved from http://www.ncbi.nlm.nih.gov/pubmed/11968523

Vankatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User Acceptance of Information Technology : Toward a Unified View. *MIS Quarterly*, *27*(3), 425–478.

Verbrugge, L. M., & Steiner, R. P. (1981). Physician treatment of men and women patients: sex bias or appropriate care? *Medical care*, *19*(6), 609–32. Retrieved from http://www.ncbi.nlm.nih.gov/pubmed/7266112

Vleugel, A., Spruit, M., & Daal, A. Van. (2009). Historical data analysis through data mining from an outsourcing perspective : the Three-phases model, *1*(3), 42–65. doi:10.4018/jbir.2010070104

Wallen, J., Waitzkin, H., & Stoeckle, J. D. (1979). Physician stereotypes about female health and illness: a study of patient's sex and the informative process during medical interviews. *Women & health*, *4*(2), 135–46. doi:10.1300/J013v04n02_03

Weisman, C. S., & Teitelbaum, M. a. (1985). Physician gender and the physician-patient relationship: recent evidence and relevant questions. *Social science & medicine (1982)*, *20*(11), 1119–27. Retrieved from http://www.ncbi.nlm.nih.gov/pubmed/3895448

Weiss, J. E., & Greenlick, M. R. (1970). Determinants of Medical Care Utilization : The Effect of Social Class and Distance on Contacts with the Medical Care System, *8*(6), 456–462.

Weiss, J. E., Greenlick, M. R., & Jones, J. F. (1971). Determinants of Medical Care Utilization: The Impact of Spatial Factors, *8*(4), 50–57. Retrieved from http://www.jstor.org.proxy.library.uu.nl/discover/10.2307/29770681?uid=40871&uid=3738736&uid=2134&uid=2&uid=70&uid=3&uid=67&uid=5911848&uid=62&uid=40867&sid=21101565468991

Willems, S., De Maesschalck, S., Deveugele, M., Derese, a, & De Maeseneer, J. (2005). Socio-economic status of the patient and doctor-patient communication: does it make a difference? *Patient education and counseling*, *56*(2), 139–46. doi:10.1016/j.pec.2004.02.011

Winkleby, M. a, Jatulis, D. E., Frank, E., & Fortmann, S. P. (1992). Socioeconomic status and health: how education, income, and occupation contribute to risk factors for cardiovascular disease. *American journal of public health*, *82*(6), 816–20. Retrieved from http://www.pubmedcentral.nih.gov/articlerender.fcgi?artid=1694190&tool=pmcentrez&rendertype=abstract

Yergan, J., Flood, a B., LoGerfo, J. P., & Diehr, P. (1987). Relationship between patient race and the intensity of hospital services. *Medical care*, *25*(7), 592–603. Retrieved from http://www.ncbi.nlm.nih.gov/pubmed/3695664

Zeng, B., Turkcan, A., Lin, J., & Lawley, M. (2009). Clinic scheduling models with overbooking for patients with heterogeneous no-show probabilities. *Annals of Operations Research*, *178*(1), 121–144. doi:10.1007/s10479-009-0569-5

7 Appendix

7.1 Configuring open access

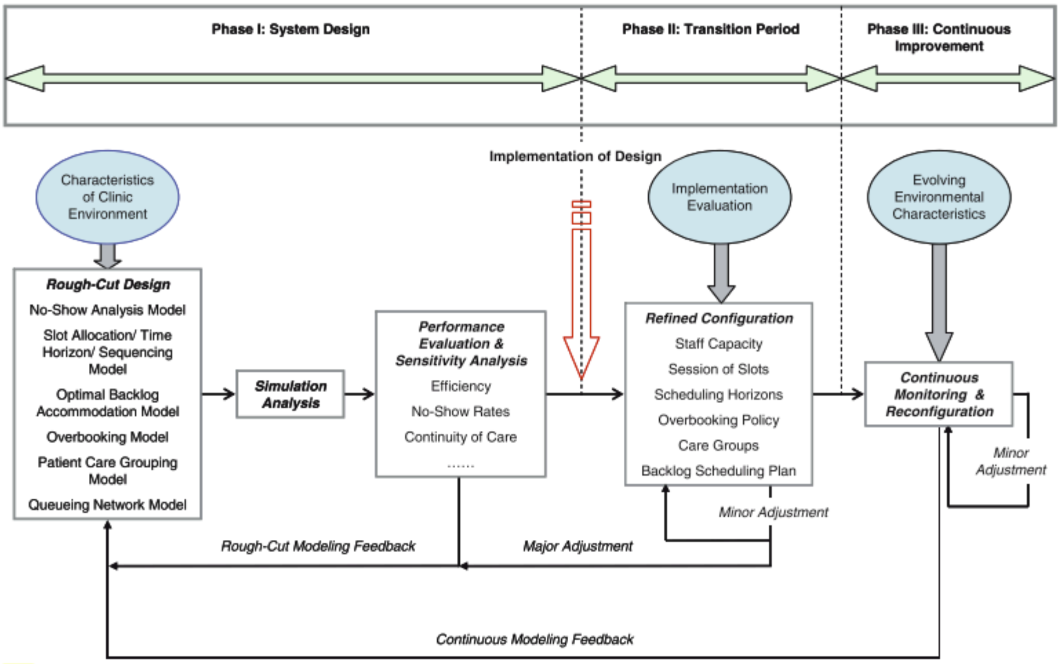


Figure 53. Framework for configuring open access (short lead-time scheduling method) (Kopach et al., 2007b)

7.2 Semi-structured interview questions

A. Introduction and general information

1. In which division do you work?
2. What is the name of your department within the UMCU?
3. How long have you been working at the UMCU?
4. In which year did you notice that the no-show of patients was becoming a problem?
5. How did you notice this?
6. How is your work influenced by the no-show of patients?
7. What for sort consequences does the no-show of patients have on UMCU?

B. Reasons and solutions towards no-show

8. What are according to you the internal reason(s) or causes why patients don't attend their appointment(s)? How would you solve these reasons or causes to reduce no show?
9. What are according to you the external reason(s) or causes why patients don't attend their appointment(s)? How would you solve these reasons or causes to reduce no show?
10. Which of the following demographic factors have according to you a direct impact on no-show? And how would you address these factors to reduce no-show?
    - Age
    - Gender

- Elapsed calendar days until the patient sees his doctor
- Low socioeconomic status of patients
- Ethnicity
- Non-chronically ill patients
- Other, namely...

11. Which of the following environmental factors correlates with the patients' demographic factors to no-show? And what would your approach be to confront this? (You can choose more than one factor)
    - Transport
    - Geographic distance between the patients' house and the hospital
    - Day of the week (Monday, Tuesday, Wednesday, Thursday or Friday)
    - Weather
    - The season of the year
    - Other, namely...

C. Reduction

12. What does the UMCU do to reduce the number of no-show patients? Think of methods, techniques, models and technologies. What else can be done to reduce the number of no-show?
13. How should or can the communication between doctor and patient be improved?
14. How can social media help with the reduction of the number of no-show patients?
15. How can smart-phone applications help with the reduction of the number of no-show patients?
16. How can (web) applications help with the reduction of the number of no-show patients?

D. Method, part 1: PDD

17. Do you think the six main activities of the 'system approach method' concern the collection of valuable patient data in order to form a strategy to reduce the no-show of patients? And why?
18. Which part of the 'system approach process' can be improved and how can this be improved? Please specify.
19. Do you miss one or more important (sub) activities in the "system approach method '? If yes, please specify.
20. Do you think that the order of the (sub) activities is correct? If yes / no, please specify.
21. What do you think about the usability of the 'system approach method'? Please specify.
22. Do you think this 'System approach method' can be used in practice? If not, what are its limitations?

E. Method, part 2: Flowchart

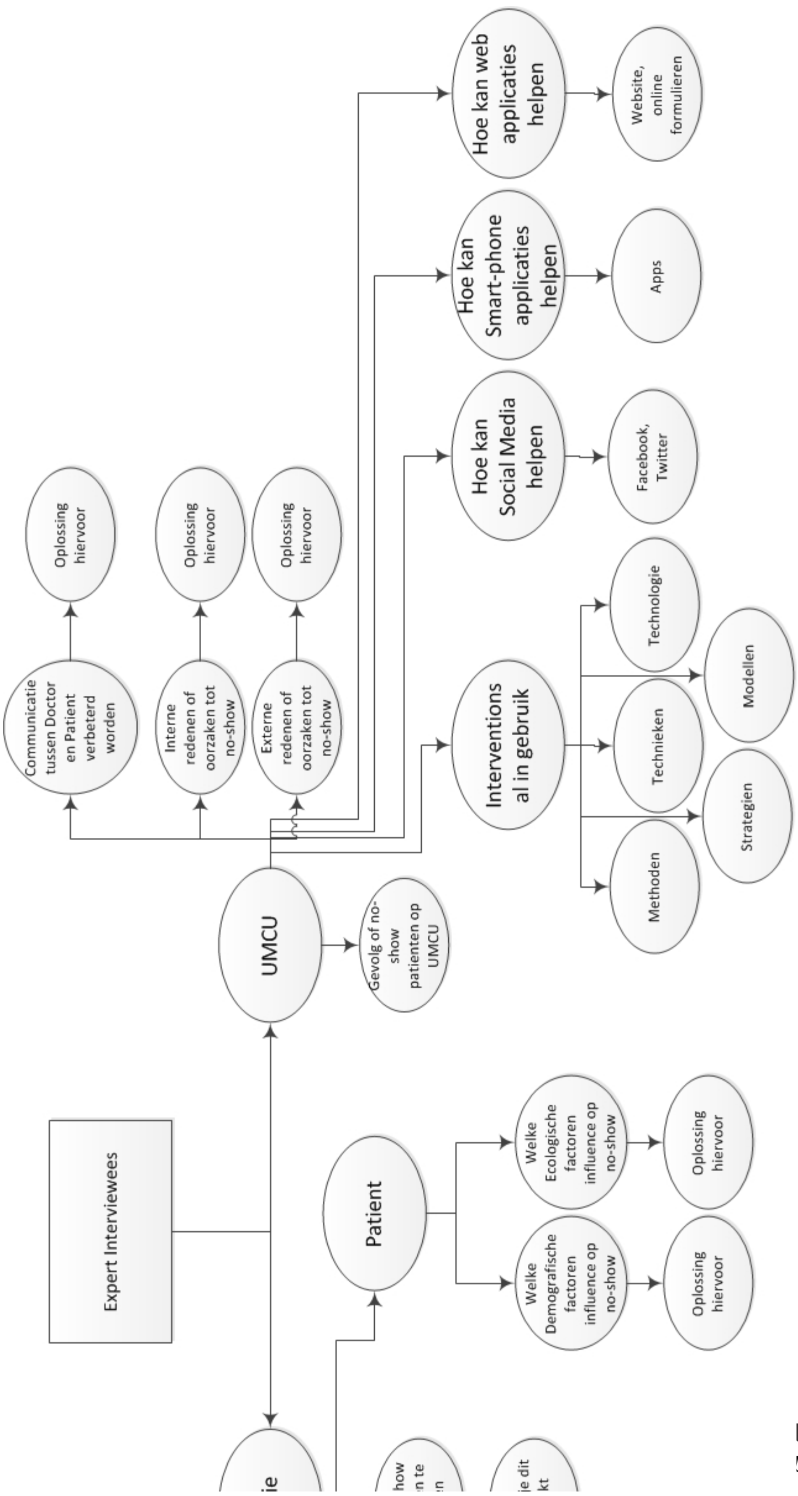
23. What do you think of the approach of the flowchart drawn to reduce the number of no-show patients? Please specify.
24. Which part of 'flowchart' can be improved and how can it be improved? Please specify
25. Is there still an important process missing in the flowchart? If so, please specify.

26. Do you think the order of the processes is correct? If yes, please specify why.
27. What do you think about the usability of the flowchart?
28. Do you think this flowchart can be used in practice? If yes please explain why, if not, explain, if not, what are the limitations?

Completeness	Consistency	Efficiency	Applicability
16	18	20	21
17	19	16	
22	24	26	27
23	25		

Table 36. Quality criteria for the method.

7.3 *NVIVO precoding*



7.4 NVIVO nodes

Name	Sources	References
Interventions	0	0
Future want to have interventions	0	0
Smart-phone	0	0
Map	1	1
pop-up alert	2	2
see Appointments	1	1
SMS	2	3
Social-media	0	0
Idea	3	3
Privacy	4	4
Web-applicaties	0	0
Chat services	1	1
Patient portal	4	7
Privacy	2	2
See their appointment	3	3
Methods	0	0
Models	0	0
Strategies	4	8
Techniques	0	0
Appointment card	2	2
Folder	1	1
Give fine	1	1
Reminders	5	9
Method part 1 (System approach process)	0	0
Applicability	0	0
Negative	0	0
Positive	5	5
Completeness	0	0
Negative	1	1
Positive	5	10
Consistency	0	0
Negative	2	2
Positive	5	8
Efficiency	0	0
Negative	0	0
Positive	5	5
Reliability	0	0
Negative	0	0
Positive	0	0

Figure 54. NVIVO node. Part 1 of 3

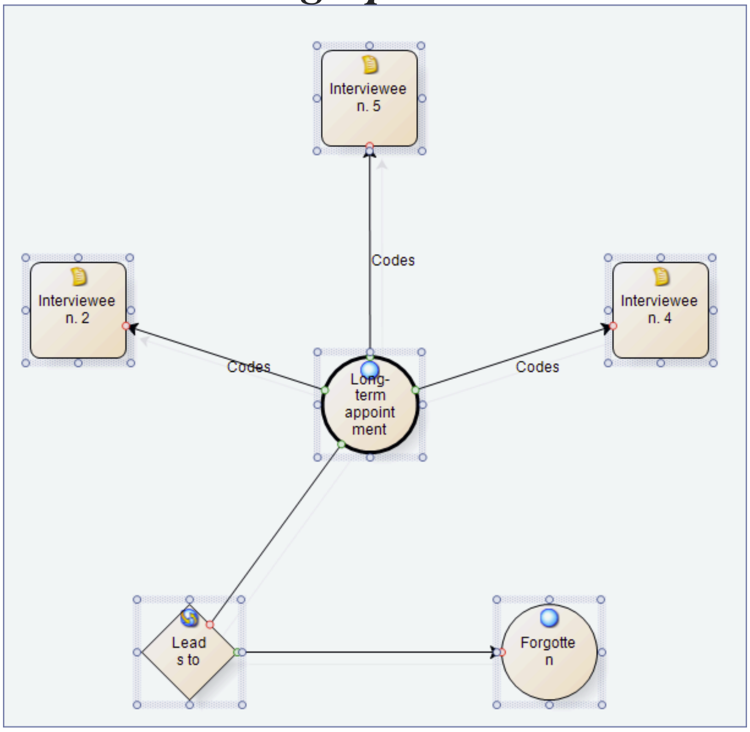
Method part 2 (Flowchart)	0	0
Applicability	0	0
Negative	0	0
Positive	5	5
Completeness	0	0
Negative	3	3
Positive	5	8
Consistency	0	0
Negative	0	0
Positive	5	9
Efficiency	0	0
Negative	0	0
Positive	5	5
Reliability	0	0
Negative	0	0
Positive	0	0
Patient	0	0
Demographic factor	0	0
Age	4	4
Solution	3	3
Elapsing calendar days	4	4
Solution	3	3
Etnicity	2	2
Gender	0	0
Low Socio-economic status	2	2
Non-chronic patients	3	3
Ecological factor	0	0
Day of the week	1	1
Solution	1	1
Season of the year	5	5
Solution	2	2
Solutions	0	0
The weather	5	5
Solution	1	1
Transport	3	3
Solution	3	3

Figure 55. NVIVO nodes. Part 2 of 3

Reasons of no-show	0	0
External reasons	0	0
Distance	1	1
Dont call	1	1
Forgotten	5	5
No complaints anymore	1	1
Undesirable date or time	2	2
Went to another hospital	2	2
Internal reasons	0	0
Create unnecessary appointments	3	4
Doctors forget	1	1
Long-term appointment	3	3
No fine are given	1	1
No use of any reminders	1	1
Weak or bad communication	5	10

Figure 56. NVIVO nodes. Part 3 of 3

7.5 NVIVO graph result



7.6 SPSS Chi-square analysis

7.6.1 Demographic factors

Demographic factors → Show/No-Show – χ^2 *table*

	Show for the appointments No	Show for the appointments Yes	SYSMIS	χ^2 (df)	P	φc (strength)
Variables	**26432**	**868122**	**0**			
Gender						
Men	13533 (51.2%)	402656 (46.4%)	0	239.221[a] (1)	< .001	.016 (weak)
Women	12899 (48.8%)	465466 (53.6%)	0			
	26432	**868122**	**0**			
Age						
Children (0-14)	4226 (16.0%)	149564 (17.2%)	0	1450.578[a] (3)	< .001	.040 (weak)
Youth (15-24)	3789 (14.3%)	75166 (8.7%)	0			
Adults (25-64)	14373 (54.4%)	455952 (52.5%)	0			
Seniors (65+)	4044 (15.3%)	187440 (21.6%)	0			
	25745	**858079**	**10730**			
Socio status						
Low	8762 (34.0%)	227174 (26.5%)	n/a	729.842[a] (1)	< .001	.029 (weak)
High	16983 (66.0%)	630905 (73.5%)	n/a			
	25961	**838618**	**29975**			
Elapsing calendar days						
<= 30	12230 (47.1%)	579737 (69.1%)		7008.646[a] (17)	< .001	.090 (weak)
31-60	5181 (20.0%)	118108 (14.1%)				
61-90	2805 (10.8%)	58985 (7.0%)				
91-120	2715 (10.5%)	43063 (5.1%)				
121-150	896 (3.5%)	12303 (1.5%)				
151-180	423 (1.6%)	6364 (0.8%)				
181-210	1074 (4.1%)	12800 (1.5%)				
211-240	84 (0.3%)	1498 (0.2%)				
241-270	55 (0.2%)	793 (0.1%)				

271-300	49 (0.2%)	551 (0.1%)
301-330	26 (0.1%)	348 (0.04%)
331-360	88 (0.3%)	720 (0.1%)
361-390	315 (1.2%)	2986 (0.4%)
391-420	16 (0.1%)	275 (0.03%)
421-450	2 (0.008%)	47 (0.005%)
451-480	2 (0.007%)	24 (0.002%)
481-510	0 (0.0%)	12 (0.001%)
511-540	0 (0.0%)	4 (0.0004%)

