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Patient Willingness to Undergo Robotic Surgery: Identification and Validation of a Predictive Model

Emily C. Anania
Embry-Riddle Aeronautical University

PATIENT WILLINGNESS TO UNDERGO ROBOTIC SURGERY:

IDENTIFICATION AND VALIDATION OF A PREDICTIVE MODEL

By

EMILY C. ANANIA

B.S., Psychology, University of Delaware, 2015

M.S., Human Factors, Embry-Riddle Aeronautical University, 2017

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SIGNATURE PAGE

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EMILY C. ANANIA

This dissertation was prepared under the direction of the candidate's Dissertation Committee Chair, Dr. Stephen Rice and has been approved by the members of the dissertation committee. It was submitted to the College of Arts and Sciences and was accepted in partial fulfilment of the requirements for the Degree of Doctor of Philosophy in Human Factors

Stephen Rice, Ph.D.
Committee Chair

Albert J. Boquet, Ph.D.
Committee Member

Scott A. Shappell, Ph.D.
Department Chair, Human Factors

Christina Frederick, Ph.D.
Committee Member

Karen F. Gaines, Ph.D.
Dean, College of Arts and Sciences

Scott R. Winter, Ph.D.
Committee Member

Lon Moeller, J.D.
Senior Vice President for Academic Affairs and Provost

Date

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ABSTRACT

INTRODUCTION: The purpose of the current dissertation is to better understand the factors which make an individual willing (or unwilling) to undergo robotic surgery. Though surgical feasibility and provider perceptions are often studied, little research has investigated how patients perceive robotic surgical systems.

METHOD: A two-stage approach was taken in order to build and validate a regression equation in order to predict an individual's willingness to undergo robotic surgery based on several factors. Stage 1 employed a sample size of 1324 participants in order to build the model. Participants responded to a survey indicating their willingness to undergo robotic surgery, and answered questions related to their perceptions of the system, demographic information, and emotional responses. Stage 2 employed a sample size of 1335 participants, who responded to the exact same survey as Stage 2. The regression equation developed via Stage 1 was then tested using the participants from Stage 2 in order to validate the equation.

RESULTS: In Stage 1, a backward stepwise regression was conducted on the twenty-one predictive factors of interest (age, gender, income, education level, ethnicity, perceived complexity, perceived value, familiarity, wariness of new technologies, fear of surgery, personality factors (openness, conscientiousness, extraversion, agreeableness, neuroticism), and affect (in the form of the six universal emotions). Of these twenty-one factors, eight were indicated to be significant predictors: perceived value, familiarity, wariness of new technologies, fear of surgery, openness, anger, fear, and happiness. These factors accounted for 62.7% of the variance in the model (62.4% adjusted).

In Stage 2, several methods were used to validate the regression model, including: correlational analyses, a *t*-test, and calculation of the cross-validity coefficient. Correlational analyses indicated that the predicted scores of willingness in Stage 2 generated using the regression analyses were significantly correlated with the actual scores of willingness reported by participants. In addition, results of the *t*-test indicated that the predicted scores and actual scores were not significantly different. Further, the cross-validity coefficient was similar to the initial R^2, indicating good fit of the model.

CONCLUSION: Results of the study indicate that perceived value, familiarity, wariness of new technologies, fear of surgery, openness, anger, fear, and happiness are all significant predictors of willingness to undergo robotic surgery. These results not only benefit the literature on technology acceptance and robotic surgery, but also have practical applications for the way these systems are designed and marketed, and the way that patients are educated.

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Chapter 1

Introduction

Purpose Statement

The purpose of the current research is to gain a better understanding of which factors affect an individual's willingness to interface with automation in the context of healthcare treatment. Specifically, what makes an individual willing (or unwilling) to undergo robotic surgery? Robotic surgery is in its infancy as a treatment mechanism and is largely not understood by consumers. As the field grows exponentially, more doctors and hospitals are adopting use of these robots (Tsui, Klein, & Garabrant, 2013). In addition, the uses and capabilities of automation are always growing, and robotic surgical systems are no exception. Therefore, it is important to understand the factors which may influence an individual's perception of robotic surgery. This study's main aim was to create a predictive model related to patient willingness to undergo robotic surgery, considering demographic factors as well as other potential predictors such as emotional responses, patient personality, and understanding/familiarity with robotic surgery and new technologies as a whole.

Chapter 1 will detail the background and rationale for the current dissertation. In order to facilitate clear understanding, all terms will be defined operationally. Research questions and hypotheses will be clearly stated for reference. The potential significance of the study will be discussed, as well as the limitations and assumptions made relevant to this research.

Background and Rationale

The ultimate goal of the current dissertation is to create a predictive model of patient willingness to undergo robotic surgery. The inherent complexity of the healthcare system coupled with the growing capabilities of automation will lead to novel healthcare environments with which patients will likely have cause to interact. One of the automated technologies currently in development is the robotic surgical system.

There has been some evidence that preoperative interventions (such as education) may influence postoperative outcomes (e.g., Asilioglu & Celik, 2004). There has also been a consistent line of research indicating that doctor-patient communication is positively linked to health outcomes through intermediary factors, such as better patient education and stricter adherence to clinician guidelines (Street, 2013; Street, Makoul, Arora, & Epstein, 2009). Specifically related to surgery, studies have found that pre-operative patient education for reduces post-operative pain, and anxiety for general surgery (Shuldham, 1999) and musculoskeletal trauma (Wong, Chen, & Chair, 2010).

A thirteen-year review of surgical patient education studies did find evidence that educating patients did influence health outcomes (Johnansson, Salanterä, Heikkinen, Kuusisto, Virtanen, & Leino-Kilpi, 2004). These types of results have also been found for orthopedic patients, though the methodologic rigor of such studies has been called into question (Johansson, Nuutila, Virtanen, Katajisto, & Salanterä, 2004). Overall, educating patients has been shown to have an effect on patient outcomes. Therefore, it is important to understand how patients may feel about robotic surgery and the factors which influence these feelings, in order to decide whether or not intervention measures must be taken. However, there is very little research about patient education about technology within the healthcare domain.

Though some research has been performed in the realm of technology acceptance, and patient decision making, the two fields rarely intersect (e.g., Alaid & Zhou, 2014). Only one study to date has investigated patient perceptions of robotic surgical technologies, with an incredibly limited sample and limited conclusions (Zineddine & Arafa, 2013). This research found, in general, that individuals in the United Arab Emirates largely did not believe that robotic-assisted surgery was safe and were not comfortable with the concept. The current research delves beyond surface perceptions, attempting to understand the factors which may influence this view of robotic surgery, in a U. S. population. Likely, there are individual differences and more nuanced perceptions which influence willingness as a whole. The potential predictors of willingness to undergo robotic surgery being studied include: age, gender, income, education level, perceived complexity, perceived value, familiarity, wariness of new technologies, personality factors, and affect (in the form of the six universal emotions).

To this end, the current research aims to build a predictive model of patient willingness to undergo robotic surgery. This model (equation) could potentially be used by many domains in the healthcare industry to not only better understand patient perceptions of robotic surgical systems, but also potentially influence these perceptions for the better, through education and advertising. The healthcare system can benefit from understanding and improving patient perceptions of robotic surgery, and the factors which may influence these perceptions.

Problem Statement

As robotic surgery advances in scope and capability, there is a clear trend of research investigating the benefits and drawbacks of robotic surgical systems as they relate to surgical technique (BenMessaoud, Kharrazi, & MacDorman, 2011; De Wilde & Herrmann, 2013; Lanfranco et al., 2004). In addition, it is common to study provider acceptance of robotic surgical systems (e.g., how do surgeons and nurses feel about these systems; e.g., BenMessaoud, Kharrazi, & MacDorman, 2011). Essentially, most main groups that interact with these systems are studied, with one notable exception: patients. There is a major gap in the literature where patient perceptions and opinions are not solicited about these systems. The healthcare system relies on patients as a source of income and work, and patients are largely able to make their own healthcare-based decisions in terms of where and when to receive treatment (barring emergency care). It is possible that new technologies largely not understood by the general public may cause fear and hesitation within the healthcare system, creating a delay or fear of care which could be avoided. First, it is important to understand current patient perceptions of robotic surgical systems, before targeting any changes or educational initiatives.

Only one study to date has previously investigated patient perceptions of robotic surgery (Zineddine & Arafa, 2013). However, this study did not focus on individual attributes or more nuanced perceptions than “support”. Therefore, it is important to investigate further how patients may feel about these robotic surgical systems, in order to start a dialogue about how these systems are designed, marketed, and how they are explained to patients undergoing surgery. This dissertation provides a basis for further investigation, by providing a first look at the facets of an individual which may influence willingness to undergo robotic surgery.

Operational Definitions of Terms

1. *Patient willingness* refers to the participants'/patients' willingness to undergo robotic surgery under different automated conditions. This is measured from the average score on the Willingness to Undergo Robotic Surgery Scale (see Appendix A).
2. *Age* refers to the participants' age measured in years.
3. *Gender* refers to the participant's gender, either male, female, or a written-in "other."
4. *Income* refers to the participant's annual earnings, measured in U.S. Dollars.
5. *Education level* refers to the participant's highest degree earned. Participants are limited to the following seven options: 1) less than high school; 2) high school graduate (includes equivalency); 3) some college, no degree; 4) associate's degree; 5) bachelor's degree; 6) master's degree; and 7) doctorate degree (or terminal degree).
6. *Ethnicity* refers to the participant's self-selected ethnicity out of the following options: 1) Caucasian, 2) African descent (e.g., African American), 3) Hispanic descent (e.g., Latin America), 4) Asian descent, 5) India (not Asian), or 6) Other.
7. *Perceived complexity* refers to the participants' perception of the complexity of the automation which controls robotic surgery. This is measured from the average score on the Perceived Complexity scale (see Appendix B).

8. *Familiarity* refers to the participants' familiarity with robotic surgery. This is measured from the average score on the Familiarity scale (see Appendix C).
9. *Perceived Value* refers to the participants' perception of the value of robotic surgery. This is measured from the average score on the Perceived Value scale (see Appendix D).
10. *Wariness of new technologies* refers to the participants' wariness of or hesitation to use new technologies in general. This is measured from the average score on the Wariness of new technologies scale (see Appendix E).
11. *Fear of Surgery* refers to the participant's overall fear of surgery, whether or not the surgery includes a robotic surgical system. This is measured using the single question: What is your general level of fear of surgery? Participant respond on a 10-point scale from 1 (I have no fear of surgery) to 10 (Extremely fear surgery).
12. *Personality* refers to five individual variables which represent aspects of the participant's personality: Openness to Experience, Conscientiousness, Extraversion, Agreeableness, and Neuroticism. Each of these five personality traits is measured by the participants score on four questions of the Mini International Personality Item Pool (Mini-IPIP; Donnellan, Oswald, Baird, & Lucas, 2006). All five personality constructs are represented on the scale, for a total of 20 questions.
13. *Affect* refers to the participants' emotional response toward a given scenario, represented by six separate emotions: happiness, sadness, anger, disgust, surprise, and fear. This is measured by participants' responses to one question about each

emotion, "*Based on the scenario above, how strongly do you feel like the image shown?*" This is in reference to a pictorial representation of each emotion.

Research Questions

1. RQ1: Are any basic demographic variables (gender, income, age, education level) significant predictors of patient willingness when controlling for all other variables?
2. RQ2: Are current consumer perceptions (perceived complexity, perceived value, familiarity) significant predictors of patient willingness when controlling for all other variables?
3. RQ3: Is wariness of new technologies a significant predictor of patient willingness when controlling for all other variables?
4. RQ4: Are any personality traits (Big Five) significant predictors of patient willingness when controlling for all other variables?
5. RQ5: Are any of Ekman and Friesens' (1971) six universal emotions (affect) significant predictors of patient willingness when controlling for all other variables?
6. RQ6: Is Fear of Surgery a significant predictor of patient willingness when controlling for all other variables?

Research Hypotheses

Null Hypothesis 1

H_{01}: Demographic variables (gender, income, age, education level) do not significantly predict consumer willingness when controlling for all other variables.

Alternate Hypothesis 1

H_{A1}: At least one demographic variable (gender, income, education level) is a significant predictor of patient willingness when controlling for all other variables.

Null Hypothesis 2

H_{02}: Current consumer perceptions (perceived complexity, perceived value, familiarity) do not significantly predict patient willingness when controlling for all other variables.

Alternate Hypothesis 2

H_{A2}: At least one current consumer perception (perceived complexity, perceived value, familiarity) is a significant predictor of patient willingness when controlling for all other variables.

Null Hypothesis 3

H_{03}: Wariness of new technologies is not a significant predictor of patient willingness when controlling for all other variables.

Alternate Hypothesis 3

H_{A3}: Wariness of new technologies is a significant predictor of patient willingness when controlling for all other variables.

Null Hypothesis 4

H_{04}: Personality traits (Big Five) do not significantly predict patient willingness when controlling for all other variables

Alternate Hypothesis 4

H_{A4}: At least one of the big five personality traits is a significant predictor of patient willingness when controlling for all other variables.

Null Hypothesis 5

H_{05}: Affect is not a significant predictor of patient willingness when controlling for all other variables.

Alternate Hypothesis 5

H_{A5}: At least one affective emotion (of the six universal emotions) is a significant predictor of patient willingness when controlling for all other variables.

Null Hypothesis 6

H_{06}: Fear of surgery is not a significant predictor of patient willingness when controlling for all other variables.

Alternate Hypothesis 6

H_{A6}: Fear of surgery is a significant predictor of patient willingness when controlling for all other variables.

Significance of Study

Research into the healthcare system and into automation is abundant. Healthcare research relating to patient perceptions and satisfaction is growing in scope and in clinical importance. In addition, automation is constantly evolving and developing new capabilities. There are likely many factors which will influence an individual's willingness to interact with automated technologies in a healthcare setting (in the case of this dissertation, undergoing robotic surgery). Chapter 2 will address the healthcare domain, patient-based research, and the factors which may affect an individual's willingness to undergo robotic surgery.

Previous research (see Chapter 2 for a detailed account) has investigated the Technology Acceptance Model and what factors may influence technology adoption in a healthcare setting, from the perspective of both patients and providers (Porter & Donthu, 2006; Venkatesh, 2000; Vijayasarathy, 2004). However, no studies to date have investigated adoption of robotic surgical systems from the view of the patient. Though it may seem initially that it does not matter whether or not a patient likes their treatment option, patient education and satisfaction have been shown to have some link to patient outcomes (e.g., Johnansson et al., 2004). Therefore, it is pertinent to understand what factors may influence patient willingness to undergo robotic surgery. Only one previous study has investigated perceptions of robotic surgery, and it did so with a United Arab Emirates sample, and limited findings (Zineddine & Arafa, 2013). Therefore, the current research addresses a gap not yet seen in healthcare or automation-based research, creating a contribution to the current literature.

The practical significance of the current research is primarily that it can inform the healthcare industry about patients and their reasons for certain perceptions. With the recent push for patient satisfaction, it is important to understand patient perceptions and how they may be altered. Patient satisfaction has direct links to hospital choice, and therefore hospitals which have a high level of satisfaction may be able to increase profits (Kessler & Mylod, 2011). Therefore, patient perceptions should be of interest to hospitals in terms of financial stability. However, as discussed earlier patient perceptions may also be linked to patient health outcomes, another key concern for hospitals (Johnansson et al., 2004). However, further research will likely be needed to replicate and build upon the current research in order to provide more concrete theoretical contributions and address the practical significance of the current research.

Study Limitations and Delimitations

Limitations

All research has limitations, and the current dissertation is no exception. The main limitation for the current research is that it utilizes convenience sampling. Amazon's ® Mechanical Turk ® (MTurk) will be utilized to collect data. MTurk allows individuals to complete Human Intelligence Tasks (HITs) for monetary compensation. The use of MTurk allows researchers to gather a large number of participants quickly, economically, and with ease. However, by use of an online survey, researchers have less control than in a controlled laboratory environment. However, in this case, the benefit is access to a large number of participants who are potential patients, which strengthens the current research's ability to generalize and draw conclusions. In addition, research has indicated that data gathered via MTurk is just as reliable as standard laboratory data (Buhrmester, Kwang, & Gosling, 2011; Germine et al., 2012). However, it is important to note that though the target population is all potential surgical patients in the United States, the accessible population is online MTurk users who are over 18.

Other limitations regarding the method of data collection include that subjects are paid. Due to the nature of MTurk, participants may be inclined to rush through HITs in order to earn more money. This could compromise the data collected. This study assumes that participants are taking the time to provide thoughtful, truthful answers, which is a limitation. However, this limitation is alleviated by constraints which MTurk allows researcher to put on a particular HIT. In order to ensure quality data, participants will be required to have at least a 98% approval rate from MTurk and have completed more than 100 HITs prior to the current survey.

The instruments used for this study are all self-report inventories which assess perceptions and other information quickly. Individuals may be affected by a response bias, such that different individuals place different significance on questions or answers. For example, two individuals may have different ideas of what *Agree* and *Strongly Agree* mean as they relate to a question. In addition, though conducting survey research allows for a wide variety of data types, the nuanced reasons behind participant answers are not always clear. For example, participants may have had previous beneficial or detrimental effects of surgery, which color their perceptions of robotic surgery.

Delimitations

For the purposes of this research, certain boundaries were put in place in order to ensure that the research questions are answered in an appropriate and straightforward way. This results in certain delimitations of the population, literature, methodological procedures, and analyses. These are discussed within this section. Regarding the population and sample, only U. S. participants are being surveyed, and as such, the results of the study cannot necessarily be generalized to other, global populations. Though robotic surgery is present in many countries, only U. S. perceptions are sought in the current research. In addition, the current research does not screen out individuals who have not had surgery, or those who do not utilize the healthcare system. The rationale for this inclusion is that these individuals may be future patients, and their perceptions of robotic surgery are still valid.

The current research chose to focus on the use and adoption of technologies and automation by consumers, and where available, adoption of technologies and automation by patients in the healthcare domain. As the goal of the present research is to create and validate a predictive model of patient willingness to undergo robotic surgery, adoption of healthcare technologies was largely considered the most important body of literature. There are current theories which assist in the modeling of technology adoption, such as Davis's (1986) Technology Acceptance Model (TAM) which has been repeatedly expanded and adapted. However, as Holden and Karsh (2010) note, healthcare technologies require substantial modification of the TAM, and as such, the TAM is not a focus of the current dissertation. Where appropriate, the TAM is mentioned in regard to potential predictors. However, due to the research questions the current study focuses on a rationale for building a model as opposed to adapting a current one. Therefore, the TAM will not be discussed in detail.

The current research chose to use online surveys through Google Forms and MTurk due to the ease of data collection and ability to gather a large sample size. Due to the nature of robotic surgery and its limited use in the healthcare system, it would be time intensive, expensive, and difficult to assess patient perceptions in a healthcare setting. In addition, self-report data was sought, again due to the ease of the process. Observations and other n-person methodological measures would not necessarily yield useful data for many of the variables in question and would be excessively time consuming. In addition, as discussed earlier, the use of MTurk allows for all *potential* patients to be surveyed, which is a population not easily accessed otherwise.

In addition, several scales were adapted for the purposes of this research. In the case of these researcher-made scales, no pre-existing instruments were found to be available which satisfied the content and length requirements for this study (e.g., lengthy scales, or not wholly appropriate). Though the initial scales were previously tested for validity and reliability, it is an assumption that the adapted scales will be valid and reliable as well. These adapted scales can be found in Appendices A-E and include the Willingness to Undergo Surgery Scale, Complexity Perceptions Scale, Familiarity Scale, Perceived Value Scale, and Wariness of New Technologies Scale. In order to account for the limitations of having new, untested scales, Cronbach's Alpha and Guttman's split-half tests were conducted on each of the five scales in order to ensure reliability and validity similar to that of the adapted scale. These values are included in the relevant sections of the current document.

Assumptions of Regression

The current research will utilize multiple regression for data analyses in order to create and validate a prediction model. In this section, the assumptions of multiple regression will be detailed in order to understand the constraints which the design and data must fit, in order for this analysis to be appropriate. The assumptions discussed below will again be referred to when discussing the data, in order to ensure that all have been satisfied. The assumptions of multiple regression are as follows:

1. There is one, continuous, dependent variable.
2. There are two or more independent variables.
3. There is independence of observations.
4. There is a linear relationship between the dependent variable and each of the independent variables, as well as between the dependent variable and the independent variables collectively.
5. There is homoscedasticity in the data.
6. There is no multicollinearity in the data.
7. There are no significant outliers in the data.
8. The residuals (errors) are normally distributed.

The first two assumptions are related to study design, and how the instrumentation is designed. Assumption 1 notes that the dependent variable must be continuous; assumption 2 notes that the presence of at least two independent variables is necessary.

Assumption 3 indicates that observations should be independent. Specifically, assumption 3 means that the error of each observation should not be correlated. This ensures that the observations are not linked in some way, in which case multiple regression would not be the appropriate analysis. Using SPSS, independence of observations can be tested with the Durbin-Watson statistic. Independence of observations can also be assessed by viewing the residuals scatterplot. Assumption 4 states that there should be a linear relationship between the independent variables and the dependent variable. This can also be tested by viewing the residuals scatterplot. Assumption 5, homoscedasticity, can also be tested using the residuals scatterplot. Homoscedasticity refers to the fact that the variance and standard deviation of the residuals (error) should be the same for predicted dependent variable scores.

Assumption 6, no multicollinearity, indicates that independent variables should not be highly correlated, and can be tested using Tolerance/VIF and correlation values. Assumption 7 states that there should be no significant outliers in the data, as multiple regression tends to be sensitive to outliers. The data will be screened for outliers prior to analysis, and if any are found, measures will be taken to alter or remove them from the data. Assumption 8, normal distribution of residuals, is also tested by viewing a superimposed normal curve or a P-P plot.

Summary

The main purpose of Chapter 1 was to discuss the background and rationale for the current dissertation, as well as to provide a clear set of operational definition, research questions, and hypotheses. In addition, the significance of the current research was discussed, and the limitations and assumptions were noted. In the following chapter, Chapter 2, the relevant literature will be discussed in detail. This will include information about the healthcare system, automation in surgery, patient perceptions, and justification for the inclusion of each independent variable as a potential predictor for the regression model.

Chapter 2

Review of Related Literature

Introduction

The healthcare system is a high-risk, high-complexity industry which is responsible for not only individuals' time and money, but also lives. The introduction of automation into this industry is only making it increasingly complex, with new moving parts and interactions. Though technologies such as robotic surgery are becoming safe and efficient means of providing healthcare, individuals are not always accepting of new technologies (La Porte & Metlay, 1975). In the recent decades, there has been a push for patient involvement and patient education (e.g., Smith, Dixon, Trevena, Nutbean, & McCaffrey, 2009). Therefore, it is important to better understand how patients view these new technologies, and whether or not they are willing to interact with them. Though much of the decision regarding the use of technology lies within the hospital and the providers, individuals do have a modicum of control over their own healthcare and will make decisions accordingly. In addition, patient satisfaction influences hospital finances, and patient outcomes. In this section, I will discuss healthcare and surgery, and how these fields interact with robotic surgery.

The purpose of the current dissertation is to provide a prediction model for individuals' willingness to undergo robotic surgery. Therefore, I will be accounting for multiple factors which may influence willingness to undergo robotic surgery, and how they relate to the healthcare field and patient decision making. For each factor, I will discuss a rationale for inclusion. In addition, I will discuss the use of regression and prediction models, and a rationale for their usage in this dissertation.

Sources

For this literature review, information was collected from various sources. Google Scholar was the main portal used for procuring information. In addition, Embry-Riddle Aeronautical University’s Hunt Library portal was used to access journals and databases. Some databases included were: PubMed Central, PLOS ONE, ProQuest Central, ScienceDirect, Scopus, and PSYCInfo, among others. From these sources, different formats of information were found, including but not limited to: peer-reviewed journal articles, books, conference papers and presentations, and public reports. In order to obtain these resources, keywords pertaining to the variables of interest were used. These keywords and phrases included, but were not limited to: automation in healthcare, robotic surgery, patient agency, laparoscopic surgery, age, gender, education level, income, complexity of automation, familiarity of automation, value of automation, wariness of new technologies, personality factors and/or traits, affect, six universal emotions, decision making, regression analysis, prediction models, and model fit.

Healthcare Industry

Healthcare is a massive industry, with services are split between inpatient services (admission to a hospital) and outpatient services (non- hospital admission). Because of the high-risk nature of medical care, it is incredibly important to ensure effective, efficient, and safe practices in medicine. To this end, the National Academy of Medicine (NAM), formerly the Institute of Medicine (IOM) has put out several reports, in order to guide research and practice initiatives in the field of healthcare. These reports, which have largely focused on human error and patient safety, have called for research into patient outcomes as well hospital processes and practices (e.g., IOM, 2001). Research is an important part of the health care system, not only in order to advance the field and develop new technologies and treatments, but also in order to improve patient satisfaction, patient care, and ultimately patient outcomes through medical treatment, and process improvement.

