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Initiating change in care: socially assistive robots

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INITIATING CHANGE IN CARE: SOCIALLY ASSISTIVE ROBOTS

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DEDICATION

I dedicate this dissertation to those who have been my pillars of strength and unwavering support throughout this incredible journey. To my family, whose boundless love, encouragement, and sacrifices have been the driving force behind my pursuit of knowledge and growth. To my advisors, mentors, and educators, for their guidance, wisdom, and expertise that have shaped my research and scholarly development.

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ABSTRACT

Socially assistive robots (SAR) are autonomous machines equipped with sensors and software that allow them to interact socially with humans (Montaño-Serrano et al., 2021). SAR robots are commonly used in healthcare settings to provide patients with non-clinical support, such as conversation and emotional companionship. SARs can also deliver reminders, monitor vital signs, and provide educational information about health conditions or medications.

Researchers have studied SAR applications in detail. Additionally, there has been prior research on SAR where users' sociodemographic factors and technology acceptance were studied (Flandorfer, 2012). But even though the backbone of SAR is an advanced technology, no known research has been done on users' technology adoption propensity and SAR features. Hence this quantitative study focuses on SAR users' technology adoption propensity index and SAR robot features.

This study will use a quantitative approach to collect data from hospital nurses regarding SARs. The data will be collected through surveys. The outcomes of this study can be used to enhance the design of SARs and their applications in hospitals. The importance of this study is twofold. First, this study will contribute to the research on using SARs in a hospital setting. Second, this study will provide insights into the design of SARs and their applications. This study can potentially improve the quality of life for nurses using SARs for patient care in hospital settings.

Keywords: Socially Assistive Robots, Systems theory, Ethics, Safety, Reliability, Utility, Accuracy, Patient-centered Care, Satisfaction, System theory.

Chapter 1: Introduction

Chapter Overview

This preliminary chapter provides exposure to Socially Assistive Robots (SAR or SARs) and their applications. This chapter introduces the problem statement and establishes the foundation and reasoning for the author's intent and interest in contributing to the effectiveness of SARs used in the hospital setting. This chapter's sections include the introduction with the explanation of the issue, Problem Statement, Purpose Statement, Significance of the Study, Theoretical Framework, Conceptual framework, Definition of Terms, Research Questions, Limitations, Delimitations, Assumptions, Positionality, Organization of the Study, and a Chapter Summary. The Introduction with Problem Statement section explains how current approaches to health care are inadequate and how assistive robots may provide a solution to better patient outcomes.

The *Purpose Statement* explains the precise ambitions of the study and how it will contribute to the advancement of knowledge in this area. The significance of the study will be evident in how this research can improve patient care, safety, and satisfaction, as well as reduce healthcare costs. The *Theoretical Framework* provides an overview of the relevant theories and models that will guide the research. The *Conceptual Framework* is a pictorial representation of how the study's variables are expected to interact. A definition of *Terms* is provided to ensure a common understanding of key concepts by all readers.

Research Questions serve as a guide for data collection and analysis. *Limitations, Delimitations, Assumptions, and Positionality* provide transparency of the Study's constraints and the author's personal biases. The organization of the Study outlines the sequence in which subsequent chapters will be presented. The chapter Summary provides a brief overview of what has been covered. The current approaches to healthcare are inadequate and assistive robots may provide a solution to better patient outcomes.

Introduction with the Explanation of the Issue

Globally, the healthcare industry is under persistent pressure to do more with less available resources. The demand for care will only increase with an aging population and a lack of healthcare professionals. Poor patient outcomes are due to the lack of individualized care, long wait times, and high readmission rates. SARs are designed to assist and support patients and care providers. SARs have the potential to improve patient care by providing personalized care, reducing wait times, and preventing readmissions. However, there is a scarcity of research on the effectiveness of using assistive robots in hospital settings. This study aims to contribute to the advancement of knowledge in this area by investigating the effectiveness of using assistive robots in hospital settings.

Socially assistive robots are autonomous machines equipped with sensors and software that allow them to interact socially with humans (Montaño-Serrano et al., 2021). They are primarily used in healthcare settings to provide patients with non-clinical support, such as conversation and emotional companionship (Aymerich-Franch & Ferrer, 2021). SARs can be used to deliver reminders, observe vital signs, and provide educational information about health conditions or medications (Trafton, 2020).

Socially assistive robots typically have three main components: a sensing system, a reasoning system, and an actuator system. The sensing system allows the robot to gather data about its environment and the people it interacts with (Yu et al., 2022). The reasoning system processes this data so the robot can decide how to act (S. Lee & Seymour, 2019). The actuator system allows the robot to execute these actions, including moving its arms or legs, speaking, or displaying emotions on its face (Manfredi et al., 2021).