7.6.2 Environmental factors

Ecological factors → Show/No-Show – χ^2 ***table***

	Show for the appointments			χ^2 *(df)*	P	φc (strength)
	No	Yes	SYSMIS			
Variables	**26432**	**868122**	**0**			
Day of the week						
Monday	6136 (23.2%)	180682 (20.8%)	0			
Tuesday	5703 (21.6%)	184544 (21.3%)	0			
Wednesday	5149 (19.5%)	176238 (20.3%)	0			
Thursday	5292 (20.0%)	182846 (21.1%)	0	266.415[a] (6)	< .001	.017 (weak)
Friday	4146 (15.7%)	137769 (15.9%)	0			
Saturday	5 (0.0%)	3466 (0.4%)	0			
Sunday	1 (0.0%)	2577 (0.3%)	0			
	26432	**868122**	**0**			
Week or weekend						
Week	26426 (99.9%)	862079 (99.3%)	0	173.189[a] (1)	< .001	.014 (weak)
Weekend	6 (0.1%)	6043 (0.7%)	0			
	26432	**868122**	**0**			
Month						
January	2368 (9.0%)	75679 (8.7%)	0			
February	2465 (9.3%)	71285 (8.2%)	0	134.468[a] (11)	< .001	.012 (small)
March	2392	77642	0			

	(9.0%)	(8.9%)				
April	2103	67074	0			
	(8.0%)	(7.7%)				
Mei	2418	72350	0			
	(9.1%)	(8.3%)				
June	2345	72464	0			
	(8.9%)	(8.3%)				
July	2018	68095	0			
	(7.6%)	(7.8%)				
August	2134	71163	0			
	(8.1%)	(8.2%)				
September	2034	69259	0			
	(7.7%)	(8.0%)				
October	2226	79845	0			
	(8.4%)	(9.2%)				
November	2191	79502	0			
	(8.3%)	(9.2%)				
December	1738	63764	0			
	(6.6%)	(7.3%)				
	26432	**868122**	**0**			
Season						
Spring	6949	216083	0			
	(26.3%)	(24.9%)				
Summer	6387	211558	0			
	(24.2%)	(24.4%)		97.826[a] (3)	< .001	.010 (weak)
Autumn	6436	232975	0			
	(24.3%)	(26.8%)				
Winter	6660	207506	0			
	(25.2%)	(23.9%)				
	26432	**868119**	**3**			
Part of the day						
Morning	14453	450153	n/a			
	(54.7%)	(51.9%)				
Noon	11893	406759	n/a			
	(45.0%)	(46.9%)		276.065[a] (3)	< .001	.018 (weak)
Night	1	6355	n/a			
	(0.0%)	(0.7%)				
Evening	85	4852	n/a			
	(0.3%)	(0.6%)				

7.7 SPSS Multivariate logistic regression

7.7.1 Gender

The multivariate logistic regression analysis shows that variable Gender (R^2 = 0.1%, O.R. = 1.213, 95% CI = 1.183 - 1.243, $p < .001$) and variable Distance (R^2 = 0.1%, O.R. = .997, 95% CI = .996-.997, $p < .001$) were significant predictors for the dependent variable. In the table below we can see that Distance is not a significant (R^2 = 0.2%, $p = .832$) moderator between the predictor (Gender) and the dependent variable (show/no-show).

Multivariate Binary logistic regression model - Preference of showing or not showing – Distance as moderator

Variables	B	S.E.	Wald	df	Sig.	Exp. (B)	95% C.I for EXP(B)

							Lower	Upper
Gender(1)	.202	.019	113.257	1	< .001	1.223	1.179	1.270
Distance	-.004	.000	116.649	1	< .001	.996	.996	.997
Gender(1) by Distance*	.000	.000	.045	1	.832	1.000	.999	1.001

* p > .05

The multivariate logistic regression analysis shows that variable Gender (R^2 = 0.1%, O.R. = 1.213, 95% CI = 1.183 - 1.243, p < .001) and variable Day of the week (R^2 = 0.2%, p < .001) were significant predictors for the dependent variable. In the table below we can see that Day of the week as a whole variable is not a significant (R^2 = 0.3%, p = .098) moderator between the predictor (Gender) and the dependent variable (show/no-show), however Tuesday and Thursday are significant, respectively (O.R. = .928, p = .045, O.R. = .919, p = .027).

Multivariate Binary logistic regression model - Preference of showing or not showing – Day of the week as moderator

Variables	B	S.E.	Wald	df	Sig.	Exp. (B)	95% C.I for EXP(B)	
							Lower	Upper
Gender(1)	.227	.026	76.205	1	< .001	1.255	1.192	1.320
Day of the week			69.813	6	< .001			
D.o.t.w.(1)	-.055	.027	4.332	1	.037	.946	.898	.997
D.o.t.w.(2)	-.147	.028	27.896	1	< .001	.863	.818	.912
D.o.t.w.(3)	-.117	.027	18.573	1	< .001	.890	.844	.938
D.o.t.w.(4)	-.114	.029	14.833	1	< .001	.893	.842	.946
D.o.t.w.(5)	-4.241	1.000	17.973	1	< .001	.014	.002	.102
D.o.t.w.(6)	-4.120	1.000	16.964	1	< .001	.016	.002	.115
D.o.t.w. * Gender*			10.707	6	.098			
D.o.t.w(1) by Gender(1)	-.075	.037	4.027	1	.045	.928	.862	.998
D.o.t.w(2) by Gender(1)*	-.013	.038	.113	1	.737	.987	.916	1.064
D.o.t.w(3) by Gender(1)	-.084	.038	4.864	1	.027	.919	.853	.991
D.o.t.w(4) by Gender(1)*	-.018	.041	.198	1	.656	.982	.906	1.064
D.o.t.w(5) by Gender(1)*	1.822	1.119	2.652	1	.103	6.185	.690	55.428

D.o.t.w(6) by Gender(1)*	-13.815	1713.834	.000	1	.994	.000	.000	.

* p > .05

The multivariate logistic regression analysis shows that variable Gender (R^2 = 0.1%, O.R. = 1.213, 95% CI = 1.183 - 1.243, $p < .001$) and variable Week or weekend (R^2 = 0.1%, O.R. = .032, 95% CI = .015-.072, $p < .001$) were significant predictors for the dependent variable. In the table below we can see that Week or Weekend not a significant (R^2 = 0.3%, p = .101) moderator is between the predictor (Gender) and the dependent variable (show/no-show).

Multivariate Binary logistic regression model - Preference of showing or not showing – Week or weekend as moderator

Variables	B	S.E.	Wald	df	Sig.	Exp. (B)	95% C.I for EXP(B)	
							Lower	Upper
Gender(1)	.188	.012	225.889	1	< .001	1.207	1.177	1.236
Week or weekend(1)	-4.100	.707	33.595	1	< .001	.017	.004	.066
Gender(1) by Week or weekend(1)*	1.420	.867	2.684	1	.101	4.136	.757	22.605

* p > .05

The multivariate logistic regression analysis shows that variable Gender (R^2 = 0.1%, O.R. = 1.213, 95% CI = 1.183 - 1.243, $p < .001$) and variable Month of the year (R^2 = 0.1%, $p < .001$) were significant predictors for the dependent variable. In the table below we can see that Month of the year as a whole variable is not a significant (R^2 = 0.2%, p = .625) moderator between the predictor (Gender) and the dependent variable (show/no-show), however only the month of April is significant, respectively (O.R. = .1.134, p = .039).

Multivariate Binary logistic regression model - Preference of showing or not showing – Month of the year as moderator

Variables	B	S.E.	Wald	df	Sig.	Exp. (B)	95% C.I for EXP(B)	
							Lower	Upper
Gender(1)	.134	.042	10.348	1	.001	1.144	1.054	1.241
Month			69.772	11	< .001			
Month(1)	.056	.042	1.779	1	.182	1.057	.974	1.148
Month(2)	-.057	.042	1.845	1	.174	.944	.869	1.026
Month(3)	-.062	.044	2.003	1	.157	.940	.863	1.024
Month(4)	.043	.042	1.049	1	.306	1.043	.962	1.132
Month(5)	.011	.042	.068	1	.795	1.011	.931	1.098
Month(6)	-.063	.043	2.106	1	.147	.939	.862	1.022
Month(7)	-.079	.043	3.320	1	.068	.924	.849	1.006
Month(8)	-.059	.043	1.879	1	.170	.943	.866	1.026
Month(9)	-.145	.042	11.736	1	.001	.865	.796	.940

Month(10)	-.168	.043	15.534	1	< .001	.845	.777	.919
Month(11)	-.184	.046	16.313	1	< .001	.832	.760	.909
Gender * Month			8.970	11	.625			
Gender(1) by Month(1)*	.083	.059	2.022	1	.155	1.087	.969	1.219
Gender(1) by Month(2)*	.077	.059	1.718	1	.190	1.080	.962	1.213
Gender(1) by Month(3)	.126	.061	4.277	1	.039	1.134	1.007	1.278
Gender(1) by Month(4)*	.047	.059	.652	1	.420	1.049	.935	1.177
Gender(1) by Month(5)*	.044	.059	.549	1	.459	1.045	.930	1.173
Gender(1) by Month(6)*	.018	.062	.087	1	.768	1.018	.903	1.149
Gender(1) by Month(7)*	.071	.061	1.361	1	.243	1.073	.953	1.209
Gender(1) by Month(8)*	-.008	.061	.018	1	.892	.992	.879	1.118
Gender(1) by Month(9)*	.062	.060	1.065	1	.302	1.064	.946	1.196
Gender(1) by Month(10)*	.084	.060	1.944	1	.163	1.087	.967	1.224
Gender(1) by Month(11)*	.093	.064	2.108	1	.146	1.098	.968	1.244

* $p > .05$

The multivariate logistic regression analysis shows that variable Gender (R^2 = 0.1%, O.R. = 1.213, 95% CI = 1.183 - 1.243, $p < .001$) and variable Season of the year (R^2 = < .001%, $p < .001$) were significant predictors for the dependent variable. In the table below we can see that Season of the year as a whole variable is not a significant (R^2 = 0.2%, $p = .148$) moderator between the predictor (Gender) and the dependent variable (show/no-show), however only the second (i.e., Summer) season opposed to the first season (i.e., Spring) is significant (O.R. = .926, $p = .029$).

Multivariate Binary logistic regression model - Preference of showing or not showing – Season of the year as moderator

Variables	B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I.for EXP(B) Lower	Upper
Gender(1)	.228	.024	87.526	1	< .001	1.256	1.198	1.318
Season			48.456	3	< .001			
S.o.t.y(1)	-.024	.025	.881	1	.348	.977	.930	1.026
S.o.t.y(2)	-.140	.025	30.765	1	< .001	.870	.828	.914

S.o.t.y(3)	.022	.025	.803	1	.370	1.023	.974	1.074
Season of the year * Gender			5.352	3	.148			
S.o.t.y(1) by Gender(1)	-.077	.035	4.756	1	.029	.926	.864	.992
S.o.t.y(2) by Gender(1)*	-.021	.035	.370	1	.543	.979	.914	1.049
S.o.t.y(3) by Gender(1)*	-.049	.035	1.951	1	.163	.952	.890	1.020

* p > .05

The multivariate logistic regression analysis shows that variable Gender (R^2 = 0.1%, O.R. = 1.213, 95% CI = 1.183 - 1.243, $p < .001$) and variable Part of the day (R^2 = 0.2%, $p < .001$) were significant predictors for the dependent variable. In the table below we can see that Part of the day as a whole variable is not a significant (R^2 = 0.3%, p = .122) moderator between the predictor (Gender) and the dependent variable (show/no-show)

Multivariate Binary logistic regression model - Preference of showing or not showing – Part of the day as moderator

Variables	**B**	**S.E.**	**Wald**	**df**	**Sig.**	**Exp(B)**	**95% C.I.for EXP(B)**	
							Lower	**Upper**
Gender(1)	.207	.017	150.524	1	.000	1.231	1.190	1.272
Part of the day			42.109	3	.000			
P.o.t.d(1)	-.078	.018	18.980	1	.000	.925	.893	.958
P.o.t.d(2)	-17.664	729.576	.001	1	.981	.000	.000	.
P.o.t.d(3)	-.684	.135	25.621	1	.000	.505	.387	.658
Part of the day * Gender*			5.793	3	.122			
P.o.t.d(1) by Gender(1)*	-.034	.025	1.815	1	.178	.967	.920	1.016
P.o.t.d(2) by Gender(1)*	12.888	729.577	.000	1	.986	395436.812	.000	.
P.o.t.d(3) by Gender(1)*	.447	.232	3.709	1	.054	1.564	.992	2.464

* p > .05

7.7.2 Age

The multivariate logistic regression analysis shows that variable Age (R^2 = 0.6%, $p < .001$) and variable Distance (R^2 = 0.1%, O.R. = .997, 95% CI = .996-.997, $p < .001$) were significant predictors for the dependent variable. In the table below we can see that Distance is a significant (R^2 = 0.7%, $p < .001$) moderator (interaction) between the predictor (Age) and the dependent variable (show/no-show), however Adults and

Seniors opposed to Children are not significant, respectively (O.R. = .999, p = .075, O.R. = .999, p = .093).

Multivariate Binary logistic regression model - Preference of showing or not showing – Distance as moderator

Variables	B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I.for EXP(B) Lower	Upper
Age			670.946	3	< .001			
Age(1)	.649	.036	325.355	1	< .001	1.914	1.783	2.054
Age(2)	.120	.028	18.865	1	< .001	1.127	1.068	1.190
Age(3)	-.254	.034	54.784	1	< .001	.776	.725	.830
Distance	-.003	.001	25.889	1	< .001	.997	.996	.998
Age * Distance			16.528	3	.001			
Age(1) by Distance	-.003	.001	16.069	1	< .001	.997	.995	.998
Age(2) by Distance*	-.001	.001	3.166	1	.075	.999	.998	1.000
Age(3) by Distance*	-.001	.001	2.815	1	.093	.999	.997	1.000

* p > .05

The multivariate logistic regression analysis shows that variable Age (R^2 = 0.6%, p < .001) and variable Day of the week (R^2 = 0.2%, p < .001) were significant predictors for the dependent variable. In the table below we can see that Day of the week is a significant (R^2 = 0.9%, p < .001) moderator (interaction) between the predictor (Age) and the dependent variable (show/no-show).

Multivariate Binary logistic regression model - Preference of showing or not showing – Day of the week as moderator

Variables	B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I.for EXP(B) Lower	Upper
Age			272.286	3	< .001			
Age(1)	.501	.048	106.729	1	< .001	1.650	1.501	1.815
Age(2)	.087	.037	5.462	1	.019	1.091	1.014	1.173
Age(3)	-.295	.047	39.763	1	< .001	.745	.680	.816
Day of the week			51.638	6	< .001			
D.o.t.w(1)	-.066	.046	2.110	1	.146	.936	.855	1.023
D.o.t.w(2)	-.323	.051	40.116	1	< .001	.724	.655	.800
D.o.t.w(3)	-.217	.047	20.867	1	< .001	.805	.734	.884

D.o.t.w(4)	-.090	.050	3.181	1	.074	.914	.828	1.009
D.o.t.w(5)	-17.771	3999.351	.000	1	.996	.000	.000	.
D.o.t.w(6)	-17.771	4874.113	.000	1	.997	.000	.000	.
Day of the week * Age			47.060	18	< .001			
D.o.t.w(1) by Age(1)*	.017	.068	.061	1	.805	1.017	.890	1.162
D.o.t.w(1) by Age(2)*	-.034	.052	.434	1	.510	.966	.872	1.070
D.o.t.w(1) by Age(3)*	-.076	.067	1.301	1	.254	.927	.813	1.056
D.o.t.w(2) by Age(1)	.254	.073	12.116	1	.001	1.289	1.117	1.487
D.o.t.w(2) by Age(2)	.180	.057	9.926	1	.002	1.197	1.070	1.339
D.o.t.w(2) by Age(3)	.263	.070	14.337	1	< .001	1.301	1.135	1.491
D.o.t.w(3) by Age(1)*	.120	.069	3.018	1	.082	1.128	.985	1.291
D.o.t.w(3) by Age(2)*	.043	.054	.625	1	.429	1.044	.939	1.160
D.o.t.w(3) by Age(3)*	.086	.068	1.627	1	.202	1.090	.955	1.245
D.o.t.w(4) by Age(1)*	.039	.075	.276	1	.600	1.040	.898	1.205
D.o.t.w(4) by Age(2)*	-.020	.057	.124	1	.724	.980	.876	1.097
D.o.t.w(4) by Age(3)	-.148	.074	4.018	1	.045	.862	.746	.997
D.o.t.w(5) by Age(1)*	-.501	5114.198	.000	1	1.000	.606	.000	.
D.o.t.w(5) by Age(2)*	13.974	3999.351	.000	1	.997	1172124.469	.000	.
D.o.t.w(5) by Age(3)*	16.076	3999.351	.000	1	.997	9583305.273	.000	.
D.o.t.w(6) by Age(1)*	-.501	6317.573	.000	1	1.000	.606	.000	.
D.o.t.w(6) by Age(2)*	13.510	4874.113	.000	1	.998	736438.984	.000	.
D.o.t.w(6) by Age(3)*	.295	5274.084	.000	1	1.000	1.343	.000	.

* p > .05

The multivariate logistic regression analysis shows that variable Age (R^2 = 0.6%, p < .001) and variable Week or Weekend (R^2 = 0.1%, p < .001) were significant predictors for the dependent variable. In the table below we can see that Week or Weekend is not a significant (R^2 = 0.8% p = .174) moderator between the predictor (Age) and the dependent variable (show/no-show).

Multivariate Binary logistic regression model - Preference of showing or not showing – Week or weekend as moderator

Variables	B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I.for EXP(B) Lower	Upper
Age			1409.533	3	< .001			
Age(1)	.581	.023	648.843	1	< .001	1.788	1.710	1.870
Age(2)	.118	.018	44.257	1	< .001	1.125	1.087	1.165
Age(3)	-.266	.022	142.466	1	< .001	.767	.734	.801
Week or weekend(1)	-17.638	3091.761	.000	1	.995	.000	.000	.
Age * Week or weekend*			4.970	3	.174			
Age(1) by Week or weekend(1)*	-.581	3974.461	.000	1	1.000	.559	.000	.
Age(2) by Week or weekend (1)*	13.763	3091.761	.000	1	.996	949003.448	.000	.
Age(3) by Week or Weekend(1)*	15.585	3091.761	.000	1	.996	5870419.878	.000	.

* p > .05

The multivariate logistic regression analysis shows that variable Age (R^2 = 0.6%, p < .001) and variable Month of the year (R^2 = 0.1%, p < .001) were significant predictors for the dependent variable. In the table below we can see that Month of the year is a significant (R^2 = 0.7% p < .001) moderator between the predictor (Age) and the dependent variable (show/no-show).