Healthcare involves not only patients and providers, but also many other competing interests. Oftentimes, the process of a patient going through treatment is complex – many providers may need to work together to ensure the patient receives optimal care. In addition, there are many patient-related factors which will influence the process. However, one factor which continues to change and progress is technology, which plays a vital role in patient-provider interactions. This can range from medical devices and equipment, to telemedicine and communicative technologies.

The current dissertation focuses on the role of technology in surgery – specifically investigating robotic and automated surgical procedures, and how patients perceive this realm of modern technology. As robotic surgery advances, it is important to understand how patients perceive and understand these new technologies. As discussed in Chapter 1, patient perceptions have the ability to shape hospital finances, patient decisions, and ultimately patient outcomes.

Surgery and Patients

The practice of surgery involves care and treatment of medical patients with incision or intrusion, in order to look into the body. Research by Lee, Regenbogen, and Gawande (2008) indicated that Americans may undergo an average of 9.2 surgical procedures in a lifetime, including inpatient and outpatient surgeries. Prevalence data from the Global Burden of Disease Study (GBD) estimated that more than 300 million “surgical procedures would be needed to address the burden of disease for a global population of 6·9 billion in 2010” and that many countries cannot meet the demand for the necessary procedures (Rose et al., 2015, p. S13). In addition, the likelihood of undergoing surgery increases as patients age, which is important for the current aging population (Lee et al., 2008).

Surgery has a long history of innovation, from creating new tools, to integrating new technologies (Riskin, Longaker, Gertner, & Krummel, 2006). Many different approaches to surgery have been developed over time, making the process safer, quicker, and more efficient, with better patient outcomes. Most notable was the introduction of minimally invasive techniques, allowing doctors to make smaller incisions and operate somewhat remotely. These techniques, tools, and procedures, which allow minimally invasive surgery have also been shown to have significant health benefits – including better patient outcomes and fewer complications (Mack, 2001). Mack (2001) notes that for open surgery – specifically cholecystectomy (gallbladder removal), the long hospitalization following surgery was not due to the gallbladder removal, but due to the mechanisms of the surgery – having to incise the abdominal wall. Currently in medicine, procedures often use some type of camera to look into an area inside the body – this is known as endoscopy (laparoscopy when considering the abdomen, which is a popular term). Generally, minimally invasive surgery requires fewer incisions, smaller incisions, and is, as the name would suggest, less invasive than open surgery.

Further advances in surgical tools and techniques have been able to enhance surgical capabilities by giving surgeons the ability carry out procedures in new, more efficient ways (e.g., tools to steady hand motions, project the path of an instrument, or provide previously impossible visualizations. Some of these enhancements are termed part of “robotic surgical systems.” One generally accepted definition of robotic surgery is “a surgical procedure or technology that adds a computer technology–enhanced device to the interaction between a surgeon and a patient during a surgical operation and assumes some degree of control heretofore completely reserved for the surgeon.” (Herron & Marohn, 2008, p.314) Herron and Marohn further note that robotic surgery tools and techniques may be better termed as “remote telepresence manipulators,” because at the time the article was written in 2008, as well as now, surgical robots require some control from a human. The robotic technologies are more so used to provide the surgeon with enhanced viewing and maneuvering capabilities. There are currently few fully automated components when considering robotic surgical systems, but as technology advances, it is likely that the degree of automation performed by robots will grow.

Robotic surgery was first considered as a way to operate remotely, though that is not the only way that the field has developed (Mack, 2001; Takács, Nagy, Rudas, & Haidegger, 2016). There are multiple cases claiming to be the “first robotic surgery” in the early to mid-1980’s. One, in particular was in 1985 at Vancouver General Hospital, where a robotic-assisted system manipulated and positioned the surgical patient’s arm during orthopedic surgery (Lechky, 1985). Since the inception of robotic surgical systems, there have been many advances in technology, and the use of robotic systems has spread throughout many disciplines. Robotic surgery has been used with mixed results for many different procedures, including robotic gastrectomy (Kim, Heo, & Jung, 2010), and vascular and endovascular surgery (Antoniou, Riga, Mayer, Cheshire, & Bicknell, 2011), Some research has indicated that robotic surgery may be cheaper than other surgical alternatives for specific procedures (Barnett et al., 2010). However, other research has denied that robotic surgery is cost effective (for urologic surgery, in this case; Lotan, 2012). The most popular current robotic surgical system is Intuitive Surgical's da Vinci ® robotic surgery system. The da Vinci ® system has been used to assist with many different surgical procedures, and has three major components: surgeon console, patient trolley with arms, and the imaging system (Pugin, Bucher, & Morel, 2011). The da Vinci ® employs endoscopic techniques and allows the surgeon to see enhanced 3D visualizations. It has several robotic arms which have more degrees of freedom than the human wrist and fingers. De Wilde and Herrmann (2013) note the benefits of using robotic surgery as reduction of physiological tremors, magnification of the surgical site, improved dexterity, and reduced fatigue for surgeons. However, they also note several drawbacks to the system –extensive costs and training requirements, the bulkiness of the equipment, and reduced tactile feedback. These benefits and limitations are similar to those noted for robotic surgery in general.

The benefits and drawbacks of robotic surgery as a whole are well-documented, especially when it comes to comparing open, laparoscopic, and robotic approaches. Generally, these benefits and drawbacks echo the benefits and drawbacks of automation-based versus human-based actions. There are some human limitations which a computer or robot can overcome, and vice-versa. In addition, there are limitations to endoscopic surgical procedures which can be mitigated through the use of robotic enhancements and systems. Advantages of robotic surgery include but are not limited to: larger range of motion, reduced physiological tremors, ergonomically user station, possibility for telesurgery, and 3D visualizations (De Wilde & Herrmann, 2013; Lanfranco et al., 2004). Robots in general tend to have better accuracy than humans, are more stable, can be sterilized, and do not suffer the effects of fatigue (Lanfranco et al., 2004).

Drawbacks and disadvantages of robotic surgery include but are not limited to: costliness, reduced access to patient, large space requirements, limited tactile feedback, potential for maintenance, and the fact that they are largely unproven in terms of benefits, especially when considering long-term patient outcomes (De Wilde & Herrmann, 2013; Lanfranco et al., 2004). In addition, using robotic surgical systems for specific procedures (e.g., Total Endoscopic Coronary Artery Bypass [TECAB]) can be “technically demanding and time-consuming” (Khajuria, 2015, p. 266). Robots also suffer in the fact that they cannot (yet) make judgement calls or use qualitative data (Lanfranco et al., 2004). Robotic surgery is still a relatively new technology, which is garnering more capability as the years progress.

Moving forward, it is clear that robotic surgical systems will continue to advance in complexity, as well as capability. Kranzfelder et al. (2013) note that though there are several technological hurdles to jump, that the increasing autonomy of the operating room (OR) will necessitate that robotics develop some type of procedural autonomy, assuming control over a section of the surgical process (e.g., tissue dissection). Some procedures or parts of procedures are very time consuming, but this time could feasibly be reduced by a surgical robot. Other advances may include intelligent instruments or an adaptive OR setting. There is currently a demand for these robotic, autonomous systems, and as such, it is important to understand how patients may feel about the current state of robotic surgery and the future of robotic surgery.

Patient Perception-based Research

Patients have widely differing roles in deciding upon their own care. This is dependent on a number of factors, including the patient, the physician(s) and provider(s), and the nature of the patient's need. For example, a patient who experiences a severe trauma may not be involved in the decision for immediate surgery, due to being incapacitated and/or unconscious. In this case, the patient has no say in their care. This is not a variable which can necessarily be controlled. At that specific point, the patient's care is dependent upon their providers and medical protocols.

However, when this is not the case, patients have some control (albeit varying levels) over their own healthcare. At the bare minimum, they can usually decide when and where to seek treatment. A 2001 report by the Institute of Medicine (IOM) notes that "Patients should be given the necessary information and opportunity to exercise the degree of control they choose over health care decisions that affect them. The system should be able to accommodate differences in patient preferences and encourage shared decision making," (pp. 3-4). Indeed, some individuals want more control than others; previous research has indicated that most individuals want to be offered choices in their medical care, and that women, more educated individuals, and healthier individuals preferred a more active role in their care (Levinson, Kao, Kuby, & Thisted, 2005). With the understanding that patients would like to be involved in their care, there has been a history of soliciting patient opinions. Indeed, patient satisfaction is a goal for many hospitals, and research has investigated some of the reasons for, and results of patient satisfaction (e.g., Fenton, Jerant, Bertakis, & Franks, 2012). However, research has gone further, from investigating patient satisfaction in general, to asking individuals more specifically about the care they received, their opinions, their preferences, and their outcomes.

Research on patient perceptions has largely focused on how successful patients believe their surgery has been – this has been studied for shoulder surgery (Dawson, Fitzpatrick, & Carr, 1996), hip replacements (Dawson, Fitzpatrick, Carr, & Murray, 1996), knee replacement (Dawson, Fitzpatrick, Murray, & Carr, 1998), and outpatient surgery (Mitchell, 1999). These studies have been focused on developing and using instruments designed to assess patients' level of functioning post-surgical procedure. Patient perceptions have also been solicited about their experiences under general anesthesia (Schwender, Kunze-Kronawitter, Dietrich, Klasing, Forst, & Madler, 1998), their level of satisfaction with the care received (Schoenfelder, Klewer, & Kugler, 2010), and their impressions of "awake" surgery for the removal of a brain tumor (Whittle, Midgley, Georges, Pringle, & Taylor, 2005). In most studies focusing on patient perceptions, interviews or surveys were the primary methodologies used. Surveys used were either created or validated for the purposes of the study, or already-validated instruments were used. Results greatly vary, but generally focus on satisfaction and individualized experiences (e.g., Dawson et al., 1998; Schoenfelder et al., 2010, Schwender et al., 1998).

Some research has also investigated the factors which may influence an individual's decision to undergo different types of surgery or in different contexts, such as surgery when diagnosed with lung cancer (Cykert et al., 2010), orthognathic surgery (corrective jaw surgery; Bell, Kiyak, Joondeph, McNeill, & Wallen, 1985), and cosmetic and reconstructive surgery (Didie & Sarwer, 2003; Heinberg, Fauerbach, Spence, &

Hackerman, 1997; Nold, Beamer, Helmer, & McBoyle, 2000; von Soest, Kvalem, Skolleborg, & Roald, 2006). Studies investigating the decision to undergo reconstructive and cosmetic surgeries has found multiple psychosocial factors which have an influence on the decision-making process, such as perceptions of one's cosmetic appearance, personality, and perceptions of risk of further disorder. Other factors may include but are not limited to: ethnicity, family history, personal history, insurance factors, and the surgeon who would be advising them and performing the surgery (Cykert et al., 2010; Yi et al., 2010). However, there is very little research on patient perceptions of technology in a healthcare setting – specifically willingness to use new technologies in a healthcare setting, or have these technologies utilized for treatment.

A limited amount of previous research has centered on patient and provider perceptions of robotics and automation in healthcare. This includes many different provider categories or groups, from nurses to surgeons, and various subgroups of patients (e.g., elderly patients). The automated technologies studied in the aforementioned research range from socially-assistive robots (Pino, Boulay, Jouen, & Rigaud, 2015), to the health "cloud" (Hseih, 2016), and robotic-assistive surgery (BenMassoud, Kharrazi, & MacDorman, 2011; Zineddine & Arafa, 2013). When investigating home healthcare robots (HHRs), Alaid and Zhou (2014) found that intent to use was partially predicted by how patients believed the HHR would act, their trust in the HHR, ethical concerns, and social influence. Social influence in this case refers to the individual's understanding of whether or not the people whose opinions they value think that HHRs would be beneficial (e.g., a family member thinks that an individual will be in better health if using an HHR). Other research has supported these claims, indicating that social influence, understanding of the technology, and perceived usefulness influence usage intention of HHRs (Alaiad, Zhou, & Koru, 2013). Other research into adoption of technology services in healthcare has indicated that there is a long list of important considerations: cost of device or procedure, ease of use, usefulness or value, characteristics of the user, doctor's opinion, and computer anxiety, among others (Cimperman, Brenčič, & Trkman, 2016; Pino, Boulay, Jouen, & Rigaud, 2015; Topacan, Basoglu, & Daim, 2009).

Of particular relevance are studies investigating consumer perceptions and adoption of robotic and robotic-assisted surgery. When asked opinions about robotic-assisted surgery, a primarily United Arab Emirates sample largely believed that robotic-assisted surgery was not safe, and while 71% of respondents trusted surgeons in general, only 6% said they would trust a surgeon with a robot. Even if remote operation of a robot would allow an "expert" surgeon to perform the surgery, respondents were still not in favor of the process (Zineddine & Arafa, 2013). Other provider-based research has shown that surgeons may adopt robotic-assisted technologies due to the potential benefits for patients, but also partially because of their attitudes (BenMessaoud, Kharrazi, & MacDorman, 2011). Those who use robotic-assistive technologies tended to be more open to change; potential barriers to adoption may include lack of hospital support, the learning curve for the technology, and financial barriers (BenMessaoud, Kharrazi, & MacDorman, 2011). It is important to understand that not all surgeons and providers utilize these technologies, and there may be a disconnect between provider and patient as to perceptions and intent to use technologies in healthcare.

Dependent Variable: *Willingness*

This section will detail the dependent variable, willingness to undergo robotic surgery. Following a discussion of willingness, the next several sections will detail the predictive factors of interest which may influence the dependent variable. Willingness is an indication of support – is the individual in question willing to interact with a certain type of technology? For the purposes of the current dissertation, willingness is measured using the Willingness to Undergo Robotic Surgery Scale, adapted from Rice, Winter, Kraemer, Mehta, and Oyman's (2015) Willingness to Fly scale. This scale can be found in Appendix A. A pilot study was run in order to gauge the reliability and validity of scales adapted for this dissertation. Results of that study indicated that for the newly adapted Willingness to Undergo Robotic Surgery Scale, Cronbach's alpha was .949, and Guttman's split-half was .927. In addition, using a principal components extraction with varimax rotation, all items loaded onto one factor. Therefore, the adapted scale has sufficient psychometric properties to be used in the current research.

Willingness to interact with automated technologies has been studied in the context of driverless cars (Anania, Mehta, Marte, Rice, & Winter; 2018; Anania et al., 2018), autonomous ambulances (Winter, Keebler, Rice, Mehta, & Baugh, 2018), driverless school busses (Anania et al., 2018), and autonomous airplanes (Mehta, Rice, Winter, & Eudy, 2017). From these studies, many factors have been shown to influence willingness, such as demographic factors, context-specific factors, and perception-based factors. These are discussed more in detail below when relevant to a specific predictor. However, there is a distinct lack of research done to assess willingness to interact with technologies in the medical domain.

Predictive Factors of Interest to this Study

The current dissertation examines 21 factors that may significantly predict an individual's willingness to undergo robotic surgery. These predictors were selected due to current technology adoption research as well as healthcare-based research. They include: age, gender, income, education level, ethnicity, perceived complexity, perceived value, familiarity, wariness of new technologies, fear of surgery, personality factors (5 factors), and affect (in the form of the six universal emotions).

Age

For the purposes of this dissertation, age refers to the age of the participant measured in years. All participants are assumed to be potential patients of the healthcare industry who at some point may require surgical care. Previous research has indicated that Americans may undergo an average of 9.2 surgical procedures in a lifetime (Lee, Regenbogen, & Gawande, 2008). As such, it is not an unfunded assumption to consider American individuals as people who may interact with robotic surgical procedures or traditional surgical procedures within their lifetime. This section investigates the influence of age as a predictor for willingness to undergo robotic surgery. Age is included as a predictor due to inherent changes that come with aging in decision making, preferences, attitudes, and behaviors.

One meta-analysis investigated the differences between young, middle-aged, and old participants and found that there are differences between groups in everyday problem-solving/decision-making effectiveness (EPSE; Thornton & Dumke, 2005). This was such that older participants had diminished EPSE, although this relationship was often affected by problem content, rating criteria, and sample characteristics (Thornton &

Dumke, 2005). In addition, some research has found support for the fact that older adults may have diminished EPSE as a result of underlying cognitive deficits as opposed to simply aging – the effects of age in one particular study disappeared when accounting for individual differences in processing speed and memory (Henninger, Madden, & Huettel, 2010). The same study found some support for the idea that older adults may make more risk-averse decisions (Henninger et al., 2010). In addition to making different decisions, and having cognitive changes, it is likely that as an individual ages, the decision-making process is different as well. One study found that younger participants took emotional and social factors into account more than older participants, and that older adults are more aware of a decision's complexity and the factors affecting it (Sanz de Acedo Lizárraga, Sanz de Acedo Baquedano, & Cardelle-Elawar, 2007). Knowing that age has an influence over decisions as well as the decision-making process, it is intuitive to think that perhaps this would hold true when individuals are making decisions about technology acceptance and use.

Indeed, research has provided support for the idea that age has a history of influencing technology adoption and responses to automation. Behaviorally, older adults take longer to adjust their strategies to changing automation tasks than do younger adults (Sanchez, Rogers, Fisk, & Rovira, 2014). Older adults have been shown to have differential reasons for adopting and using technology – in a workplace setting, one study found that while younger employees' usage was influenced by attitudes toward technology, older employees' usage was more influenced by the control they believed they had, and initially by the social norm (Morris & Venkatesh, 2000). Morris and Venkatesh (2000) postulated that actual system use would be influenced by participants' attitudes toward the technology, the subjective norm, and the participants' perceived behavioral control. When considering other applied technologies, such as driverless vehicles, younger participants are more accepting of travelling in autonomous cars (Hulse, Xie, & Galea, 2018; Schoettle & Sivak, 2014). Further research by Morris, Ventakkesh, and Ackerman (2005) indicated that gender and age are intertwined when considering intent and behavioral use of new technologies (in this case, a software technologies). The literature surrounding age differences in technology and automation perceptions/use does indicate that age influences and is influenced by other factors, which makes it an appropriate variable to be included in a model with other factors (e.g., gender and affect). These factors are discussed in following sections.

Gender

Gender indicates the gender of the participant and is limited to either male or female participants. In this section, gender is investigated as a potential predictor of willingness to undergo robotic surgery. Gender is included as a potential predictor due to differences between males and females when it comes to decision-making (Croson & Gneezym, 2009). In addition, gender is included due to previous literature indicating differential acceptance and use of technologies by males and females (discussed in detail below). Because the current study is related to adoption of new technologies (i.e., willingness to undergo robotic assisted or fully robotic surgery), gender is a pertinent variable to include. However, before discussing previous literature's findings about gender and technology adoption, it is important to outline some basic differences in gender which likely contribute to these differences in technology adoption.

Overall, there are many gender differences in social preferences, risk preferences, and competitive preferences (Croson & Gneezym, 2009). In other words, females and males respond differently to risky situations, social situations, and situations where competition is a factor. In general, women tend to avoid “riskier” decisions, are less competitive, and women’s behavior in social situations is more variable – possibly explained by a better affinity for understanding social cues (Croson & Gneezym, 2009). Of most relevance to the current research are gender differences in decision making under risky constraints.

Males and females tend to have differential behaviors when it comes to decision making and risk aversion. Females tend to make more risk-averse decisions in a number of contexts (Borghans, Heckman, Golsteyn, & Meijers, 2009; Powell & Ansic, 1997). A comprehensive review concluded that females are more risk averse across abstract gambling experiments, applied experiments, and in field studies, with field studies providing the most conclusive support for this claim (Eckel & Grossman, 2008). Eckel and Grossman (2008) also note that this risk aversion difference is in part due to differences in *perception* of risk, such that women perceive situations as riskier.

In terms of perceptions of risk, much research has been done investigating perceptions of different automated technologies. Research by Winter, Keebler, Rice, Mehta, and Baugh (2018) indicates that females are less willing to ride in an autonomous ambulance, a situation which may be considered unfamiliar and risky. Similar results have found that females are less willing to fly in autonomous airplanes (Mehta, Rice, Winter, & Eudy, 2017), and less willing to ride in driverless cars (Anania et al., 2018). It seems that from past research, females are less willing to utilize and adopt automated technologies.

In addition, a previous study by Venkatesh, Morris, and Ackerman (2000) noted that female and male participants had different reasons for the adoption of technology in the workplace, and initial usage rates. Specifically, females were more concerned with subjective norms and their perceived control, while males' adoption and use were more related to their attitude towards the technology (Venkatesh, Morris, & Ackerman, 2000). Based upon gender's prevalence in decision making research, and its past influence on willingness to adopt new technologies, it is likely that gender plays a predictive role in the current research. However, it is also clear that gender likely has a reciprocal relationship with other factors (e.g., personality or emotions) and as such it is appropriate to consider gender in the construction of a predictive model, as the current research attempts to do, as opposed to alone.

Income

Income refers to the annual earnings of the participant. This is measured in United States (US) Dollars, as all participants are from the US. Income is included due to the finances associated with medical care, considering that individuals with a lower income may be less willing to undergo a medical procedure (in this case, robotic surgery). In addition, there is a link between income and perceptions of different technologies. Therefore, it is reasonable to hypothesize that income may influence an individual's willingness to undergo robotic surgery.

Income is one demographic factor which Porter and Donthu (2006) note is a barrier to internet usage – those with a lower income have lower usage rates of the

Internet. Lower Internet usage rates may be attributed to the cost of accessing, or other barriers to access. Porter and Donthu’s (2006) research indicated that income influenced beliefs about the internet, which influenced actual usage. Those with different levels of income may perceive technology differently due to availability, familiarity, usefulness, etc. Similar results were found in the contexts of online banking and online shopping. Pikkarainen, Pikkarainen, Karjaluoto, and Pahnila (2004) found a positive correlation between income and online banking use. Bellman, Lohse, and Johnson (1999) found that income was a predictor of online buying behavior. Those with less income were less likely to purchase online. In the context of using technology to buy goods and services, or buying technological goods and services, income is a consideration. Those with more buying power are simply more able to adopt those technologies or use those technologies.

Income has also been shown to influence decision making in the medical contexts – both regarding decisions about treatment, as well as acceptance of healthcare technologies. Data from the Swedish Level of Living Survey in 1991 indicates that as income increases, the probability of deciding to visit a physician increases (Gerdtham, 1997). Similar results were found by researchers investigating use of medical services among a sample of Medicare beneficiaries, finding that those with higher income had been utilizing more services than those with lower income (Gornick et al., 1996). Some researchers have also found that income has an effect on utilization of preventative medical care, though these results were significantly modified by race and ethnicity (Holden, Chen, & Dagher, 2015).

Little research has been conducted regarding the influence of income on decisions to accept medical technologies. However, device cost is a common cited issue for adoption of these technologies. When considering socially-assistive robots, one of the major barriers to acceptance is their cost (Pino et al., 2015). Though no direct link has been made to income, it is important to note that those who have a greater income will more likely be able to handle the financial burden of a high-cost robot. As robotic surgery likely has a cost associated with the procedure (potentially greater for the patient than a traditional surgery), it is included here as a potential predictor of willingness to undergo robotic surgery at different levels of automation.

Education Level

For the current research, education denotes the highest level of education which the participant has completed. The following options are available to the participant for selection: 1) less than high school; 2) high school graduate (includes equivalency); 3) some college, no degree; 4) associate's degree; 5) bachelor's degree; 6) master's degree; and 7) doctorate degree (or terminal degree). Education level is included in part because it is assumed that those with a higher education have more knowledge and skills. This does not necessarily mean that those with higher degrees make better decisions or make them more efficiently, but there are numerous areas of literature which support the idea that individuals with differing levels of education make different decisions or have different preferences for decision making. Raymond Cattel's (1963) work with intelligence separated fluid intelligence and crystallized intelligence, where fluid intelligence refers to the ability to problem solve, and crystallized intelligence refers to experiences and learned knowledge. Those with more years of formal education would have more learned knowledge, and therefore likely have more crystallized intelligence, with the potential of increased problem solving and thereby fluid intelligence as well.

This section will have a specific focus on preferences for making medical decisions or decisions about technology.

In regard to technology use, one study found education level to be a predicting factor (Czaja et al., 2006). This was such that those who were better educated tended to use more types of technology. The same study also found that education had an effect on fluid and crystallized intelligence, which were also influencing factors of technology usage (Czaja et al., 2006). However, it is important to note that technology use could not be predicted alone by education – other variables must be considered. Similar results were found by Ellis and Allaire (1999), who modeled the process of computer interest, and found that higher education levels were related to more interest in computers, as well as related to more computer knowledge. However, these were entwined with other variables, and unable to be considered alone. However, it is clear that education level has some effect on attitudes toward technology.