The interaction between these three systems allows the robot to engage effectively with humans (Ondrus et al., 2020). For example, if a patient tells the robot she is feeling pain, the sensing system will detect this information and send it to the reasoning system. The reasoning system will then determine that the best course of action is for the robot to provide solace and aid to the patient. The actuator system will then cause the robot to display pleasant emotions on its face and offer encouraging words to the patient. Socially assistive robots are becoming increasingly sophisticated and are able to perform more complex tasks as time goes on.

As technology grows, we can expect to see even more impressive applications of SARs in healthcare settings. There are many potential benefits of using SARs in healthcare settings (Christoforou et al., 2020; Getson & Nejat, 2021). First and foremost, they can help reduce the workload of nurses and other health care professionals (Christoforou et al., 2020). SARs can be used to perform routine tasks, such as checking vital signs or delivering reminders, which frees up nurses to focus on more critical tasks. Additionally, SARs can provide emotional support to patients and their families, which is an essential but often overlooked aspect of healthcare. Finally, SARs can be used to educate patients about their health conditions or medications, which can help ensure that they receive the best possible care. When patients are discharged, patients are given a lot of information to remember. This can be overwhelming, as it is easy to forget things or get confused. However, when patients receive discharge instructions from a SAR, they retain more information and make fewer mistakes (Getson & Nejat, 2021). That is because SARs can repeat information as often as necessary and answer any patient questions.

One of the most exciting aspects of SARs is that they can be tailored to each patient's needs (Irfan et al., 2022). For example, some patients may respond well to a SAR that takes on a human-like form, while others may prefer a more animal-like robot (Getson & Nejat, 2021). Human-like robots can incline individuals into believing it has a mind of their own (Baker, 2022). The possibilities are truly endless. SARs are also much more affordable than hiring additional staff members. They can be used 24/7, which means they can provide care and support to patients around the clock.

Although there are many probable benefits of using SARs in healthcare settings, there are also some potential drawbacks. One of the greatest problems is the possibility of cyber-attacks. As more and more devices are connected to the internet, they become potential targets for hackers. Additionally, some people may feel uncomfortable interacting with robots, preferring instead to interact with human beings. Finally, there is a risk that patients may become too dependent on SARs and lose the ability to complete basic tasks on their own.

Improve Patient Outcome

As the world progresses, technology does too. Technological progress has been through multiple avenues, including but not limited to the advent of smartphones, social media, and now socially assistive robots (SARs). These platforms share a common goal: to make human interaction easier and more efficient. The newer the technology, the more likely people will be interested in using it. This trend is also evident with SARs.

SARs are a relatively new technology, first developed in the early 2000s. Their popularity has grown in recent years as they are becoming more advanced. There are many different types of SARs, and they possess distinct abilities that set them apart from one another.

The most common type of SAR is the domestic robot, which is designed to assist with duties at home, such as cleaning, cooking, and laundry.

SARs have the potential to improve the quality of life for people with disabilities. For example, domestic robots can help people with limited mobility to live independently. There are also SARs designed explicitly for therapeutic purposes, such as those used in rehabilitation centers. These robots can give patients the motivation and encouragement they need to keep up with their therapy.

The future of SARs is inspiring. As they become more and more advanced, they will be able to help with an even more comprehensive range of tasks. In the future, SARs might become capable of delivering comprehensive care for individuals, from essential needs like food and shelter to more complicated conditions like emotional support. This stands to improve the quality of life for people with disabilities and make life easier for their caregivers. SARs are still in the early phases of development but have already shown great promise.

One of the ways SARs can help us is by improving patient outcomes (Briggs et al., 2015; Rabbit et al., 2015; Van der Putte et al., 2019; Wilson et al., 2016). For example, SoftBank Robotics' NAO humanoid robot is specially designed to provide social and emotional support. They are currently being used in settings like hospitals, schools, and homes for the elderly. In healthcare specifically, SARs have the potential to revolutionize the way we provide care. Studies have shown that patients who interact with SARs have lower anxiety levels (Fang et al., 2022) and higher rates of compliance with their treatment plans (Guemghar et al., 2022). They also report higher satisfaction levels with their care (Sætra, 2020). Additionally, patients who received check-ins from a SAR were more likely to take their medicine as specified than those who didn't interact with a SAR (Ferrante et al., 2021).

Problem Statement

Due to the growth of the aging population, hospital nurses, and caregivers are burdened by the growing number of senior patients. This group may need an increase in medical robotics, especially in the form of socially assistive robots to assist them with senior patients in hospital settings. A wide variety of such robots are being developed and trialed worldwide, each with unique capabilities. SARs have the capacity to engage with patients and offer crucial information and prompts, like reminding them when to take their medicine. The robot can also monitor patients' vital signs and report any changes to staff. Other examples of medical robots include those that are designed for use in hospitals and clinics. Autonomous robots can also deliver medications and supplies to patients in hospital rooms.

Additionally, there is a high demand for nurses and caretakers in hospitals. The cost of hiring a 24/7 caretaker is very high in developed countries. One solution that can be foreseen to solve this issue in the future is fully automated artificial intelligence robots that can act as workers. But currently, full automation is impossible due to the technological limitations and risks of safety with artificial intelligence. Hence, this gap may be met by introducing SARs.