Multivariate Binary logistic regression model - Preference of showing or not showing – Month of the year as moderator

Variables	B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I.for EXP(B) Lower	Upper
Age			125.118	3	< .001			
Age(1)	.629	.078	65.514	1	< .001	1.876	1.611	2.185
Age(2)	.234	.061	14.762	1	< .001	1.263	1.121	1.423
Age(3)	-.184	.076	5.820	1	.016	.832	.717	.966

Month			35.318	11	< .001			
Month(1)	.130	.075	2.991	1	.084	1.139	.983	1.320
Month(2)	.079	.074	1.133	1	.287	1.082	.936	1.251
Month(3)	.017	.079	.047	1	.829	1.017	.872	1.187
Month(4)	.079	.077	1.054	1	.305	1.082	.931	1.257
Month(5)	.092	.075	1.493	1	.222	1.096	.946	1.271
Month(6)	.064	.080	.634	1	.426	1.066	.911	1.246
Month(7)	.274	.074	13.738	1	< .001	1.316	1.138	1.521
Month(8)	.129	.076	2.892	1	.089	1.138	.981	1.320
Month(9)	.009	.075	.014	1	.906	1.009	.870	1.170
Month(10)	-.034	.076	.198	1	.656	.967	.833	1.122
Month(11)	-.113	.083	1.871	1	.171	.893	.760	1.050
Age * Month			74.358	33	< .001			
Age(1) by Month(1)*	-.052	.109	.224	1	.636	.950	.767	1.176
Age(1) by Month(2)*	.005	.107	.002	1	.964	1.005	.815	1.239
Age(1) by Month(3)*	.008	.113	.005	1	.943	1.008	.807	1.259
Age(1) by Month(4)*	.064	.109	.338	1	.561	1.066	.860	1.320
Age(1) by Month(5)*	-.075	.110	.472	1	.492	.927	.748	1.150
Age(1) by Month(6)*	-.043	.115	.142	1	.707	.958	.764	1.200
Age(1) by Month(7)	-.315	.110	8.164	1	.004	.730	.588	.906
Age(1) by Month(8)*	-.179	.112	2.553	1	.110	.836	.671	1.041
Age(1) by Month(9)*	-.056	.110	.259	1	.611	.946	.763	1.173
Age(1) by Month(10)*	.008	.110	.005	1	.943	1.008	.813	1.250
Age(1) by Month(11)*	.036	.119	.090	1	.764	1.036	.821	1.308
Age(2) by Month(1)*	-.043	.085	.257	1	.612	.958	.811	1.131
Age(2) by Month(2)	-.182	.084	4.643	1	.031	.834	.707	.984
Age(2) by Month(3)*	-.055	.089	.385	1	.535	.946	.795	1.126

Age(2) by Month(4)*	-.061	.086	.494	1	.482	.941	.795	1.114
Age(2) by Month(5)*	-.060	.085	.492	1	.483	.942	.797	1.113
Age(2) by Month(6)*	-.131	.090	2.132	1	.144	.877	.736	1.046
Age(2) by Month(7)	-.390	.085	21.206	1	< .001	.677	.573	.799
Age(2) by Month(8)	-.231	.086	7.159	1	.007	.793	.670	.940
Age(2) by Month(9)*	-.158	.086	3.422	1	.064	.854	.722	1.009
Age(2) by Month(10)*	-.152	.086	3.126	1	.077	.859	.725	1.017
Age(2) by Month(11)*	-.017	.093	.033	1	.855	.983	.820	1.180
Age(3) by Month(1)*	.014	.106	.018	1	.895	1.014	.824	1.247
Age(3) by Month(2)*	.021	.104	.041	1	.839	1.021	.833	1.253
Age(3) by Month(3)*	.101	.109	.856	1	.355	1.106	.893	1.370
Age(3) by Month(4)*	.073	.106	.476	1	.490	1.076	.874	1.326
Age(3) by Month(5)*	-.092	.107	.732	1	.392	.912	.739	1.126
Age(3) by Month(6)*	-.200	.112	3.154	1	.076	.819	.657	1.021
Age(3) by Month(7)	-.393	.108	13.233	1	< .001	.675	.546	.834
Age(3) by Month(8)	-.266	.110	5.813	1	.016	.766	.617	.951
Age(3) by Month(9)	-.168	.108	2.417	1	.120	.846	.684	1.045
Age(3) by Month(10)*	-.064	.108	.355	1	.551	.938	.759	1.159
Age(3) by Month(11)*	-.126	.118	1.142	1	.285	.881	.699	1.111

* p > .05

The multivariate logistic regression analysis shows that variable Age ($R^2 = 0.6\%$, $p < .001$) and variable Season of the year ($R^2 = 0.000473\%$, $p < .001$) were significant predictors for the dependent variable. In the table below we can see that Season of the year is a significant ($R^2 = 0.7\%$ $p < .001$) moderator between the predictor (Age) and the dependent variable (show/no-show).

Multivariate Binary logistic regression model - Preference of showing or not showing – Season of the year as moderator

Variables	B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I.for EXP(B) Lower	Upper
Age(1)	.658	.045	213.845	1	< .001	1.930	1.767	2.108
Age(2)	.171	.035	23.252	1	< .001	1.186	1.107	1.272
Age(3)	-.123	.043	8.059	1	.005	.884	.812	.963
Season			24.529	3	< .001			
Season(1)	.131	.044	8.924	1	.003	1.140	1.046	1.242
Season(2)	-.084	.044	3.599	1	.058	.919	.843	1.003
Season(3)	.014	.044	.104	1	.747	1.014	.930	1.107
Season * Age			41.893	9	< .001			
Season(1) by Age(1)	-.209	.064	10.539	1	.001	.812	.716	.921
Season(1) by Age(2)	-.198	.050	15.777	1	< .001	.820	.744	.904
Season(1) by Age(3)	-.353	.063	31.744	1	< .001	.703	.621	.794
Season(2) by Age(1)*	-.048	.064	.551	1	.458	.953	.841	1.081
Season(2) by Age(2)*	-.060	.050	1.434	1	.231	.942	.853	1.039
Season(2) by Age(3)	-.172	.063	7.570	1	.006	.842	.744	.952
Season(3) by Age(1)*	-.065	.064	1.023	1	.312	.937	.826	1.063
Season(3) by Age(2)*	.008	.050	.028	1	.866	1.009	.914	1.113
Season(3) by Age(3)*	-.077	.062	1.514	1	.219	.926	.820	1.046

* p > .05

The multivariate logistic regression analysis shows that variable Age ($R^2 = 0.6\%$, $p < .001$) and variable Part of the day ($R^2 = 0.2\%$, $p < .001$) were significant predictors for the dependent variable. In the table below we can see that Part of the day is a significant ($R^2 = 0.9\%$ $p = .001$) moderator between the predictor (Age) and the dependent variable (show/no-show).

Multivariate Binary logistic regression model - Preference of showing or not showing – Part of the day as moderator

Variabels	B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I.for EXP(B) Lower	Upper

Age			819.427	3	.000			
Age(1)	.557	.031	318.037	1	.000	1.745	1.641	1.855
Age(2)	.058	.024	5.972	1	.015	1.060	1.012	1.110
Age(3)	-.361	.031	139.709	1	< .001	.697	.656	.740
Part of the day			47.822	3	< .001			
P.o.t.d(1)	-.212	.031	45.297	1	< .001	.809	.761	.861
P.o.t.d(2)	-17.736	10741.988	.000	1	.999	.000	.000	.
P.o.t.d(3)	-.628	.337	3.473	1	.062	.534	.276	1.033
Part of the day * Age			29.450	9	.001			
P.o.t.d(1) by Age(1)*	.069	.046	2.276	1	.131	1.072	.980	1.173
P.o.t.d(1) by Age(2)	.127	.036	12.477	1	< .001	1.135	1.058	1.218
P.o.t.d(1) by Age(3)	.231	.045	26.661	1	< .001	1.260	1.154	1.375
P.o.t.d(2) by Age(1)*	-.557	11054.712	.000	1	1.000	.573	.000	.
P.o.t.d(2) by Age(2)*	13.131	10741.988	.000	1	.999	504477.151	.000	.
P.o.t.d(2) by Age(3)*	.361	10766.359	.000	1	1.000	1.435	.000	.
P.o.t.d(3) by Age(1)*	-.069	.439	.025	1	.875	.933	.395	2.207
P.o.t.d(3) by Age(2)*	-.033	.361	.009	1	.926	.967	.477	1.962
P.o.t.d(3) by Age(3)*	-.419	.786	.285	1	.594	.657	.141	3.068

* p > .05

7.7.3 Socioeconomic status

The multivariate logistic regression analysis shows that variable Socioeconomic status (R^2 = 0.3%, O.R. = .698, 95% CI = .680 - .716, $p < .001$) and variable Distance (R^2 = 0.1%, O.R. = .997, 95% CI = .996 - .997, $p < .001$) were significant predictors for the dependent variable. In the table below we can see that Distance a significant (R^2 = 0.5%, $p < .001$) moderator is between the predictor (Socioeconomic status) and the dependent variable (show/no-show).

Multivariate Binary logistic regression model - Preference of showing or not showing – Distance as moderator

Variables	**B**	**S.E.**	**Wald**	**df**	**Sig.**	**Exp(B)**	**95% C.I.for EXP(B)**	

							Lower	Upper
Sociostatus (1)	-.391	.013	841.386	1	.000	.677	.659	.695
Distance	-.005	.000	249.332	1	.000	.995	.995	.996
Distance by Sociostatus (1)	.002	.000	15.491	1	.000	1.002	1.001	1.003

* p > .05

The multivariate logistic regression analysis shows that variable Socioeconomic status ($R^2 = 0.3\%$, O.R. = .698, 95% CI = .680 - .716, $p < .001$) and variable Day of the week ($R^2 = 0.2\%$, $p < .001$) were significant predictors for the dependent variable. In the table below we can see that Day of the week not a significant ($R^2 = 0.5\%$, $p = .705$) moderator is between the predictor (Socioeconomic status) and the dependent variable (show/no-show).

Multivariate Binary logistic regression model - Preference of showing or not showing – Day of the week as moderator

Variables	B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I.for EXP(B)	
							Lower	Upper
Sociostatus(1)	-.371	.028	178.606	1	.000	.690	.653	.729
Day of the week			54.491	6	.000			
D.o.t.w(1)	-.099	.032	9.397	1	.002	.905	.849	.965
D.o.t.w(2)	-.180	.033	28.963	1	.000	.835	.782	.892
D.o.t.w(3)	-.186	.033	31.008	1	.000	.830	.777	.886
D.o.t.w(4)	-.116	.035	10.727	1	.001	.890	.831	.954
D.o.t.w(5)	-3.712	1.001	13.755	1	.000	.024	.003	.174
D.o.t.w(6)*	-18.069	1496.864	.000	1	.990	.000	.000	.
Day of the week * Sociostatus*			3.793	6	.705			
D.o.t.w(1) by Sociostatus(1)*	-.012	.040	.094	1	.759	.988	.913	1.068
D.o.t.w(2) by Sociostatus(1)*	.051	.041	1.564	1	.211	1.053	.971	1.141
D.o.t.w(3) by Sociostatus(1)*	.026	.041	.407	1	.524	1.026	.947	1.112
D.o.t.w(4) by Sociostatus(1)*	-.013	.044	.082	1	.774	.988	.907	1.076
D.o.t.w(5) by Sociostatus(1)*	.771	1.119	.475	1	.491	2.162	.241	19.378

D.o.t.w(6) by Sociostatus(1)*	14.051	1496.865	.000	1	.993	1264899.939	.000	.

* p > .05

The multivariate logistic regression analysis shows that variable Socioeconomic status (R^2 = 0.3%, O.R. = .698, 95% CI = .680 - .716, p < .001) and variable Week or weekend (R^2 = 0.1%, O.R. = .032, 95% CI = .015 - .072, p < .001) were significant predictors for the dependent variable. In the table below we can see that Week or weekend not a significant (R^2 = 0.5%, p = .361) moderator is between the predictor (Socioeconomic status) and the dependent variable (show/no-show).

Multivariate Binary logistic regression model - Preference of showing or not showing – Week or weekend as moderator

Variables	B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I.for EXP(B)	
							Lower	Upper
Sociostatus (1)*	-.360	.013	724.596	1	.000	.698	.679	.716
Week or Weekend (1)	-4.167	1.000	17.352	1	.000	.015	.002	.110
Sociostatus (1) by Week or Weekend(1)*	1.002	1.096	.836	1	.361	2.723	.318	23.331

* p > .05

The multivariate logistic regression analysis shows that variable Socioeconomic status (R^2 = 0.3%, O.R. = .698, 95% CI = .680 - .716, p < .001) and variable Month of the year (R^2 = 0.1%, p < .001) were significant predictors for the dependent variable. In the table below we can see that Month of the year a significant (R^2 = 0.4%, p = .020) moderator is between the predictor (Socioeconomic status) and the dependent variable (show/no-show).

Multivariate Binary logistic regression model - Preference of showing or not showing – Month of the year as moderator

Variables	B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I.for EXP(B)	
							Lower	Upper
Sociostatus (1)	-.304	.045	45.940	1	.000	.738	.675	.805
Month			38.165	11	.000			
Month(1)	.102	.052	3.889	1	.049	1.107	1.001	1.225
Month(2)*	-.034	.052	.416	1	.519	.967	.873	1.071
Month(3)*	.040	.053	.572	1	.450	1.041	.938	1.156
Month(4)	.141	.051	7.656	1	.006	1.152	1.042	1.273
Month(5)*	.006	.053	.011	1	.916	1.006	.907	1.115
Month(6)*	-.037	.054	.469	1	.494	.964	.867	1.072
Month(7)*	.047	.052	.820	1	.365	1.049	.946	1.162

Month(8)*	-.002	.053	.002	1	.965	.998	.898	1.108
Month(9)	-.105	.053	3.936	1	.047	.901	.812	.999
Month(10)*	-.027	.052	.270	1	.604	.973	.879	1.078
Month(11)	-.065	.055	1.351	1	.245	.938	.841	1.045
Month * Sociostatus			22.567	11	.020			
Month(1) by Sociostatus(1)*	.003	.063	.003	1	.958	1.003	.887	1.135
Month(2) by Sociostatus(1)*	.020	.064	.101	1	.750	1.020	.901	1.156
Month(3) by Sociostatus(1)*	-.067	.065	1.056	1	.304	.935	.823	1.063
Month(4) by Sociostatus(1)*	-.118	.063	3.543	1	.060	.888	.786	1.005
Month(5) by Sociostatus(1)*	.036	.064	.319	1	.572	1.037	.914	1.176
Month(6) by Sociostatus(1)*	-.031	.066	.224	1	.636	.969	.851	1.103
Month(7) by Sociostatus(1)	-.135	.065	4.368	1	.037	.874	.770	.992
Month(8) by Sociostatus(1)*	-.099	.066	2.286	1	.131	.905	.796	1.030
Month(9) by Sociostatus(1)*	-.029	.064	.203	1	.653	.971	.856	1.102
Month(10) by Sociostatus(1)	-.153	.064	5.723	1	.017	.858	.756	.973
Month(11) by Sociostatus(1)*	-.116	.068	2.897	1	.089	.890	.778	1.018

* p > .05

The multivariate logistic regression analysis shows that variable Socioeconomic status ($R^2 = 0.3\%$, O.R. = .698, 95% CI = .680 - .716, $p < .001$) and variable Season of the year ($R^2 = 0.000473\%$, $p < .001$) were significant predictors for the dependent variable. In the table below we can see that Season of the year a significant ($R^2 = 0.04\%$, $p = .034$) moderator is between the predictor (Socioeconomic status) and the dependent variable (show/no-show).

Multivariate Binary logistic regression model - Preference of showing or not showing – Season of the year as moderator

Variables	B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I.for EXP(B) Lower	Upper
Sociostatus(1)	-.349	.026	177.063	1	< .001	.706	.670	.743
Season			14.285	3	.003			

Season(1)*	-.046	.031	2.197	1	.138	.955	.900	1.015
Season(2)	-.112	.030	13.387	1	< .001	.894	.843	.950
Season(3)*	-.030	.031	.936	1	.333	.971	.914	1.031
Season * Sociostatus			8.644	3	.034			
Season(1) by Sociostatus(1)*	-.026	.038	.485	1	.486	.974	.905	1.049
Season(2) by Sociostatus(1)*	-.064	.038	2.877	1	.090	.938	.872	1.010
Season(3) by Sociostatus(1)*	.045	.037	1.420	1	.233	1.046	.972	1.125

* p > .05

The multivariate logistic regression analysis shows that variable Socioeconomic status (R^2 = 0.3%, O.R. = .698, 95% CI = .680 - .716, p < .001) and variable Part of the day (R^2 = 0.2%, p < .001) were significant predictors for the dependent variable. In the table below we can see that Part of the day not a significant (R^2 = 0.6%, p = .722) moderator is between the predictor (Socioeconomic status) and the dependent variable (show/no-show).

Variables	B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I.for EXP(B) Lower	Upper
Sociostatus(1)	-.363	.018	400.917	1	< .001	.695	.671	.721
Part of the day			43.087	3	< .001			
P.o.t.d(1)	-.097	.022	19.687	1	< .001	.907	.869	.947
P.o.t.d(2)	-4.156	1.000	17.259	1	< .001	.016	.002	.111
P.o.t.d(3)	-.465	.165	7.940	1	.005	.628	.455	.868
Part of the day * Sociostatus*			1.330	3	.722			
P.o.t.d(1) by Sociostatus(1)*	.008	.027	.096	1	.757	1.008	.957	1.063
P.o.t.d(2) by Sociostatus(1)*	-13.483	581.958	.001	1	.982	.000	.000	.
P.o.t.d(3) by Sociostatus(1)*	-.241	.221	1.192	1	.275	.786	.509	1.212

* p > .05

7.7.4 Elapsing calendar days

The multivariate logistic regression analysis shows that variable Elapsing calendar days (R^2 = 2.9%, p < .001) and variable Distance (R^2 = 0.1%, O.R. = .997% CI = .996 - .997, p < .001) were significant predictors for the dependent variable. In the table below we can see that Distance not a significant (R^2 = 3.2%, p = .709) moderator is between the predictor (Elapsing calendar days) and the dependent variable (show/no-show).