In addition, there are some links in the literature regarding a patient's desire to be involved in their care and their education, such that more educated individuals tend to want to be more included in decision-making about their care (Levinson, Kao, Kuby, & Thisted, 2005; Thompson, Pitts, & Schwankovsky, 1993). Specifically, one study investigating rheumatology care found that in their study, patients with over 12 years of formal education tended to have a higher level of current involvement in their care (Kieken et al., 2006). This, along with the understanding that education level influences technology attitudes, suggests that education level may have some influence on willingness to undergo robotic surgery, and as such is included as a predictor in the current research.

Ethnicity

Ethnicity refers to the participant's self-selected ethnicity out of the following options: 1) Caucasian, 2) African descent (e.g., African American), 3) Hispanic descent (e.g., Latin America), 4) Asian descent, 5) India (not Asian), or 6) Other. An individual's ethnicity refers to a social or cultural group with which they share common attributes or traditions (e.g., holidays, languages, etc.). Ethnicity is included as a predictor due to its common inclusion in understanding individual differences, as well as its possible role in technology acceptance and understanding. In a 2007 paper, Bagozzi called for a paradigm shift in the Technology Acceptance Model – and one of his proposed additions was sociocultural variables. Bagozzi's (2007) rationale for this inclusion was the nature of how cultural differences and social norms can influence decision making, as well as simply the individual differences between cultures.

Indeed, Srite, and Karahanna (2006) found that cultural values such as uncertainty avoidance were moderators in the technology acceptance model, such that they had an influence of the behavioral intention to use technology. This indicates that perhaps there are cultural values across ethnicities which may influence an individual's willingness to adopt a new technology. One meta-analysis regarding the technology acceptance model indicated that cultural influences had a significant moderation effect (Schepers & Wetzels, 2007). Schepers and Wetzels (2007) found that though perceived usefulness was important in Western cultures, perceived ease of use was more important in non-Western studies. In addition, one study found that ethnic diversity in small businesses influenced information technology (IT) adoption (Chuang, Nakatani, & Zhou, 2009).

As individuals of different ethnicities tend to have different cultural values, it is possible that ethnicity is a predictor of willingness to undergo robotic surgery, such that those of different ethnicities will be more or less willing to undergo robotic surgery. Therefore, it is pertinent to include ethnicity as a possible predictor.

Perceived Complexity

Perceived complexity refers to the participant's understanding of the automation controlling the robotic surgery process. This is measured using a 5-item Likert-type scale, with all items positively worded. Participants respond to each statement from Strongly Disagree (-2) to Strongly Agree (2) with a zero-neutral option. This metric and its associated psychometric properties can be found in Appendix B. Complexity is included in part because of the inherent complexity within automation. Not all individuals understand how automation functions, whether it be an autonomous system, or human-assisted system.

The complexity of an automated system is one variable related to operator trust in that system (Hoff & Bashir, 2015). In order for an individual to trust a system, or be comfortable with using it, they must have some level of understanding of its actions. Research from aviation has indicated that automation has created an increase in mode errors (Sarter & Woods, 1995). In other words, there are so many states the automation and system can be in that the user loses track of what the system is doing and what proper function should be. One analysis of automation indicated that there was some confusion over the state that the automation was currently in, given the vast number of options. (Wiener, 1989). This is likely not a result of the automation malfunctioning, but rather that the automation is not designed in a way that individuals can intuitively understand.

There is often a lack of feedback from the automation, which keeps those who interact with it in the dark as to its “thought process” (Norman, 1989).

In the medical field, there is a constant need to keep patients well-informed and educated about their diagnosis, prognosis, and treatment. Many initiatives have been targeted at increasing patient understanding of complex health issues (Varkey et al., 2009). Adding complex automation into a healthcare system with already complex decision-making on behalf of the patient and provider will create added confusion. New technologies are not always easily accepted, and it is important to understand that hesitation to accept these technologies will likely be stronger in a medical setting, as the technology has the ability to affect lives, which is not the case for most other technologies (Montague, Kleiner, & Winchester, 2009). Due to the complex nature of automation and healthcare, it is important to assess how complex an individual believes robotic surgery automation to be, and whether or not this perception influences their willingness to utilize this technology. Therefore, perceived complexity is included as a predictor in the current model.

Perceived Value

For this research, perceived value indicates the value robotic dentistry has to the participant, and the level of benefit that the participants thinks robotic surgery would have. This is measured using a 5-item Likert-type scale, with all items positively worded. Participants respond to each statement from Strongly Disagree (-2) to Strongly Agree (2) with a zero-neutral option. This metric and its associated psychometric properties can be found in Appendix D. Most items indicate that “value” is related to personal benefit and usefulness. This predictor is included due to the strong link between value and acceptance of new technologies. This section will review the relevant literature and investigate perceived value as it applies specifically to medical choices and medical technologies.

First of all, it is intuitive to think that as an individual perceives more value in a piece of technology, they are more likely to use it. If someone finds no value or use in a new piece of technology, why would they spend their time and/or money adopting that technology? In order for individuals to change their regular behavior, there must be some type of "incentive." One study investigated customer loyalty and found that the consumer's perceived value as well as satisfaction were the two most important aspects for maintaining loyalty (Yang & Peterson, 2004). Though perceived value is often considered in marketing research and literature, it is also important when considering responses to technology.

In the realm of information and communication technologies, perceived usefulness has been shown to impact adoption of mobile internet technologies (Kim, Chan, & Gupta, 2007), microcomputer technology (Igbaria, Schiffman, & Wieckowski, 1994), and online learning (Saadé & Bahli, 2005). Perceived usefulness is often integrated into the TAM, alongside perceived ease of use (e.g., Saadé & Bahli, 2005), however, given that providers and not patients will be using the robotic and robotic-assisted technologies for surgery, ease of use is not considered in the current prospective model. Further, these concepts have been studied specifically in the healthcare domain.

In terms of health care technologies, perceived usefulness or value has not been assessed for healthcare robots. However, perceived usefulness has been shown to have an influence over patient adoption of provider-delivered e-health systems (Wilson & Lankton, 2004), and online electronic medical records (EMR; Winkelman, Leonard, &

Rossos, 2005). In the case of Wilson and Lankton's (2004) study, perceived usefulness was measured using three items (e.g., "Overall, [e-health] will be useful in managing my health care."). However, Winkelman et al., (2005) used a qualitative investigation to understand perceived usefulness of online EMR, including attitudes towards the EMR and expectations of quality and usefulness. The current study uses a 5-item scale (similar to the questions used by Wilson & Lankton, 2005) to assess perceived value of robotic surgery technologies. Due to perceived usefulness's prevalence in the technology acceptance literature, and its introduction into understanding acceptance of medical technologies, it is an appropriate factor to be assessed in the current model.

Familiarity

Familiarity indicates how familiar the participant is with robotic surgery, including if they have read information about it, and have prior knowledge of the process. This is measured using a 5-item Likert-type scale, with all items positively worded. Participants respond to each statement from Strongly Disagree (-2) to Strongly Agree (2) with a zero-neutral option. This metric and its associated psychometric properties can be found in Appendix C. The idea of the "mere exposure effect," first studied by Zajonc (1968) indicates that an individual's attitude toward a stimulus will become more favorable as that individual is repeatedly exposed to the stimulus in question. He notes that this happens unconsciously, and that attitudes toward the stimulus can change. However, this provides some initial indication that things that are familiar will be perceived in a more positive way (in this case, perhaps that individuals will be more willing to undergo robotic surgery if they are familiar with the concept).

In business contexts, familiarity seems to influence trust in a positive way (Gulati, 1995). It is easy to understand how previous experiences with an individual, or product or system, would make an individual more comfortable in future interactions. In this vein, familiarity has also been studied in regard to technology and automation. Exposure to mobile technologies has a positive influence on intention to use mobile e-commerce – though this study indicated that exposure and individual attitudes had a relationship as well, which related to behavioral intention (Khalifa & Cheng, 2002). Khalifa and Cheng (2002) note that exposure can take multiple forms – observation, communication, and trial. The more exposure an individual has with a particular technology (or similar technologies) the more familiar they will find it.

Ibrahim, Siminoff, Burant, and Kwoh (2002) investigated differences in perceptions of joint replacement, finding that those who had less familiarity and understanding of joint replacement, and expected longer hospital stays and more pain following surgery. This is likely due to their lack of familiarity – if they had not seen friends and family undergo and recover from the procedure, their knowledge of the surrounding prospects was different (and in this case, more negative). More recent research by Kwoh et al., (2015) performed a similar study with similar results, indicating that willingness to undergo surgery was influenced by the level of understanding of the procedure.

As familiarity happens over time, as a result of exposure, it is likely that familiarity is linked to other variables. It stands to reason that as an individual becomes more familiar with a technology, their perception of the technology will change in many respects. Therefore, familiarity is integrated as a potential predictor in the current model.

Wariness of New Technologies

Wariness of new technologies is a construct which refers to how the participant responds to new technologies in general, with no reference to a specific type of technology (i.e., robotic surgery). For the purposes of this dissertation, this is measured using a 5-item Likert-type scale, with all items positively worded. Participants respond to each statement from Strongly Disagree (-2) to Strongly Agree (2) with a zero-neutral option. This metric and its associated psychometric properties can be found in Appendix E.

As discussed in previous sections, adoption of new technologies is dependent on many factors. Research has investigated barriers to adoption of new technologies, as well as individuals' wariness to technology and resistance to change (e.g., Fagnant & Kockelman, 2015; La Porte & Metlay, 1975; Lee, Scheufele, & Lewenstein, 2005). "Wariness" refers to a certain amount of caution, or distrust that the individual holds (Wariness, n.d.).

Distrust, fears, and wariness towards different technologies are common, and have been widely studied throughout the previous decades. Technologies which seem commonplace today once were distrusted and not widely adopted or accepted, such as electronic marketplaces (Hsiao, 2003) and electronic banking (Benamati & Serva, 2010). This holds true especially for automated technologies, where trust is a consideration when understanding human interaction with automation (Parasuraman & Riley, 1997).

In addition, previous research has indicated that trust in medical technologies is empirically different that trust in other types of technologies (Montague et al., 2009). This is likely due to the role that the patient plays. In some medical situations, the health, well-being, and potentially life of the patient may depend on the medical technology in question. One study showed that individuals define their comfort in and trust of medical technologies through attributes such as ability to affect lives, healthfulness, and security in caring, which are not present when considering general trust in technology (Montague et al., 2009). Therefore, it is important to assess perceptions of automated healthcare technologies, as results from automation research may not always generalize to healthcare devices.

Wariness and discomfort with technologies may not be insurmountable. In a study of air traffic controllers using a new type of automated sequencing and spacing tool, a training and trial period of actually interacting with the automation increased trust in the tool, and controllers showed less overall wariness of the automation after the completion of the study (McGarry, Martin, & Witzberger, 2016). This could provide some understanding as to how to alter perceptions of new technologies, if necessary. However, it is important to note that wariness (and trust to some extent) influences and is influenced by other variables, such as training and exposure in the case of McGarry et al. (2016). Therefore, it is important to study wariness in conjunction with other variables, such as the others considered in this dissertation. Due to public uneasiness about new technologies, and a history of not easily adopting new automated technologies, wariness is included here as a variable.

Fear of Surgery

Fear of surgery refers to an individual's response to one question about their general level of fear of surgery on a 10-point Likert-type question. Fear of surgery is included in part to include a domain-specific variable, as well as due to the prevalence of fear of surgery, and its ability to influence patient outcomes (e.g., post-operative pain; Carr, Brockbank, Allen, & Strike, 2006). It is very common to assess preoperative anxiety and fear both qualitatively and quantitatively (e.g., Carr et al., 2006; Spalding, 2003; Welsh, 2000). Being admitted to the hospital is stressful, and this stress and anxiety can even influence a patient's recovery time post-surgery (Welsh, 2000).

Carr et al. (2006) found that in women undergoing gynecological surgery, the four main causes of anxiety were: organization and delivery of care, becoming a patient, not knowing (e.g., complications, pain, unexpected events), and concerns about other patients and family/friends. Robotic surgery is arguably present in all four of these categories and could certainly compound this issue. However, it is important to note that anxiety and fear over surgery are common even without the inclusion of a robotic surgical system. One study indicated that women may be more fearful of surgery (Karlson, Daltroy, Liang, Eaton, & Katz, 1997). However, Spalding (2003) found that pre-operative education can decrease anxiety by "making the unknown familiar" (p. 278), which indicates that this barrier is not insurmountable. However, prior to addressing this barrier, it must first be investigated, which is a key reason why fear of surgery is included here as a predictive variable of interest.

Personality (Big Five)

Personality, for the purposes of this dissertation, refers to five different personality traits: openness to experience, conscientiousness, extraversion, agreeableness, and neuroticism. Specifically, personality refers to the participant's scores on the Mini International Personality Item Pool (Mini-IPIP; Donnellan et al., 2006) in the aforementioned five areas. The Mini-IPIP is a 20-item scale and was chosen largely in part due to its brevity while still maintaining the psychometric properties of strong validity and reliability.

Personality is included as a potential predictor due to its history of influence over a wide variety of perceptions, attitudes, and behaviors. Personality has been studied for decades in many contexts, basic and applied. There are many theories of personality, and when researchers assess personality in relation to perceptions and behaviors, they often use different personality models or specific traits of interest. The most widely accepted model of personality is the Five Factor Model, most widely researched and developed by McCrae and Costa (e.g., 1987). The Five Factor Model is the personality model most predominately used by researchers to study and understand personality; it allows both prediction and explanation of behavior (Feist, Feist, & Roberts, 2012). The five factors mentioned above in relationship to the Mini-IPIP include Openness to Experience, Conscientiousness, Extraversion, Agreeableness, and Neuroticism.

Openness to Experience is oftentimes also known as Intellect/Imagination, and many researchers have argued over the terminology; either way, this term refers to openness to change, creativity and flexibility, and originality (DeYoung, 2014; Feist et al., 2012). In addition, Hills & Argyle (2001) among others, note that a better term for neuroticism would be "emotional stability," however the definition remains similar, the term refers to negative emotionality (e.g., anxiety; Feist et al., 2012). The terms Extraversion, Conscientiousness, and Agreeableness are more or less agreed upon. Extraversion indicates socialness, friendliness, and warmth (Feist et al., 2012). Conscientiousness indicates how careful, detail-oriented, and reliable someone is (Feist et al., 2012). Agreeableness is almost self-explanatory, this trait refers to how easy someone is to get along with, including cooperation, lenience, and forgiveness (Feist et al., 2012).

Personality has a significant influence on many behaviors, including job performance and proficiency (Barrick & Mount, 1991), as well as retail relationships and purchases (Odekerken-Schröder, De Wulf, & Schumacher, 2003). Specifically, Odekerken-Schröder et al.'s research found that a company's marketing scheme interacted with some consumer personality traits in order to predict some German consumers' relationship commitment with retailers, as well as their buying behaviors. This is fundamentally similar to the potential influence of personality in the current research, attempting to predict perceptions and attitudes (and how behavior may be influenced).

Personality also has a history of being included with technological acceptance models for information technologies. Previous research has shown that personality (as measured by a version of the IPIP inventory) has an influence on behavioral intention, as well as technology acceptance (Svendsen, Johnsen, Almås-Sørensen, & Vittersø, 2013). Research by Halko and Kientz (2010) has shown that scores on the Big Five traits influence how individuals perceive technologies in a multitude of ways – noting that some newer technologies were more readily accepted by those who score higher on the "Openness to Experience" trait. They also found that those who score high in "Conscientious" prefer socially-based technologies, and that those scoring high in "Neuroticism" do not prefer socially-based technologies, among other findings (Halko & Kientz, 2010). The broad finding that personality does affect technology preferences and behavioral intentions provides support for the inclusion of personality in the current research. Further, given the state of robotic surgery systems as a developing technological industry, the inclusion of personality in this research is appropriate and timely.

Affect and the Six Universal Emotions

Affect, or emotion, has long been understood to hold a prominent role in decision-making. Affect, for the purposes of the current research, refers to an individual's emotional response. Very generally, there are two types of affect: positive affect and negative affect, which independently affect decisions, attitudes, and behaviors (Diener & Emmons, 1984). Positive affect refers to emotions such as happiness and excitement, whereas negative affect refers to emotions such as guilt and sadness. These broad dimensions of positive and negative affect are measures using the Positive and Negative Affect Schedule (PANAS; Watson, Clark, & Tellegen, 1988). However, research by Ekman and Friesen (1971) has indicated that across cultures, there are more specific emotions which are universally recognized – known fittingly as the "Six Universal Emotions." These emotions are: happiness, sadness, surprise, fear, anger, and disgust. Ekman and Friesen (1971) studied many cultures, including those with limited contact with other civilizations and found that overwhelmingly, individuals were able to distinguish these six emotions by facial expressions. Therefore, affect is oftentimes also measured using pictorial representations of Ekman and Friesen's (1971) six universal emotions (see Figure 1; as first used in Rice & Winter, 2015). This allows for a more nuanced view of participant affect.

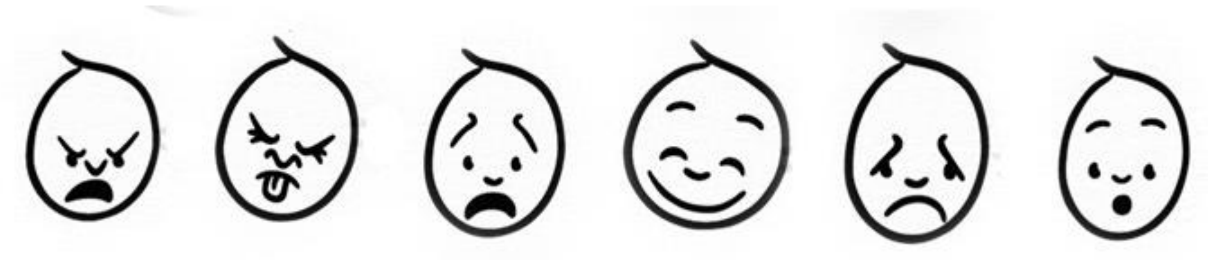

Figure 1. Six emotions from Ekman and Friesen's (1971) work are represented here with images. They represent anger, disgust, fear, happiness, sadness, and surprise, respectively.

Affect and emotion's influence on decision-making is well-documented. This holds true for negative affect (Raghunathan & Pham, 1999) and for positive affect (Isen & Means, 1983). Raghunathan and Pham's (1999) work notes that different emotions (in their case, sadness and anxiety) prime participants to behave a certain way and make a certain decision. In this case, affect is a source of information; for example, those who were anxious preferred low-risk, low-reward scenarios, presumably because they were using their anxiety as a motivation to make a certain decision (Raghunathan & Pham, 1999).

When considering consumers, some research has indicated that cognition and affect work together to provide support for the decision-making process (Shiv & Fedorikhin, 1999). Affect has also been implicated in the decisions about whether or not to use new technologies and automation. Foremost, the well-known technology acceptance model (TAM), designed for assessing acceptance of information technologies, has previously included emotion in the model (Venkatesh, 2000). However, emotion was operationalized as a score on a "computer anxiety" scale, thereby only measuring one possible emotional influence (Venkatesh, 2000).

Some research has specifically used Ekman and Friesen's (1971) six universal emotions to further understand individuals' responses to new technologies, including automated technologies. Happiness and surprise were shown to have an influence over a consumer's willingness to pay more for airline flights using biofuels (a greener alternative to traditional fuel; Rains et al., 2017). Happiness and fear were shown to partially predict a consumer's willingness to ride in a driverless vehicle (Anania et al., 2018). Happiness, anger, surprise, and sadness were all found to have an influence on whether or not a participant was willing to let their child ride in a driverless school bus, indicating that some participants felt happier when considering a traditional school bus, and felt angrier, sadder, or more fear when considering an autonomous school bus (Anania et al., 2018).

When considering medical decisions, many researchers have investigated the role of patient emotions in the decision-making process, finding that current and anticipated emotions influence how the patient responds to their health concerns (Power, Swartzman, & Robinson, 2011). Power et al., (2011) introduced a decision-making framework in which patient cognitions and emotions work in tandem to produce a decision. In addition, some research has indicated that emotions can lead patients to make decisions that are not necessarily in their best interests (Redelmeier, Rozin, & Kahneman, 1993). Due to the prevalent nature of emotions in decision making, and the influence of certain emotions on individual willingness to interact with automated technologies, affect is a pertinent variable to include.

Regression and Prediction Models

This study aims to create a prediction equation for patient willingness to undergo robotic surgery at differing levels of automation (e.g., robotic-assisted and fully robotic). The 21 factors which may be elements of this equation include: age, gender, education level, income, perceived complexity, perceived value, familiarity, wariness of new technologies, fear of surgery personality (Openness, Conscientiousness, Extraversion, Agreeableness, and Neuroticism), and Affect/emotion (happiness, sadness, fear, surprise, disgust, and anger). The justification for each factor's inclusion has been detailed in earlier sections. The current section will focus on previous literature which has used similar methodology, in order to partially justify the use of the model fit technique in this research.

Currently, technology acceptance often focuses on the Technology Acceptance Model (TAM), originally designed for assessing acceptance of computer-based information technologies (IT; Davis, 1986). When investigating adoption of technologies, it is common for researchers to utilize the TAM and potentially add new constructs or elements to the model, then test it in some way. Though the TAM is sometimes investigated through Structural Equation Modeling (SEM), it is important to note that SEM is most often used to assess information technologies. There are likely other factors due to the nature of robotic surgery and its future autonomous implications.

In addition, there is a precedent for using regression analyses as is done in this dissertation. Previous research has investigated which kinds of people are willing to ride in driverless cars, investigating situational factors and individual difference variables and their ability to predict willingness (Anania et al., 2018). Researchers have also adapted the TAM to consider some extra factors such as privacy, security, and self-efficacy (Vijayasarathy, 2004). In this particular study, they used prediction models and regression analyses to assess whether or not these factors predicted consumer intent to use online shopping (Vijayasarathy, 2004). In the medical realm, Gönül, Carter, and Wind (2000) used multiple regression to predict what type of patients and providers are more accepting of direct-to-consumer advertisement for prescription drugs. Ayatollahi et al., (2013) used regression analyses to predict emergency department staff attitudes about IT.

The first stage of this research will create a regression equation used to predict an individual's willingness to undergo robotic surgery. The second stage will use a second sample of participants to test the model created in the first stage. Due to the precedent set above, as well as a need to explore numerous factors concurrently, linear multiple regression is the appropriate statistical method to employ.

Summary

The purpose of Chapter 2 is to review the associated literature in the fields related to the current dissertation. In doing so, it is clear that the current work addresses a gap to study consumer acceptance of robotic surgery technologies, both current and future. The chapter provided an in-depth view of the potential predictors, related research, and justification for inclusion. Chapter 3 will detail the methodology used for the current dissertation. Chapter 3 will include information about the population, sample, instrumentation, procedures, variables, design, and expected analysis tools. The information provided in Chapter 3 should be comprehensive enough to easily facilitate any replication efforts.

Chapter 3

Methodology

Introduction

The current chapter will detail the methodology used for this dissertation. All of the steps, tools, and ancillary information will be discussed. This chapter will provide detail enough that replication studies could be carried out. This will include information about the design, population and sample, procedure and methods for data collection, variables and expected data analysis. The chapter will also include a description of the legal and ethical procedures taken, including participant anonymity and confidentiality.

Research Design

The aim of the current dissertation is to build and validate a regression equation for patient willingness to undergo robotic surgery. The design is focused around a quantitative study using a correlational design. Solely quantitative measures will be employed. Qualitative designs, though able to provide a very nuanced look at individual cases and reasons for perceptions, are difficult to compare in large numbers and allow little in the way of prediction. Qualitative designs do not allow for statistical analyses of data trends and cannot be validated. In addition, qualitative data is very time-consuming to collect for both researchers and participants. Therefore, the current research employs a quantitative design.

The current quantitative research utilizes a correlational design. A correlational design is the most appropriate method for prediction and model fit. Multiple linear regression and model fit analyses will be used as the statistical procedures. Linear regression was chosen due to the relevance and practical benefit of creating an equation to better understand the reasons for patient willingness (or unwillingness) to undergo robotic surgery. As the current research does not plan to assess differences between groups, no statistical techniques used to compare groups will be utilized (e.g., *t*-test or Analysis of Variance [ANOVA]). Multiple regression can provide a more nuanced look at the factors which may affect individuals to have a certain perception. The current dissertation is interested in several variables; these variables do not all lend themselves to categorizing participants into groups (e.g., treatment groups). Therefore, no group comparison analyses are planned. In addition, the correlational design will utilize a survey, as naturalistic observation and archival research would be of practical difficulty. Many of the variables that will be collected have no already been measured and recorded prior to the study and cannot be observed easily. A survey-based correlational quantitative design is appropriate, as well as feasible.

Population and Sample

Population

The aim of the current dissertation is to create a prediction model of patient willingness to undergo robotic surgery. The ultimate goal is to be able to generalize the findings of this research to the target population, which is all potential patients in the United States. It is important to understand consumer/patient preferences in healthcare treatments, and how these change with the addition of automation. For the purposes of this dissertation, the accessible population is all patients who have internet access and are users of Amazon's ® Mechanical Turk ® (MTurk) who complete human intelligence tasks (HITs). The accessible population is limited to American patients who are at least 18 years of age.