SARs are robots designed to interact with humans in a social way, to help them with tasks or provide them with assistance. SARs are becoming popular as they are seen as a potential tool to help people with various tasks, including providing companionship, helping with household chores, and even healthcare services. There is increasing research on socially assistive robots and their potential applications. It is expected that these types of robots will become more prevalent.

SAR features should be helpful and acceptable to hospital nurses and caretakers for the patients. Moreover, to be acceptable to these robots would also need to have high degrees of social intelligence so that they can interact and provide care to the people they are assisting. Social intelligence would require them to communicate effectively, show empathy, and understand emotions.

In the future, it is hoped that social robots will become more widespread and affordable to assist people who need them. Social robots may eventually replace human caretakers in some situations, freeing people to live their lives without worrying about providing constant care for others. However, many hurdles on safety, ethics, usability, etc. need to be removed before SAR provides care.

As the number of elderly patients keeps growing, so too will the need for medical robots that can assist in their care. With the help of these robots, healthcare providers will be able to manage their workloads better and provide better care for their patients. Some researchers think that medical robots are a valuable idea because they can help remove some burdens from caregivers (Robinson et al., 2013). Others are concerned about the increasing use of technology in healthcare and feel that it could lead to even more dehumanization of the patient experience (Kyrarini et al., 2021; D. Lee et al., 2021; Maibaum et al., 2022). Hence acceptance of the features of the SAR robots needs to be studied based on SAR users' technology adoption propensity.

Importance of the Study

This study will help understand using SARs in hospital settings to help hospital nurses. Additionally, the study will also help to gain insights into studying robotic features based on the technology adoption propensity of nurses. SARs can potentially support and improve people's lives in several ways. Robots are increasingly used in healthcare settings to assist patients and staff. Examples include providing reminders to take medicine, assisting with physical therapy, and providing emotional support.

Additionally, SARs can be used in senior care facilities to provide assistance and friendship to residents. Additionally, robots are being used in various other settings, such as government agencies, retail stores, and hotels. With the growing prevalence of robots, it is crucial to comprehend how individuals interact with them and the factors that impact these interactions.

Robots have become increasingly prevalent in various industries, including healthcare. While robots have the potential to perform multiple tasks, such as assisting with surgeries and dispensing medication, they currently lack empathy (Huang & Rust, 2018), which is an essential trait for nurses (Penprase et al., 2013). Nurses are responsible for providing medical care and emotional support to patients. Patients rely on nurses' human connection and empathy, which robots cannot replicate.

Therefore, nurses should not be concerned about losing jobs due to the increasing role of robots in healthcare; since robots cannot replace nurses, they can only supplement their work. Additionally, AI develops from lower intelligence (mechanical) to higher intelligence (empathetic), replacing specific tasks with automation instead of entire job positions. As AI takes over more analytical tasks, analytical skills will become less critical, while "softer" skills such as intuition or empathy gain importance in human employment opportunities (Huang & Rust, 2018).

There is a need to study robotic features based on the technology adoption propensity of nurses since they are potential end-users of such technology in hospital settings. This may help in understanding how best to design and implement SAR robots in order to promote their acceptability and use by nurses. Additionally, this study stands to gain insights into the potential benefits of using SARs in hospital settings. The findings of this study could be utilized for enhancing the SARs' design and encouraging their acceptance and usage in healthcare environments.

Research Question

To what extent, if at all, do four aspects of the propensity for adopting technology predict three aspects of social attitudes towards SARs among hospital nurses?

Hypotheses

The alternate hypothesis (Ha) is that the four aspects of the propensity for adopting technology predict three aspects of social attitudes towards SARs among hospital nurses. The rationale for this expectation derives from the following literature:

The foundation for the hypothesis rests on two distinct dimensions. First, the propensity for embracing technology is explored through four facets: Optimism, Proficiency, Dependence, and Vulnerability (Ratchford & Barnhart, 2012). Optimism represents the belief that technology provides increased control and flexibility in life, while Proficiency indicates confidence in quickly understanding new technologies and feeling skilled (Ratchford & Barnhart, 2012). On the flip side, Dependence encapsulates feeling overly reliant and enslaved by technology, and Vulnerability entails the perception that technology exposes one to exploitation by malicious actors (Ratchford & Barnhart, 2012).

Secondly, social attitudes toward Socially Assistive Robots (SARs) are characterized by Warmth, Competence, and Discomfort. Warmth and Competence render individuals more positively regarded and facilitate favorable social interactions (Carpinella et al., 2017). Conversely, Discomfort corresponds to a sense of unease regarding robotic technology (Carpinella et al., 2017).