Multivariate Binary logistic regression model - Preference of showing or not showing – Distance as moderator

Variables	B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I.for EXP(B)	
							Lower	Upper
Elapsing calendar days			6505.161	17	< .001			
E.c.d(1)	.746	.017	1873.999	1	< .001	2.109	2.039	2.182
E.c.d(2)	.850	.022	1555.011	1	< .001	2.339	2.243	2.440
E.c.d(3)	1.130	.022	2642.829	1	< .001	3.096	2.965	3.232
E.c.d(4)	1.273	.036	1252.796	1	< .001	3.571	3.328	3.832
E.c.d(5)	1.185	.051	531.187	1	< .001	3.269	2.956	3.616
E.c.d(6)	1.407	.033	1770.134	1	< .001	4.083	3.824	4.360
E.c.d(7)	1.015	.113	81.078	1	< .001	2.759	2.212	3.441
E.c.d(8)	1.229	.141	76.453	1	< .001	3.419	2.595	4.503
E.c.d(9)	1.460	.152	92.202	1	< .001	4.308	3.197	5.804
E.c.d(10)	1.300	.204	40.491	1	< .001	3.669	2.459	5.476
E.c.d(11)	1.790	.114	245.744	1	< .001	5.987	4.787	7.489
E.c.d(12)	1.644	.061	735.611	1	< .001	5.174	4.594	5.826
E.c.d(13)	.992	.277	12.831	1	< .001	2.698	1.567	4.643
E.c.d(14)*	.659	.771	.729	1	.393	1.932	.426	8.762
E.c.d(15)*	-24.804	29.831	.691	1	.406	.000	.000	416545688998269.440
E.c.d(16)*	-17.307	13048.984	.000	1	.999	.000	.000	.
E.c.d(17)*	-17.307	22305.603	.000	1	.999	.000	.000	.
Distance	-.004	.000	140.354	1	< .001	.996	.995	.997
Distance * Elapsing calendar days*			13.402	17	.709			
Distance by E.c.d(1)*	.000	.001	.038	1	.846	1.000	.999	1.001
Distance by E.c.d(2)*	.001	.001	.517	1	.472	1.001	.999	1.002

Distance by E.c.d(3)*	.000	.001	.067	1	.795	1.000	.999	1.002
Distance by E.c.d(4)*	.002	.001	2.355	1	.125	1.002	.999	1.004
Distance by E.c.d(5)*	.002	.002	1.107	1	.293	1.002	.999	1.005
Distance by E.c.d(6)*	.002	.001	3.757	1	.053	1.002	1.000	1.005
Distance by E.c.d(7)*	.001	.004	.088	1	.766	1.001	.994	1.009
Distance by E.c.d(8)*	.004	.004	.883	1	.347	1.004	.996	1.012
Distance by E.c.d(9)*	-.002	.006	.107	1	.744	.998	.987	1.009
Distance by E.c.d(10)*	.005	.006	.648	1	.421	1.005	.993	1.016
Distance by E.c.d(11)*	-.001	.004	.079	1	.779	.999	.991	1.007
Distance by E.c.d(12)*	.004	.002	3.192	1	.074	1.004	1.000	1.008
Distance by E.c.d(13)*	-.005	.011	.231	1	.631	.995	.973	1.017
Distance by E.c.d(14)*	.015	.020	.577	1	.447	1.015	.976	1.057
Distance by E.c.d(15)*	-1.012	1.069	.897	1	.344	.363	.045	2.952
Distance by E.c.d(16)*	.004	479.065	.000	1	1.000	1.004	.000	.

Distance by E.c.d(17)*	.004	2659.702	.000	1	1.000	1.004	.000	.

* p > .05

The multivariate logistic regression analysis shows that variable Elapsing calendar days ($R^2 = 2.9\%$, $p < .001$) and variable Day of the week ($R^2 = 0.2\%$, $p < .001$) were significant predictors for the dependent variable. In the table below we can see that Day of the week not a significant ($R^2 = 3.1\%$, $p = .376$) moderator is between the predictor (Elapsing calendar days) and the dependent variable (show/no-show).

Multivariate Binary logistic regression model - Preference of showing or not showing – Day of the week as moderator

Variables	B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I.for EXP(B)	
							Lower	Upper
Elapsing calendar days			1513.348	17	< .001			
E.c.d(1)	.701	.035	410.127	1	< .001	2.015	1.883	2.156
E.c.d(2)	.788	.043	336.769	1	< .001	2.199	2.022	2.393
E.c.d(3)	1.126	.046	610.280	1	< .001	3.083	2.820	3.372
E.c.d(4)	1.158	.075	236.648	1	< .001	3.183	2.747	3.689
E.c.d(5)	.998	.116	73.745	1	< .001	2.713	2.160	3.407
E.c.d(6)	1.449	.074	382.627	1	< .001	4.259	3.683	4.925
E.c.d(7)	.818	.266	9.469	1	.002	2.265	1.346	3.813
E.c.d(8)	1.364	.290	22.051	1	< .001	3.912	2.214	6.913
E.c.d(9)	1.205	.393	9.403	1	.002	3.337	1.545	7.210
E.c.d(10)*	.736	.592	1.546	1	.214	2.087	.654	6.655
E.c.d(11)	2.424	.210	133.443	1	< .001	11.289	7.483	17.032
E.c.d(12)	1.815	.121	224.327	1	< .001	6.138	4.841	7.784
E.c.d(13)*	.727	.724	1.009	1	.315	2.070	.500	8.562
E.c.d(14)	2.649	.817	10.522	1	.001	14.144	2.853	70.108
E.c.d(15)*	-17.455	12710.133	.000	1	.999	.000	.000	.
E.c.d(16)*	-17.455	40192.970	.000	1	1.000	.000	.000	.
E.c.d(17)*	-17.455	28420.722	.000	1	1.000	.000	.000	.
Day of the week			97.569	6	< .001			
D.o.t.w(1)	-.058	.027	4.620	1	.032	.943	.894	.995
D.o.t.w(2)	-.187	.029	41.995	1	< .001	.830	.784	.878
D.o.t.w(3)	-.170	.028	36.492	1	< .001	.844	.798	.892
D.o.t.w(4)	-.116	.030	15.490	1	< .001	.890	.840	.943

D.o.t.w(5)	-3.490	.708	24.318	1	< .001	.031	.008	.122
D.o.t.w(6)	-3.895	1.000	15.155	1	< .001	.020	.003	.145
Day of the week * Elapsing calendar days*			85.428	82	.376			
D.o.t.w(1) by E.c.d(1)*	.020	.050	.165	1	.684	1.021	.925	1.126
D.o.t.w(1) by E.c.d(2)*	-.088	.064	1.902	1	.168	.916	.808	1.038
D.o.t.w(1) by E.c.d(3)*	-.107	.067	2.581	1	.108	.898	.788	1.024
D.o.t.w(1) by E.c.d(4)*	-.098	.114	.735	1	.391	.907	.726	1.134
D.o.t.w(1) by E.c.d(5)*	.159	.156	1.035	1	.309	1.172	.863	1.592
D.o.t.w(1) by E.c.d(6)*	.031	.101	.095	1	.757	1.032	.846	1.258
D.o.t.w(1) by E.c.d(7)*	.379	.346	1.201	1	.273	1.461	.742	2.879
D.o.t.w(1) by E.c.d(8)*	-.590	.465	1.615	1	.204	.554	.223	1.377
D.o.t.w(1) by E.c.d(9)*	.255	.526	.235	1	.628	1.290	.460	3.617
D.o.t.w(1) by E.c.d(10)*	-.121	.835	.021	1	.885	.886	.172	4.552
D.o.t.w(1) by E.c.d(11)	-1.016	.379	7.183	1	.007	.362	.172	.761

D.o.t.w(1) by E.c.d(12)*	-.277	.185	2.231	1	.135	.758	.527	1.090
D.o.t.w(1) by E.c.d(13)*	-.160	1.022	.024	1	.876	.852	.115	6.318
D.o.t.w(1) by E.c.d(14)*	-20.046	15191.515	.000	1	.999	.000	.000	.
D.o.t.w(1) by E.c.d(15)*	.058	22014.596	.000	1	1.000	1.060	.000	.
D.o.t.w(1) by E.c.d(16)*	.058	49226.134	.000	1	1.000	1.060	.000	.
D.o.t.w(2) by E.c.d(1)*	-.024	.053	.215	1	.643	.976	.880	1.082
D.o.t.w(2) by E.c.d(2)*	.025	.063	.160	1	.690	1.026	.906	1.161
D.o.t.w(2) by E.c.d(3)*	-.006	.066	.009	1	.925	.994	.873	1.131
D.o.t.w(2) by E.c.d(4)*	.179	.108	2.734	1	.098	1.196	.967	1.477
D.o.t.w(2) by E.c.d(5)*	.148	.159	.862	1	.353	1.159	.849	1.583
D.o.t.w(2) by E.c.d(6)*	-.100	.100	.991	1	.320	.905	.744	1.101
D.o.t.w(2) by E.c.d(7)*	.134	.370	.131	1	.717	1.143	.554	2.360
D.o.t.w(2) by E.c.d(8)*	-.414	.449	.851	1	.356	.661	.274	1.593
D.o.t.w(2) by E.c.d(9)*	.440	.478	.849	1	.357	1.553	.609	3.962

D.o.t.w(2) by E.c.d(10)	1.553	.652	5.671	1	.017	4.724	1.316	16.955
D.o.t.w(2) by E.c.d(11)	-1.141	.377	9.185	1	.002	.319	.153	.668
D.o.t.w(2) by E.c.d(12)*	-.216	.172	1.582	1	.209	.806	.575	1.128
D.o.t.w(2) by E.c.d(13)*	.746	.825	.819	1	.366	2.109	.419	10.621
D.o.t.w(2) by E.c.d(14)*	-19.918	12118.636	.000	1	.999	.000	.000	.
D.o.t.w(2) by E.c.d(15)*	.187	20755.561	.000	1	1.000	1.205	.000	.
D.o.t.w(2) by E.c.d(16)*	.187	56841.443	.000	1	1.000	1.205	.000	.
D.o.t.w(2) by E.c.d(17)*	.187	49226.134	.000	1	1.000	1.205	.000	.
D.o.t.w(3) by E.c.d(1)*	.024	.051	.216	1	.642	1.024	.926	1.133
D.o.t.w(3) by E.c.d(2)*	.057	.065	.761	1	.383	1.058	.932	1.202
D.o.t.w(3) by E.c.d(3)*	-.070	.066	1.153	1	.283	.932	.819	1.060
D.o.t.w(3) by E.c.d(4)*	.129	.108	1.433	1	.231	1.138	.921	1.405
D.o.t.w(3) by E.c.d(5)*	.167	.164	1.028	1	.311	1.181	.856	1.631
D.o.t.w(3) by E.c.d(6)*	-.178	.104	2.911	1	.088	.837	.682	1.027

D.o.t.w(3) by E.c.d(7)*	.217	.345	.397	1	.528	1.243	.632	2.444
D.o.t.w(3) by E.c.d(8)*	.043	.390	.012	1	.912	1.044	.486	2.244
D.o.t.w(3) by E.c.d(9)*	-.047	.511	.009	1	.926	.954	.350	2.597
D.o.t.w(3) by E.c.d(10)*	.138	.836	.027	1	.869	1.148	.223	5.913
D.o.t.w(3) by E.c.d(11)	-.680	.301	5.087	1	.024	.507	.281	.915
D.o.t.w(3) by E.c.d(12)*	-.277	.178	2.416	1	.120	.758	.535	1.075
D.o.t.w(3) by E.c.d(13)*	.387	.889	.189	1	.663	1.473	.258	8.410
D.o.t.w(3) by E.c.d(14)*	-19.934	11147.524	.000	1	.999	.000	.000	.
D.o.t.w(3) by E.c.d(15)*	20.967	12710.133	.000	1	.999	1276458597.845	.000	.
D.o.t.w(3) by E.c.d(16)*	.170	43413.370	.000	1	1.000	1.185	.000	.
D.o.t.w(4) by E.c.d(1)	.111	.054	4.260	1	.039	1.118	1.006	1.242
D.o.t.w(4) by E.c.d(2)*	.136	.071	3.676	1	.055	1.145	.997	1.316
D.o.t.w(4) by E.c.d(3)*	.030	.073	.171	1	.679	1.031	.893	1.189
D.o.t.w(4) by E.c.d(4)*	.178	.115	2.367	1	.124	1.194	.953	1.497

D.o.t.w(4) by E.c.d(5)*	.294	.175	2.830	1	.093	1.342	.953	1.890
D.o.t.w(4) by E.c.d(6)*	-.068	.120	.321	1	.571	.934	.739	1.182
D.o.t.w(4) by E.c.d(7)*	-.089	.432	.042	1	.837	.915	.392	2.135
D.o.t.w(4) by E.c.d(8)*	.006	.453	.000	1	.990	1.006	.414	2.444
D.o.t.w(4) by E.c.d(9)*	.611	.544	1.262	1	.261	1.843	.634	5.353
D.o.t.w(4) by E.c.d(10)*	-1.030	1.169	.777	1	.378	.357	.036	3.527
D.o.t.w(4) by E.c.d(11)	-.791	.360	4.819	1	.028	.454	.224	.919
D.o.t.w(4) by E.c.d(12)*	-.327	.215	2.310	1	.129	.721	.473	1.099
D.o.t.w(4) by E.c.d(13)*	-.419	1.247	.113	1	.737	.658	.057	7.572
D.o.t.w(4) by E.c.d(14)*	-19.988	13397.657	.000	1	.999	.000	.000	.
D.o.t.w(4) by E.c.d(16)*	.116	49226.134	.000	1	1.000	1.123	.000	.
D.o.t.w(4) by E.c.d(17)*	.116	49226.134	.000	1	1.000	1.123	.000	.
D.o.t.w(5) by E.c.d(1)*	1.855	1.229	2.277	1	.131	6.389	.574	71.073
D.o.t.w(5) by E.c.d(2)	2.424	1.233	3.865	1	.049	11.289	1.007	126.507

D.o.t.w(5) by E.c.d(3)*	-15.092	10048.243	.000	1	.999	.000	.000	.
D.o.t.w(5) by E.c.d(4)*	-15.123	20096.485	.000	1	.999	.000	.000	.
D.o.t.w(5) by E.c.d(5)*	-14.963	23205.422	.000	1	.999	.000	.000	.
D.o.t.w(5) by E.c.d(6)*	-15.415	17974.843	.000	1	.999	.000	.000	.
D.o.t.w(5) by E.c.d(7)*	-14.783	40192.970	.000	1	1.000	.000	.000	.
D.o.t.w(5) by E.c.d(8)*	-15.330	28420.722	.000	1	1.000	.000	.000	.
D.o.t.w(5) by E.c.d(10)*	-14.701	40192.970	.000	1	1.000	.000	.000	.
D.o.t.w(5) by E.c.d(12)*	26.626	40192.969	.000	1	.999	365943134115.535	.000	.
D.o.t.w(6) by E.c.d(1)*	-14.261	15191.515	.000	1	.999	.000	.000	.
D.o.t.w(6) by E.c.d(2)*	-14.349	28420.722	.000	1	1.000	.000	.000	.
D.o.t.w(6) by E.c.d(7)*	-14.378	40192.970	.000	1	1.000	.000	.000	.
D.o.t.w(6) by E.c.d(10)*	-14.296	23205.422	.000	1	1.000	.000	.000	.
D.o.t.w(6) by E.c.d(11)*	-15.984	28420.722	.000	1	1.000	.000	.000	.
D.o.t.w(6) by E.c.d(12)*	-15.375	16408.711	.000	1	.999	.000	.000	.

D.o.t.w(6) by E.c.d(14)*	-16.210	40192.970	.000	1	1.000	.000	.000	.

* p > .05

The multivariate logistic regression analysis shows that variable Elapsing calendar days (R^2 = 2.9%, $p < .001$) and variable Week or weekend (R^2 = 0.1%, O.R. = .032, 95% C.I. .015 - .072, $p < .001$) were significant predictors for the dependent variable. In the table below we can see that Week or weekend not a significant (R^2 = 3.0%, p = .359) moderator is between the predictor (Elapsing calendar days) and the dependent variable (show/no-show).

Multivariate Binary logistic regression model - Preference of showing or not showing – Week or weekend as moderator

Variables	B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I.for EXP(B) Lower	Upper
Elapsing calendar days			6300.666	17	< .001			
E.c.d(1)	.725	.017	1842.335	1	< .001	2.064	1.997	2.134
E.c.d(2)	.805	.021	1418.466	1	< .001	2.237	2.145	2.333
E.c.d(3)	1.087	.022	2487.086	1	< .001	2.965	2.841	3.095
E.c.d(4)	1.231	.036	1183.359	1	< .001	3.425	3.193	3.674
E.c.d(5)	1.140	.051	498.864	1	< .001	3.127	2.829	3.455
E.c.d(6)	1.373	.033	1724.661	1	< .001	3.947	3.699	4.211
E.c.d(7)	.971	.113	74.457	1	< .001	2.640	2.118	3.291
E.c.d(8)	1.185	.140	71.846	1	< .001	3.269	2.486	4.299
E.c.d(9)	1.431	.149	91.747	1	< .001	4.181	3.120	5.603
E.c.d(10)	1.268	.204	38.785	1	< .001	3.554	2.384	5.296
E.c.d(11)	1.751	.113	238.887	1	< .001	5.762	4.615	7.196
E.c.d(12)	1.600	.060	710.549	1	< .001	4.954	4.404	5.573
E.c.d(13)	1.006	.257	15.293	1	< .001	2.736	1.652	4.530
E.c.d(14)*	.715	.722	.980	1	.322	2.044	.496	8.422
E.c.d(15)*	1.366	.736	3.442	1	.064	3.918	.926	16.580
E.c.d(16)*	-17.352	11602.711	.000	1	.999	.000	.000	.
E.c.d(17)*	-17.352	20096.485	.000	1	.999	.000	.000	.
Week or weekend(1)*	-3.541	.578	37.582	1	< .001	.029	.009	.090
Elapsing calendar days * Week or weekend*			13.143	12	.359			

E.c.d(1) by W.o.w(1)*	1.922	1.159	2.751	1	.097	6.833	.705	66.205
E.c.d(2) by W.o.w(1)	2.526	1.162	4.721	1	.030	12.500	1.281	122.002
E.c.d(3) by W.o.w(1)*	-14.898	10048.243	.000	1	.999	.000	.000	.
E.c.d(4) by W.o.w(1)*	-15.043	20096.485	.000	1	.999	.000	.000	.
E.c.d(5) by W.o.w(1)*	-14.951	23205.422	.000	1	.999	.000	.000	.
E.c.d(6) by W.o.w(1)*	-15.184	17974.843	.000	1	.999	.000	.000	.
E.c.d(7) by W.o.w(1)*	-14.782	28420.722	.000	1	1.000	.000	.000	.
E.c.d(8) by W.o.w(1)*	-14.996	28420.722	.000	1	1.000	.000	.000	.
E.c.d(10) by W.o.w(1)*	-15.079	20096.485	.000	1	.999	.000	.000	.
E.c.d(11) by W.o.w(1)*	-15.563	28420.722	.000	1	1.000	.000	.000	.
E.c.d(12) by W.o.w(1)	3.999	1.226	10.637	1	.001	54.568	4.933	603.620
E.c.d(14) by W.o.w(1)*	-14.526	40192.970	.000	1	1.000	.000	.000	.