Sample

The current dissertation utilizes a convenience sample recruited via MTurk. Participants were compensated 50-100 cents for their participation in the study, for approximately 6-8 minutes of their time. Stage 1 used 1324 participants and Stage 2 used 1335 participants, for a total of 2659.

Tabachnik and Fidell (2007) indicate that for multiple regression, sample size should follow the formula $N \geq 50+8m$, where m is the number of independent variables; testing individual predictors should follow the rule $N \geq 104+m$, where m is the number of independent variables. If the research seeks to test both, the higher number should be adhered to. In the case of the current research, $m = 19$. For the current research, $N \geq 202$, and $N \geq 123$, respectively, therefore an N of 300 for each stage is more than adequate. Tabachnik and Fidell (2007) also indicate that for stepwise regression, a cases-to-IV ratio of 40 to 1 is appropriate. With 21 variables, this would necessitate an $N = 840$. In addition, due to the lengthy nature of the survey, it is likely that many participants will have missing data. Therefore, approximately 3000 participants total were surveyed, in order to deal with missing data and proper methodology for stepwise regression. The number of participants takes into account outliers and potential other participant issues that would result in exclusion from analyses.

In addition, though convenience sampling is a potential limitation, this does allow for a much larger sample than would be able to be obtained otherwise. The study will measure whether or not an individual has undergone surgery before, but will not exclude these participants, as they may be future patients who will undergo surgery.

Power Analysis

A priori sample size determination was conducted in order to ensure validity of the results to infer conclusions with more confidence. The program G*Power 3.1.9.2 was used to perform these analyses. With effect size of .05, power (beta) of .80, and alpha level of significance .05, it was determined that each step will need a sample size of 444 at minimum. The study will be conducted twice, first to create the model/regression equation, and second to test the model. To create and test the model, a total amount of 888 (at minimum) participants will be needed. As mentioned in the earlier section, approximately 1500 participants will be utilized for each Stage 1 as well as each Stage 2, in order to account for any possible need to exclude participants or data points from analysis. The choice has been made to run significantly more participants than the power analysis necessitates, in part because of the type of regression being performed – stepwise regression.

Research Methodology

As mentioned above, participants were recruited online using Amazon's ® MTurk. The survey was developed and administered via Google Forms ®. Participants read instructions and answered free-response as well as multiple-choice questions. All participants responded to the same survey, regardless of the Stage.

First, participants answered 4 Likert-type scales. These were the Perceived Complexity of Robotic Surgery Scale (see Appendix B), Familiarity with Robotic Surgery Scale (see Appendix C), Perceived Value of Robotic Surgery Scale (see Appendix D) and the Wariness of New Technologies Scale (see Appendix E). The order of each of these scales was randomized by Google Forms ® for each participant. In addition, these four scales all had 5-items. Items within each scale were also presented in random order. The directions for these four metrics were identical, and presented before each new set of questions:

"Please respond to each of the statements below indicating how strongly you agree or disagree with each statement."

Following responses to the four 5-item scales, participants were presented with the Mini International Personality Item Pool (Mini-IPIP; Donnellan et al., 2006), a 20-item survey. This scale measures five dimensions of participant personality: Openness to experience, Conscientiousness, Extraversion, Agreeableness, and Neuroticism. Each of these five personality traits is considered an individual predictor for the current dissertation. The directions prior to the questions read:

"Describe yourself as you generally are now, not as you wish to be in the future. Describe yourself as you honestly see yourself, in relation to other people you know of the same sex as you are, and roughly your same age. Indicate for each statement whether it is Very Inaccurate, Moderately Inaccurate, Neither Accurate Nor Inaccurate, Moderately Accurate, or Very Accurate as a description of you."

The following section assessed the participant's affective (emotional) response to robotic surgery. Participants were shown the following directions.

"Imagine that you have just gone to your physician for tests, and were told that you had to have your gallbladder removed, and the fastest and cheapest option is to have robotic surgery where the surgeon performs the surgery largely aided by a robot. The human surgeon programs and controls the robot at all times, but has

no direct access to your body during surgery. The only entity actually touching your body throughout the surgery is the robot.

Based on the scenario above, how strongly do you feel like the image shown?"

Following the directions, participants were shown pictorial images of each of Ekman and Friesen's (1971) six universal emotions: happiness, sadness, fear, anger, surprise, and disgust (see Figure 1). All participants will respond to all emotions. Each of these six emotions is considered as a predictor in the model. As discussed in Chapter 2, the six universal emotions are included due to importance of affect and emotion in decision making. Each emotion will be presented separately to the participants, they will see a pictorial image of one face (e.g., happiness) and then be asked how strongly they feel like the image shown, on a scale of I do not feel this way at all (1) to Extremely feel this way (10). Emotions will be presented in random order.

Following the affective responses, participants will respond to seven questions assessing their willingness to undergo the robotic surgery. This was a 7-item Likert-type scale, and the directions prior were as follows:

"Imagine that you have just gone to your physician for tests, and were told that you had to have your gallbladder removed, and the fastest and cheapest option is to have robotic surgery where the surgeon performs the surgery largely aided by a robot. The human surgeon programs and controls the robot at all times, but has no direct access to your body during surgery. The only entity actually touching your body throughout the surgery is the robot."

Last, participants will answer a series of demographic questions relating to some predictors of the study. These are as follows:

1. *What is your gender?*
    - *Female*
    - *Male*
    - *Other* ____________
2. *What is your ethnicity?*
    - *Caucasian*
    - *African descent (e.g., African American)*
    - *Hispanic descent (e.g., Latin America)*
    - *Asian descent*
    - *India (not Asian)*
    - *Other*
3. *What is your highest level of education?*
    - Less than high school
    - High school graduate (includes equivalency)
    - Some college, no degree
    - Associate's degree
    - Bachelor's degree
    - Master's degree
    - Doctorate degree (or terminal degree).
4. *What is your age?*
5. *What is your gross yearly income (in US dollars)?*

6. *What is your general level of fear of surgery?*
7. *Have you ever had surgery?*
8. *Have any of your prior surgeries been performed with the assistance of a robotic surgical system, such as the da Vinci?*
9. *Have you experienced any complications or unexpected events as a result of a prior surgery?*
10. *Please provide as much detail as you are able and willing about any previous complication or unexpected difficulty you have experienced due to a prior surgical procedure.*

The survey detailed above is the only instrument used to collect data for the current dissertation. Participants were recruited via Amazon's ® MTurk ® for the survey, which is considered a human intelligence task (HIT). MTurk users are compensated for their participation in HITs. The current research was completed in two stages; the same instrument was utilized for each stage. Following completion of the survey, participants were given instructions on how to collect their compensation from MTurk.

Variables

Independent Variables

The independent variables in this dissertation are the predictors being used for model development, in order to predict the dependent variable. These factors include: age, gender, ethnicity, income, education level, ethnicity, perceived complexity, perceived value, familiarity, wariness of new technologies, fear of surgery, personality factors (Openness to experience, Conscientiousness, Extraversion, Agreeableness, and Neuroticism), and affect (in the form of the six universal emotions). See Table 1 for an at-a-glance look at the predictors, how they will be assessed, and the Appendix where the instrument can be found, if appropriate. In addition, where appropriate, reliability estimates are provided for scales, calculated from a pilot study intending to assess reliability and validity of these instruments.

Table 2. At-a-glance look at the predictor variables and how they are being measured.

Independent Variable	Question Type	Measurement Type	Cronbach's Alpha	Guttman's Split Half	Appendix
Age	Free response	Categorical			
Gender	Multiple choice/ free response	Continuous			
Income	Free response	Continuous			
Education Level	Multiple choice	Categorical			
Ethnicity	Multiple choice	Categorical			
Perceived Complexity	Likert-type scale	Continuous	.863	.901	Appendix B
Perceived Value	Likert-type scale	Continuous	.912	.898	Appendix C
Familiarity	Likert-type scale	Continuous	.909	.871	Appendix D
Wariness of New Technologies	Likert-type scale	Continuous	.913	.883	Appendix E
Fear of Surgery	Likert-type question	Continuous			
Openness to Experience	Subscale of Mini-IPIP (Donnellan et al., 2006)	Continuous	.767	.851	
Conscientiousness	Subscale of Mini-IPIP (Donnellan et al., 2006)	Continuous	.711	.553	

Extraversion	Subscale of Mini-IPIP (Donnellan et al., 2006)	Continuous	.770	.629
Agreeableness	Subscale of Mini-IPIP (Donnellan et al., 2006)	Continuous	.800	.624
Neuroticism	Subscale of Mini-IPIP (Donnellan et al., 2006)	Continuous	.727	.562
Happiness	Likert-type question	Continuous		
Sadness	Likert-type question	Continuous		
Anger	Likert-type question	Continuous		
Disgust	Likert-type question	Continuous		
Fear	Likert-type question	Continuous		
Surprise	Likert-type question	Continuous		

It is important to note that several variables (Perceived Complexity, Perceived Value, Familiarity, Wariness of New Technologies, Personality factors, and Willingness) are measured via Likert-type scales, which are inherently ordinal. However, by indexing each scale to obtain a single number, the data can be treated as interval data (Brown, 2011).

Age was treated as a continuous variable; participants self-reported their age in the form of a free-response question. Gender was treated as a categorical variable with three options: male, female, and other. This was presented to participants as a multiple-choice question with mutually-exclusive responses. Income, similarly to age, was treated as a continuous variable. Participants self-reported their annual income in the form of a free-response question. Education level, similarly to gender, was treated as a categorical variable. Participants responded to a multiple-choice option asking their highest level of education completed (6 levels of response). The only available responses will be: 1) less than high school; 2) high school graduate (includes equivalency); 3) some college, no degree; 4) associate's degree; 5) bachelor's degree; 6) master's degree; and 7) doctorate degree (or terminal degree).

Perceived complexity was measured as the participant's average score across 5 questions designed to assess how complex they believe the automation controlling robotic surgery to be. Participants responded to 5 Likert-type questions on a 5-point scale ranging from Strongly Disagree (-2) to Strongly Agree (2) with a zero-neutral point. The scale of measurement for this variable (as with all other continuous variables) is ordinal but was treated as an interval scale of measurement. Perceived value was measured as the participant's average score across 5 questions designed to assess how valuable a service they believe robotic surgery to be. Participants responded to 5 Likert-type questions on a 5-point scale ranging from Strongly Disagree (-2) to Strongly Agree (2) with a zero-neutral point. Familiarity was measured as the participant's average score across 5 questions designed to assess how familiar with robotic surgery the participant is. Participants responded to 5 Likert-type questions on a 5-point scale ranging from Strongly Disagree (-2) to Strongly Agree (2) with a zero-neutral point. Wariness of new technologies was measured as the participant's average score across 5 questions designed to assess how wary of new technologies (in general) the participants tend to be.

Participants responded to 5 Likert-type questions on a 5-point scale ranging from Strongly Disagree (-2) to Strongly Agree (2) with a zero-neutral point.

Personality factors were measured as 5 individual variables – the participant's average response to questions about Openness to Experience, Conscientiousness, Extraversion, Agreeableness, and Neuroticism. Participants responded to the Mini International Personality Item Pool (Mini-IPIP; Donnellan et al., 2006), a 20-item survey. Each personality factor is represented by the average to 4 Likert-type questions on the 20-item scale. Participants responded to these questions on a 5-point scale and were asked to assess the statement and select how accurate that statement is as it applies to them (e.g., "Don't talk a lot.") with 5 options, ranging from Very Inaccurate to Very Accurate with a zero-neutral option "Neither accurate nor inaccurate." Scoring for these variables is dependent on whether the question is positively or negatively worded; regardless, a summed score of all responses represents the final value for the variable.

Affect was measured as six individual variables (reflecting the six universal emotions), happiness, disgust, sadness, anger, fear, and surprise. Participants were shown pictorial representations of each emotion individually (see Figure 1). Participants responded to each emotion picture on a ten-point Likert-type scale from "I do not feel this way at all" (1) to "Extremely feel this way" (10).

Dependent Variable

The dependent variable for the current research is patient willingness to undergo robotic surgery (see Appendix A). This is measured as the average score of participants on a 7-item, 5-point Likert-type scale. The 7 items assess how willing the participant is to undergo robotic surgery, and participants can select a response from Strongly Disagree (-

2) to Strongly Agree (2) with a zero-neutral point. The scale of measurement for the dependent variable is ordinal but will be treated as interval.

Data Analysis

As discussed earlier, the current dissertation employs a correlational design, and as such, multiple linear regression was used to analyze Stage 1 data. Stage 2 data involved model fit testing in order to determine whether or not the model was valid. Using standard multiple linear regression is appropriate due to the mature of the variables and hypotheses. Using this data, a regression equation was calculated, including coefficients for each individual independent variable that is significantly related to patient willingness. For stage 2, the second data set was used to test the first model, by inputting each independent variable into the model, obtaining predicted willingness scores, and assessing these against the actual willingness scores.

Because the current research attempts to build a predictive model, statistical techniques used to compare groups are inappropriate. Instead, it is important to understand the relationships between variables, and as such, a correlational method is being employed. The use of multiple regression will allow exploratory research in order to build a model and test that model for its predictive value. Standard multiple regression is appropriate as opposed to hierarchical multiple regression or structural equation modeling, as there is no theoretical basis to the order or organization of independent variables from the related literature. In addition, multiple regression will be used instead of logistical regression, as the dependent variable in the study (willingness) is an interval scale of measurement, rather than categorical.

In addition, the decision has been made to not utilize the method of Structural Equation Modeling (SEM) for this dissertation. SEM is used as a confirmatory analysis tool for theory-based models. Though there is justification for including each predictor (see Chapter 2 for specific justifications), there is little theory as to how these predictors may influence each other. Therefore, SEM is inappropriate, as a model cannot be created and confirmed using the data. Instead, the current dissertation employs the use of multiple regression. Multiple regression allows researchers to investigate the relationship of multiple independent variables on one continuous dependent variable. Multiple regression is ideal to assess how well a group of variables is able to predict a certain outcome and can assess whether or not these variables predict the outcome when all of the other variables are being controlled for. The resulting model could be used by the healthcare community to better understand and educate patients about robotic surgery and its benefits.

Participant Eligibility requirements

In order to participate in the study, participants were at least 18 years of age – screened prior to beginning the survey via a dichotomous-choice questions where respondents must certify that they are above 18 years of age to continue. The current research should pose no harm to any participant, and the survey and methods have been carefully crafted to ensure that this is the case. The protocol, instrumentation, and associated materials will be assessed and approved by the Institutional Review Board (IRB) for suitability. IRB application and approval are included in Appendix F.

Participants' Protection

As discussed above, the current research utilized a convenience sample from Amazon's ® Mechanical Turk ® (MTurk). No confidential information about participants is given from MTurk to researchers. No names or contacting information is provided to researchers. This ensures the anonymity and confidentiality of participant responses. Further, participant information was utilized for model construction, but no individual values will be published or available beyond inclusion in aggregated data analyses.

Legal and Ethical Consideration

This research posed no risks to the human subjects participating. As discussed, a convenience sample from MTurk will be used; MTurk is responsible for screening all participants. The current research only accepted participants over the age of 18 and ensured that the procedure and instrumentation did not expose participants to any physical, psychological, social, or legal risks. The IRB approved the study and methodology prior to data collection.

Summary

The purpose of this chapter was to discuss in detail the methodologies for carrying out the current research. Included were details about design, procedure, participants, variables, and ethical considerations for the current research. This chapter should provide adequate detail to facilitate any replication studies. The final purpose for the current chapter is to provide a background to understand the following data analysis and discussion of results. In Chapter 4, I will discuss the data analyses performed and resulting statistics.

Chapter 4

Results

Introduction

The purpose of the current dissertation was to create a prediction model of willingness to undergo robotic surgery. In order to achieve this goal, two regression analyses were performed. The previous section (Chapter 3) outlined the design and construction of the research, including all methodology, ethical considerations, and instrumentation. The current chapter will detail the analyses performed after data collection, including descriptive and inferential statistics. These will detail the demographics of the sample and calculate Cronbach's alpha and Guttman's half-split of some of the instrumentation used, as well as conducting the proposed regression analyses. As the dependent variable (and several of the independent variables) were adapted from previous scales for the purposes of this research, it is important to assess internal consistency and reliability. These analyses and their rationale are further detailed in the following sections of Chapter 4. All data analyses were conducted using Microsoft Excel, and the statistical analysis tool IBM SPSS Statistics Software.

General Design

As explained in Chapter 3, this study utilized a correlational research design. Regression analyses were used to create a regression equation in order to determine which factors influenced patient willingness to undergo robotic surgery. The study tested twenty-one factors that could have a predictive influence on patient willingness. The independent variables: age, gender, income, ethnicity, education level, fear of surgery, perceived complexity, perceived value, familiarity, wariness of new technologies, 5 personality factors, and affect (in the form of the six universal emotions). The dependent variable was the individual's willingness to undergo robotic surgery. The regression equation was created in Stage 1. In Stage 2, a secondary sample was used to test the resulting equation and create a prediction model of patient willingness to undergo robotic surgery.

Research Tool and Instrument

To collect data for building and validating this model, a questionnaire was developed using Google Forms ®. A full version of this questionnaire can be found in Appendix F. Participants responded to a variety of question types, including selecting responses on a linear scale (e.g., 1 to 10), selecting responses on a Likert-type scale, selecting multiple-choice responses for categorical variables, or writing in free response questions. The instrument was administered once, ensuring that the questionnaire remained the same for Stage 1 and Stage 2 analyses. For these stages, the data was randomly split into two groups, prior to any data cleaning and analyses. The participants were all recruited through Amazon's ® Mechanical Turk ® (MTurk) and were paid $0.5 – 1.0 (US currency) as compensation for completing the study.

Results

Descriptive Statistics

The current research, as detailed above, was conducted in two separate stages. The first stage aimed to create a regression equation of patient willingness to undergo robotic surgery. The second stage was to test the regression equation with a separate sample, in order to validate the equation built in Stage 1. This section details the descriptive statistics from both stages. The total sample size for this dissertation was 2659 (1377 females).

Missing and Excluded Data

The rationale for exclusion of cases was identical within Stage 1 and Stage 2 data. For the Willingness, Complexity, Familiarity, Value, and Wariness scales, a participant was excluded if they did not respond to all of the questions in a scale (e.g., did not answer all five questions about perceived value), as this would not allow an average score to be produced. For all Personality subscales, a participant was excluded if they did not answer even one of the questions. By nature of the instrument, missing one value would produce an erroneous sum. For all other variables (affect, gender, ethnicity, education, age, income, and fear of surgery), a participant was excluded from the analyses if they did not answer the single question designed to measure that variable (e.g., selecting a gender, or self-reporting their age). In addition, participants were excluded if they wrote in an "other" for gender (e.g., "nonbinary") as these cell counts were very small. Participants were also excluded if they wrote words in the free-response space for income (e.g., "N/A" or "don't know").

There are many potential reasons for missing values in a dataset. As required by the Institutional Review Board, participants must be able to bypass any and all questions that they do not wish to answer for any reason. Therefore, it is impossible to tell whether or not a participant has chosen not to answer a question or has simply missed it by mistake. No clear patterns were found in the missing data in Stage 1 or Stage 1. In addition, outliers were removed from the data; this process is discussed in the Assumptions section.

Table 4 shows the frequency counts as well as percentages of the full data set (Stage 1 N = 1528 prior to data exclusion, and Stage 2 N = 1527 prior to data exclusion), which were excluded based on the criteria above. A total of 1324 participants were utilized for Stage 1, and 204 were excluded – 183 due to exclusion criteria above and 21 due to outliers. A total of 1335 participants were utilized for Stage 2, and 192 were excluded – 170 due to exclusion criteria and 22 due to outliers.

Table 4
Summary of Missing and Excluded Data

Variable		Stage 1	Stage 2
Willingness		0 (0%)	0 (0%)
Complexity		2 (.13%)	0 (0%)
Familiarity		2 (.13%)	0 (0%)
Value		2 (.13%)	0 (0%)
Wariness		1 (.07%)	0 (0%)
	Conscientiousness	15 (1%)	18 (1.18%)
	Agreeableness	15 (1%)	18 (1.18%)
Personality	Neuroticism	34 (2.22%)	22 (1.44%)
	Openness	22 (1.44%)	25 (1.64%)
	Extraversion	24 (1.57%)	16 (1.05%)
	Anger	5 (.33%)	3 (.20%)
	Disgust	3 (.20%)	2 (.13%)
Affect	Fear	2 (.13%)	1 (.07%)
	Happiness	5 (.33%)	4 (.26%)
	Sadness	1 (.07%)	1 (.07%)
	Surprise	4 (.26%)	1 (.07%)
Gender		7 (.46%)	8 (.52%)
Ethnicity		2 (.13%)	2 (.13%)
Education		0 (0%)	4 (.26%)
Age		29 (1.90%)	19 (1.24%)
Income		37 (2.42%)	45 (2.94%)
Fear of Surgery		8 (.52%)	5 (.33%)
Total		183 (12.00%)[a]	170 (11.11%)

a. Total is not sum of all missing data, as some cases had multiple missing data points; does not include removal of outliers

Stage 1

For Stage 1, the resulting sample size (after data exclusion) was N = 1324. Of the 1324, 699 (53%) were female. The mean age of the sample was 37.71 (SD = 12.49). The mean income was 45,633.12 USD (*SD* = 31,658.87). The highest level of education completed by the participants is broken down as follows: .6% Less than high school (*N* = 9), 7.5% High school graduate (includes equivalency; *N* = 99), 24.4% Some college, no degree (*N* = 324), 13.1% Associate's Degree (*N* = 174), 38.6% Bachelor's Degree (*N* = 511), 13.2% Master's Degree (*N* = 175), and 2.4% Doctorate Degree (or terminal degree; *N* = 32). The ethnicity of the participants was broken down as follows: 75% Caucasian (*N* = 993), 6.6% African descent (e.g., African American; *N* = 88), 7.1% Asian descent (*N* = 94), 7.6% Hispanic descent (e.g., Latin American; *N* = 100), .6% Indian (Not Asian; *N* = 8), and 3.1% Other (*N* = 41). The mean overall fear of surgery as self-reported by participants was 6.08 (on a 10-point scale; *SD* = 2.57). Of the 1324 participants, 866 (65.4%) reported that they had undergone surgery before. Of these 866, 67 reported that at least one of their surgeries had been robotic-assisted. When surveying for negative surgical outcomes, 135 participants reported that they had some type of negative outcome as a result of their surgery (robotic assisted and non-robotic assisted). A summary of the descriptive statistics for Stage 1 is available in Table 2.

Table 2
Summary of Stage 1 Descriptive Statistics

	Variable	N	M	SD
	Age	1324	37.1	12.49
	Income	1324	45,633.12	31,658.87
	Fear of Surgery	1324	6.08	2.57
Gender	Male	625 (47.2%)		
	Female	699 (52.8%)		
Education Level	Less than high school	9 (0.6%)		
	High school graduate	99 (7.5%)		
	Some college, no degree	324 (24.4%)		
	Associate's Degree	174 (13.1%)		

	Bachelor’s Degree	511 (38.6%)
	Master’s Degree	175 (13.2%)
	Doctorate Degree	32 (2.4%)
Ethnicity	Caucasian	933 (75%)
	African descent	88 (6.6%)
	Asian descent	94 (7.1%)
	Hispanic descent	100 (7.6%)
	Indian	8 (0.6%)
	Other	41 (3.1%)
Had Surgery	Yes	866 (65.4)
	No	438 (33.1%)
	Not Sure	21 (1.5%)
Had Robotic Surgery	Yes	67 (5.1%)
	No	709 (53.5%)
	Not Sure	89 (6.7%)
	N/A or did not answer	459 (34.7)
Had Adverse Surgical Outcome	Yes	135 (10.2%)
	No	719 (54.3%)
	Not Sure	11 (0.8%)
	N/A or did not answer	459 (34.7%)

Stage 2

For Stage 2, the resulting sample size (after data exclusion) was N = 1335. Of the 1335, 678 (50.8%) were female. The mean age of the sample was 37.59 (SD = 11.86). The mean income was 46,632.82 USD (SD = 39,622.34). The highest level of education completed by the participants is broken down as follows: .5% Less than high school (N = 7), 9.4% High school graduate (includes equivalency; N = 126), 20.9% Some college, no degree (N = 279), 12.0% Associate’s Degree (N = 160), 40.9% Bachelor’s Degree (N = 546), 13.3% Master’s Degree (N = 177), and 3.0% Doctorate Degree (or terminal degree; N = 40). The ethnicity of the participants was broken down as follows: 76.2% Caucasian (N = 1017), 7.9% African descent (e.g., African American; N = 106), 6.1% Asian descent

(N = 82), 6.3% Hispanic descent (e.g., Latin American; N = 84), .3% Indian (Not Asian; N = 4), and 3.2% Other (N = 42). The mean overall fear of surgery as self-reported by participants was 6.06 (on a 10-point scale; SD = 2.58). Of the 1335 participants, 875 (65.5%) reported that they had undergone surgery before. Of these 866, 68 reported that at least one of their surgeries had been robotic-assisted. When surveying for negative surgical outcomes, 122 participants reported that they had some type of negative outcome as a result of their surgery (robotic assisted and non-robotic assisted). A summary of the descriptive statistics for Stage 2 is available in Table 3.