Drawing on these dimensions, it becomes evident that Optimism and Proficiency propel technology adoption while Dependence and Vulnerability impede it. Similarly, Warmth and Competence foster the adoption of Robotic technology, while Discomfort serves as an impediment. This interplay substantiates our hypothesis, indicating the intricate dynamics between these factors and the propensity to embrace innovative technological advancements.

The null hypothesis (H_0) is that four aspects of the propensity for adopting technology do not predict three aspects of social attitudes towards SARs hospital among nurses.

Purpose Statement

This quantitative study aims to understand the degree to which perceived warmth, competence and discomfort of SARs among hospital nurses is predicted by their optimism, proficiency, dependence and vulnerability regarding technology adoption propensity.

Operational Definitions

Perceived Warmth and Competence with SAR Caretakers

Individuals who are perceived as both warm and competent tend to be viewed more positively and encounter more favorable social exchanges. (Carpinella et al., 2017). These variables will be collected through the perceived warmth and competence subscale of the Robotic Social Attribute (RoSAS) scale (Carpinella et al., 2017).

Perceived Discomfort with SAR Caretakers

Discomfort relates to "awkwardness" regarding robotic technology (Carpinella, et al., 2017, p. 257). This variable will be collected through the perceived discomfort subscale of the Robotic Social Attribute (RoSAS) scale (Carpinella et al., 2017).

Optimism Regarding Technology

Optimism is a belief that technology provides increased control and flexibility in life. This variable will be collected through the optimism subscale of the Technology Adoption Propensity Index (TAP) scale (Ratchford & Barnhart, 2012).

Proficiency Regarding Technology

Proficiency refers to confidence in one's ability to quickly and easily learn to use new technologies, as well as a sense of being technologically competent. This variable will be collected through the Proficiency subscale of the Technology Adoption Propensity Index (TAP) scale (Ratchford & Barnhart, 2012).

Dependence Regarding Technology

Dependence refers to feeling excessively reliant on and enslaved by technology. This variable will be collected through the Dependence subscale of the Technology Adoption Propensity Index (TAP) scale (Ratchford & Barnhart, 2012).

Vulnerability Regarding Technology

“Vulnerability refers to a belief that technology increases one's chances of being taken advantage of by criminals or firms" (Ratchford & Barnhart, 2012, p.1212). This variable will be collected through the Vulnerability subscale of the Technology Adoption Propensity Index (TAP) scale (Ratchford & Barnhart, 2012).

Key Terms

Socially Assistive Robots

Socially assistive robots (SAR) are autonomous machines equipped with sensors and software that allow them to interact socially with humans (Montaño-Serrano et al., 2021). SARs are commonly used in healthcare settings to provide patients with non-clinical support, such as conversation and emotional companionship. SARs can also deliver reminders, monitor vital signs, and provide educational information about health conditions or medications.

Systems Theory

Systems theory is a branch of science that generally studies systems and attempts to determine what principles they all obey. It looks at how systems work together and how they affect each other. It tries to understand how a change in one part of a system can cause changes in other parts (Von Bertalanffy, 1972). It forms the theoretical framework for this study.

Complex Systems

A complex system comprises many interacting components or agents that exhibit emergent behavior that cannot be predicted by analyzing the individual parts in isolation (Hmelo-Silver & Azevedo, 2006). Complex systems can be found in many areas of science, including physics, biology, economics, and social sciences (Auyang, 1998).

General Systems Theory

General System Theory posits that complex systems should be studied as whole systems rather than as collections of individual parts. It emphasizes the relationships and interactions between the components of a system and seeks to identify common principles and patterns that are shared across different types of systems (Von Bertalanffy, 1972).

Design for Six Sigma (DFSS)

DFSS is a methodology used to design products or services that meet customer expectations and specifications (Jenab et al., 2018). DFSS uses various tools and techniques to identify problems and root causes, understand customer needs, and design solutions that address these issues. The DFSS methodology starts with understanding customer needs and requirements. Once these are understood, the next step is to design a solution that meets these needs. The solution must then be verified to ensure it works as intended before being deployed to customers. DFSS is a powerful tool for organizations looking to achieve operational excellence and optimize their business processes.

Diffusion of Innovations Theory

The diffusion of innovations theory (Rogers, 1995) has been used in different fields to explain how new ideas and technologies spread throughout society. The theory's basic premise is that there are four main groups of people within any given population: innovators, early adopters, early majority, and late majority. It contributes to the conceptual framework for this study.

Unified Theory of Acceptance and Use of Technology

The Unified Theory of Acceptance and Use of Technology helps explain how people accept and use new technologies (Venkatesh et al., 2016). The model is based on four main factors that affect a person's decision to adopt new technology. The factors identified in UTAUT are performance expectancy, effort expectancy, social influence, and facilitating conditions. It also contributes to the conceptual framework for this study.

The Technology Acceptance Model

The Technology Acceptance Model (TAM) is a widely recognized theoretical framework developed to understand individuals' adoption of new technologies. TAM posits that perceived usefulness and perceived ease of use significantly influence users' attitudes and intentions toward adopting a technology (Davis, 1985). These factors, in turn, impact their actual usage behavior. TAM has been extensively applied to various contexts to explain technology adoption.