* p > .05

The bivariate logistic regression analysis shows that variable Elapsing calendar days ($R^2 = 2.9\%$, $p < .001$) and variable Month of the year ($R^2 = 0.1\%$, $p < .001$) were significant predictors for the dependent variable. In the table below we can see that Month of the year a significant ($R^2 = 3.1\%$, $p = .007$) moderator is between the predictor (Elapsing calendar days) and the dependent variable (show/no-show).

Multivariate Binary logistic regression model - Preference of showing or not showing – Month of the year as moderator

Variables	**B**	**S.E.**	**Wald**	**df**	**Sig.**	**Exp(B)**	**95% C.I.for EXP(B)**	
							Lower	**Upper**
Elapsing calendar days			731.098	17	< .001			
E.c.d(1)	.711	.055	168.818	1	< .001	2.035	1.828	2.265
E.c.d(2)	.781	.070	123.672	1	< .001	2.185	1.903	2.507
E.c.d(3)	1.162	.075	240.655	1	< .001	3.196	2.760	3.702
E.c.d(4)	1.346	.111	146.377	1	< .001	3.841	3.089	4.777
E.c.d(5)	1.462	.164	79.214	1	< .001	4.314	3.127	5.952
E.c.d(6)	1.250	.115	118.371	1	< .001	3.489	2.786	4.370

E.c.d(7)*	-17.350	6892.933	.000	1	.998	.000	.000	.
E.c.d(8)*	-.373	1.007	.137	1	.711	.689	.096	4.958
E.c.d(9)	1.476	.467	9.990	1	.002	4.377	1.752	10.933
E.c.d(10)	1.459	.522	7.830	1	.005	4.304	1.548	11.962
E.c.d(11)	1.968	.287	46.935	1	< .001	7.159	4.076	12.571
E.c.d(12)	1.741	.153	129.329	1	< .001	5.700	4.223	7.694
E.c.d(13)*	-17.259	8204.342	.000	1	.998	.000	.000	.
E.c.d(14)*	-17.259	12710.133	.000	1	.999	.000	.000	.
E.c.d(15)	2.558	.791	10.450	1	.001	12.911	2.738	60.891
E.c.d(16)*	-17.259	23205.422	.000	1	.999	.000	.000	.
E.c.d(17)*	-17.259	28420.722	.000	1	1.000	.000	.000	.
Month			108.901	11	< .001			
Month(1)	.212	.042	25.265	1	<.001	1.237	1.138	1.343
Month(2)*	.016	.043	.137	1	.711	1.016	.933	1.107
Month(3)*	.016	.045	.119	1	.730	1.016	.930	1.110
Month(4)*	.074	.044	2.842	1	.092	1.077	.988	1.174
Month(5)*	.050	.044	1.298	1	.255	1.051	.965	1.146
Month(6)*	-.021	.045	.206	1	.650	.980	.897	1.070
Month(7)	-.130	.047	7.740	1	.005	.878	.802	.962
Month(8)*	-.047	.046	1.043	1	.307	.954	.873	1.044
Month(9)	-.097	.045	4.711	1	.030	.908	.832	.991
Month(10)	-.103	.045	5.290	1	.021	.903	.827	.985
Month(11)*	-.091	.047	3.770	1	.052	.913	.833	1.001
Month * Elapsing calendar days			175.206	132	.007			
Month(1) by E.c.d(1)*	-.139	.079	3.066	1	.080	.870	.745	1.017
Month(1) by E.c.d(2)*	-.093	.100	.854	1	.355	.911	.749	1.110
Month(1) by E.c.d(3)	-.210	.105	4.000	1	.046	.810	.659	.996
Month(1) by E.c.d(4)*	-.289	.171	2.862	1	.091	.749	.536	1.047

Month(1) by E.c.d(5)*	-.465	.260	3.211	1	.073	.628	.377	1.045
Month(1) by E.c.d(6)*	.112	.158	.500	1	.479	1.118	.821	1.523
Month(1) by E.c.d(7)*	18.036	6892.933	.000	1	.998	68038919.712	.000	.
Month(1) by E.c.d(8)*	1.999	1.258	2.526	1	.112	7.382	.627	86.855
Month(2) by E.c.d(1)*	-.044	.079	.315	1	.575	.957	.819	1.117
Month(2) by E.c.d(2)*	.120	.101	1.403	1	.236	1.127	.924	1.375
Month(2) by E.c.d(3)*	-.183	.107	2.954	1	.086	.833	.676	1.026
Month(2) by E.c.d(4)*	.012	.160	.006	1	.940	1.012	.740	1.384
Month(2) by E.c.d(5)*	.003	.222	.000	1	.990	1.003	.649	1.549
Month(2) by E.c.d(6)*	.056	.156	.129	1	.720	1.058	.779	1.436
Month(2) by E.c.d(7)*	18.613	6892.933	.000	1	.998	121246520.099	.000	.
Month(2) by E.c.d(8)*	1.879	1.083	3.014	1	.083	6.550	.785	54.679
Month(2) by E.c.d(9)*	.569	.715	.634	1	.426	1.767	.435	7.169
Month(3) by E.c.d(1)*	-.003	.082	.001	1	.974	.997	.850	1.171
Month(3) by E.c.d(2)*	-.028	.106	.069	1	.792	.972	.790	1.197
Month(3) by E.c.d(3)*	-.087	.108	.656	1	.418	.916	.742	1.132
Month(3) by E.c.d(4)*	.099	.158	.390	1	.532	1.104	.810	1.505
Month(3) by E.c.d(5)	-.518	.249	4.326	1	.038	.596	.366	.971
Month(3) by E.c.d(6)	.464	.157	8.662	1	.003	1.590	1.167	2.165
Month(3) by E.c.d(7)*	19.077	6892.933	.000	1	.998	192782329.066	.000	.
Month(3) by E.c.d(8)*	.627	1.237	.257	1	.612	1.872	.166	21.139

Month(3) by E.c.d(9)*	.444	.670	.440	1	.507	1.560	.420	5.796
Month(3) by E.c.d(10)*	-18.825	13397.657	.000	1	.999	.000	.000	.
Month(4) by E.c.d(1)*	.002	.079	.001	1	.981	1.002	.859	1.169
Month(4) by E.c.d(2)*	.015	.100	.022	1	.882	1.015	.835	1.234
Month(4) by E.c.d(3)*	.014	.101	.020	1	.887	1.014	.832	1.238
Month(4) by E.c.d(4)*	.152	.160	.907	1	.341	1.164	.851	1.593
Month(4) by E.c.d(5)*	-.309	.234	1.746	1	.186	.734	.464	1.161
Month(4) by E.c.d(6)*	.148	.154	.920	1	.337	1.159	.857	1.568
Month(4) by E.c.d(7)*	18.248	6892.933	.000	1	.998	84125579.911	.000	.
Month(4) by E.c.d(8)*	1.190	1.169	1.037	1	.308	3.289	.333	32.501
Month(4) by E.c.d(9)*	.451	.603	.558	1	.455	1.569	.481	5.117
Month(4) by E.c.d(10)*	-.453	.897	.255	1	.614	.636	.110	3.687
Month(4) by E.c.d(11)*	.019	.817	.001	1	.981	1.019	.206	5.051
Month(5) by E.c.d(1)*	.003	.079	.001	1	.972	1.003	.859	1.171
Month(5) by E.c.d(2)*	.028	.100	.077	1	.782	1.028	.845	1.250
Month(5) by E.c.d(3)*	.027	.103	.068	1	.795	1.027	.839	1.257
Month(5) by E.c.d(4)*	-.226	.167	1.842	1	.175	.798	.575	1.106
Month(5) by E.c.d(5)*	-.124	.238	.271	1	.603	.884	.555	1.408
Month(5) by E.c.d(6)*	.149	.167	.790	1	.374	1.160	.836	1.610
Month(5) by E.c.d(7)*	18.450	6892.933	.000	1	.998	102999060.575	.000	.
Month(5) by E.c.d(8)*	1.925	1.061	3.290	1	.070	6.854	.856	54.853

Month(5) by E.c.d(9)*	.290	.587	.244	1	.622	1.336	.423	4.223
Month(5) by E.c.d(10)*	.552	.663	.693	1	.405	1.736	.473	6.369
Month(5) by E.c.d(11)*	-.395	.441	.804	1	.370	.673	.284	1.598
Month(5) by E.c.d(12)*	.143	.277	.267	1	.605	1.154	.671	1.984
Month(6) by E.c.d(1)*	.055	.081	.467	1	.495	1.057	.902	1.239
Month(6) by E.c.d(2)*	.132	.104	1.613	1	.204	1.141	.931	1.399
Month(6) by E.c.d(3)*	-.078	.113	.481	1	.488	.925	.741	1.154
Month(6) by E.c.d(4)*	-.323	.182	3.150	1	.076	.724	.507	1.034
Month(6) by E.c.d(5)*	.152	.219	.480	1	.488	1.164	.757	1.789
Month(6) by E.c.d(6)*	.106	.176	.360	1	.549	1.112	.787	1.571
Month(6) by E.c.d(7)*	18.365	6892.933	.000	1	.998	94612021.615	.000	.
Month(6) by E.c.d(8)*	1.041	1.167	.796	1	.372	2.833	.288	27.914
Month(6) by E.c.d(9)*	.000	.633	.000	1	.999	1.000	.289	3.458
Month(6) by E.c.d(10)*	-18.789	6793.852	.000	1	.998	.000	.000	.
Month(6) by E.c.d(11)*	.216	.427	.256	1	.613	1.241	.537	2.866
Month(6) by E.c.d(12)*	-.289	.240	1.455	1	.228	.749	.468	1.198
Month(6) by E.c.d(13)*	-.071	16408.705	.000	1	1.000	.932	.000	.
Month(7) by E.c.d(1)	.201	.079	6.463	1	.011	1.223	1.047	1.428
Month(7) by E.c.d(2)	.240	.100	5.795	1	.016	1.271	1.046	1.545
Month(7) by E.c.d(3)*	.098	.108	.822	1	.365	1.103	.892	1.363
Month(7) by E.c.d(4)*	.158	.162	.956	1	.328	1.171	.853	1.608

Month(7) by E.c.d(5)	-.538	.265	4.140	1	.042	.584	.347	.980
Month(7) by E.c.d(6)*	.060	.173	.119	1	.730	1.061	.756	1.489
Month(7) by E.c.d(7)*	18.723	6892.933	.000	1	.998	135243706.639	.000	.
Month(7) by E.c.d(8)*	1.958	1.073	3.328	1	.068	7.087	.865	58.087
Month(7) by E.c.d(9)*	-1.405	1.113	1.594	1	.207	.245	.028	2.174
Month(7) by E.c.d(10)*	.372	.705	.278	1	.598	1.450	.364	5.771
Month(7) by E.c.d(11)*	.165	.408	.164	1	.686	1.179	.530	2.624
Month(7) by E.c.d(12)*	.174	.222	.616	1	.432	1.190	.771	1.837
Month(7) by E.c.d(13)*	19.072	8204.342	.000	1	.998	191892735.483	.000	.
Month(7) by E.c.d(14)*	.039	20755.560	.000	1	1.000	1.039	.000	.
Month(8) by E.c.d(1)*	.031	.084	.136	1	.712	1.031	.875	1.215
Month(8) by E.c.d(2)*	.045	.100	.203	1	.652	1.046	.860	1.273
Month(8) by E.c.d(3)*	-.040	.107	.138	1	.710	.961	.780	1.184
Month(8) by E.c.d(4)*	-.312	.176	3.128	1	.077	.732	.518	1.034
Month(8) by E.c.d(5)	-.914	.278	10.806	1	.001	.401	.232	.691
Month(8) by E.c.d(6)*	.142	.162	.771	1	.380	1.153	.839	1.585
Month(8) by E.c.d(7)*	17.842	6892.933	.000	1	.998	56048461.315	.000	.
Month(8) by E.c.d(8)*	.941	1.167	.650	1	.420	2.562	.260	25.210
Month(8) by E.c.d(9)*	.190	.635	.089	1	.765	1.209	.348	4.202
Month(8) by E.c.d(10)*	-.268	.898	.089	1	.766	.765	.132	4.448
Month(8) by E.c.d(11)*	-.420	.440	.912	1	.340	.657	.278	1.555

Month(8) by E.c.d(12)*	.003	.216	.000	1	.989	1.003	.656	1.533
Month(8) by E.c.d(13)*	18.807	8204.342	.000	1	.998	147160736.239	.000	.
Month(8) by E.c.d(14)*	-.044	19065.199	.000	1	1.000	.956	.000	.
Month(8) by E.c.d(15)*	-19.861	28420.722	.000	1	.999	.000	.000	.
Month(9) by E.c.d(1)*	.030	.080	.140	1	.708	1.031	.880	1.206
Month(9) by E.c.d(2)*	.015	.103	.021	1	.884	1.015	.829	1.243
Month(9) by E.c.d(3)*	-.050	.103	.233	1	.630	.951	.777	1.165
Month(9) by E.c.d(4)*	-.327	.171	3.656	1	.056	.721	.515	1.008
Month(9) by E.c.d(5)*	-.458	.251	3.328	1	.068	.632	.387	1.035
Month(9) by E.c.d(6)*	.099	.158	.395	1	.530	1.105	.810	1.506
Month(9) by E.c.d(7)*	18.116	6892.933	.000	1	.998	73760263.909	.000	.
Month(9) by E.c.d(8)*	1.951	1.082	3.250	1	.071	7.039	.844	58.735
Month(9) by E.c.d(9)*	-.602	.754	.638	1	.424	.548	.125	2.398
Month(9) by E.c.d(10)*	-.362	.791	.210	1	.647	.696	.148	3.281
Month(9) by E.c.d(11)*	-.434	.439	.980	1	.322	.648	.274	1.530
Month(9) by E.c.d(12)*	.014	.203	.005	1	.946	1.014	.682	1.508
Month(9) by E.c.d(13)*	17.337	8204.342	.000	1	.998	33842244.601	.000	.
Month(9) by E.c.d(14)*	.006	16641.470	.000	1	1.000	1.006	.000	.
Month(9) by E.c.d(15)*	-19.811	13397.657	.000	1	.999	.000	.000	.
Month(9) by E.c.d(16)*	.006	46410.844	.000	1	1.000	1.006	.000	.
Month(10) by E.c.d(1)*	.123	.079	2.402	1	.121	1.131	.968	1.321

Month(10) by E.c.d(2)*	-.035	.105	.112	1	.738	.966	.786	1.186
Month(10) by E.c.d(3)*	-.118	.106	1.235	1	.266	.888	.721	1.094
Month(10) by E.c.d(4)*	-.200	.168	1.409	1	.235	.819	.589	1.139
Month(10) by E.c.d(5)*	-.438	.245	3.198	1	.074	.646	.400	1.043
Month(10) by E.c.d(6)*	-.001	.163	.000	1	.994	.999	.726	1.375
Month(10) by E.c.d(7)*	18.273	6892.933	.000	1	.998	86262590.651	.000	.
Month(10) by E.c.d(8)*	2.083	1.067	3.813	1	.051	8.032	.992	65.019
Month(10) by E.c.d(9)*	-1.171	.856	1.873	1	.171	.310	.058	1.658
Month(10) by E.c.d(10)*	-.448	.790	.322	1	.570	.639	.136	3.004
Month(10) by E.c.d(11)*	-.203	.391	.269	1	.604	.816	.379	1.758
Month(10) by E.c.d(12)*	-.353	.218	2.632	1	.105	.703	.459	1.076
Month(10) by E.c.d(13)*	17.894	8204.342	.000	1	.998	59060126.620	.000	.
Month(10) by E.c.d(14)*	19.710	12710.133	.000	1	.999	363110373.481	.000	.
Month(10) by E.c.d(15)*	-19.805	17974.843	.000	1	.999	.000	.000	.
Month(10) by E.c.d(16)*	.011	27210.769	.000	1	1.000	1.011	.000	.
Month(10) by E.c.d(17)*	.011	40192.970	.000	1	1.000	1.011	.000	.
Month(11) by E.c.d(1)*	.033	.086	.147	1	.701	1.033	.874	1.222
Month(11) by E.c.d(2)*	-.061	.112	.298	1	.585	.941	.756	1.171
Month(11) by E.c.d(3)*	-.178	.115	2.424	1	.120	.837	.668	1.047
Month(11) by E.c.d(4)*	-.127	.187	.459	1	.498	.881	.611	1.271
Month(11) by E.c.d(5)*	-.458	.252	3.320	1	.068	.632	.386	1.035

Month(11) by E.c.d(6)*	.318	.171	3.446	1	.063	1.375	.982	1.924
Month(11) by E.c.d(7)*	17.412	6892.933	.000	1	.998	36487818.583	.000	.

* p > .05

The multivariate logistic regression analysis shows that variable Elapsing calendar days ($R^2 = 2.9\%$, $p < .001$) and variable Season of the year ($R^2 = 0.000473\%$, $p < .001$) were significant predictors for the dependent variable. In the table below we can see that Season of the year a significant ($R^2 = 3.0\%$, $p = .007$) moderator is between the predictor (Elapsing calendar days) and the dependent variable (show/no-show).