Table 3
Summary of Stage 2 Descriptive Statistics

Variable		N	M	SD
	Age	1335	37.59	11.86
	Income	1335	46,632.82	39,622.34
	Fear of Surgery	1335	6.06	2.58
Gender	Male	657 (49.2%)		
	Female	678 (50.8%)		
Education Level	Less than high school	7 (0.5%)		
	High school graduate	126 (9.4%)		
	Some college, no degree	279 (20.9%)		
	Associate’s Degree	160 (12.0%)		
	Bachelor’s Degree	546 (40.9%)		
	Master’s Degree	177 (13.3%)		
	Doctorate Degree	40 (3.0%)		
Ethnicity	Caucasian	1017 (76.2%)		
	African descent	106 (7.9%)		
	Asian descent	82 (6.1%)		
	Hispanic descent	84 (6.3%)		
	Indian	4 (0.3%)		
	Other	42 (3.2%)		
Had Surgery	Yes	875 (65.5%)		
	No	447 (33.5%)		

	Not Sure	13 (1.0%)
	Yes	68 (5.1%)
Had Robotic Surgery	No	724 (54.2%)
	Not Sure	81 (6.1%)
	N/A or did not answer	462 (34.6%)
Had Adverse Surgical Outcome	Yes	122 (9.1%)
	No	740 (54.5%)
	Not Sure	13 (1.0%)
	N/A or did not answer	460 (34.5%)

Inferential Statistics

Sample Sizes, Effect Size and Observed Power

A convenience sample was utilized via Amazon's ® Mechanical Turk ®. As detailed in Chapter 3, a priori power analyses were conducted in order to determine adequate sample sizes. The a priori analyses suggested that at least 444 participants were necessary to complete each stage of the model, with a small effect size of .05, an alpha level of .05, a power of .80, and 21 predictors. Due to the large requirement for participants in a stepwise regression, as well as the likelihood of missing data, over 3000 participants were surveyed total (over 1500 for each stage).

Though the a priori analyses used a small effect size of .05, post hoc tests of actual effect size can be calculated using the overall R^2 of the model. The overall R^2 = .627. For multiple regression, effect size can be calculated using the following formula: $f^2 = R^2/(1- R^2)$. Following this formula, the post hoc effect size for Stage 1 of the model was $f^2 = 1.68$.

Though power analyses indicated that sample size needed to be at least 444 for each stage, significantly more participants were run for several reasons, detailed in prior sections. The post hoc test to compute achieved power, using G*Power 3.1.9.2 showed that the observed power was > .99.

Internal Consistency and Reliability

Cronbach's alpha and Guttman's split half tests were conducted on several of the scales used for this study, including the dependent variable, and three of the independent variables. These scales were adapted from previously validated scales in order to be appropriate for the current research, and include: Perceived Complexity of Robotic Surgery, Familiarity of Robotic Surgery, Perceived Value of Robotic Surgery, and Willingness to Undergo Robotic Surgery (the dependent variable). Cronbach's alpha, created by Cronbach (1951) is a measure of internal consistency, which explains how well all of the items in an instrument are inter-related, or measuring the same concept (Tavakol & Dennick, 2011). Ideally, Cronbach's alpha should fall within the range of .70 to .95 (Tavakol & Dennick, 2011). Guttman's split half test measures test-retest reliability (Guttman, 1945).

In each scale, before averaging the items to one score, it is important to determine internal consistency and reliability. Cronbach's alpha and Guttman's split-half coefficient were calculated during both Stage 1 and Stage 2 for the following scales: Willingness to Undergo Robotic Surgery, Perceived Complexity of Robotic Surgery, Familiarity of Robotic Surgery, and Perceived Value of Robotic Surgery. Table 5 summarizes the findings from reliability and consistency analyses on the aforementioned scales.

Table 5
Summary of Stage 1 and Stage 2 Internal Consistency and Reliability Analyses

	Stage 1		Stage 2	
Variable	Cronbach	Guttman	Cronbach	Guttman
Willingness	.950	.921	.951	.923
Complexity	.857	.884	.864	.886
Familiarity	.897	.862	.897	.856
Value	.910	.892	.896	.876

Assumptions of Regression

Before completing all inferential statistics, it is important to ensure that the data meet all of the assumptions of the primary statistical technique: regression. In Chapter 1, each of the assumptions was explained; in this section, each assumption will be discussed in relation to the data, and whether or not the assumption was satisfied. The assumptions of regression are as follows:

1. There is one, continuous, dependent variable.
2. There are two or more independent variables.
3. There is independence of observations.
4. There is a linear relationship between the dependent variable and each of the independent variables, as well as between the dependent variable and the independent variables collectively.
5. There is homoscedasticity in the data.
6. There is no multicollinearity in the data.
7. There are no significant outliers in the data.
8. The residuals (errors) are normally distributed.

Assumption 1 was satisfied, as the dependent variable was treated as continuous by averaging the seven Likert-type questions to obtain one score for each participant (see

Brown, 2011). Assumption 2 was met, as there were 21 independent variables, a mix of categorical and continuous. Assumption 3 (regarding independence of observations) was met, as there was a Durbin-Watson (DW) statistic of 1.94. The DW statistic indicates the presence of independence of errors of prediction. A DW statistic of exactly 2 would indicate complete independence (De Boef, 2007). The DW statistic for the current research is very close to 2, and as such, satisfied this particular assumption.

Assumption 4 (regarding linearity) is tested by observing several scatterplots. First, the Unstandardized Predicted Values were graphed against the Studentized Residuals. The Unstandardized Predicted Values represent the values that, given the results of the regression analyses, the regression equation would predict for each individual participant. The Studentized Residual is a measure of how far from the actual value the predicted value is. Ideally, these values should have a linear relationship. Figure 2 shows that this is indeed the case.

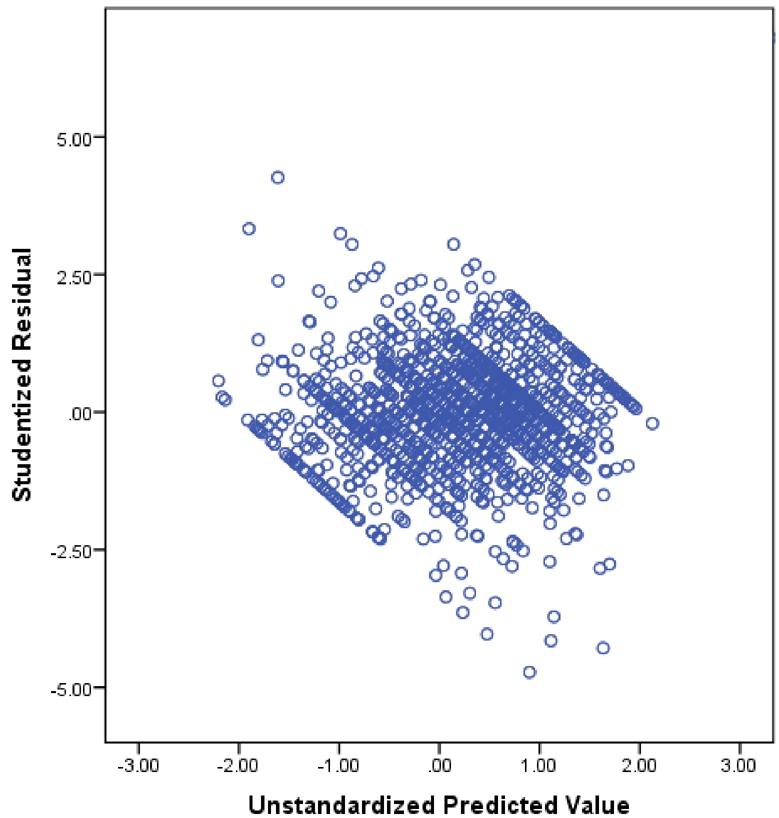

Figure 2. Studentized Residuals and Unstandardized Predicted Values of Willingness

In addition, the Partial Regression Plots for the variables included in the final regression model were viewed. These were the plots for: Familiarity, Value, Wariness, Openness, Fear of Surgery, Anger, Fear, and Happiness. A partial regression plot intends to show the relationship between the independent variable in question and the dependent variable, while considering the effect of the other independent variables in the model. The partial regression plots all indicated a linear relationship and are Figures 3 – 10.

Figure 3. Partial regression plot for familiarity

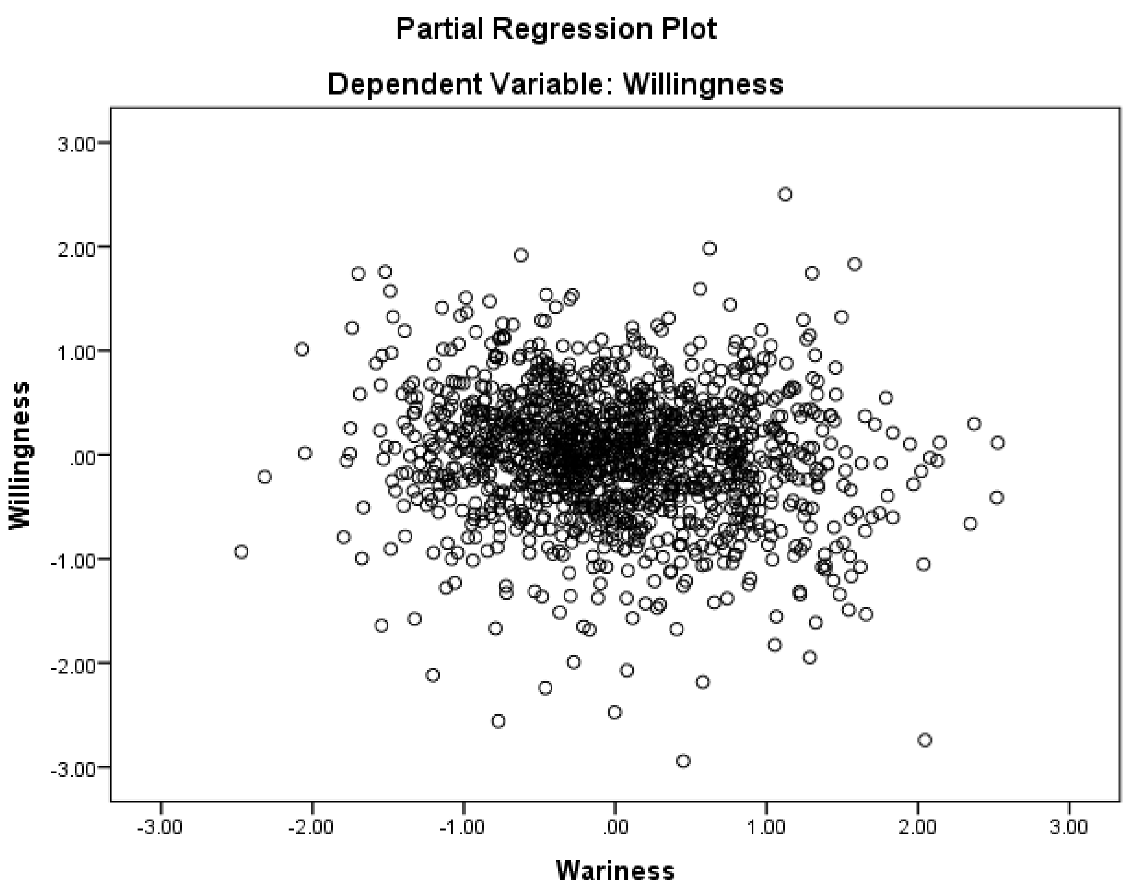

Figure 4. Partial regression plot for wariness

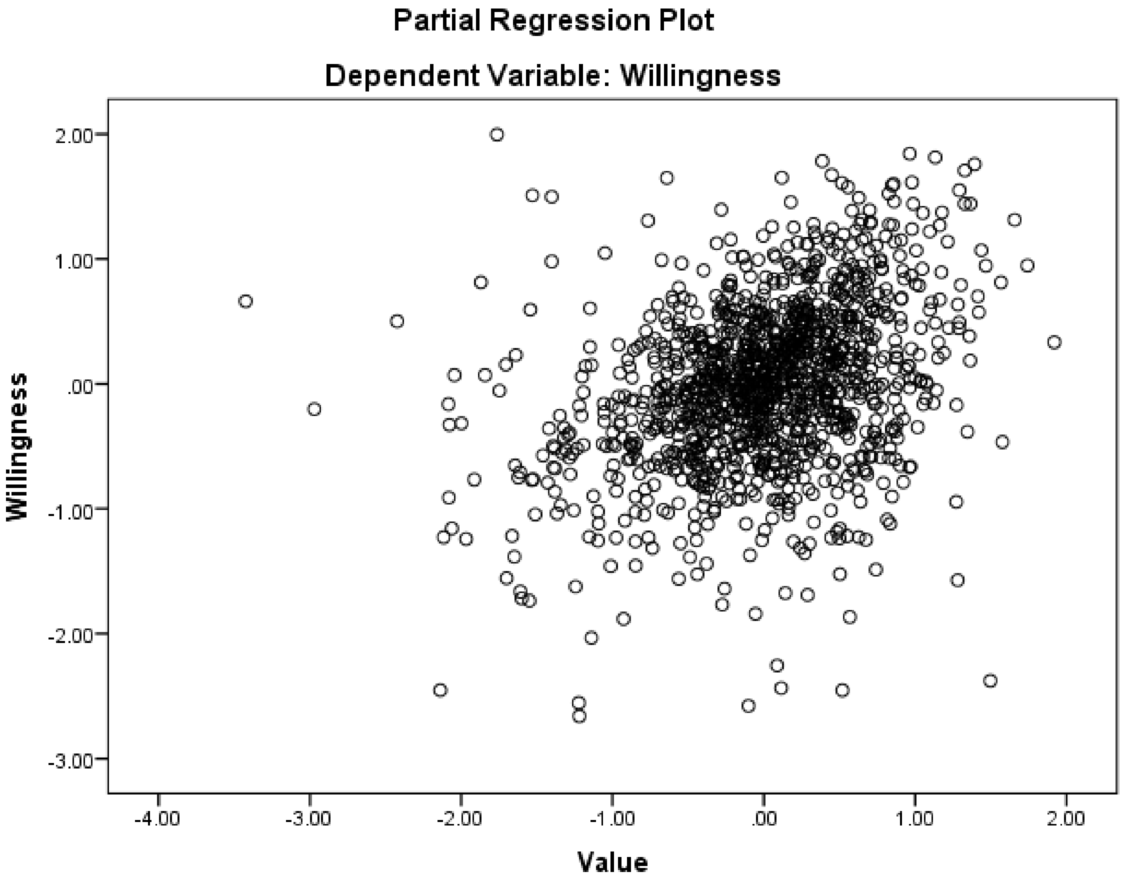

Figure 5. Partial regression plot for value

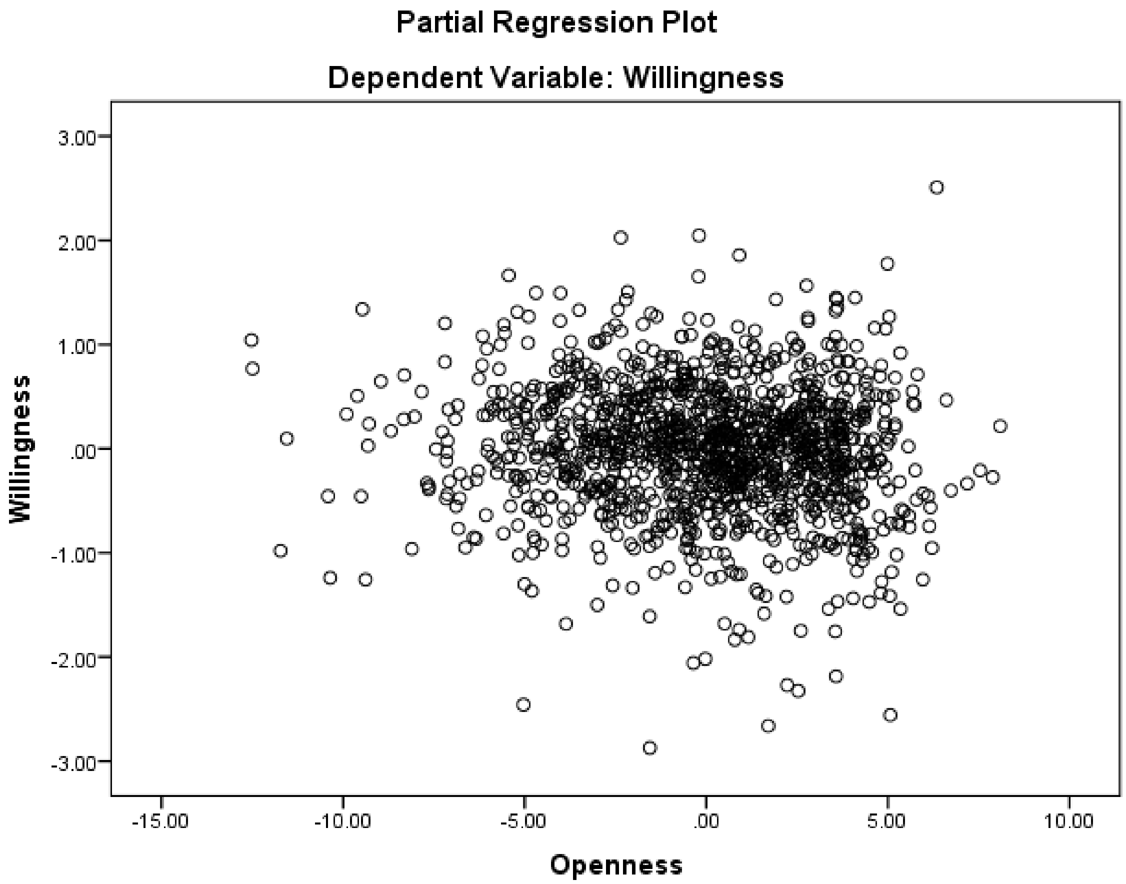

Figure 6. Partial regression plot for openness

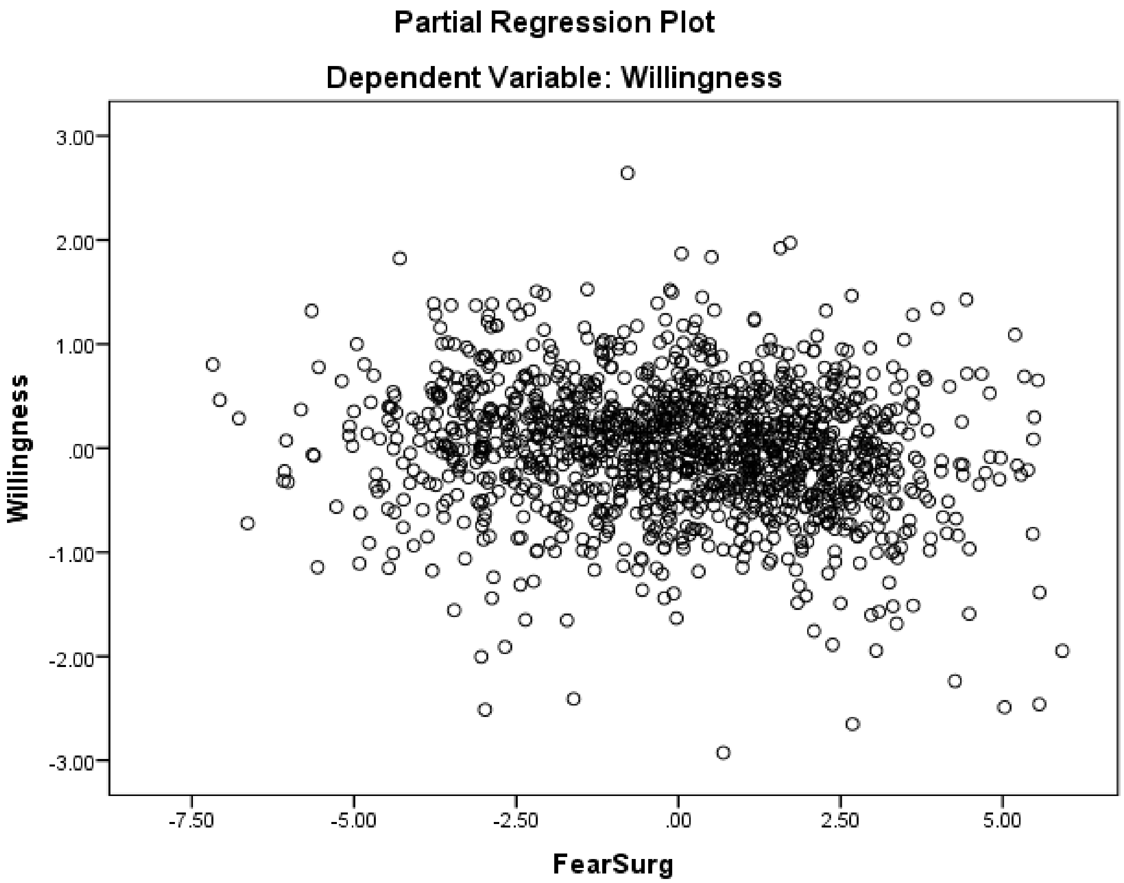

Figure 7. Partial regression plot for fear of surgery

Figure 8. Partial regression plot for anger

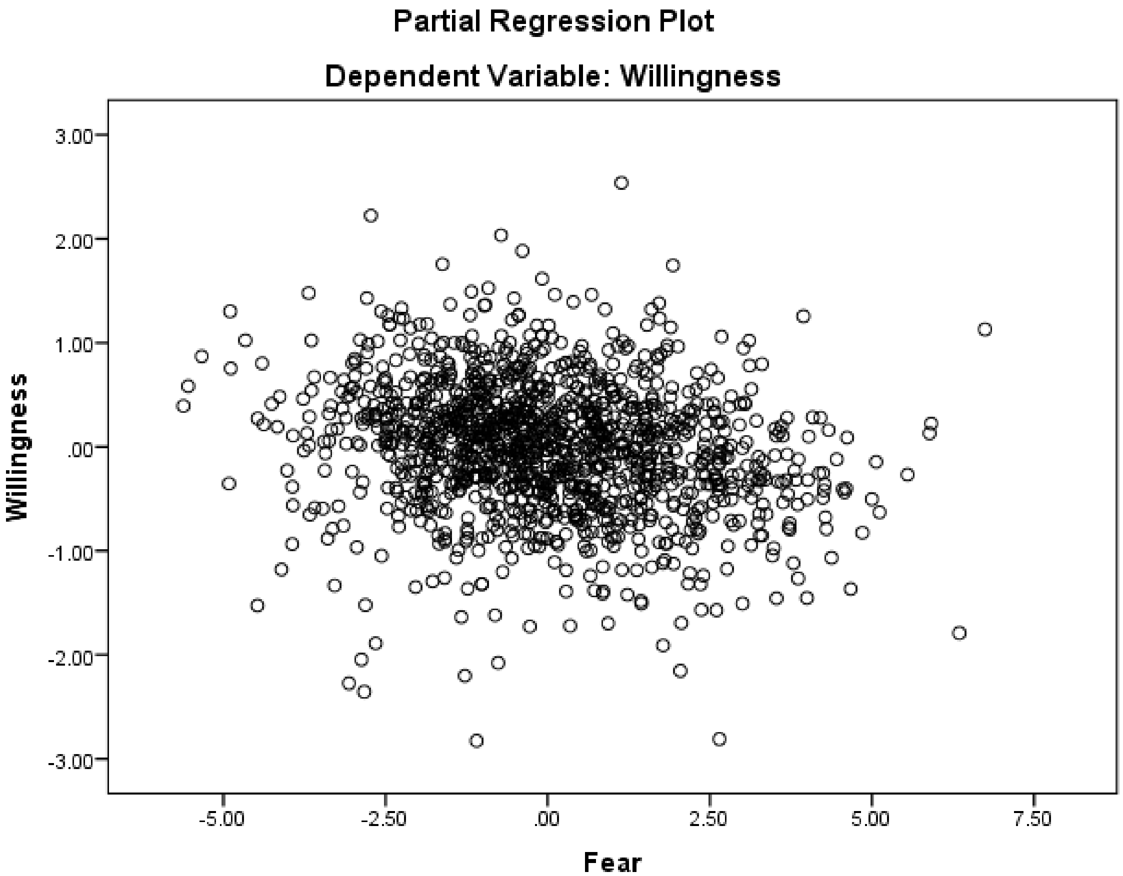

Figure 9. Partial regression plot for fear

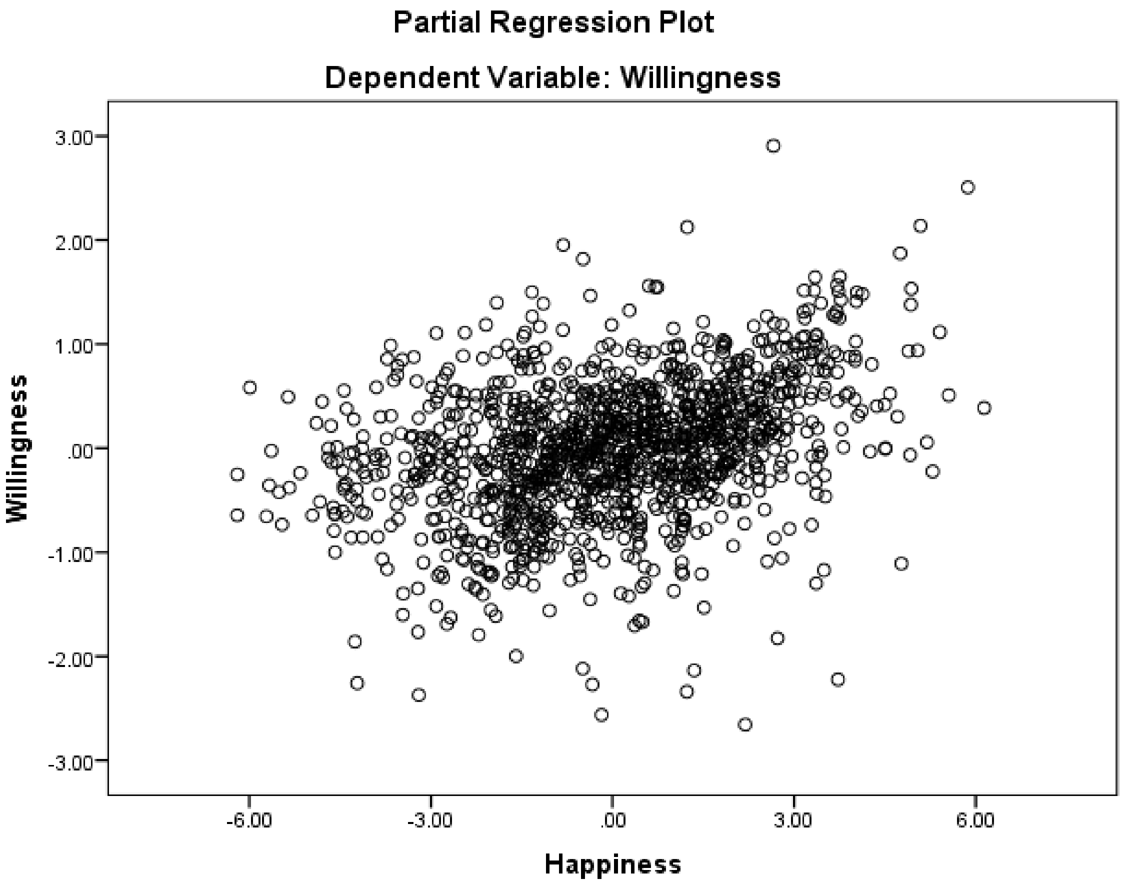

Figure 10. Partial regression plot for happiness

Assumption 5 (regarding homoscedasticity) is addressed by reviewing the scatterplot that plots Unstandardized Predicted Values against Studentized Residuals (Figure 2). Homoscedasticity refers to the fact that the standard deviations of the errors should be similar. As the band of predicted values does not become wider at lower or higher values, it is safe to assume homoscedasticity within the data.