In the realm of a study focused on socially assistive robots, integrating the TAM into the conceptual framework can offer valuable insights. By analyzing participants' perceptions of the usefulness and ease of use of socially assistive robots, researchers can determine how these factors affect individuals' intentions to adopt and use such robots. The TAM's core elements align well with the challenges of introducing robots in a social context, allowing researchers to systematically assess the potential benefits and challenges of integrating socially assistive robots into different environments. This framework aids in understanding the factors that drive or hinder the acceptance of these robots, guiding the development and implementation of effective interventions and strategies to enhance their adoption and usability.

Technology Readiness Index

The Technology Readiness Index (TRI) represents a scale with multiple components designed to gauge an individual's preparedness for adopting novel technologies (Parasuraman, 2000). This index comprises three distinct factors: perceived advantages, perceived disadvantages, and perceived simplicity of utilization. The TRI has been established as a dependable and valid gauge of a person's readiness to engage with technology. Perceived advantages pertain to how much an individual believes that utilizing new technology will yield favorable consequences. Perceived disadvantages involve the extent to which an individual anticipates unfavorable outcomes from using new technology. Perceived ease of use concerns to an individual's belief in the effortlessness of operating a new technology.

Integrating TRI into a study focused on socially assistive robots enhances the conceptual framework by systematically gauging individuals' readiness to embrace new technologies, offering insights into perceived benefits, risks, and ease of use. This inclusion provides a comprehensive understanding of factors influencing the acceptance and integration of socially assistive robots within diverse social contexts.

Human-Robot Interaction

Human-robot interaction is a relatively new field of study that focuses on how humans and robots interact with each other (Sheridan, 2016). Human-robot interaction encompasses aspects of psychology and engineering, and its goal is to create robotic systems that can effectively interact with and assist humans. Additionally, the purpose of Human-robot interaction is to develop robots that are more efficient, safer, and easier to use.

Limitations

To understand the relationship between SAR robot features and technology adoption data will be collected based on a convenience sample of nurses in the United States and Canada. Inference based on this survey might not accurately represent the nurses within these countries nor worldwide. To mitigate any issues with unequal representation of nurses' perspectives, the researcher will increase the sample size as necessary to obtain equal representation of nurses who have high, low and average technological propensity until the minimal sample size for all groups is obtained.

Delimitations

Data will be collected from participants who may have cultural differences such as race, ethnicity, religion. Research has shown that different cultures have different attitudes towards SARs (Bartneck et al., 2005). Researchers have also found that people are more willing to accept SARs that behave in manner close to what is expected in their respective culture (Papadopoulos & Koulouglioti 2018).

Assumptions

- Participants will provide honest responses.

- The RoSAS and TAP scales provide accurate representations of the participants' beliefs.

Theoretical Framework

The theoretical foundation of this study rests on two fundamental frameworks: systems theory, as introduced by Von Bertalanffy in 1972, and Design for Six Sigma (DFSS) as articulated by Brue and Launsby in 2003. Systems theory mainly applied in science and engineering, focusing on studying complex systems (Auyang, 1998). Complex systems are made up of interacting components that work together to produce collective behaviors. These behaviors can emerge in several ways and can be difficult to predict. Systems theory is rooted in several fields, including mathematics, engineering, and biology. It has been used to study a wide range of phenomena, from the behavior of cells to the dynamics of social networks. In recent years, systems theory has been increasingly applied to the study of human behavior. This is mainly due to the growing recognition that humans are themselves complex systems. Consequently, the associations between SAR characteristics and users' inclination to adopt technology are likely to become more obvious. As integrated systems' research approaches are currently absent to forecast the competence of SAR robots in a macroscopic scale, a General Systems Theory (Von Bertalanffy, 1972). framework is hereby suggested. This will provide a systematic way to interpret the findings related to the potential of SARs in healthcare settings.

DFSS, or Design for Six Sigma, is a comprehensive approach that helps organizations design products and services that fully satisfy customer expectations and requirements (Jenab et al., 2018). It leverages various tools and techniques to identify the root causes of problems and find effective solutions that address customer needs. At its core, DFSS methodology emphasizes the importance of understanding customer needs and requirements before moving on to the design phase. This involves gathering customer feedback, analyzing data, and engaging with stakeholders to gain a deep understanding of what customers expect from a product or service.

Once customer requirements are clearly defined, the DFSS process moves into the design phase, where solutions are developed that meet these needs. The design phase involves a rigorous analysis of potential solutions, with the goal of identifying the most effective approach that aligns with customer expectations (Francisco et al., 2020). To ensure that the solution is effective and works as intended, DFSS emphasizes the importance of verification and validation. This involves rigorous testing and analysis to confirm that the solution meets customer needs and requirements, and that it is robust enough to be deployed at scale.