Multivariate Binary logistic regression model - Preference of showing or not showing – Season of the year as moderator

Variables	B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I.for EXP(B)	
							Lower	Upper
Elapsing calendar days			1789.227	17	< .001			
E.c.d(1)	.719	.033	473.146	1	< .001	2.052	1.924	2.190
E.c.d(2)	.785	.042	341.707	1	< .001	2.193	2.018	2.383
E.c.d(3)	1.107	.042	687.336	1	< .001	3.025	2.785	3.286
E.c.d(4)	1.392	.066	451.062	1	< .001	4.023	3.538	4.574
E.c.d(5)	1.205	.098	151.669	1	< .001	3.338	2.755	4.043
E.c.d(6)	1.482	.062	577.461	1	< .001	4.403	3.902	4.969
E.c.d(7)	1.260	.194	42.316	1	< .001	3.524	2.411	5.150
E.c.d(8)	.987	.286	11.909	1	.001	2.683	1.532	4.700
E.c.d(9)	2.096	.218	92.421	1	< .001	8.130	5.303	12.463
E.c.d(10)	1.354	.426	10.120	1	.001	3.875	1.682	8.925
E.c.d(11)	1.796	.308	34.048	1	< .001	6.027	3.297	11.019
E.c.d(12)	1.889	.437	18.652	1	< .001	6.615	2.806	15.592
E.c.d(13)	-17.428	28419.901	.000	1	1.000	.000	.000	.
E.c.d(14)*	1.065	.727	2.146	1	.143	2.900	.698	12.049
E.c.d(15)	1.470	.736	3.988	1	.046	4.350	1.028	18.414
E.c.d(16)*	-17.248	11602.711	.000	1	.999	.000	.000	.
E.c.d(17)*	-17.248	20096.485	.000	1	.999	.000	.000	.
Season			59.469	3	< .001			
Season(1)	-.083	.026	10.186	1	.001	.920	.875	.968
Season(2)	-.144	.026	31.210	1	< .001	.866	.823	.911
Season(3)*	.036	.025	2.019	1	.155	1.037	.986	1.089

Season * Elapsing calendar days			64.283	39	.007			
Season(1) by E.c.d(1)*	.059	.048	1.523	1	.217	1.060	.966	1.164
Season(1) by E.c.d(2)	.118	.059	3.958	1	.047	1.125	1.002	1.264
Season(1) by E.c.d(3)*	.089	.061	2.133	1	.144	1.094	.970	1.233
Season(1) by E.c.d(4)*	-.175	.099	3.134	1	.077	.839	.691	1.019
Season(1) by E.c.d(5)*	-.073	.141	.266	1	.606	.930	.706	1.225
Season(1) by E.c.d(6)	-.189	.096	3.852	1	.050	.828	.686	1.000
Season(1) by E.c.d(7)*	-.258	.286	.814	1	.367	.773	.441	1.353
Season(1) by E.c.d(8)*	.142	.385	.137	1	.712	1.153	.542	2.455
Season(1) by E.c.d(9)	-.804	.353	5.189	1	.023	.448	.224	.894
Season(1) by E.c.d(10)*	-.008	.549	.000	1	.989	.992	.338	2.910
Season(1) by E.c.d(11)*	.079	.358	.049	1	.825	1.082	.536	2.185
Season(1) by E.c.d(12)*	-.135	.447	.091	1	.762	.874	.364	2.099
Season(1) by E.c.d(13)*	19.088	28419.901	.000	1	.999	194955033.872	.000	.

Season(1) by E.c.d(14)*	-18.373	12118.636	.000	1	.999	.000	.000	.
Season(2) by E.c.d(1)*	.056	.048	1.380	1	.240	1.058	.963	1.161
Season(2) by E.c.d(2)*	-.003	.061	.003	1	.957	.997	.884	1.124
Season(2) by E.c.d(3)*	-.055	.060	.832	1	.362	.946	.841	1.065
Season(2) by E.c.d(4)	-.310	.101	9.461	1	.002	.734	.602	.894
Season(2) by E.c.d(5)*	-.214	.145	2.190	1	.139	.807	.608	1.072
Season(2) by E.c.d(6)*	-.075	.089	.712	1	.399	.928	.779	1.104
Season(2) by E.c.d(7)*	-.567	.309	3.364	1	.067	.567	.310	1.040
Season(2) by E.c.d(8)*	.383	.372	1.057	1	.304	1.467	.707	3.044
Season(2) by E.c.d(9)	-1.209	.391	9.577	1	.002	.299	.139	.642
Season(2) by E.c.d(10)*	-.089	.528	.028	1	.866	.915	.325	2.574
Season(2) by E.c.d(11)*	-.012	.349	.001	1	.973	.988	.499	1.958
Season(2) by E.c.d(12)*	-.274	.445	.379	1	.538	.760	.318	1.819
Season(2) by E.c.d(13)*	17.688	28419.901	.000	1	1.000	48041853.954	.000	.

Season(3) by E.c.d(1)*	-.062	.047	1.740	1	.187	.940	.857	1.031
Season(3) by E.c.d(2)*	-.007	.061	.012	1	.911	.993	.882	1.119
Season(3) by E.c.d(3)*	-.065	.062	1.130	1	.288	.937	.830	1.057
Season(3) by E.c.d(4)*	-.152	.097	2.442	1	.118	.859	.710	1.039
Season(3) by E.c.d(5)*	.089	.143	.390	1	.532	1.093	.827	1.445
Season(3) by E.c.d(6)*	-.167	.091	3.393	1	.065	.846	.708	1.011
Season(3) by E.c.d(7)*	-.327	.345	.895	1	.344	.721	.367	1.419
Season(3) by E.c.d(8)*	.515	.490	1.105	1	.293	1.673	.641	4.367
Season(3) by E.c.d(9)*	-19.523	14210.361	.000	1	.999	.000	.000	.
Season(3) by E.c.d(10)*	-18.782	40192.970	.000	1	1.000	.000	.000	.
Season(3) by E.c.d(11)*	-19.224	16408.711	.000	1	.999	.000	.000	.
Season(3) by E.c.d(12)*	-.162	.688	.055	1	.814	.851	.221	3.279

* $p > .05$

The multivariate logistic regression analysis shows that variable Elapsing calendar days ($R^2 = 2.9\%$, $p < .001$) and variable Part of the day ($R^2 = 0.2\%$, $p < .001$) were significant predictors for the dependent variable. In the table below we can see that Part of the day a significant ($R^2 = 3.1\%$, $p = 0.05$) moderator is between the predictor (Elapsing calendar days) and the dependent variable (show/no-show).

Multivariate Binary logistic regression model - Preference of showing or not showing – Part of the day as moderator

Variables	B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I.for EXP(B) Lower	Upper
Elapsing calendar days			3097.859	17	< .001			
E.c.d(1)	.663	.023	846.721	1	< .001	1.941	1.856	2.030
E.c.d(2)	.708	.029	594.690	1	< .001	2.029	1.917	2.148
E.c.d(3)	1.036	.029	1298.674	1	< .001	2.818	2.663	2.981
E.c.d(4)	1.188	.047	639.306	1	< .001	3.280	2.991	3.596
E.c.d(5)	1.096	.068	256.807	1	< .001	2.993	2.618	3.423
E.c.d(6)	1.322	.044	903.598	1	< .001	3.753	3.443	4.091
E.c.d(7)	.705	.173	16.531	1	< .001	2.023	1.440	2.841
E.c.d(8)	1.207	.184	43.130	1	< .001	3.342	2.332	4.791
E.c.d(9)	1.311	.209	39.537	1	< .001	3.712	2.466	5.586
E.c.d(10)	1.314	.269	23.834	1	< .001	3.720	2.195	6.304
E.c.d(11)	1.618	.158	105.154	1	< .001	5.044	3.702	6.873
E.c.d(12)	1.547	.081	365.373	1	< .001	4.697	4.008	5.504
E.c.d(13)	.675	.457	2.181	1	.140	1.964	.802	4.812
E.c.d(14)*	-17.410	8380.813	.000	1	.998	.000	.000	.
E.c.d(15)	2.184	.775	7.945	1	.005	8.878	1.945	40.528
E.c.d(16)*	-17.410	23205.422	.000	1	.999	.000	.000	.
E.c.d(17)*	-17.410	40192.970	.000	1	1.000	.000	.000	.
Part of the day			40.116	3	< .001			
P.o.t.d(1)	-.112	.018	37.269	1	< .001	.894	.862	.927
P.o.t.d(2)*	-17.410	514.492	.001	1	.973	.000	.000	.
P.o.t.d(3)	-.274	.132	4.328	1	.037	.760	.587	.984
Part of the day * Elapsing calendar days			43.800	30	.050			
P.o.t.d(1) by E.c.d(1)	.126	.034	13.640	1	< .001	1.134	1.061	1.212
P.o.t.d(1) by E.c.d(2)	.203	.043	22.232	1	< .001	1.225	1.126	1.332
P.o.t.d(1) by E.c.d(3)	.097	.044	4.830	1	.028	1.102	1.011	1.202
P.o.t.d(1) by E.c.d(4)*	.072	.073	.970	1	.325	1.074	.932	1.239
P.o.t.d(1) by E.c.d(5)*	.087	.103	.710	1	.400	1.090	.892	1.334

P.o.t.d(1) by E.c.d(6)*	.097	.067	2.125	1	.145	1.102	.967	1.256
P.o.t.d(1) by E.c.d(7)	.502	.228	4.848	1	.028	1.652	1.057	2.583
P.o.t.d(1) by E.c.d(8)*	-.074	.283	.069	1	.793	.929	.533	1.617
P.o.t.d(1) by E.c.d(9)*	.250	.299	.701	1	.402	1.284	.715	2.307
P.o.t.d(1) by E.c.d(10)*	-.141	.412	.117	1	.733	.869	.388	1.947
P.o.t.d(1) by E.c.d(11)*	.270	.227	1.421	1	.233	1.310	.840	2.044
P.o.t.d(1) by E.c.d(12)*	.105	.120	.766	1	.381	1.111	.877	1.407
P.o.t.d(1) by E.c.d(13)*	.540	.553	.953	1	.329	1.717	.580	5.079
P.o.t.d(1) by E.c.d(14)*	18.830	8380.814	.000	1	.998	150591447.219	.000	.
P.o.t.d(1) by E.c.d(15)*	-19.481	10742.023	.000	1	.999	.000	.000	.
P.o.t.d(1) by E.c.d(16)*	.112	26795.313	.000	1	1.000	1.119	.000	.
P.o.t.d(1) by E.c.d(17)*	.112	46410.844	.000	1	1.000	1.119	.000	.
P.o.t.d(2) by E.c.d(1)*	18.594	514.493	.001	1	.971	118902688.695	.000	.
P.o.t.d(2) by E.c.d(2)*	-.708	40196.263	.000	1	1.000	.493	.000	.
P.o.t.d(2) by E.c.d(3)*	-1.036	40196.263	.000	1	1.000	.355	.000	.
P.o.t.d(2) by E.c.d(4)*	-1.188	40196.263	.000	1	1.000	.305	.000	.
P.o.t.d(3) by E.c.d(1)*	-.434	.301	2.073	1	.150	.648	.359	1.170

P.o.t.d(3) by E.c.d(2)*	.022	.437	.002	1	.961	1.022	.434	2.405
P.o.t.d(3) by E.c.d(3)*	-.264	.733	.130	1	.718	.768	.183	3.226
P.o.t.d(3) by E.c.d(4)*	1.088	.558	3.804	1	.051	2.968	.995	8.856
P.o.t.d(3) by E.c.d(5)*	-18.232	9220.900	.000	1	.998	.000	.000	.
P.o.t.d(3) by E.c.d(6)*	-18.458	11147.524	.000	1	.999	.000	.000	.
P.o.t.d(3) by E.c.d(7)*	-17.840	28420.722	.000	1	.999	.000	.000	.
P.o.t.d(3) by E.c.d(9)*	-18.447	28420.722	.000	1	.999	.000	.000	.
P.o.t.d(3) by E.c.d(11)*	-18.754	40192.970	.000	1	1.000	.000	.000	.

* $p > .05$

7.8 SPSS Backwards-logistic regression

7.8.1 Gender

Backward - Multivariate Binary logistic regression model - Preference of showing or not showing – Dependent variable = Gender. Independent variable = Show/no-show, Moderator variable = Environmental factors

Variables	B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I.for EXP(B)	
							Lower	Upper
Gender(1)	.236	.029	66.644	1	.000	1.266	1.196	1.340
Distance	-.003	.000	247.774	1	.000	.997	.996	.997
Day of the week			78.897	6	.000			
D.o.t.w(1)	-.095	.027	12.292	1	.000	.910	.863	.959
D.o.t.w(2)	-.164	.028	34.446	1	.000	.849	.803	.896
D.o.t.w(3)	-.122	.027	20.021	1	.000	.885	.839	.934
D.o.t.w(4)	-.144	.030	23.304	1	.000	.866	.816	.918
D.o.t.w(5)	-4.242	1.000	17.977	1	.000	.014	.002	.102
D.o.t.w(6)	-4.411	1.000	19.445	1	.000	.012	.002	.086
Month			153.822	11	.000			
Month(1)	.110	.030	13.735	1	.000	1.116	1.053	1.183
Month(2)	-.014	.030	.230	1	.631	.986	.930	1.045
Month(3)	.004	.031	.017	1	.897	1.004	.945	1.067
Month(4)	.075	.030	6.285	1	.012	1.078	1.016	1.142
Month(5)	.031	.030	1.035	1	.309	1.031	.972	1.093
Month(6)	-.064	.031	4.166	1	.041	.938	.883	.997
Month(7)	-.038	.031	1.513	1	.219	.963	.907	1.023
Month(8)	-.073	.031	5.471	1	.019	.930	.875	.988
Month(9)	-.130	.030	18.239	1	.000	.878	.828	.932
Month(10)	-.130	.030	18.161	1	.000	.878	.827	.932
Month(11)	-.150	.032	21.302	1	.000	.861	.808	.917
Part of the day			40.431	3	.000			
P.o.t.d(1)	-.076	.018	17.255	1	.000	.927	.895	.961
P.o.t.d(2)	-17.671	728.299	.001	1	.981	.000	.000	.
P.o.t.d(3)	-.686	.135	25.636	1	.000	.504	.386	.657

Day of the week * Gender			13.562	5	.019			
D.o.t.w(1) by Gender(1)	-.038	.038	1.004	1	.316	.963	.894	1.037
D.o.t.w(2) by Gender(1)	.017	.039	.201	1	.654	1.018	.943	1.098
D.o.t.w(3) by Gender(1)	-.095	.039	6.059	1	.014	.909	.843	.981
D.o.t.w(4) by Gender(1)	.013	.041	.106	1	.745	1.014	.934	1.099
D.o.t.w(5) by Gender(1)	1.831	1.119	2.678	1	.102	6.240	.696	55.929
Part of the day * Gender			6.268	3	.099			
P.o.t.d(1) by Gender(1)	-.036	.026	1.986	1	.159	.965	.918	1.014
P.o.t.d(2) by Gender(1)	12.870	728.300	.000	1	.986	388336.268	.000	.
P.o.t.d(3) by Gender(1)	.464	.232	3.980	1	.046	1.590	1.008	2.508
Constant	-3.426	.029	14257.243	1	.000	.033		

7.8.2 Age

Variables	**B**	**S.E.**	**Wald**	**df**	**Sig.**	**Exp(B)**	**95% C.I.for EXP(B)**	
							Lower	**Upper**
Age			85.243	3	.000			
Age(1)	.527	.093	32.249	1	.000	1.694	1.412	2.032
Age(2)	.141	.071	3.943	1	.047	1.151	1.002	1.322
Age(3)	-.309	.089	12.107	1	.001	.734	.617	.874
Distance	-.002	.001	23.277	1	.000	.998	.997	.999
Day of the week			48.147	6	.000			
D.o.t.w(1)	-.064	.046	1.924	1	.165	.938	.857	1.027
D.o.t.w(2)	-.312	.051	36.919	1	.000	.732	.662	.810
D.o.t.w(3)	-.220	.048	21.165	1	.000	.803	.731	.882
D.o.t.w(4)	-.115	.051	5.147	1	.023	.891	.807	.984
D.o.t.w(5)	-17.787	4032.655	.000	1	.996	.000	.000	.

D.o.t.w(6)	-17.767	4864.273	.000	1	.997	.000	.000	.
Month			38.358	11	.000			
Month(1)	.146	.075	3.736	1	.053	1.157	.998	1.341
Month(2)	.086	.074	1.352	1	.245	1.090	.943	1.260
Month(3)	.018	.079	.051	1	.822	1.018	.872	1.188
Month(4)	.094	.077	1.519	1	.218	1.099	.946	1.277
Month(5)	.093	.075	1.533	1	.216	1.098	.947	1.273
Month(6)	.057	.080	.506	1	.477	1.059	.905	1.238
Month(7)	.289	.074	15.125	1	.000	1.335	1.154	1.544
Month(8)	.132	.076	3.004	1	.083	1.141	.983	1.325
Month(9)	-.002	.076	.000	1	.984	.998	.861	1.158
Month(10)	-.028	.076	.136	1	.712	.972	.838	1.128
Month(11)	-.109	.083	1.749	1	.186	.897	.763	1.054
Part of the day			42.912	3	.000			
P.o.t.d(1)	-.202	.032	40.598	1	.000	.817	.768	.869
P.o.t.d(2)	-17.725	10727.331	.000	1	.999	.000	.000	.
P.o.t.d(3)	-.605	.337	3.212	1	.073	.546	.282	1.058
Distance * Age			16.780	3	.001			
Distance by Age(1)	-.003	.001	16.463	1	.000	.997	.995	.998
Distance by Age(2)	-.001	.001	4.025	1	.045	.999	.998	1.000
Distance by Age(3)	-.002	.001	3.557	1	.059	.998	.997	1.000
Day of the week * Age			41.403	18	.001			
D.o.t.w(1) by Age(1)	-.046	.071	.417	1	.518	.955	.832	1.097
D.o.t.w(1) by Age(2)	-.048	.053	.837	1	.360	.953	.859	1.057
D.o.t.w(1) by Age(3)	-.095	.067	2.029	1	.154	.909	.797	1.036
D.o.t.w(2) by Age(1)	.239	.074	10.404	1	.001	1.270	1.098	1.469
D.o.t.w(2) by Age(2)	.169	.058	8.653	1	.003	1.184	1.058	1.326

D.o.t.w(2) by Age(3)	.238	.070	11.630	1	.001	1.269	1.107	1.456
D.o.t.w(3) by Age(1)	.077	.072	1.160	1	.281	1.080	.939	1.243
D.o.t.w(3) by Age(2)	.050	.055	.832	1	.362	1.051	.944	1.169
D.o.t.w(3) by Age(3)	.076	.068	1.253	1	.263	1.079	.944	1.233
D.o.t.w(4) by Age(1)	.035	.077	.208	1	.649	1.036	.890	1.206
D.o.t.w(4) by Age(2)	-.005	.058	.009	1	.926	.995	.888	1.114
D.o.t.w(4) by Age(3)	-.121	.074	2.667	1	.102	.886	.766	1.025
D.o.t.w(5) by Age(1)	-.399	5127.069	.000	1	1.000	.671	.000	.
D.o.t.w(5) by Age(2)	14.001	4032.655	.000	1	.997	1203386.059	.000	.
D.o.t.w(5) by Age(3)	16.082	4032.655	.000	1	.997	9642528.826	.000	.
D.o.t.w(6) by Age(1)	-.459	6300.655	.000	1	1.000	.632	.000	.
D.o.t.w(6) by Age(2)	13.514	4864.273	.000	1	.998	739724.011	.000	.
D.o.t.w(6) by Age(3)	.262	5264.181	.000	1	1.000	1.299	.000	.
Age * Month			77.935	33	.000			
Age(1) by Month(1)	-.053	.112	.222	1	.637	.949	.762	1.181
Age(1) by Month(2)	-.009	.110	.007	1	.935	.991	.799	1.229
Age(1) by Month(3)	-.020	.117	.029	1	.866	.980	.779	1.233
Age(1) by Month(4)	.040	.112	.128	1	.721	1.041	.835	1.298
Age(1) by Month(5)	-.113	.113	1.000	1	.317	.893	.715	1.115
Age(1) by Month(6)	-.050	.118	.181	1	.671	.951	.754	1.199
Age(1) by Month(7)	-.328	.113	8.347	1	.004	.721	.577	.900