Assumption 6 (regarding multicollinearity) was addressed in two ways: correlation coefficients, and VIF/Tolerance values. The correlation analysis indicated that two relationships exceeded a correlation coefficient above .7, anger and disgust (r = .744) and fear and sadness (r = .764). (For a full table of variable correlations, see Appendix H). However, when assessing Tolerance and VIF statistics, the only cases of issue

(Tolerance below .1 or VIF above 10) were the dummy coded variables for Education Level. None of these ended up in the final model, which had all acceptable Tolerance and VIF values, and is presented in Table 6. Though it seems that the emotional data may suffer from multicollinearity, there is no theoretical basis to exclude only one of either pair that was correlated above .7 (anger and disgust, or fear and sadness). Therefore, though Assumption 6 was not totally met, the data has not been modified to reflect this, and thus any results including these variables must be interpreted cautiously.

Table 6
Summary of Collinearity Statistics

Model	Collinearity Statistics	
	Tolerance	VIF
(Constant)		
Familiarity	.771	1.298
Value	.625	1.599
Wariness	.700	1.428
Openness	.868	1.152
Fear of Surgery	.814	1.229
Anger	.523	1.914
Fear	.406	2.462
Happiness	.563	1.776

Assumption 7 (regarding outliers) was investigated using the Mahalanobis Distance test to find outliers and remove them from the dataset. Twenty-one cases were removed, as their Mahalanobis Distance exceeded the critical value, using the criterion $\alpha = .001$. Twenty-one cases of the original 1345 represent approximately 1.7% of the population. Osbourne and Overbay (2004) indicate that while a potential reason for outliers is that they are a true case sampled from the targeted population, there is roughly a 1% chance of sampling an outlying data point in a normal population. Therefore, as the outlying cases represent more than 1% of the dataset, it is possible that they suffer from data errors, misreporting, sampling error, or other issues (all discussed by Osbourne and Overbay, 2004). Therefore, these 21 cases have been removed from the dataset.

Assumption 8 (regarding normality of residuals) was satisfied when investigating a histogram with superimposed normal curve and the normal probability Plot (p-p plot; see Figures 11 and 12). The residuals were not completely normal, but were sufficiently normally distributed. The normal probability plot showed similar results; though the residuals did not completely align with the diagonal normal, they were very close. These two visuals indicate normality of residuals, and satisfy Assumption 8.

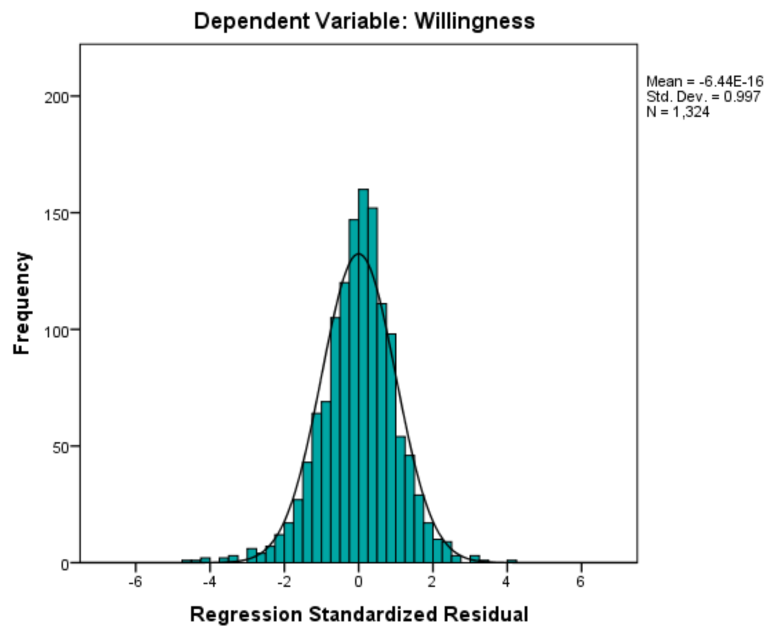

Figure 11. Frequency Distribution Histogram of Residuals

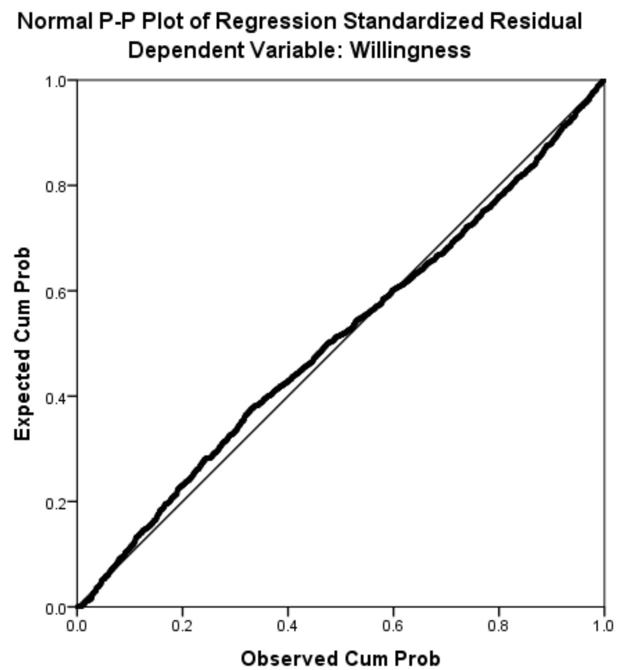

Figure 12. Normal Probability Plot (p-p plot)

Stage 1

The purpose of stage 1 was to build a regression equation in order to predict patient willingness to undergo robotic surgery. This section will detail the data analysis used to create the regression equation. The predictors being tested for this regression analysis were: age, gender, income, ethnicity, education level, perceived complexity, perceived value, familiarity, wariness of new technologies, fear of surgery, personality factors (Openness to experience, Conscientiousness, Extraversion, Agreeableness, and Neuroticism), and affect (in the form of the six universal emotions). A backward stepwise regression was used in order to eliminate statistically insignificant predictors, resulting in a final model with all significant predictors. The final model included eight significant predictors: Familiarity of Robotic Surgery, Wariness of New Technologies, Fear of Surgery, Openness (Personality Trait), Happiness, Perceived Value of Robotic Surgery, Anger, and Fear. The regression equation created as a result of this analysis was:

$$Y = .316 + .122X_1 + .349X_2 - .098X_3 - .016X_4 - .041X_5 - .032X_6 - .066X_7 + .111X_8$$

Where Y is predicted willingness to undergo robotic surgery, and X_1, X_2, X_3, X_4, X_5, X_6, X_7, and X_8 are Familiarity of Robotic Surgery, Perceived Value of Robotic Surgery, Wariness of New Technologies, Openness (Personality Trait), Fear of Surgery, Anger, Fear, and Happiness, respectively.

Analyses showed an $R^2 = .627$ (adjusted $R^2 = .624$), indicating that with the eight abovementioned predictors, this study has 62.7% (62.4% adjusted) of the information needed to properly predict an individual's willingness to undergo robotic surgery. Individual's responses to these eight variables accounted for 62.7% (62.4% adjusted) of the variance in the resulting model. The model was also statistically significant, $F(8,1323) = 275.876$, $p < .001$. Appendices F and G present the overall model summary, and the F values of significance, respectively.

The final model in the regression analyses indicated eight significant predictors of willingness to undergo robotic surgery, the coefficients of which can be found in Table 7. These predictors were: familiarity of robotic surgery, perceived value of robotic surgery, wariness of new technologies, fear of surgery, anger, fear, and happiness. The model indicates that holding all other variables constant in the model, for every unit increase in familiarity with robotic surgery, willingness increases .122 units on average; the coefficient was significant $t(1315) = 6.001$, $p <.001$. Holding all other variables constant, for each unit increase in perceived value of robotic surgery, willingness increases .349 units; the coefficient was significant $t(1315) = 13.103$, $p <.001$. Holding all other variables constant, for each unit increase in wariness of new technologies, willingness decreases .098 units; the coefficient was significant $t(1315) = -4.369$, $p <.001$. Holding all other variables constant, for each unit increase in openness, willingness decreases .016 units; the coefficient was significant $t(1315) = -3.147$, $p = .002$. Holding all other variables constant, for each unit increase in fear of surgery, willingness decreases .041 units; the coefficient was significant $t(1315) = -5.562$, $p = .002$. Holding all other variables constant, for each unit increase in anger, willingness decreases .032 units; the coefficient was significant $t(1315) = -3.457$, $p = .001$. Holding all other variables constant, for each unit increase in fear, willingness decreases .066 units; the coefficient was significant $t(1315) = -7.310$, $p < .001$. Holding all other variables constant, for each unit increase in happiness, willingness increases .111 units; the coefficient was significant $t(1315) = 13.819$, $p < .001$.

Table 7
Regression Coefficients (Model 23)

Model[a]		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Correlations		
		B	Std. error	Beta			Zero-order	Partial	Part
23	(Constant)	.316	.123		2.576	.010			
	Familiarity	.122	.020	.115	6.001	.000	.359	.163	.101
	Value	.349	.027	.279	13.103	.000	.611	.340	.221
	Wariness	-.098	.022	-.088	-4.369	.000	-.372	-.120	-.074
	Openness	-.016	.005	-.057	-3.147	.002	.063	-.086	-.053
	Fear of Surgery	-.041	.007	-.104	-5.562	.000	-.331	-.152	-.094
	Anger	-.032	.009	-.081	-3.457	.001	-.426	-.095	-.058
	Fear	-.066	.009	-.193	-7.310	.000	-.611	-.198	-.123
	Happiness	.111	.008	.310	13.819	.000	.641	.356	.233

a. Dependent Variable: Willingness

Stage 2

The objective of stage 2 was to test the regression equation from Stage 1 against a new sample in order to validate the equation and finalize the prediction model of patient willingness to undergo robotic surgery. This was done several ways including: *t*-tests, correlations between actual and predicted scores of willingness, and cross-validated R^2. Initially, the regression equation from Stage 1 was applied to the second sample, in order to obtain predicted scores of the dependent variable (willingness). Then, these predicted scores were compared against the participants' actual reported scores.

The first test performed was a *t*-test, in order to compare the predicted and actual scores of willingness to undergo robotic surgery. This analysis yielded a non-significant result, $t(2630) = -.067$, $p = .946$. These results are displayed below in Table 8. Non-significance of the *t*-test indicates that the scores of willingness predicted by the equation were not significantly different from participants' actual willingness scores. Though the results of the *t*-test would suggest validation of the model, further analyses were performed.

Table 8
T-Test between Actual and Predicted Scores of Willingness

	Levene's Test for Equality of Variances		t-test for Equality of Means						
								95% Confidence Interval	
	F	Sig.	t	df	Sig.	Mean Difference	Std. Error Difference	Lower	Upper
Equal Variances Assumed	73.317	.000	-.067	2630	.946	-.00237	.03515	-.07130	.06656

In addition, a correlation was performed between the actual and predicted willingness scores. The aim of the correlational test was in order to discern whether or not the two sets of data (actual scores and predicted scores) were significantly different. Results showed a strong positive correlation between actual and predicted willingness scores $r(1316) = .79$, $p < .001$. A significant correlation indicates that the scores (predicted and actual) are not significantly different. These results supplement the findings of the t-test, providing support for validation of the regression equation created in Stage 1. Table 9 shows the results of the correlation test.

Table 9
Correlational Analysis Between Actual and Predicted Willingness Scores

		Actual	Predicted
Actual	Pearson	1	.790
	Sig.		.000
	N	1316	1316
Predicted	Pearson	.790	1
	Sig.	.000	
	N	1316	1316

The last test performed in order to test for validation is cross validated R^2. The estimated squared cross-validity coefficient is calculated as follows:

$$R_{cv}^2 = 1 - (\frac{N-1}{N})(\frac{N+k+1}{N-k-1})(1 - R^2)$$

where N = sample size, k = number of predictors, and R^2 = observed squared multiple correlation (Pedhazur, 1997).

For Stage two, the cross-validity coefficient is calculated as follows:

$$.622 = 1 - (\frac{1324-1}{1324})(\frac{1324+8+1}{1324-8-1})(1 - .627)$$

where N = 1325, k = 8, and R^2 = .627. The cross-validity coefficient is R^2_{cv} = .622, which indicates good fit of the model, as the cross-validity coefficient is similar to the original R^2 obtained for the model in Stage 1.

Summary

The aim of this dissertation was to build and validate a prediction model of patient willingness to undergo robotic surgery. To this end, the current research was split into two stages; Stage 1 used one sample to build a regression equation and Stage 2 performed several analyses to validate that model. Stage 1 indicated that with eight significant predictors, the model explained 62.7% (62.4% adjusted) of the variance in the resulting model. The eight predictors were familiarity of robotic surgery, perceived value of robotic surgery, wariness of new technologies, openness (a personality trait), fear of surgery, anger, fear, and happiness. This is a relatively robust model, even though it does not account for all of the variance. It provides not only a basis for further research, but also provides knowledge immediately for the healthcare domain, and specifically those involved in robotic surgery. These implications and further discussion of the results are present in Chapter 5.

Chapter 5

Discussion

Overview

The purpose of the current research was to better understand the factors that influence an individual's willingness to undergo robotic surgery. In order to do so, regression and model fit analyses were performed. Previous chapters of the dissertation have operationally defined all terms and provided a rationale for each predictor's inclusion in the model, as well as detailed all of the methodology and results. Overall, 2659 participants (1377 females) participated in the study, in the combined Stages 1 and 2. Participants in the first stage were used to build the model (initial regression analyses) and participants in the second stage were used to validate the model (model fit analyses). Participants in both stages responded to the same survey, details about which can be found in Chapter 3.

This study employed a correlational design, using multiple regression and model fit as the analyses of choice. The dependent variable was willingness to undergo robotic surgery. The independent variables were the twenty-one predictors entered into the regression model: age, gender, ethnicity, income, education level, perceived complexity, perceived value, familiarity, wariness of new technologies, fear of surgery, personality factors (Openness to experience, Conscientiousness, Extraversion, Agreeableness, and Neuroticism), and affect (in the form of the six universal emotions). The research hypotheses (as further detailed in Chapter 1) were as follows:

H_{A1}: At least one demographic variable (gender, income, education level) is a significant predictor of patient willingness when controlling for all other variables.

H_{A2}: At least one current consumer perception (perceived complexity, perceived value, familiarity) is a significant predictor of patient willingness when controlling for all other variables.

H_{A3}: Wariness of new technologies is a significant predictor of patient willingness when controlling for all other variables.

H_{A4}: At least one of the big five personality traits is a significant predictor of patient willingness when controlling for all other variables.

H_{A5}: At least one affective emotion (of the six universal emotions) is a significant predictor of patient willingness when controlling for all other variables.

H_{A6}: Fear of Surgery is a significant predictor of patient willingness when controlling for all other variables.

Chapter 5 will discuss the implications of this study, considering the results detailed in Chapter 4. It will include a discussion of hypotheses and the support found (or not found) for each, practical applications of the research, limitations, and future directions based on the current study.

Summary of Findings

In order to better understand consumer perceptions of robotic surgery, the current dissertation's main purpose was to create and validate a prediction model of willingness to undergo robotic surgery, using regression and model fit. A full explanation of the results is detailed in Chapter 4. In Stage 1, using backward stepwise regression, eight predictors were found to be significant in predicting willingness: familiarity of robotic surgery, perceived value of robotic surgery, fear of surgery, wariness of new technologies, openness (personality trait), happiness, fear, and anger. Together, these eight variables accounted for 62.7% (62.4% adjusted) of the variance in the resulting model. Stage 2 tested this regression model (equation) with a separate sample – predicted scores were calculated for this sample using the regression equation, which allowed the predicted scores to be compared to the actual scores. This was done by performing a *t*-test, correlation analysis, and calculating a cross-validity coefficient. The t-test yielded a non-significant result, $t(2630) = -.067$, $p = .946$. In addition, a strong positive correlation between actual and predicted willingness scores exists, $r(1316) = .79$, $p < .001$. Further, the cross-validity coefficient is $R^2_{cv} = .622$, which indicates good fit, as the original R^2 obtained in Stage 1 was $R^2 = .627$, and the values are very similar.

Overall findings indicate the strength and validity of the model. The following sections will discuss a rationale as to why some predictors may have been significant while others were not, as well as the practical applications of this research, its limitations, and how it may inform future research.

General Discussion

The General Discussion will interpret the results found in Chapter 4; though all statistics have been reported, it is important to put these findings into context in order to better understand the results. The current dissertation is one of the first studies to investigate current consumer perceptions of robotic surgery. Though the rational and variables included come from prior research, this study does provide a new look at the topic. Not all hypotheses were supported, and the current section will discuss why this may be.

The first hypothesis predicted that at least one of the demographic variables (age, gender, income, ethnicity, education level) would be a significant predictor of patient willingness when controlling for all other variables. The results of the regression did not support this hypothesis. This prediction was made based on previous literature suggesting that these demographic variables may influence decision making (Croson & Gneezym, 2009; Thornton & Dumke, 2005), technology adoption (Czaja et al., 2006; Morris & Venkatesh, 2000; Venkatesh, Morris, & Ackerman, 2000), and responses to medical decisions and technologies (Gerdtham, 1997; Gornick et al., 1996; Levinson, Kao, Kuby, & Thisted, 2005; Pino et al., 2015; Thompson, Pitts, & Schwankovsky, 1993). However, none of the demographic predictors were found to significantly predict willingness to undergo robotic surgery.

One reason that this hypothesis may have not been supported is due to the pervasive nature of medical care. Individuals of all ages, gender, ethnicities, income brackets, and education levels need medical care. Therefore, there may not be a discernable difference in willingness within these variables. Perhaps, as all these individuals would be interfacing with the same healthcare systems, their perceptions do not vary greatly based on demographic factors. In addition, it is important to note that some variables may be limited by the sample being used. Using an MTurk convenience sample, though it allows for a large number of participants to be captured at once, does not necessarily equalize groups on all demographic variables. It is possible that some ethnicities, and education levels were underrepresented, and therefore no difference was able to be detected.

The second hypothesis predicted that at least one current “consumer perception” (perceived complexity, perceived value, familiarity) would be a significant predictor of patient willingness when controlling for all other variables. This hypothesis was supported in the sense that both perceived value and familiarity were significant predictors of willingness; however, perceived complexity was not. Perceived complexity was included in part because of the inherent complexity of the technology used in robotic surgery, as well as in healthcare as a whole (Varkey et al., 2009). Previous research has indicated that technology, and specifically automation, can be very confusing for those interacting with it (Hoff & Bashir, 2015; Norman, 1989; Wiener, 1989). However, it is possible that robotic surgery is too unknown by the general public for perceived complexity to have a significant effect on willingness, or it is plausible that individuals have differing levels of trust in technology, such that some are more willing to trust a technology that they do not understand than others. This is further discussed later, as wariness of new technologies was a significant predictor.

The results did suggest that individuals that were more familiar with robotic surgery were also more willing to undergo robotic surgery. This is supported by prior literature which indicates that familiarity influences expectations – those who are more familiar with a procedure have more accurate and more positive perceptions of that procedure and are more willing to undergo that procedure (Ibrahim, Siminoff, Burant, & Kwoh, 2002; Kwoh et al., 2015). It is possible that those who are more familiar with robotic surgery (e.g., have read about it or undergone robotic surgery) have more accurate ideas about the risks and realities of robotic surgery, and therefore are more willing to undergo robotic surgery.

In addition, the results suggested that individuals who perceived a higher value (personal benefit) of robotic surgery were more willing to undergo robotic surgery. This is in line with a large body of research indicating that perceived value and perceived usefulness has influenced adoption of a host of different technologies, including health technologies (e.g., Wilson & Lankton, 2004; Winkelman, Leonard, & Rossos, 2005). It is intuitive to think that those who perceive a higher personal value or benefit in or service are more willing to utilize that service. Those who do not think that robotic surgery would be of any benefit to them would be less willing to educate themselves about it, understand the risks, and eventually less willing to actually undergo robotic surgery.

The third hypothesis predicted that wariness of new technologies would be a significant predictor of patient willingness when controlling for all other variables. The results of this research supported this hypothesis. Wariness of new technologies was included as a potential predictor because of the long history of resistance to changing technologies, and barriers to adoption of new technology (La Porte & Metlay, 1975). The results of this study suggested that individuals who were warier of new technologies were less willing to undergo robotic surgery. As this "wariness" is completely separate from any mention of medical technologies, it is likely that this variable would also influence other types of technologies. It is possible that individuals have some kind of predisposition to either be wary or comfortable with new technologies, perhaps based on prior experiences or other perceptions.

The fourth hypothesis predicted that at least one of the big five personality traits would be a significant predictor of patient willingness when controlling for all other variables. The results of this research supported this hypothesis. Personality was considered for this research due to previous research indicating that personality traits influence perceptions of technology, as well as buying behaviors (Halko & Kientz, 2010; Odekerken-Schröder, De Wulf, & Schumacher, 2003). Results of the regression indicated that as an individual scored higher on the "Openness" trait, the less willing they were to undergo robotic surgery. This finding is unclear and seems counterintuitive. It would be more intuitive to think that those who score higher on "openness," a trait about being good at abstract thought and liking new experiences, would be more willing to undergo robotic surgery. However, results of the regression indicated that the beta weight for openness (though small) was negative. One potential reason for this could be that openness does not extend to medical technologies. Perhaps the fact that trust in medical technologies is fundamentally different from trust in other types of technologies (Montague et al., 2009) means that the intuitive connection does not exist.