In today's highly competitive business environment, DFSS is a powerful tool that can help organizations achieve operational excellence and optimize their business processes. By prioritizing customer needs and using a data-driven approach to design and testing, DFSS can help organizations deliver products and services that exceed customer expectations and drive business success.

Systems Theory

This Figure 1 illustrates the key components integral to the successful implementation of SARs within hospital contexts. The depicted components include Patients, Patient Families, Nurses, and the Hospital as interconnected elements. Each component plays a distinct role in shaping the integration and impact of SARs. Patients and their families represent the beneficiaries of SAR interaction, while Nurses are central in managing the robot-patient interaction. The Hospital encompasses the organizational context in which SARs are deployed. For a visual overview of the System Components for SAR's Deployment in Hospitals, refer to Figure 1.

Figure 1

System Components for SAR's Deployment in Hospitals

Systems theory is a branch of science that generally studies systems and attempts to determine what principles they all obey (Von Bertalanffy, 1972). Systems theory is the study of systems. It is used to look at how systems work together and how they affect each other and is applied to attempt to understand how a change in one part of a system can cause changes in other parts of the system.

In other words, systems theory examines how things work together. A system can be anything from a group of people to an ecosystem. The primary objective of systems theory is to develop a collection of fundamental concepts that can be applied to elucidate the functioning of any system. These principles can then be used to design or improve systems. One of the most famous systems theorists was German biologist Ludwig von Bertalanffy, who developed the General System Theory (GST). GST is a framework for understanding how systems work that can be applied to any system, including social systems such as organizations.

At its most basic, systems theory is the idea that everything is connected (Von Bertalanffy, 1972). This may seem like a grandiose or even impossible claim, but systems theory offers an understanding of how different elements in the world are interconnected. Doing so can provide valuable insight into how to create change or solve problems. Systems theory originated in biology, but it has since been applied to various disciplines, including psychology, sociology, economics, and even computer science. In each case, systems theory can offer a different perspective on complex issues and help us to see the world in new ways.

Systems also have specific characteristics, such as boundary, input, output, and feedback (Whitchurch & Constantine, 2009). According to this definition, a system will consist of repetitive, consistent patterns and structures that interact with each other. These elements can be people, organizations, or knowledge itself. The interactions between these elements are what create meaning within the system. One of the key insights of systems theory is that every system is composed of smaller subsystems, each of which has its own goals and functions. For example, a family is a system made up of smaller subsystems like the parents, children, and extended relatives. Each subsystem has its own distinct function within the family system, but they all work together to support the family as a whole.

Systems theory is useful for understanding how different social institutions (like families, schools, businesses, etc.) work together to produce complex outcomes. It can also be applied to problem-solving; by understanding how different parts of a system interact with each other, we can identify potential areas of intervention that can lead to positive change.

Key Concepts in Systems Theory

A fundamental idea in systems theory involves feedback loops, as discussed by McBride et al. in 2019.A feedback loop is a process where one element's output becomes the input for another. This process can then repeat itself indefinitely. Feedback loops are critical because they can help to regulate system behavior. For example, imagine you have a friend who is always late for your meetings. You might get frustrated and think your friend doesn't value your time. But from a systems perspective, we would say that there is likely a feedback loop at play here. The output (a friend being late) becomes the input (frustration) which then leads to the output (that friend being late). This feedback loop can only be broken if one of the elements changes.

Other key concepts in systems theory include:

- Boundaries. All systems have boundaries that define what is and is not part of the system (Kast & Rosenzweig, 1972);
- Equilibrium. All systems tend towards equilibrium or a state of balance (Von Bertalanffy, 1972);
- Interdependence. The elements within a system are interdependent, meaning they rely on each other to function properly.
- Countervailing Forces. There are always opposing forces at play within a system which can lead to either stability or change.

How Systems Theory Relates to Other Areas of Study

As mentioned earlier, systems theory is used in many different disciplines. In biology, systems theory is used to understand how different parts of an organism work together. For example, how do the cells in the human body work together to keep humans alive? How does the human digestive system work with the immune system?

In sociology, systems theory is used to understand how different parts of society work together. For example, how do families interact with schools? How do businesses interact with governments? In economics, systems theory is used to understand how different parts of the economy work together. For example, how does the stock market work with interest rates? How do workers interact with businesses? In engineering, systems theory is used to understand how different parts of a machine work together. For example, how do the gears in a car engine work together to make the car move? How do the pipes in a plumbing system work together to bring water into our homes?

There are four main components of systems theory: transactions, control systems, boundary systems, and networks (Von Bertalanffy, 1972).

Transactions

Transactions are the basic building blocks of systems theory. A transaction is any exchange between two or more elements in a system. Transactions can be physical (like when two gears engage) or abstract (like when two people have a conversation). All interactions within a system are composed of transactions.