Age(1) by Month(8)	-.215	.116	3.449	1	.063	.807	.643	1.012
Age(1) by Month(9)	-.082	.113	.524	1	.469	.921	.737	1.151
Age(1) by Month(10)	-.014	.113	.015	1	.901	.986	.791	1.230
Age(1) by Month(11)	-.030	.123	.061	1	.805	.970	.762	1.234
Age(2) by Month(1)	-.050	.085	.342	1	.559	.951	.805	1.124
Age(2) by Month(2)	-.186	.085	4.865	1	.027	.830	.703	.979
Age(2) by Month(3)	-.048	.089	.291	1	.589	.953	.800	1.135
Age(2) by Month(4)	-.067	.087	.608	1	.436	.935	.789	1.108
Age(2) by Month(5)	-.058	.085	.469	1	.493	.943	.798	1.115
Age(2) by Month(6)	-.134	.090	2.207	1	.137	.875	.733	1.044
Age(2) by Month(7)	-.399	.085	21.964	1	.000	.671	.568	.793
Age(2) by Month(8)	-.237	.087	7.463	1	.006	.789	.665	.935
Age(2) by Month(9)	-.155	.086	3.221	1	.073	.857	.724	1.014
Age(2) by Month(10)	-.158	.086	3.330	1	.068	.854	.721	1.012
Age(2) by Month(11)	-.021	.093	.051	1	.822	.979	.816	1.175
Age(3) by Month(1)	.006	.106	.003	1	.958	1.006	.817	1.237
Age(3) by Month(2)	.023	.105	.048	1	.827	1.023	.834	1.256
Age(3) by Month(3)	.099	.110	.819	1	.366	1.104	.891	1.369
Age(3) by Month(4)	.065	.107	.366	1	.545	1.067	.865	1.315
Age(3) by Month(5)	-.092	.108	.731	1	.393	.912	.738	1.126
Age(3) by Month(6)	-.204	.113	3.299	1	.069	.815	.654	1.016

Age(3) by Month(7)	-.411	.108	14.410	1	.000	.663	.536	.820
Age(3) by Month(8)	-.292	.111	6.923	1	.009	.747	.601	.928
Age(3) by Month(9)	-.184	.108	2.880	1	.090	.832	.673	1.029
Age(3) by Month(10)	-.083	.108	.584	1	.445	.921	.745	1.138
Age(3) by Month(11)	-.155	.118	1.712	1	.191	.857	.679	1.080
Part of the day * Age			25.304	9	.003			
P.o.t.d(1) by Age(1)	.091	.048	3.649	1	.056	1.095	.998	1.202
P.o.t.d(1) by Age(2)	.122	.036	11.403	1	.001	1.130	1.053	1.213
P.o.t.d(1) by Age(3)	.220	.045	23.947	1	.000	1.246	1.141	1.361
P.o.t.d(2) by Age(1)	-.531	11038.227	.000	1	1.000	.588	.000	.
P.o.t.d(2) by Age(2)	13.122	10727.331	.000	1	.999	499619.415	.000	.
P.o.t.d(2) by Age(3)	.285	10751.648	.000	1	1.000	1.329	.000	.
P.o.t.d(3) by Age(1)	.032	.440	.005	1	.943	1.032	.436	2.446
P.o.t.d(3) by Age(2)	-.058	.362	.026	1	.872	.944	.464	1.917
P.o.t.d(3) by Age(3)	-.480	.786	.372	1	.542	.619	.133	2.892

7.8.3 Socio-status

Variables	**B**	**S.E.**	**Wald**	**df**	**Sig.**	**Exp(B)**	**95% C.I.for EXP(B)**	
							Lower	**Upper**
Socio-status(1)	-.341	.045	57.622	1	.000	.711	.651	.776
Distance	-.005	.000	249.878	1	.000	.995	.995	.996
Day of the week			164.840	6	.000			
D.o.t.w(1)	-.116	.019	37.513	1	.000	.890	.858	.924

D.o.t.w(2)	-.153	.019	61.785	1	.000	.859	.827	.892
D.o.t.w(3)	-.170	.019	76.841	1	.000	.844	.812	.876
D.o.t.w(4)	-.137	.021	43.598	1	.000	.872	.837	.908
D.o.t.w(5)	-3.157	.448	49.723	1	.000	.043	.018	.102
D.o.t.w(6)	-4.476	1.000	20.018	1	.000	.011	.002	.081
Month			44.485	11	.000			
Month(1)	.109	.052	4.483	1	.034	1.115	1.008	1.234
Month(2)	-.029	.052	.310	1	.578	.971	.877	1.076
Month(3)	.047	.053	.791	1	.374	1.049	.944	1.164
Month(4)	.148	.051	8.334	1	.004	1.159	1.049	1.281
Month(5)	.005	.053	.010	1	.920	1.005	.906	1.115
Month(6)	-.047	.054	.750	1	.386	.954	.858	1.061
Month(7)	.043	.052	.685	1	.408	1.044	.942	1.158
Month(8)	-.007	.054	.015	1	.901	.993	.894	1.103
Month(9)	-.117	.053	4.898	1	.027	.890	.802	.987
Month(10)	-.032	.052	.383	1	.536	.968	.874	1.072
Month(11)	-.076	.056	1.884	1	.170	.927	.831	1.033
Part of the day			109.957	3	.000			
P.o.t.d(1)	-.094	.013	54.520	1	.000	.910	.888	.933
P.o.t.d(2)	-5.331	1.000	28.413	1	.000	.005	.001	.034
P.o.t.d(3)	-.619	.110	31.664	1	.000	.539	.434	.668
Distance by Socio-status(1)	.002	.000	16.227	1	.000	1.002	1.001	1.003
Month * Socio-status			21.522	11	.028			
Month(1) by Socio-status(1)	.004	.063	.003	1	.954	1.004	.887	1.135
Month(2) by Socio-status(1)	.025	.064	.152	1	.696	1.025	.905	1.161
Month(3) by Socio-status(1)	-.064	.065	.966	1	.326	.938	.825	1.066
Month(4) by Socio-status(1)	-.110	.063	3.084	1	.079	.895	.792	1.013
Month(5) by Socio-status(1)	.041	.064	.411	1	.521	1.042	.919	1.182
Month(6) by Socio-status(1)	-.025	.066	.145	1	.704	.975	.856	1.110
Month(7) by Socio-status(1)	-.124	.065	3.648	1	.056	.884	.778	1.003

Month(8) by Socio-status(1)	-.097	.066	2.193	1	.139	.907	.797	1.032
Month(9) by Socio-status(1)	-.022	.065	.117	1	.732	.978	.862	1.110
Month(10) by Socio-status(1)	-.148	.064	5.307	1	.021	.863	.761	.978
Month(11) by Socio-status(1)	-.112	.068	2.689	1	.101	.894	.782	1.022
Constant	-3.067	.039	6206.036	1	.000	.047		

7.8.4 Elapsing calendar days

Variables	**B**	**S.E.**	**Wald**	**df**	**Sig.**	**Exp(B)**	**95% C.I.for EXP(B)**	
							Lower	**Upper**
Elapsing calendar days			479.811	17	.000			
E.c.d(1)	.660	.064	104.568	1	.000	1.934	1.704	2.195
E.c.d(2)	.686	.083	68.828	1	.000	1.986	1.689	2.335
E.c.d(3)	1.168	.087	178.601	1	.000	3.216	2.710	3.817
E.c.d(4)	1.253	.135	86.251	1	.000	3.501	2.687	4.561
E.c.d(5)	1.285	.201	41.063	1	.000	3.616	2.441	5.358
E.c.d(6)	1.251	.137	83.813	1	.000	3.492	2.672	4.564
E.c.d(7)	-17.864	6851.834	.000	1	.998	.000	.000	.
E.c.d(8)	-.013	1.045	.000	1	.990	.988	.127	7.661
E.c.d(9)	1.022	.632	2.613	1	.106	2.779	.805	9.593
E.c.d(10)	1.245	.789	2.486	1	.115	3.471	.739	16.304
E.c.d(11)	2.498	.348	51.413	1	.000	12.164	6.144	24.080
E.c.d(12)	1.949	.197	98.004	1	.000	7.022	4.774	10.329
E.c.d(13)	-18.024	8087.267	.000	1	.998	.000	.000	.
E.c.d(14)	-48.152	29146.954	.000	1	.999	.000	.000	.
E.c.d(15)	-21.037	35268.338	.000	1	1.000	.000	.000	.
E.c.d(16)	-17.388	58493.674	.000	1	1.000	.000	.000	.
E.c.d(17)	-17.286	24118.736	.000	1	.999	.000	.000	.

Week or weekend(1)	-3.928	1.000	15.414	1	.000	.020	.003	.140
Distance	-.004	.000	136.297	1	.000	.996	.995	.997
Day of the week			56.292	5	.000			
D.o.t.w(1)	-.071	.028	6.432	1	.011	.932	.882	.984
D.o.t.w(2)	-.178	.029	37.093	1	.000	.837	.790	.886
D.o.t.w(3)	-.179	.029	38.158	1	.000	.837	.790	.885
D.o.t.w(4)	-.130	.030	18.289	1	.000	.878	.828	.932
D.o.t.w(5)	.418	1.225	.117	1	.733	1.519	.138	16.770
Month			117.407	11	.000			
Month(1)	.231	.043	28.793	1	.000	1.260	1.158	1.372
Month(2)	.017	.045	.153	1	.696	1.018	.933	1.110
Month(3)	.016	.046	.114	1	.736	1.016	.928	1.112
Month(4)	.073	.045	2.593	1	.107	1.075	.984	1.175
Month(5)	.045	.045	1.011	1	.315	1.046	.958	1.143
Month(6)	-.031	.046	.438	1	.508	.970	.886	1.062
Month(7)	-.119	.048	6.228	1	.013	.888	.809	.975
Month(8)	-.056	.047	1.437	1	.231	.945	.863	1.036
Month(9)	-.112	.046	6.051	1	.014	.894	.818	.977
Month(10)	-.101	.046	4.907	1	.027	.904	.827	.988
Month(11)	-.098	.048	4.222	1	.040	.906	.825	.995
Part of the day			27.349	3	.000			
P.o.t.d(1)	-.093	.019	24.579	1	.000	.911	.878	.945
P.o.t.d(2)	-17.412	514.412	.001	1	.973	.000	.000	.
P.o.t.d(3)	-.264	.132	3.981	1	.046	.768	.593	.995
Distance * Elapsing calendar days			11.594	17	.824			
Distance by E.c.d(1)	.000	.001	.114	1	.735	1.000	.999	1.001

Distance by E.c.d(2)	.000	.001	.407	1	.523	1.000	.999	1.002
Distance by E.c.d(3)	.000	.001	.082	1	.775	1.000	.999	1.002
Distance by E.c.d(4)	.002	.001	2.487	1	.115	1.002	1.000	1.004
Distance by E.c.d(5)	.002	.002	1.464	1	.226	1.002	.999	1.005
Distance by E.c.d(6)	.002	.001	3.631	1	.057	1.002	1.000	1.005
Distance by E.c.d(7)	.000	.004	.011	1	.915	1.000	.993	1.008
Distance by E.c.d(8)	.004	.004	.794	1	.373	1.004	.996	1.012
Distance by E.c.d(9)	-.003	.006	.276	1	.600	.997	.986	1.008
Distance by E.c.d(10)	.003	.006	.244	1	.621	1.003	.991	1.015
Distance by E.c.d(11)	.000	.004	.000	1	.993	1.000	.992	1.008
Distance by E.c.d(12)	.003	.002	2.489	1	.115	1.003	.999	1.008
Distance by E.c.d(13)	-.007	.012	.381	1	.537	.993	.971	1.016
Distance by E.c.d(14)	.017	183.069	.000	1	1.000	1.018	.000	6.855E+155
Distance by E.c.d(15)	-2.908	578.235	.000	1	.996	.055	.000	.
Distance by E.c.d(16)	.004	576.532	.000	1	1.000	1.004	.000	.
Distance by E.c.d(17)	.002	2781.138	.000	1	1.000	1.002	.000	.

Day of the week * Elapsing calendar days			85.538	69	.086			
D.o.t.w(1) by E.c.d(1)	-.011	.051	.044	1	.834	.989	.895	1.093
D.o.t.w(1) by E.c.d(2)	-.072	.064	1.258	1	.262	.930	.820	1.056
D.o.t.w(1) by E.c.d(3)	-.100	.067	2.198	1	.138	.905	.793	1.033
D.o.t.w(1) by E.c.d(4)	-.085	.115	.550	1	.458	.918	.732	1.151
D.o.t.w(1) by E.c.d(5)	.186	.158	1.392	1	.238	1.205	.884	1.642
D.o.t.w(1) by E.c.d(6)	.029	.103	.078	1	.780	1.029	.841	1.259
D.o.t.w(1) by E.c.d(7)	.460	.351	1.713	1	.191	1.584	.795	3.154
D.o.t.w(1) by E.c.d(8)	-.643	.477	1.819	1	.177	.526	.206	1.338
D.o.t.w(1) by E.c.d(9)	.225	.543	.171	1	.679	1.252	.432	3.632
D.o.t.w(1) by E.c.d(10)	-.065	.852	.006	1	.939	.937	.176	4.980
D.o.t.w(1) by E.c.d(11)	-1.108	.389	8.126	1	.004	.330	.154	.707
D.o.t.w(1) by E.c.d(12)	-.278	.187	2.218	1	.136	.757	.525	1.092
D.o.t.w(1) by E.c.d(13)	-.159	1.063	.022	1	.881	.853	.106	6.855
D.o.t.w(1) by E.c.d(14)	-35.780	13823.520	.000	1	.998	.000	.000	.
D.o.t.w(1) by E.c.d(15)	-22.173	17003.034	.000	1	.999	.000	.000	.

D.o.t.w(1) by E.c.d(16)	.071	50833.933	.000	1	1.000	1.073	.000	.
D.o.t.w(2) by E.c.d(1)	-.039	.053	.536	1	.464	.962	.866	1.068
D.o.t.w(2) by E.c.d(2)	.021	.064	.111	1	.740	1.021	.901	1.158
D.o.t.w(2) by E.c.d(3)	-.015	.067	.052	1	.820	.985	.865	1.122
D.o.t.w(2) by E.c.d(4)	.170	.109	2.425	1	.119	1.185	.957	1.469
D.o.t.w(2) by E.c.d(5)	.200	.160	1.561	1	.211	1.222	.892	1.672
D.o.t.w(2) by E.c.d(6)	-.117	.101	1.322	1	.250	.890	.729	1.086
D.o.t.w(2) by E.c.d(7)	.188	.373	.253	1	.615	1.207	.580	2.508
D.o.t.w(2) by E.c.d(8)	-.423	.464	.832	1	.362	.655	.264	1.626
D.o.t.w(2) by E.c.d(9)	.410	.496	.685	1	.408	1.507	.570	3.984
D.o.t.w(2) by E.c.d(10)	1.523	.671	5.146	1	.023	4.586	1.230	17.099
D.o.t.w(2) by E.c.d(11)	-1.191	.385	9.556	1	.002	.304	.143	.647
D.o.t.w(2) by E.c.d(12)	-.244	.174	1.960	1	.161	.783	.556	1.103
D.o.t.w(2) by E.c.d(13)	.974	.860	1.284	1	.257	2.649	.491	14.287
D.o.t.w(2) by E.c.d(14)	-37.017	14162.741	.000	1	.998	.000	.000	.
D.o.t.w(2) by E.c.d(15)	-59.067	35426.137	.000	1	.999	.000	.000	.
D.o.t.w(2) by E.c.d(16)	.272	67243.152	.000	1	1.000	1.312	.000	.

D.o.t.w(2) by E.c.d(17)	.155	48529.853	.000	1	1.000	1.167	.000	.
D.o.t.w(3) by E.c.d(1)	.005	.052	.009	1	.925	1.005	.907	1.114
D.o.t.w(3) by E.c.d(2)	.068	.066	1.061	1	.303	1.070	.941	1.217
D.o.t.w(3) by E.c.d(3)	-.061	.066	.846	1	.358	.941	.826	1.071
D.o.t.w(3) by E.c.d(4)	.138	.109	1.592	1	.207	1.148	.927	1.422
D.o.t.w(3) by E.c.d(5)	.170	.167	1.034	1	.309	1.185	.854	1.645
D.o.t.w(3) by E.c.d(6)	-.181	.105	2.943	1	.086	.834	.679	1.026
D.o.t.w(3) by E.c.d(7)	.243	.349	.484	1	.487	1.275	.643	2.527
D.o.t.w(3) by E.c.d(8)	-.034	.399	.007	1	.932	.966	.442	2.113
D.o.t.w(3) by E.c.d(9)	-.054	.520	.011	1	.917	.947	.342	2.627
D.o.t.w(3) by E.c.d(10)	-.099	.854	.013	1	.908	.906	.170	4.826
D.o.t.w(3) by E.c.d(11)	-.714	.310	5.323	1	.021	.490	.267	.898
D.o.t.w(3) by E.c.d(12)	-.260	.179	2.095	1	.148	.771	.543	1.096
D.o.t.w(3) by E.c.d(13)	.450	.908	.245	1	.620	1.568	.264	9.294
D.o.t.w(3) by E.c.d(14)	-2.831	24057.691	.000	1	1.000	.059	.000	.
D.o.t.w(3) by E.c.d(15)	-39.315	35464.472	.000	1	.999	.000	.000	.
D.o.t.w(3) by E.c.d(16)	.179	45808.615	.000	1	1.000	1.195	.000	.