The fifth hypothesis predicted that at least one affective emotion (of the six universal emotions) would be a significant predictor of patient willingness when controlling for all other variables. The results of this research supported this hypothesis. Affect was included (as six variables) due to a history of emotions playing a role in decision making (Shiv & Fedorikhin, 1999). Emotions have been shown to influence willingness to utilize other technologies, such as driverless vehicles (Anania et al., 2018), as well as responses to health concerns (Power, Swartzman, & Robinson, 2011). In this study, regression analyses indicated that three emotions were significant predictors of willingness. Respondents who were angrier about the situation were less willing to undergo robotic surgery. Respondents who were more fearful about the situation were less willing to undergo robotic surgery. Respondents who were happier about the situation were more willing to undergo robotic surgery.

It is understandable that the two negative emotions would have a negative relationship with willingness, while the positive emotion would have a positive relationship with willingness. If an individual feels fearful or angry about the situation at hand, this would likely decrease their willingness to engage in that situation. By the same token, individuals who feel happier about a situation would likely be more willing to engage in that situation. Though it is unlikely that individuals are particularly happy about undergoing robotic surgery, it is intuitive to think that those who respond with lower values of happiness about the situation would be less willing to undergo the robotic surgery than those who respond with higher values of happiness.

The sixth hypothesis predicted that fear of surgery would be a significant predictor of patient willingness when controlling for all other variables. The results of this research supported this hypothesis. Anxiety and fears about surgery have previously been measured in order to better understand patient outcomes and perceptions. (Shafer, Fish, Gregg, Seavello, & Kosek, 1996). Results of this study indicated that individuals who have a higher overall fear of surgery are less willing to undergo robotic surgery. It is likely that these individuals would respond the same way had they been asked about non-robotic surgery. However, it is important to note that preexisting perceptions of the medical field (in this case, fear of surgery) likely influence an individual's perception of medical technologies, and their willingness to interact with them.

All of the potential predictors were included based on past literature and findings which would indicate that they may have had an influence on willingness to undergo robotic surgery. However, only eight of twenty-one predictors were significant, which means that some hypotheses were unsupported or only partially supported. These eight variables (age, perceived value, familiarity, wariness of new technologies, fear of surgery happiness, anger, and fear) help to predict willingness to undergo robotic surgery

Practical Applications

The most important aim of this study was to better understand the factors that influence an individual to be willing (or unwilling) to undergo robotic surgery. This was done by building and validating a prediction model using regression and model fit analyses. Though this research makes a contribution to the field by supplementing our current understanding of the predictors at hand, technology acceptance, and consumer perceptions of robotic surgery, it also has real-world applications.

This study was the first to take an in-depth look at perceptions of robotic surgery, and the first to build a regression model in order to predict willingness to undergo robotic surgery. This model can be used by the healthcare and technology domains to understand why an individual (or the population as a whole) may not be willing to undergo robotic surgery. This can be broken into two – the individual, and the population as a whole. Medical professionals can use the results of this study to perhaps tailor their own explanations and educate patients in such a way that they are more willing to undergo robotic surgery. For example, understanding that perceived value is one of the strongest predictors of patient willingness, a surgeon may be able to better communicate the personal benefit of robotic surgery (e.g., quicker healing time, better cosmetic outcomes) in order to increase that individual's perceived value of the surgery.

In addition, understanding the factors that influence willingness to undergo surgery as it applies to the targeted population (all potential patients) can help inform medical centers and robotic surgical system development. When designing and developing technology, it is important to consider the end user. When discussing robotic surgical systems, patients as well as medical professionals can be considered the end user. Therefore, this research could be considered part of an iterative design process, by which developers can better understand how the system must be designed and marketed moving forward. As discussed in earlier sections, there are often barriers to adoption of new technologies. As robotic surgery has been shown to have many objective benefits to patients and doctors (e.g., BenMessaoud, Kharrazi, & MacDorman, 2011; De Wilde & Herrmann, 2013; Lanfranco et al., 2004) it would be ideal to increase the public awareness and support for these technologies, as public opinion has the ability to drive the market.

Limitations

Though the study limitations were addressed in Chapter 1, it is important to discuss them in the context of the results and discussion. Limitations not only help researchers understand to what extent results can be generalized, but also are an important factor in suggesting future avenues of study too build off the current research.

The current research utilized a convenience sample of U.S. participants from Amazon's ® Mechanical Turk ®. Though this allowed for quick collection of an extensive amount of data, it does limit the accessible population. Therefore, the results cannot necessarily be generalized to the target population – which is all potential surgical patients. The results can only be generalized to online survey respondents who complete human intelligence tasks in return for compensation. MTurk data has been shown to be as reliable as standard laboratory data (Buhrmester et al., 2011; Germine, et al., 2012; Rice, et al., 2017). However, it is important to note that the population on MTurk does not represent the entire population who makes medical decisions about care. Oftentimes, an adult is making decisions on behalf of a child, or another adult who is unable to make their own decisions. In addition, some patients may make decisions in conjunction with their spouses and families. Therefore, there may be outside influences on perceptions and decisions which cannot be captured by the nature of a survey and the accessible population.

In addition, participants responded to hypothetical questions. It would arguably be better to survey individuals who will certainly be patients in the future, such as those who are being scheduled for surgery. In those circumstances, researchers would be better able to understand how an individual perceives the robotic surgical system, how accurate their perceptions are, and how comfortable he or she is moving forward with the surgery. However, the complexity of healthcare and the novelty of robotic surgical systems makes this difficult to study in an applied context. The use of hypothetical situations and surveys also relies on self-report data, which relies on participants being honest and forthcoming. Human subjects do not always answer honestly, either due to their own misgivings, or simply misreading or missing a question. Therefore, the nature of the survey itself is a limitation.

In addition, participants were paid 50-100 cents for their time completing the study. The voluntary, paid nature of the research means that perhaps individuals rushed through the survey and skipped or misread, or simply ignored questions in order to click responses and complete the survey very quickly. It is very difficult, if not impossible, to discern which participants put thought and effort into their responses, and which did not. This is nearly unavoidable with survey-based research, especially that which is conducted online.

Future Research

No one study stands alone; it is with the repeated and building nature of research that science comes to conclusions. This research has built off previous research and can inform future studies in turn. Specifically, the limitations of this study provide a foundation for which to move forward.

Addressing the limitation of the sample – in this research a convenience sample of U. S. participants was used through MTurk. Future research should investigate other accessible populations. This means not only other countries, which may have different healthcare systems, but also the individuals who are specifically utilizing that system for surgical purposes. It is important to understand the perceptions of individuals who will actually be undergoing surgery and robotic surgery, and to compare their pre and post-surgery beliefs. In addition, it will be important to connect these perceptions to objective surgical outcomes (e.g., does more comfort with the idea of undergoing robotic surgery influence recovery time or post-operative pain). These studies will be paramount to the developers and users of robotic surgical systems, as improved surgical outcomes are the main aim of new technologies and techniques.

In addition, studying patients who will be undergoing surgery will allow for a more comprehensive view of the factors which may influence willingness. This can be done through other research design methods, such as interviewing, focus groups, and case studies. In order to form a whole picture of robotic surgical system perceptions, it would be ideal to capture qualitative data as well as quantitative. Though quantitative results such as those obtained in the current research allow researchers to make comparisons and features objectivity, qualitative data can produce richer data and allow for results to be seen directly in an applied context.

As a limitation of any study, the current research focused on specific variables. It is possible (and likely) that there are other variables which influence an individual's willingness to undergo robotic surgery. For example, complexity of the surgery, or expertise of the surgeon may play a role. Future research could build additional prediction models to test other factors or could address them in other experimental ways. This can be done in both basic and applied contexts, using many methodologies. As the literature investigating patient perceptions of robotic surgery is still very sparse, there are innumerable opportunities to research this topic.

In addition, this study found very promising results using regression and model fit analyses to predict willingness to undergo robotic surgery. This research can be built upon by using the same type of methodology to study other constructs (e.g., willingness to ride in a driverless car, or willingness to interact with a home healthcare robot). Regression and model fit analyses can provide substantial information about multiple variables simultaneously. This allows researchers to cast a net as wide as desired, or narrow focus. In addition, creation of these prediction models can be valuable to whichever applied industry is of concern, whether it be healthcare, transportation, safety, or numerous others.

Conclusion

The current research found eight significant predictors of willingness to undergo robotic surgery: perceived value, familiarity, wariness of new technologies, fear of surgery, openness, happiness, fear, and anger. In Stage 1 the model was built using backwards stepwise regression; in Stage 2 the model was validated using a *t*-test, correlational analysis, and the cross-validity coefficient. All predictors had a rationale for their inclusion based on previous literature on decision making, technology acceptance, and the healthcare domain. These results have implications not only for the body of literature concerning these topics, but also for the healthcare domain as a whole. In addition, though the current research has limitations, these limitations can be leveraged into future research in order to better understand the ways individuals perceive novel medical technologies.

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Appendices

Appendix A – Patient Willingness to Undergo Surgery Scale (adapted from Consumer Willingness to Fly Scale; Rice et al., 2015)

Please respond to each of the statements below indicating how strongly you agree or disagree with each statement.

1. I would be willing to undergo surgery in this situation.

   Strongly disagree Disagree Neither disagree nor agree Agree Strongly Agree

1. I would be comfortable undergoing surgery in this situation.

   Strongly disagree Disagree Neither disagree nor agree Agree Strongly Agree

2. I would have no problem undergoing surgery in this situation.

   Strongly disagree Disagree Neither disagree nor agree Agree Strongly Agree

3. I would be happy to undergo surgery in this situation.

   Strongly disagree Disagree Neither disagree nor agree Agree Strongly Agree

4. I would feel safe undergoing surgery in this situation.

   Strongly disagree Disagree Neither disagree nor agree Agree Strongly Agree

5. I have no fear of undergoing surgery in this situation.

   Strongly disagree Disagree Neither disagree nor agree Agree Strongly Agree

6. I feel confident undergoing surgery in this situation.

   Strongly disagree Disagree Neither disagree nor agree Agree Strongly Agree

Appendix B – Complexity Perception Scale

Please respond to each of the statements below indicating how strongly you agree or disagree with each statement.

1. The automation that controls robotic surgery is very complex.

   Strongly disagree   Disagree   Neither disagree nor agree   Agree   Strongly Agree

2. I do not understand the automation that controls robotic surgery.

   Strongly disagree   Disagree   Neither disagree nor agree   Agree   Strongly Agree

3. It is difficult to know how the automation that controls robotic surgery works.

   Strongly disagree   Disagree   Neither disagree nor agree   Agree   Strongly Agree

4. I have no idea what the automation that controls robotic surgery is doing.

   Strongly disagree   Disagree   Neither disagree nor agree   Agree   Strongly Agree

5. It is a mystery to me how the automation that controls robotic surgery operates.

   Strongly disagree   Disagree   Neither disagree nor agree   Agree   Strongly Agree

Rice et al. (submitted) analyzed the psychometric properties of this scale. Principal components and varimax rotation indicated that all five items load onto one factor. Cronbach's Alpha was .84 and Guttman's split-half tests showed a coefficient of .82.

Appendix C – Familiarity Scale

Please respond to each of the statements below indicating how strongly you agree or disagree with each statement.

1. I am familiar with robotic surgery.

   Strongly disagree Disagree Neither disagree nor agree Agree Strongly Agree

2. I have a lot of knowledge about robotic surgery.

   Strongly disagree Disagree Neither disagree nor agree Agree Strongly Agree

3. I have read a lot about robotic surgery.

   Strongly disagree Disagree Neither disagree nor agree Agree Strongly Agree

4. Robotic surgery has been of interest to me for a while.

   Strongly disagree Disagree Neither disagree nor agree Agree Strongly Agree

5. I know more about robotic surgery than the average person.

   Strongly disagree Disagree Neither disagree nor agree Agree Strongly Agree

Rice et al. (submitted) analyzed the psychometric properties of this scale. Principal components and varimax rotation indicated that all five items load onto one factor. Cronbach's Alpha was .84 and Guttman's split-half tests showed a coefficient of .78.

Appendix D – Perceived Value Scale

Please respond to each of the statements below indicating how strongly you agree or disagree with each statement.

1. Robotic surgery is something that would be beneficial to me.

   Strongly disagree Disagree Neither disagree nor agree Agree Strongly Agree

2. Robotic surgery would be something valuable for me to undergo.

   Strongly disagree Disagree Neither disagree nor agree Agree Strongly Agree

3. I think robotic surgery technology is useful.

   Strongly disagree Disagree Neither disagree nor agree Agree Strongly Agree

4. There would be value in using robotic surgery.

   Strongly disagree Disagree Neither disagree nor agree Agree Strongly Agree

5. If robotic surgery were available, I think it would be beneficial to utilize.

   Strongly disagree Disagree Neither disagree nor agree Agree Strongly Agree

Rice et al. (submitted) analyzed the psychometric properties of this scale. Principal components and varimax rotation indicated that all five items load onto one factor. Cronbach's Alpha was .96 and Guttman's split-half tests showed a coefficient of .92.

Appendix E – Wariness of New Technologies Scale

Please respond to each of the statements below indicating how strongly you agree or disagree with each statement.

1. In general, I am wary of new technology.

   Strongly disagree Disagree Neither disagree nor agree Agree Strongly Agree

2. New technology scares me.

   Strongly disagree Disagree Neither disagree nor agree Agree Strongly Agree

3. New technology is not as safe as it should be.

   Strongly disagree Disagree Neither disagree nor agree Agree Strongly Agree

4. I tend to fear new technology until it is proven to be safe.

   Strongly disagree Disagree Neither disagree nor agree Agree Strongly Agree

5. New technology is likely to be dangerous.

   Strongly disagree Disagree Neither disagree nor agree Agree Strongly Agree

Rice et al. (submitted) analyzed the psychometric properties of this scale. Principal components and varimax rotation indicated that all five items load onto one factor. Cronbach's Alpha was .88 and Guttman's split-half tests showed a coefficient of .85.

Appendix F – IRB Approval and Full Instrument

Embry-Riddle Aeronautical University
Application for IRB Approval
Determination Form

Principal Investigator: Emily Anania

Other Investigators: Stephen Rice

Role: Student **Campus:** Daytona Beach **College:** Arts & Sciences

Project Title: Patient Willingness to Undergo Robotic Surgery

Review Board Use Only

Initial Reviewer: Teri Gabriel **Date:** 11/13/2018 **Approval #:** 19-062

Determination: Exempt

Dr. Michael Wiggins
IRB Chair Signature: Michael E. Wiggins, Ed.D. **Date:** 11/19/2018

Brief Description:

The purpose of this research will be to provide the healthcare industry with a new understanding of consumer perceptions about robotic surgery, and the degree to which an individual would be willing to have different procedures performed by a robotic dentist. Therefore, the objective of this study is to better understand the factors which influence willingness of an individual to undergo a robotic surgical procedure. Amazon's ® Mechanical Turk ® (MTurk) will be used to collect this data.

This research falls under the **EXEMPT** category as per 45 CFR 46.101(b) under:

☐ (1) Research, conducted in established or commonly accepted educational settings, that specifically involves normal educational practices that are not likely to adversely impact students' opportunity to learn required educational content or the assessment of educators who provide instruction. This includes most research on regular and special education instructional strategies, and research on the effectiveness of or the comparison among instructional techniques, curricula, or classroom management methods.

☑ (2) Research that only includes interactions involving educational tests (cognitive, diagnostic, aptitude, achievement), survey procedures (of adults), interview procedures (of adults), or observation of public behavior if at least one of the following criteria is met:

(i) The information obtained is recorded by the investigator in such a manner that the identity of the human subjects cannot readily be ascertained, directly or through identifiers linked to the subjects;

(ii) Any disclosure of the human subjects' responses outside the research would not reasonably place the subjects at risk of criminal or civil liability or be damaging to the subjects' financial standing, employability, educational advancement, or reputation.

☐ (4) Research involving the collection or study of **existing** data, documents, records, pathological specimens, or diagnostic specimens, if these sources are publicly available or if the information is recorded by the investigator in such a manner that subjects cannot be identified, directly or through identifiers linked to subjects.

☐ (6) Taste and food quality evaluation and consumer acceptance studies:

(i) If wholesome foods without additives are consumed, or

(ii) If a food is consumed that contains a food ingredient at or below the level and for a use found to be safe, or agricultural chemical or environmental contaminant at or below the level found to be safe, by the Food and Drug Administration or approved by the Environmental Protection Agency or the Food Safety and Inspection Service of the U.S. Department of Agriculture.

An exempt research project does not require ongoing review by the IRB, unless the project is amended in such a way that it no longer meets the exemption criteria.

Survey Study

RESEARCH PARTICIPANT CONSENT FORM
Emily Anania
Embry-Riddle Aeronautical University
College of Arts and Sciences

Purpose of Research
Automation is rapidly increasing in scope, pervading many industries – one of which is the healthcare industry. Currently, surgical robots perform and assist with surgery. Moving forward, automation is expected to evolve and take on more autonomy within surgery. The benefits and drawbacks of these robots, as well as their clinical significance, has been widely studied. However, little research has gone into consumer perceptions of these robots. Data from the current study would help us to understand consumers' willingness to undergo robotic surgical procedures. The purpose will be to provide the healthcare industry with a new understanding of consumer perceptions about robotic surgery, and the degree to which an individual would be willing to have different procedures performed by a robotic dentist. Therefore, the objective of this study is to better understand the factors which influence willingness of an individual to undergo a robotic surgical procedure.

Specific Procedures
Amazon's ® Mechanical Turk ® (MTurk) will be used to collect this data. You will be presented with some scenarios and you will then be asked some questions about those scenarios. Following that, you will be asked some demographic questions. The data collection process is anonymous and your responses will remain confidential. Once you have finished, you will be given a code, which you will input upon your return to MTurk. That will allow you to receive payment on MTurk.

Duration of Participation
The duration of this study is anticipated to take approximately 8-12 minutes.

Risks
It is anticipated that this study will pose no greater risk than you would experience through normal daily activities.

Benefits
There are no known benefits to your participation other than knowing you have contributed to the advancement of scientific knowledge.

Compensation
You will be compensated 50 cents for your time via Amazon's Mechanical Turk.

Confidentiality
The data collected during this study will be anonymous and confidential. We have no way of learning your true identity.

Voluntary Nature of Participation
You do not have to participate in this research project. If you agree to participate you can withdraw your participation at any time without penalty. Furthermore, if you withdraw from the study prior to its completion, your data will be destroyed immediately.

Contact Information:
If you have any questions about this research project, you can contact Emily Anania, principal investigator, at ananiae1@my.erau.edu, 302-507-3413. If you have concerns about the treatment of research participants, you can contact the IRB Administrator, Teri Gabriel at teri.gabriel@erau.edu or call 386-226-7179.

Documentation of Informed Consent
I have had the opportunity to read this consent form and have the research study explained. I am prepared to participate in the research project described above. I can print out a copy of this consent form. I verify that I am over 18 years of age.

* Required

1. **Are you at least 18 years of age?** *
Mark only one oval.

- Yes
- No *Skip to "I'm sorry, but you must be 18 years of age to participate. Thank you for your time. ."*

Instructions

You will be presented with some scenarios and you will then be asked some questions about them. Following that, you will be asked some demographics questions. The data collection process is anonymous and your responses will remain confidential.

Questions (1 of 4)

2. **Please respond to each of the statements below indicating how strongly you agree or disagree with each statement.**
Mark only one oval per row.

	Strongly disagree	Disagree	Neither disagree nor agree	Agree	Strongly agree
New technology scares me.					
New technology is likely to be dangerous.					
In general, I am wary of new technology.					
New technology is not as safe as it should be.					
I tend to fear new technology until it is proven to be safe.					

3. **Please respond to each of the statements below indicating how strongly you agree or disagree with each statement.**
Mark only one oval per row.

	Strongly disagree	Disagree	Neither disagree nor agree	Agree	Strongly agree
I have no idea what the automation that controls robotic surgery is doing.					
It is a mystery to me how the automation that controls robotic surgery operates.					
The automation that controls robotic surgery is very complex.					
It is difficult to know how the automation that controls robotic surgery works.					
I do not understand the automation that controls robotic surgery.					

4. **Please respond to each of the statements below indicating how strongly you agree or disagree with each statement.**
Mark only one oval per row.

	Strongly disagree	Disagree	Neither disagree nor agree	Agree	Strongly agree
Robotic surgery has been of interest to me for awhile.					
I have a lot of knowledge about robotic surgery.					
I have read a lot about robotic surgery.					
I know more about robotic surgery than the average person.					
I am familiar with robotic surgery.					

5. **Please respond to each of the statements below indicating how strongly you agree or disagree with each statement.**
Mark only one oval per row.

	Strongly disagree	Disagree	Neither disagree nor agree	Agree	Strongly agree
If robotic surgery were available, I think it would be beneficial to utilize.					
There would be value in using robotic surgery.					
Robotic surgery is something that would be beneficial to me.					
Robotic surgery would be something valuable for me to undergo.					
I think robotic surgery technology is useful.					

Questions (2 of 4)

6. **Describe yourself as you generally are now, not as you wish to be in the future. Describe yourself as you honestly see yourself, in relation to other people you know of the same sex as you are, and roughly your same age. Indicate for each statement how accurate the description is of you.**
Mark only one oval per row.

	Very Inaccurate	Moderately Inaccurate	Neither accurate nor innacurate	Moderately Accurate	Very Accurate
Am not interested in other people's problems.	⬭	⬭	⬭	⬭	⬭
Often forget to put things back in their proper place.	⬭	⬭	⬭	⬭	⬭
Don't talk a lot.	⬭	⬭	⬭	⬭	⬭
Am relaxed most of the time.	⬭	⬭	⬭	⬭	⬭
Have frequent mood swings.	⬭	⬭	⬭	⬭	⬭
Am not really interested in others.	⬭	⬭	⬭	⬭	⬭
Am the life of the party.	⬭	⬭	⬭	⬭	⬭
Keep in the background.	⬭	⬭	⬭	⬭	⬭
Do not have a good imagination.	⬭	⬭	⬭	⬭	⬭
Seldom feel blue.	⬭	⬭	⬭	⬭	⬭
Feel others' emotions.	⬭	⬭	⬭	⬭	⬭
Talk to a lot of different people at parties.	⬭	⬭	⬭	⬭	⬭
Have a vivid imagination.	⬭	⬭	⬭	⬭	⬭
Get upset easily.	⬭	⬭	⬭	⬭	⬭
Sympathize with others' feelings.	⬭	⬭	⬭	⬭	⬭
Am not interested in abstract ideas.	⬭	⬭	⬭	⬭	⬭
Get chores done right away.	⬭	⬭	⬭	⬭	⬭
Have difficulty understanding abstract ideas.	⬭	⬭	⬭	⬭	⬭
Like order.	⬭	⬭	⬭	⬭	⬭
Make a mess of things.	⬭	⬭	⬭	⬭	⬭

Questions (3 of 4)

Imagine that you have just gone to your physician for tests, and were told that you had to have your gallbladder removed, and the fastest and cheapest option is to have robotic surgery where the surgeon performs the surgery largely aided by a robot. The human surgeon programs and controls the robot at all times, but

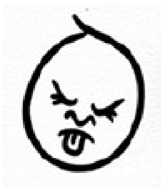
has no direct access to your body during surgery. The only entity actually touching your body throughout the surgery is the robot.

7. **Based on the scenario above, how strongly do you feel like the image shown?**

Mark only one oval.

	1	2	3	4	5	6	7	8	9	10	
I do not feel this way at all	⬭	⬭	⬭	⬭	⬭	⬭	⬭	⬭	⬭	⬭	Extremely feel this way

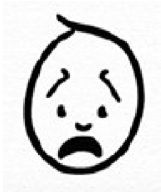
8. **Based on the scenario above, how strongly do you feel like the image shown?**



Mark only one oval.

	1	2	3	4	5	6	7	8	9	10	
I do not feel this way at all	⬭	⬭	⬭	⬭	⬭	⬭	⬭	⬭	⬭	⬭	Extremely feel this way

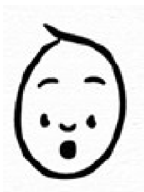
9. **Based on the scenario above, how strongly do you feel like the image shown?**



Mark only one oval.

	1	2	3	4	5	6	7	8	9	10	
I do not feel this way at all											Extremely feel this way

10. **Based on the scenario above, how strongly do you feel like the image shown?**



Mark only one oval.

	1	2	3	4	5	6	7	8	9	10	
I do not feel this way at all											Extremely feel this way

11. **Based on the scenario above, how strongly do you feel like the image shown?**

Mark only one oval.

	1	2	3	4	5	6	7	8	9	10	
I do not feel this way at all											Extremely feel this way

12. Based on the scenario above, how strongly do you feel like the image shown?

Mark only one oval.