Control Systems

Control systems help maintain order by correcting imbalances and ensuring that all elements function correctly. For example, parents might set rules for their children to keep them safe and ensure that they behave appropriately in public. In business organizations, managers typically have some degree of control over their employees' job duties and performance evaluations.

Boundary Systems

Boundary systems define what is inside or outside of a system. Families often have strict boundaries between members and non-members; only those who are related by blood or marriage are considered part of the family system. Businesses also have well-defined boundaries; employees are typically inside the organization while customers are outside it.

Networks

Networks are composed of interconnected nodes (elements) that communicate with each other through transactions. Social networks like Facebook and LinkedIn connect people from all over the world; these networks would not be possible without communication technology like the internet or telephone. It's important to note that not all networks are social in nature; transportation networks like roads and railways are another type of network that we rely on daily.

Business Applications

One area where systems theory has been instrumental is in business organizations. Organizations are complex social systems made up of many different parts that must all work together in order for the organization to function effectively. When an organization is designed properly, it can resist entropy and continue functioning effectively even as its environment changes and becomes more chaotic. However, when an organization is not designed properly, it will quickly become disordered and eventually break down completely. Hence, it is imperative for enterprises to focus on their organizational structure and manage their operations based on well-established system design principles.

There is a growing body of evidence that suggests that socially assistive robots (SARs) can be effective in providing support to people with various needs. One reason for this effectiveness is that SARs can be designed using system theory concepts. System theory offers a way to think about how different elements of a system interact with each other and how those interactions can be used to achieve specific goals.

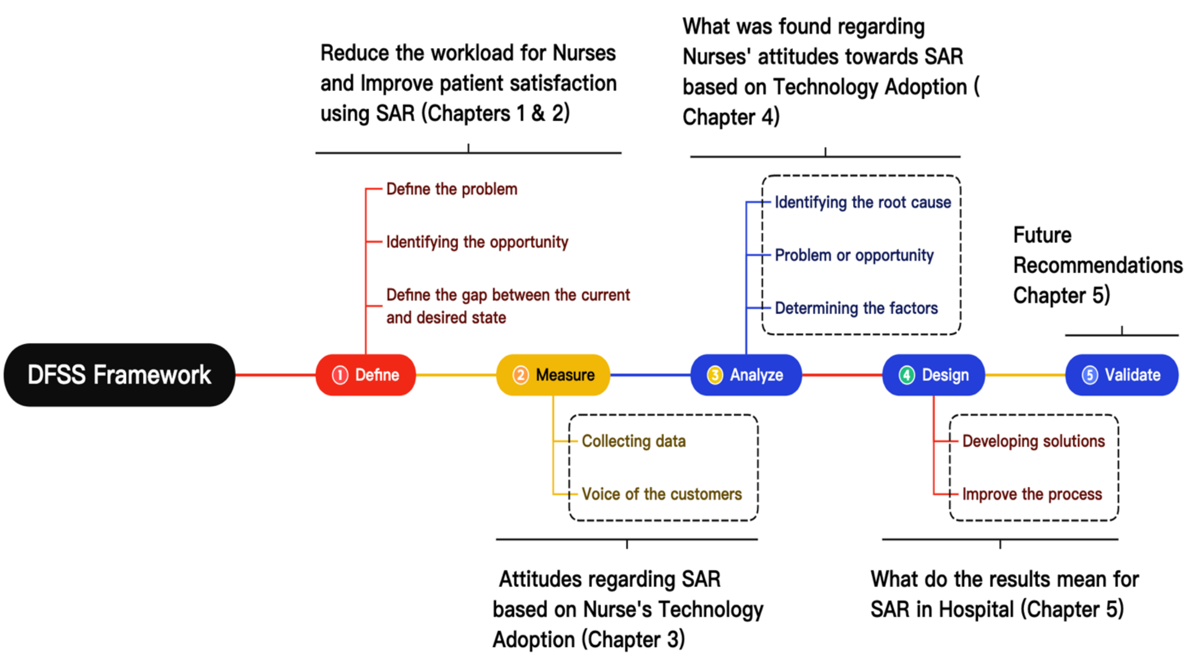
SARs are typically designed to provide assistance to people with disabilities or other special needs. For example, a SAR might be used to help a person with dementia remember to take their medication or to provide physical support to someone who is unable to walk. In each of these cases, the SAR needs to be able to interact with the person in a way that is helpful and not intrusive. System theory can be used to help design effective SARs in their interactions with people. For example, by understanding how people make decisions, SARs can be designed to provide information in a way that is most likely to be used by the person. Additionally, by understanding how people interact with their environment, SARs can be designed to avoid obstacles and provide physical support when needed. SARs designed using system theory concepts are likely to be more effective than those not. This is because system theory provides a way to think about a system as a whole.