D.o.t.w(4) by E.c.d(1)	.115	.055	4.465	1	.035	1.122	1.008	1.249
D.o.t.w(4) by E.c.d(2)	.150	.072	4.390	1	.036	1.162	1.010	1.337
D.o.t.w(4) by E.c.d(3)	.039	.074	.282	1	.595	1.040	.900	1.201
D.o.t.w(4) by E.c.d(4)	.194	.118	2.719	1	.099	1.215	.964	1.531
D.o.t.w(4) by E.c.d(5)	.297	.178	2.786	1	.095	1.346	.950	1.909
D.o.t.w(4) by E.c.d(6)	-.060	.121	.244	1	.621	.942	.743	1.194
D.o.t.w(4) by E.c.d(7)	.026	.439	.004	1	.953	1.026	.434	2.426
D.o.t.w(4) by E.c.d(8)	-.203	.473	.185	1	.667	.816	.323	2.062
D.o.t.w(4) by E.c.d(9)	.746	.571	1.706	1	.192	2.109	.688	6.460
D.o.t.w(4) by E.c.d(10)	-1.183	1.185	.996	1	.318	.306	.030	3.127
D.o.t.w(4) by E.c.d(11)	-.820	.370	4.898	1	.027	.441	.213	.910
D.o.t.w(4) by E.c.d(12)	-.314	.217	2.102	1	.147	.730	.477	1.117
D.o.t.w(4) by E.c.d(13)	-.077	1.279	.004	1	.952	.926	.075	11.346
D.o.t.w(4) by E.c.d(14)	-1.955	13462.267	.000	1	1.000	.142	.000	.
D.o.t.w(4) by E.c.d(16)	.036	62174.837	.000	1	1.000	1.037	.000	.
D.o.t.w(5) by E.c.d(1)	1.874	1.229	2.323	1	.127	6.512	.585	72.448
D.o.t.w(5) by E.c.d(2)	2.491	1.233	4.081	1	.043	12.076	1.077	135.390
D.o.t.w(5) by E.c.d(7)	-14.366	40192.970	.000	1	1.000	.000	.000	.

D.o.t.w(5) by E.c.d(10)	-14.063	40192.970	.000	1	1.000	.000	.000	.
D.o.t.w(5) by E.c.d(12)	27.015	40192.969	.000	1	.999	5398508981 12.428	.000	.
Month * Elapsing calendar days			175.49 0	131	.006			
Month(1) by E.c.d(1)	-.140	.080	3.043	1	.081	.870	.743	1.017
Month(1) by E.c.d(2)	-.103	.101	1.033	1	.309	.902	.740	1.100
Month(1) by E.c.d(3)	-.219	.106	4.276	1	.039	.803	.653	.989
Month(1) by E.c.d(4)	-.328	.172	3.632	1	.057	.720	.514	1.009
Month(1) by E.c.d(5)	-.488	.260	3.510	1	.061	.614	.369	1.023
Month(1) by E.c.d(6)	.133	.160	.686	1	.407	1.142	.834	1.564
Month(1) by E.c.d(7)	18.032	6851.834	.000	1	.998	67773197.8 96	.000	.
Month(1) by E.c.d(8)	2.055	1.261	2.655	1	.103	7.809	.659	92.539
Month(2) by E.c.d(1)	-.037	.080	.214	1	.643	.964	.824	1.127
Month(2) by E.c.d(2)	.121	.102	1.410	1	.235	1.129	.924	1.378
Month(2) by E.c.d(3)	-.188	.107	3.058	1	.080	.829	.671	1.023
Month(2) by E.c.d(4)	-.014	.161	.008	1	.930	.986	.719	1.352
Month(2) by E.c.d(5)	.008	.223	.001	1	.970	1.008	.651	1.561
Month(2) by E.c.d(6)	.119	.158	.563	1	.453	1.126	.826	1.535
Month(2) by E.c.d(7)	18.696	6851.834	.000	1	.998	131644254. 884	.000	.
Month(2) by E.c.d(8)	1.894	1.086	3.043	1	.081	6.647	.791	55.827

Month(2) by E.c.d(9)	.578	.725	.636	1	.425	1.783	.431	7.379
Month(3) by E.c.d(1)	.004	.083	.003	1	.959	1.004	.854	1.181
Month(3) by E.c.d(2)	-.033	.107	.095	1	.758	.968	.784	1.193
Month(3) by E.c.d(3)	-.081	.109	.560	1	.454	.922	.745	1.141
Month(3) by E.c.d(4)	.096	.159	.364	1	.546	1.101	.806	1.505
Month(3) by E.c.d(5)	-.610	.257	5.640	1	.018	.543	.329	.899
Month(3) by E.c.d(6)	.502	.160	9.884	1	.002	1.652	1.208	2.259
Month(3) by E.c.d(7)	19.137	6851.834	.000	1	.998	204700035.091	.000	.
Month(3) by E.c.d(8)	.636	1.239	.263	1	.608	1.889	.166	21.436
Month(3) by E.c.d(9)	.512	.680	.568	1	.451	1.669	.440	6.325
Month(3) by E.c.d(10)	-19.109	12805.411	.000	1	.999	.000	.000	.
Month(4) by E.c.d(1)	.026	.080	.109	1	.742	1.027	.878	1.200
Month(4) by E.c.d(2)	.032	.100	.101	1	.750	1.033	.848	1.257
Month(4) by E.c.d(3)	.036	.102	.124	1	.724	1.037	.848	1.267
Month(4) by E.c.d(4)	.160	.161	.985	1	.321	1.173	.856	1.608
Month(4) by E.c.d(5)	-.299	.234	1.627	1	.202	.742	.468	1.174
Month(4) by E.c.d(6)	.215	.157	1.888	1	.169	1.240	.912	1.685
Month(4) by E.c.d(7)	18.247	6851.834	.000	1	.998	84037873.600	.000	.
Month(4) by E.c.d(8)	1.291	1.172	1.213	1	.271	3.637	.365	36.197
Month(4) by E.c.d(9)	.513	.616	.693	1	.405	1.670	.499	5.586

Month(4) by E.c.d(10)	-.611	.934	.427	1	.513	.543	.087	3.388
Month(4) by E.c.d(11)	.332	.833	.159	1	.690	1.393	.272	7.133
Month(5) by E.c.d(1)	.001	.080	.000	1	.988	1.001	.856	1.171
Month(5) by E.c.d(2)	.013	.101	.017	1	.897	1.013	.832	1.234
Month(5) by E.c.d(3)	.033	.104	.100	1	.752	1.033	.843	1.266
Month(5) by E.c.d(4)	-.229	.168	1.872	1	.171	.795	.573	1.104
Month(5) by E.c.d(5)	-.114	.238	.227	1	.633	.893	.560	1.424
Month(5) by E.c.d(6)	.184	.169	1.187	1	.276	1.203	.863	1.676
Month(5) by E.c.d(7)	18.469	6851.834	.000	1	.998	104934445.219	.000	.
Month(5) by E.c.d(8)	1.860	1.065	3.050	1	.081	6.425	.797	51.814
Month(5) by E.c.d(9)	.363	.596	.371	1	.542	1.438	.447	4.630
Month(5) by E.c.d(10)	.282	.694	.165	1	.685	1.325	.340	5.166
Month(5) by E.c.d(11)	-.330	.449	.540	1	.462	.719	.298	1.734
Month(5) by E.c.d(12)	.148	.278	.282	1	.595	1.159	.673	1.997
Month(6) by E.c.d(1)	.046	.082	.312	1	.576	1.047	.891	1.230
Month(6) by E.c.d(2)	.147	.104	1.986	1	.159	1.159	.944	1.422
Month(6) by E.c.d(3)	-.068	.114	.360	1	.548	.934	.747	1.168
Month(6) by E.c.d(4)	-.315	.182	2.977	1	.084	.730	.511	1.044
Month(6) by E.c.d(5)	.164	.220	.555	1	.456	1.178	.765	1.813

Month(6) by E.c.d(6)	.142	.179	.634	1	.426	1.153	.812	1.637
Month(6) by E.c.d(7)	18.437	6851.834	.000	1	.998	101632564.312	.000	.
Month(6) by E.c.d(8)	1.043	1.171	.794	1	.373	2.838	.286	28.150
Month(6) by E.c.d(9)	-.039	.641	.004	1	.952	.962	.274	3.378
Month(6) by E.c.d(10)	-18.671	6535.367	.000	1	.998	.000	.000	.
Month(6) by E.c.d(11)	.315	.439	.515	1	.473	1.370	.580	3.236
Month(6) by E.c.d(12)	-.311	.241	1.665	1	.197	.733	.457	1.175
Month(6) by E.c.d(13)	-.171	16223.654	.000	1	1.000	.843	.000	.
Month(7) by E.c.d(1)	.190	.080	5.628	1	.018	1.210	1.034	1.416
Month(7) by E.c.d(2)	.236	.100	5.538	1	.019	1.267	1.040	1.542
Month(7) by E.c.d(3)	.094	.109	.745	1	.388	1.099	.887	1.361
Month(7) by E.c.d(4)	.141	.163	.754	1	.385	1.152	.837	1.584
Month(7) by E.c.d(5)	-.549	.265	4.281	1	.039	.577	.343	.971
Month(7) by E.c.d(6)	.112	.175	.411	1	.521	1.119	.794	1.575
Month(7) by E.c.d(7)	18.821	6851.834	.000	1	.998	149182643.603	.000	.
Month(7) by E.c.d(8)	1.910	1.075	3.153	1	.076	6.752	.820	55.574
Month(7) by E.c.d(9)	-1.389	1.120	1.538	1	.215	.249	.028	2.239
Month(7) by E.c.d(10)	.507	.741	.468	1	.494	1.661	.388	7.101

Month(7) by E.c.d(11)	.322	.420	.589	1	.443	1.380	.606	3.144
Month(7) by E.c.d(12)	.167	.222	.561	1	.454	1.181	.764	1.827
Month(7) by E.c.d(13)	19.085	8087.267	.000	1	.998	194321006.984	.000	.
Month(7) by E.c.d(14)	-2.999	30816.641	.000	1	1.000	.050	.000	.
Month(8) by E.c.d(1)	.013	.085	.023	1	.880	1.013	.857	1.197
Month(8) by E.c.d(2)	.061	.101	.370	1	.543	1.063	.873	1.296
Month(8) by E.c.d(3)	-.021	.107	.038	1	.845	.979	.794	1.208
Month(8) by E.c.d(4)	-.299	.177	2.855	1	.091	.741	.524	1.049
Month(8) by E.c.d(5)	-.886	.279	10.103	1	.001	.413	.239	.712
Month(8) by E.c.d(6)	.221	.164	1.813	1	.178	1.247	.904	1.720
Month(8) by E.c.d(7)	17.870	6851.834	.000	1	.998	57656916.327	.000	.
Month(8) by E.c.d(8)	.918	1.170	.616	1	.432	2.505	.253	24.795
Month(8) by E.c.d(9)	.174	.645	.073	1	.788	1.190	.336	4.209
Month(8) by E.c.d(10)	-.391	.943	.172	1	.678	.676	.106	4.295
Month(8) by E.c.d(11)	-.474	.447	1.123	1	.289	.623	.259	1.496
Month(8) by E.c.d(12)	-.020	.218	.008	1	.927	.980	.639	1.503
Month(8) by E.c.d(13)	18.925	8087.267	.000	1	.998	165607738.123	.000	.

Month(8) by E.c.d(14)	-2.785	28507.591	.000	1	1.000	.062	.000	.
Month(8) by E.c.d(15)	24.879	39434.651	.000	1	.999	63786280756.142	.000	.
Month(9) by E.c.d(1)	.021	.082	.068	1	.794	1.022	.870	1.199
Month(9) by E.c.d(2)	.031	.104	.090	1	.765	1.032	.841	1.265
Month(9) by E.c.d(3)	-.033	.104	.097	1	.755	.968	.789	1.187
Month(9) by E.c.d(4)	-.304	.172	3.117	1	.077	.738	.527	1.034
Month(9) by E.c.d(5)	-.419	.252	2.770	1	.096	.658	.402	1.077
Month(9) by E.c.d(6)	.154	.161	.924	1	.336	1.167	.852	1.598
Month(9) by E.c.d(7)	18.168	6851.834	.000	1	.998	77673928.522	.000	.
Month(9) by E.c.d(8)	1.935	1.087	3.166	1	.075	6.924	.822	58.339
Month(9) by E.c.d(9)	-.566	.764	.549	1	.459	.568	.127	2.538
Month(9) by E.c.d(10)	-.566	.816	.481	1	.488	.568	.115	2.810
Month(9) by E.c.d(11)	-.311	.447	.485	1	.486	.733	.305	1.759
Month(9) by E.c.d(12)	.021	.204	.010	1	.919	1.021	.685	1.522
Month(9) by E.c.d(13)	17.294	8087.267	.000	1	.998	32413008.613	.000	.
Month(9) by E.c.d(14)	-2.373	27116.667	.000	1	1.000	.093	.000	.
Month(9) by E.c.d(15)	-33.939	30827.651	.000	1	.999	.000	.000	.

Month(9) by E.c.d(16)	.200	68276.415	.000	1	1.000	1.221	.000	.
Month(10) by E.c.d(1)	.109	.080	1.836	1	.175	1.115	.953	1.306
Month(10) by E.c.d(2)	-.037	.106	.123	1	.726	.964	.783	1.186
Month(10) by E.c.d(3)	-.117	.107	1.191	1	.275	.890	.721	1.098
Month(10) by E.c.d(4)	-.215	.169	1.614	1	.204	.806	.579	1.124
Month(10) by E.c.d(5)	-.459	.248	3.432	1	.064	.632	.389	1.027
Month(10) by E.c.d(6)	.065	.165	.157	1	.692	1.068	.773	1.475
Month(10) by E.c.d(7)	18.300	6851.834	.000	1	.998	88650120.033	.000	.
Month(10) by E.c.d(8)	2.079	1.073	3.752	1	.053	7.993	.976	65.497
Month(10) by E.c.d(9)	-1.126	.864	1.699	1	.192	.324	.060	1.763
Month(10) by E.c.d(10)	-.551	.821	.451	1	.502	.576	.115	2.881
Month(10) by E.c.d(11)	-.006	.403	.000	1	.988	.994	.451	2.191
Month(10) by E.c.d(12)	-.360	.219	2.699	1	.100	.697	.454	1.072
Month(10) by E.c.d(13)	17.870	8087.267	.000	1	.998	57671006.605	.000	.
Month(10) by E.c.d(14)	34.088	27432.449	.000	1	.999	637199065243466.900	.000	.
Month(10) by E.c.d(15)	-57.014	35539.738	.000	1	.999	.000	.000	.
Month(10) by E.c.d(16)	.096	36326.294	.000	1	1.000	1.100	.000	.

Month(11) by E.c.d(1)	.001	.087	.000	1	.989	1.001	.844	1.188
Month(11) by E.c.d(2)	-.049	.112	.190	1	.663	.952	.764	1.186
Month(11) by E.c.d(3)	-.165	.115	2.046	1	.153	.848	.677	1.063
Month(11) by E.c.d(4)	-.109	.188	.339	1	.561	.896	.620	1.295
Month(11) by E.c.d(5)	-.439	.252	3.028	1	.082	.645	.393	1.057
Month(11) by E.c.d(6)	.389	.173	5.049	1	.025	1.476	1.051	2.072
Month(11) by E.c.d(7)	17.431	6851.834	.000	1	.998	37166564.313	.000	.
Part of the day * Elapsing calendar days			35.586	28	.153			
P.o.t.d(1) by E.c.d(1)	.081	.035	5.471	1	.019	1.084	1.013	1.161
P.o.t.d(1) by E.c.d(2)	.184	.043	18.039	1	.000	1.202	1.104	1.309
P.o.t.d(1) by E.c.d(3)	.077	.045	2.974	1	.085	1.080	.990	1.179
P.o.t.d(1) by E.c.d(4)	.055	.074	.546	1	.460	1.056	.914	1.221
P.o.t.d(1) by E.c.d(5)	.066	.105	.395	1	.530	1.068	.869	1.313
P.o.t.d(1) by E.c.d(6)	.075	.068	1.220	1	.269	1.078	.944	1.231
P.o.t.d(1) by E.c.d(7)	.545	.233	5.482	1	.019	1.725	1.093	2.723
P.o.t.d(1) by E.c.d(8)	-.202	.298	.458	1	.499	.817	.455	1.467
P.o.t.d(1) by E.c.d(9)	.430	.320	1.811	1	.178	1.538	.822	2.878
P.o.t.d(1) by E.c.d(10)	-.292	.448	.427	1	.514	.746	.310	1.795

P.o.t.d(1) by E.c.d(11)	.221	.233	.904	1	.342	1.247	.791	1.968
P.o.t.d(1) by E.c.d(12)	.054	.123	.197	1	.657	1.056	.830	1.343
P.o.t.d(1) by E.c.d(13)	.471	.573	.677	1	.411	1.602	.521	4.924
P.o.t.d(1) by E.c.d(14)	35.590	8834.198	.000	1	.997	2861877445 262321.500	.000	.
P.o.t.d(1) by E.c.d(15)	5.962	16490.924	.000	1	1.000	388.492	.000	.
P.o.t.d(2) by E.c.d(1)	18.596	514.413	.001	1	.971	119103445. 230	.000	.
P.o.t.d(2) by E.c.d(2)	-.700	40196.262	.000	1	1.000	.496	.000	.
P.o.t.d(2) by E.c.d(3)	-.979	40196.262	.000	1	1.000	.376	.000	.
P.o.t.d(2) by E.c.d(4)	-1.210	40196.262	.000	1	1.000	.298	.000	.
P.o.t.d(3) by E.c.d(1)	-.441	.302	2.140	1	.144	.643	.356	1.162
P.o.t.d(3) by E.c.d(2)	-.001	.438	.000	1	.997	.999	.424	2.354
P.o.t.d(3) by E.c.d(3)	-.278	.734	.143	1	.705	.758	.180	3.192
P.o.t.d(3) by E.c.d(4)	1.053	.563	3.494	1	.062	2.866	.950	8.646
P.o.t.d(3) by E.c.d(5)	-18.043	9121.261	.000	1	.998	.000	.000	.
P.o.t.d(3) by E.c.d(6)	-18.558	11141.001	.000	1	.999	.000	.000	.
P.o.t.d(3) by E.c.d(7)	-17.867	28238.588	.000	1	.999	.000	.000	.
P.o.t.d(3) by E.c.d(9)	-18.931	28400.640	.000	1	.999	.000	.000	.
P.o.t.d(3) by E.c.d(11)	-19.327	40192.970	.000	1	1.000	.000	.000	.

Constant	-3.716	.037	9843.1 11	1	.000	.024