	1	2	3	4	5	6	7	8	9	10	
I do not feel this way at all	⬭	⬭	⬭	⬭	⬭	⬭	⬭	⬭	⬭	⬭	Extremely feel this way

Questions (4 of 4)

13. Imagine that you have just gone to your physician for tests, and were told that you had to have your gallbladder removed, and the fastest and cheapest option is to have robotic surgery where the surgeon performs the surgery largely aided by a robot. The human surgeon programs and controls the robot at all times, but has no direct access to your body during surgery. The only entity actually touching your body throughout the surgery is the robot.

Mark only one oval per row.

	Strongly disagree	Disagree	Neither disagree nor agree	Agree	Strongly agree
I would be comfortable undergoing surgery in this situation.	⬭	⬭	⬭	⬭	⬭
I have no fear of undergoing surgery in this situation.	⬭	⬭	⬭	⬭	⬭
I feel confident undergoing surgery in this situation.	⬭	⬭	⬭	⬭	⬭
I would have no problem undergoing surgery in this situation.	⬭	⬭	⬭	⬭	⬭
I would be happy to undergo surgery in this situation.	⬭	⬭	⬭	⬭	⬭
I would be willing to undergo surgery in this situation.	⬭	⬭	⬭	⬭	⬭
I would feel safe undergoing surgery in this situation.	⬭	⬭	⬭	⬭	⬭

Demographics

14. What is your gross yearly income (in US dollars)?

____

15. **What is your ethnicity?**
Mark only one oval.

- ◯ Asian descent
- ◯ Other
- ◯ India (not Asian)
- ◯ African descent (e.g. African American)
- ◯ Hispanic descent (e.g. Latin America)
- ◯ Caucasian

16. **What is your highest level of education?**
Mark only one oval.

- ◯ Less than high school
- ◯ High school graduate (includes equivalency)
- ◯ Some college, no degree
- ◯ Associate's degree
- ◯ Bachelor's degree
- ◯ Master's degree
- ◯ Doctorate degree (or terminal degree)

17. **What is your general level of fear of surgery?**
Mark only one oval.

	1	2	3	4	5	6	7	8	9	10	
I have no fear of surgery	◯	◯	◯	◯	◯	◯	◯	◯	◯	◯	Extremely fear surgery

18. **What is your Age?**

____

19. **What is your gender?**
Mark only one oval.

- ◯ Male
- ◯ Female
- ◯ Other: ____________________

Surgical History

20. **Have you ever had surgery?**
Mark only one oval.

- No *Skip to question 24.*
- Yes
- Not Sure *Skip to question 24.*

Surgical History

21. **Have any of your prior surgeries been performed with the assistance of a robotic surgical system, such as the da Vinci?**
Mark only one oval.

- Yes
- No
- Not Sure

Surgical History

22. **Have you experienced any complications or unexpected events as a result of a prior surgery?**
Mark only one oval.

- Yes
- No *Skip to question 24.*
- Not Sure

Surgical History

23. **Please provide as much detail as you are able and willing about any previous complication or unexpected difficulty you have experienced due to a prior surgical procedure.**

Thank you for completing our survey! You are done now.

24. **Please input your initials followed by your age. For example, if your name is John Smith and you are 23 years old, then you would put: JS23**
*

Please return to MTurk and enter this code into the appropriate place so that you can be paid for your time.

Stop filling out this form.

I'm sorry, but you must be 18 years of age to participate. Thank you for your time.

Powered by
Google Forms

Appendix G – Model Summary

Model Summary (Model 23)

Model	R	R^2	Adjusted R^2	Std. Error of the Estimate
1	.796[a]	.633	.625	.61671
2	.796[b]	.633	.625	.61648
3	.796[c]	.633	.625	.61624
4	.796[d]	.633	.626	.61600
5	.796[e]	.633	.626	.61579
6	.796[f]	.633	.626	.61562
7	.796[g]	.633	.626	.61544
8	.796[h]	.633	.627	.61529
9	.796[i]	.633	.627	.61515
10	.795[j]	.633	.627	.61504
11	.795[k]	.633	.627	.61493
12	.795[l]	.633	.627	.61477
13	.795[m]	.632	.627	.61465
14	.795[n]	.632	.627	.61452
15	.795[o]	.632	.628	.61443
16	.795[p]	.632	.628	.61443
17	.795[q]	.631	.627	.61451
18	.794[r]	.631	.627	.61484
19	.794[s]	.630	.627	.61514
20	.793[t]	.629	.626	.61551
21	.793[u]	.628	.626	.61601
22	.792[v]	.628	.625	.61652
23	.792[w]	.627	.624	.61707

a. Predictors: (Constant), Surprise, ETH4, EDUC6, ETH3, EDUC1, ETH5, Agreeableness, ETH1, Familiarity, EDUC5, ETH2, Neuroticism, EDUC3, Wariness, Age, Income, Gender, FearSurg, Extraversion, Openness, Conscientiousness, EDUC2, Happiness, Disgust, Complexity, Value, Sadness, Anger, Fear, EDUC4

b. Predictors: (Constant), Surprise, ETH4, EDUC6, ETH3, EDUC1, ETH5, Agreeableness, ETH1, Familiarity, EDUC5, ETH2, Neuroticism, EDUC3, Wariness, Age, Income, Gender, FearSurg, Extraversion, Openness, Conscientiousness, EDUC2, Happiness, Disgust, Complexity, Value, Anger, Fear, EDUC4

c. Predictors: (Constant), Surprise, ETH4, EDUC6, ETH3, EDUC1, ETH5, Agreeableness, ETH1, Familiarity, EDUC5, ETH2, EDUC3, Wariness, Age, Income, Gender, FearSurg, Extraversion, Openness, Conscientiousness, EDUC2, Happiness, Disgust, Complexity, Value, Anger, Fear, EDUC4

d. Predictors: (Constant), Surprise, ETH4, EDUC6, ETH3, EDUC1, Agreeableness, ETH1, Familiarity, EDUC5, ETH2, EDUC3, Wariness, Age, Income, Gender, FearSurg, Extraversion, Openness, Conscientiousness, EDUC2, Happiness, Disgust, Complexity, Value, Anger, Fear, EDUC4

e. Predictors: (Constant), Surprise, ETH4, EDUC6, ETH3, EDUC1, Agreeableness, ETH1, Familiarity, EDUC5, ETH2, EDUC3, Wariness, Age, Income, Gender,

FearSurg, Extraversion, Openness, Conscientiousness, EDUC2, Happiness, Disgust, Value, Anger, Fear, EDUC4
f. Predictors: (Constant), Surprise, ETH4, EDUC6, ETH3, EDUC1, Agreeableness, ETH1, Familiarity, EDUC5, ETH2, EDUC3, Wariness, Income, Gender, FearSurg, Extraversion, Openness, Conscientiousness, EDUC2, Happiness, Disgust, Value, Anger, Fear, EDUC4
g. Predictors: (Constant), Surprise, ETH4, EDUC6, ETH3, EDUC1, Agreeableness, Familiarity, EDUC5, ETH2, EDUC3, Wariness, Income, Gender, FearSurg, Extraversion, Openness, Conscientiousness, EDUC2, Happiness, Disgust, Value, Anger, Fear, EDUC4
h. Predictors: (Constant), Surprise, ETH4, EDUC6, ETH3, EDUC1, Familiarity, EDUC5, ETH2, EDUC3, Wariness, Income, Gender, FearSurg, Extraversion, Openness, Conscientiousness, EDUC2, Happiness, Disgust, Value, Anger, Fear, EDUC4
i. Predictors: (Constant), Surprise, ETH4, EDUC6, ETH3, EDUC1, Familiarity, EDUC5, ETH2, Wariness, Income, Gender, FearSurg, Extraversion, Openness, Conscientiousness, EDUC2, Happiness, Disgust, Value, Anger, Fear, EDUC4
j. Predictors: (Constant), ETH4, EDUC6, ETH3, EDUC1, Familiarity, EDUC5, ETH2, Wariness, Income, Gender, FearSurg, Extraversion, Openness, Conscientiousness, EDUC2, Happiness, Disgust, Value, Anger, Fear, EDUC4
k. Predictors: (Constant), ETH4, EDUC6, ETH3, Familiarity, EDUC5, ETH2, Wariness, Income, Gender, FearSurg, Extraversion, Openness, Conscientiousness, EDUC2, Happiness, Disgust, Value, Anger, Fear, EDUC4
l. Predictors: (Constant), ETH4, EDUC6, ETH3, Familiarity, EDUC5, ETH2, Wariness, Income, Gender, FearSurg, Extraversion, Openness, Conscientiousness, EDUC2, Happiness, Disgust, Value, Anger, Fear
m. Predictors: (Constant), ETH4, ETH3, Familiarity, EDUC5, ETH2, Wariness, Income, Gender, FearSurg, Extraversion, Openness, Conscientiousness, EDUC2, Happiness, Disgust, Value, Anger, Fear
n. Predictors: (Constant), ETH4, ETH3, Familiarity, EDUC5, ETH2, Wariness, Income, Gender, FearSurg, Extraversion, Openness, Conscientiousness, Happiness, Disgust, Value, Anger, Fear
o. Predictors: (Constant), ETH4, ETH3, Familiarity, EDUC5, ETH2, Wariness, Income, Gender, FearSurg, Openness, Conscientiousness, Happiness, Disgust, Value, Anger, Fear
p. Predictors: (Constant), ETH4, Familiarity, EDUC5, ETH2, Wariness, Income, Gender, FearSurg, Openness, Conscientiousness, Happiness, Disgust, Value, Anger, Fear
q. Predictors: (Constant), Familiarity, EDUC5, ETH2, Wariness, Income, Gender, FearSurg, Openness, Conscientiousness, Happiness, Disgust, Value, Anger, Fear
r. Predictors: (Constant), Familiarity, EDUC5, ETH2, Wariness, Income, Gender, FearSurg, Openness, Happiness, Disgust, Value, Anger, Fear
s. Predictors: (Constant), Familiarity, EDUC5, Wariness, Income, Gender, FearSurg, Openness, Happiness, Disgust, Value, Anger, Fear
t. Predictors: (Constant), Familiarity, EDUC5, Wariness, Income, FearSurg, Openness, Happiness, Disgust, Value, Anger, Fear

u. Predictors: (Constant), Familiarity, EDUC5, Wariness, Income, FearSurg, Openness, Happiness, Value, Anger, Fear
v. Predictors: (Constant), Familiarity, Wariness, Income, FearSurg, Openness, Happiness, Value, Anger, Fear
w. Predictors: (Constant), Familiarity, Wariness, FearSurg, Openness, Happiness, Value, Anger, Fear
x. Dependent Variable: Willingness

Appendix H – F Values and Significance

Description

Model[a]		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	849.340	30	28.311	74.438	.000[b]
	Residual	491.774	1293	.380		
	Total	1341.114	1323			
2	Regression	849.340	29	29.288	77.064	.000[c]
	Residual	491.774	1294	.380		
	Total	1341.114	1323			
3	Regression	849.339	28	30.334	79.878	.000[d]
	Residual	491.774	1295	.380		
	Total	1341.114	1323			
4	Regression	849.337	27	31.457	82.900	.000[e]
	Residual	491.777	1296	.379		
	Total	1341.114	1323			
5	Regression	849.294	26	32.665	86.143	.000[f]
	Residual	491.820	1297	.379		
	Total	1341.114	1323			
6	Regression	849.192	25	33.968	89.628	.000[g]
	Residual	491.921	1298	.379		
	Total	1341.114	1323			
7	Regression	849.094	24	35.379	93.405	.000[h]
	Residual	492.019	1299	.379		
	Total	1341.114	1323			
8	Regression	848.954	23	36.911	97.498	.000[i]
	Residual	492.159	1300	.379		
	Total	1341.114	1323			
9	Regression	848.800	22	38.582	101.957	.000[j]
	Residual	492.314	1301	.378		
	Total	1341.114	1323			
10	Regression	848.602	21	40.410	106.826	.000[k]
	Residual	492.512	1302	.378		
	Total	1341.114	1323			
11	Regression	848.402	20	42.420	112.182	.000[l]
	Residual	492.711	1303	.378		
	Total	1341.114	1323			
12	Regression	848.283	19	44.646	118.132	.000[m]
	Residual	492.831	1304	.378		
	Total	1341.114	1323			
13	Regression	848.089	18	47.116	124.713	.000[n]
	Residual	493.024	1305	.378		
	Total	1341.114	1323			
14	Regression	847.925	17	49.878	132.080	.000[o]
	Residual	493.189	1306	.378		
	Total	1341.114	1323			

15	Regression	847.682	16	52.980	140.334	.000[p]
	Residual	493.431	1307	.378		
	Total	1341.114	1323			
16	Regression	847.310	15	56.487	149.625	.000[q]
	Residual	493.803	1308	.378		
	Total	1341.114	1323			
17	Regression	846.798	14	60.486	160.172	.000[r]
	Residual	494.315	1309	.378		
	Total	1341.114	1323			
18	Regression	845.894	13	65.069	172.126	.000[s]
	Residual	495.219	1310	.378		
	Total	1341.114	1323			
19	Regression	845.034	12	70.420	186.099	.000[t]
	Residual	496.079	1311	.378		
	Total	1341.114	1323			
20	Regression	844.066	11	76.733	202.544	.000[u]
	Residual	497.048	1312	.379		
	Total	1341.114	1323			
21	Regression	842.878	10	84.288	222.123	.000[v]
	Residual	498.236	1313	.379		
	Total	1341.114	1323			
22	Regression	841.661	9	93.518	246.034	.000[w]
	Residual	499.453	1314	.380		
	Total	1341.114	1323			
23	Regression	840.386	8	105.048	275.876	.000[x]
	Residual	500.727	1315	.381		
	Total	1341.114	1323			

a. Dependent Variable: Willingness
b. Predictors: (Constant), Surprise, ETH4, EDUC6, ETH3, EDUC1, ETH5, Agreeableness, ETH1, Familiarity, EDUC5, ETH2, Neuroticism, EDUC3, Wariness, Age, Income, Gender, FearSurg, Extraversion, Openness, Conscientiousness, EDUC2, Happiness, Disgust, Complexity, Value, Sadness, Anger, Fear, EDUC4
c. Predictors: (Constant), Surprise, ETH4, EDUC6, ETH3, EDUC1, ETH5, Agreeableness, ETH1, Familiarity, EDUC5, ETH2, Neuroticism, EDUC3, Wariness, Age, Income, Gender, FearSurg, Extraversion, Openness, Conscientiousness, EDUC2, Happiness, Disgust, Complexity, Value, Anger, Fear, EDUC4
d. Predictors: (Constant), Surprise, ETH4, EDUC6, ETH3, EDUC1, ETH5, Agreeableness, ETH1, Familiarity, EDUC5, ETH2, Neuroticism, EDUC3, Wariness, Age, Income, Gender, FearSurg, Extraversion, Openness, Conscientiousness, EDUC2, Happiness, Disgust, Complexity, Value, Anger, Fear, EDUC4
e. Predictors: (Constant), Surprise, ETH4, EDUC6, ETH3, EDUC1, ETH5, Agreeableness, ETH1, Familiarity, EDUC5, ETH2, EDUC3, Wariness, Age, Income, Gender, FearSurg, Extraversion, Openness, Conscientiousness, EDUC2, Happiness, Disgust, Complexity, Value, Anger, Fear, EDUC4
f. Predictors: (Constant), Surprise, ETH4, EDUC6, ETH3, EDUC1, Agreeableness, ETH1, Familiarity, EDUC5, ETH2, EDUC3, Wariness, Age, Income, Gender,

FearSurg, Extraversion, Openness, Conscientiousness, EDUC2, Happiness, Disgust, Complexity, Value, Anger, Fear, EDUC4

g. Predictors: (Constant), Surprise, ETH4, EDUC6, ETH3, EDUC1, Agreeableness, ETH1, Familiarity, EDUC5, ETH2, EDUC3, Wariness, Age, Income, Gender, FearSurg, Extraversion, Openness, Conscientiousness, EDUC2, Happiness, Disgust, Value, Anger, Fear, EDUC4

h. Predictors: (Constant), Surprise, ETH4, EDUC6, ETH3, EDUC1, Agreeableness, ETH1, Familiarity, EDUC5, ETH2, EDUC3, Wariness, Income, Gender, FearSurg, Extraversion, Openness, Conscientiousness, EDUC2, Happiness, Disgust, Value, Anger, Fear, EDUC4

i. Predictors: (Constant), Surprise, ETH4, EDUC6, ETH3, EDUC1, Agreeableness, Familiarity, EDUC5, ETH2, EDUC3, Wariness, Income, Gender, FearSurg, Extraversion, Openness, Conscientiousness, EDUC2, Happiness, Disgust, Value, Anger, Fear, EDUC4

j. Predictors: (Constant), Surprise, ETH4, EDUC6, ETH3, EDUC1, Familiarity, EDUC5, ETH2, EDUC3, Wariness, Income, Gender, FearSurg, Extraversion, Openness, Conscientiousness, EDUC2, Happiness, Disgust, Value, Anger, Fear, EDUC4

k. Predictors: (Constant), Surprise, ETH4, EDUC6, ETH3, EDUC1, Familiarity, EDUC5, ETH2, EDUC3, Wariness, Income, Gender, FearSurg, Extraversion, Openness, Conscientiousness, EDUC2, Happiness, Disgust, Value, Anger, Fear, EDUC4

l. Predictors: (Constant), ETH4, EDUC6, ETH3, EDUC1, Familiarity, EDUC5, ETH2, Wariness, Income, Gender, FearSurg, Extraversion, Openness, Conscientiousness, EDUC2, Happiness, Disgust, Value, Anger, Fear, EDUC4

m. Predictors: (Constant), ETH4, EDUC6, ETH3, Familiarity, EDUC5, ETH2, Wariness, Income, Gender, FearSurg, Extraversion, Openness, Conscientiousness, EDUC2, Happiness, Disgust, Value, Anger, Fear, EDUC4

n. Predictors: (Constant), ETH4, EDUC6, ETH3, Familiarity, EDUC5, ETH2, Wariness, Income, Gender, FearSurg, Extraversion, Openness, Conscientiousness, EDUC2, Happiness, Disgust, Value, Anger, Fear

o. Predictors: (Constant), ETH4, ETH3, Familiarity, EDUC5, ETH2, Wariness, Income, Gender, FearSurg, Extraversion, Openness, Conscientiousness, EDUC2, Happiness, Disgust, Value, Anger, Fear

p. Predictors: (Constant), ETH4, ETH3, Familiarity, EDUC5, ETH2, Wariness, Income, Gender, FearSurg, Extraversion, Openness, Conscientiousness, Happiness, Disgust, Value, Anger, Fear

q. Predictors: (Constant), ETH4, ETH3, Familiarity, EDUC5, ETH2, Wariness, Income, Gender, FearSurg, Openness, Conscientiousness, Happiness, Disgust, Value, Anger, Fear

r. Predictors: (Constant), ETH4, Familiarity, EDUC5, ETH2, Wariness, Income, Gender, FearSurg, Openness, Conscientiousness, Happiness, Disgust, Value, Anger, Fear

s. Predictors: (Constant), Familiarity, EDUC5, ETH2, Wariness, Income, Gender, FearSurg, Openness, Conscientiousness, Happiness, Disgust, Value, Anger, Fear

t. Predictors: (Constant), Familiarity, EDUC5, ETH2, Wariness, Income, Gender, FearSurg, Openness, Happiness, Disgust, Value, Anger, Fear
u. Predictors: (Constant), Familiarity, EDUC5, Wariness, Income, Gender, FearSurg, Openness, Happiness, Disgust, Value, Anger, Fear
v. Predictors: (Constant), Familiarity, EDUC5, Wariness, Income, FearSurg, Openness, Happiness, Disgust, Value, Anger, Fear
w. Predictors: (Constant), Familiarity, EDUC5, Wariness, Income, FearSurg, Openness, Happiness, Value, Anger, Fear
x. Predictors: (Constant), Familiarity, Wariness, Income, FearSurg, Openness, Happiness, Value, Anger, Fear
y. Predictors: (Constant), Familiarity, Wariness, FearSurg, Openness, Happiness, Value, Anger, Fear

Appendix I – Correlation Summary Table

Summary of Correlations Between Variables

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30
1. Willing.	-																													
2. Complex.	-.24	-																												
3. Familiarity	.35	-.43	-																											
4. Value	.61	-.12	.35	-																										
5. Wariness	-.37	.27	.02	-.33	-																									
6. Consc.	-.04	-.02	-.07	-.02	-.07	-																								
7. Agree.	.04	.03	-.05	.09	-.11	.21	-																							
8. Neurot.	-.09	.10	.00	-.06	.17	.21	-.14	-																						
9. Open.	.06	-.15	-.04	.14	-.27	-.40	.30	-.19	-																					
10. Extrav.	.13	-.12	.20	.09	.00	.14	.23	-.22	.12	-																				
11. Gender	-.12	.11	-.08	-.06	.11	.07	.22	.20	-.04	-.06	-																			
12. ETH5	-.07	.05	-.02	-.08	.06	-.08	-.04	.10	-.02	-.06	.06	-																		
13. ETH4	-.01	-.07	.00	-.01	-00	.06	.01	-.02	.05	.03	-.04	-.01	-																	
14. ETH3	.03	-.02	.05	.01	.02	-.07	-.07	.03	-.04	.03	-.07	-.05	-.02	-																
15. ETH2	-.03	.04	-.02	.04	.02	-.06	-.05	-.03	-.04	-.07	-.07	-.05	-.02	-.08	-															
16. ETH1	-.06	.03	.04	-.05	.08	.00	.00	-.03	.01	.03	-.01	-.05	-.02	-.08	-.07	-														
17. EDUC6	.02	-.01	.04	.03	-.01	.00	-.01	.04	.02	-.01	-.04	-.03	-.01	.01	-.01	-.02	-													
18. EDUC5	.03	-.01	.00	.01	.00	-.01	-.02	-.03	-.04	.01	.00	-.03	.03	.01	.00	-.04	-.06	-												
19 EDUC4	.00	-.01	.06	.05	.02	.01	-.03	.01	.03	.02	-.04	.03	.00	.03	.07	.01	-.13	-.31	-											
20. EDUC3	-.06	.02	.00	-.06	.00	.03	.01	.00	-.02	.00	.05	.03	-.03	.00	-.03	.04	-.06	-.15	-.31	-										
21. EDUC2	.02	-.03	-.06	-.01	-.01	-.05	.05	-.02	.03	.01	.01	-.04	.00	-.04	-.02	.03	-.09	-.22	-.45	-.22	-									
22. EDUC1	-.02	.05	-.05	-.02	-.01	.04	-.03	.04	-.03	-.07	.00	.03	.02	-.01	-.03	-.04	-.05	-.11	-.23	-.11	-.16	-								
23. Age	.00	.05	-.05	-.03	-.02	.20	.14	-.19	.04	-.01	.07	-.03	-.04	-.15	-.11	-.05	.08	.07	-.11	.04	.04	-.06	-							
24. Income	.10	-.08	.14	.13	-.09	.08	.02	-.12	.01	.13	-.09	-.08	.00	-.06	.03	-.08	.12	.20	.10	-.11	-.16	-.10	.09	-						
25. FearSurg	-.33	.20	-.07	-.17	.32	-.04	-.06	.18	-.12	-.10	.14	.07	-.04	.05	-.01	.06	-.02	.02	.00	.04	-.05	.03	-.01	-.07	-					
26. Anger	-.43	.13	.03	-.40	.43	-.08	-.14	.14	-.30	.05	.03	.06	-.03	.04	.03	.11	.03	.01	.05	.01	-.05	-.04	-.10	-.04	.23	-				
27. Disgust	-.38	.13	.03	-.35	.41	-.10	-.15	.12	-.26	.02	.03	.02	-.03	.04	.00	.09	.06	.00	.03	.00	-.03	-.04	-.04	-.04	.23	.74	-			
28. Fear	-.61	.26	-.14	-.42	.43	-.04	-.06	.19	-.19	-.07	.15	.08	-.02	.06	.03	.06	-.01	.02	.02	.05	-.06	-.01	-.10	-.09	.39	.61	.56	-		
29. Happ.	.64	-.20	.37	.45	-.19	-.07	-.01	-.05	-.03	.19	-.07	-.05	.01	.05	-.02	-.02	.01	.03	.03	-.04	.00	-.04	.01	.142	-.18	-.24	-.18	-.54	-	
30. Sadness	-.51	.20	-.06	-.35	.41	-.03	-.08	.17	-.19	-.02	.10	.07	-.02	.05	.01	.08	.02	-.01	.04	.04	-.05	-.03	-.07	-.08	.36	.66	.59	.76	-.46	-
31. Surprise	-.24	.17	-.07	-.13	.21	-.05	-.03	.11	-.08	-.05	.12	.02	.00	.02	.03	.030	.01	.01	.01	.04	-.05	-.01	-.09	-.02	.21	.25	.27	.46	-.19	.34