Design for Six Sigma

The DFSS approach creates products or services that fulfill customers' requirements and desires (Jenab et al., 2018). Kumar & McKewan (2011) used Six Sigma to study how nurses can play a more significant role in providing better healthcare for patients before and after their hospital stay in the United States. DFSS employs various methods and instruments to recognize problems and their underlying causes, comprehend customers' demands, and develop solutions that tackle these concerns. SARs are designed to provide social and emotional support to humans in various settings, including hospitals. SARs in healthcare have gained significant attention in recent years due to their potential to improve patient outcomes and enhance the quality of care. However, successfully implementing SARs in hospitals requires a rigorous approach that ensures the robot's effectiveness, safety, and coexistence with hospital nurses. DFSS is used to design products or services that meet stakeholder needs and expectations while minimizing waste and maximizing value (Francisco et al., 2020). DFSS is a method that begins by comprehending the needs and requirements of customers, according to Chowdhury (2002). Following that, the focus shifts to creating a solution that satisfies these needs. It is critical to validate the solution's effectiveness before delivering it to customers. DFSS is a valuable tool for organizations that want to optimize their business processes and achieve operational excellence. When used correctly, the DFSS methodology can help organizations reduce waste, improve efficiency, enhance quality, and increase customer satisfaction. By designing solutions that meet stakeholder needs, organizations can achieve these benefits. DFSS is ideal for implementing SARs in the hospital because it prioritizes nurses' needs during the planning phase. DFSS is a structured approach that consists of five steps: Define, Measure, Analyze, Design, and Verify. The use of DFSS for this study is described in Figure 2.

Figure 2

DFSS Frameworks for SAR



Define

The Define phase comprises five steps: (a) identifying the problem statement, (b) defining project goals, (c) defining project scope, (d) identifying stakeholders, and (e) defining the project team (Anbari, 2002).

Step 1. The problem statement should be brief and precise, describe the problem, understand its impact on the customer (Chowdhury, 2002) and identify the root cause.

Step 2. The project goals should determine what the project intends to achieve and set specific, measurable, achievable, relevant, and time-bound (SMART) objectives.

Step 3. Defining project scope involves identifying the project's boundaries and what is included and excluded to ensure everyone understands its limitations.

Step 4. The fourth step is identifying stakeholders, including those impacted by the project and who have a stake in its success. By identifying stakeholders early, their needs and expectations are considered throughout the project.

Step 5. Finally, defining the project team involves identifying those who will work on the project, then assigning roles and responsibilities based on their skills and expertise. Providing the necessary resources to complete the project successfully follows this. In the case of SARs in hospitals, the goal is to improve patient satisfaction and reduce the workload of hospital nurses.

Measure

The Measure phase of DFSS is a crucial step in developing products and services that meet customer needs and expectations (Chowdhury, 2002). The Measure phase is focused on collecting and analyzing data related to the process being developed, to help identify potential issues and opportunities for improvement (Anbari, 2002). The Measure phase is typically divided into four main steps. The first step is to define the process being measured. This involves creating a detailed map of the process and identifying key metrics that can be used to evaluate its performance. These metrics should be specific, measurable, and related to the project's overall goals. The second step is to collect data related to the process being measured. This involves identifying data sources, such as sensors or measurement tools, and collecting data regularly. The data collected should be accurate and reliable and represent the overall process.

The third step is to analyze the data collected. This involves using statistical analysis methods to pinpoint patterns and trends in the data and any outliers or anomalies. The goal of this analysis is to gain a deeper understanding of the process being measured and to identify areas for improvement. The final step is to verify the results of the analysis. This involves testing any hypotheses generated during the analysis phase and ensuring that any improvements made to the process are effective and sustainable. Verification may involve additional testing or data collection and should be done continuously to ensure continued success. The Measure phase is critical to the success of DFSS projects because it provides a framework for collecting and analyzing data that can be used to make informed decisions about process improvements. Organizations can ensure that they are creating products and services that meet consumer wants and expectations by defining the process being measured, collecting accurate and reliable data, analyzing data, and verifying the results. The Measure phase is an essential part of the overall DFSS process and plays a key role in achieving Six Sigma levels of quality and consistency. In the case of SARs in hospitals, the goal is to collect data on nurses' preferences for SAR features based on their technology adoption propensity.

Analyze

The Analyze phase of DFSS is a critical step in developing products and services that meet customer needs and expectations. The Analyze phase is focused on analyzing the data collected in the Measure phase to identify the root causes of any issues or opportunities for improvement in the process being developed (Anbari, 2002; Chowdhury, 2002). The Analyze phase typically involves several key steps. The first step is to hypothesize about the root causes of any issues identified during the Measure phase. This hypothesis should be based on a careful analysis of the data collected and should be supported by statistical evidence. The hypothesis should also be consistent with the overall goals of the project.

The second step is to test the hypothesis using additional data and statistical analysis techniques. This may involve collecting additional data or re-analyzing existing data to test the hypothesis. This step aims to determine whether the hypothesis is valid and to gain a deeper understanding of the process being developed. The third step is to develop and prioritize potential solutions based on the analysis conducted in the previous steps. This may involve brainstorming sessions or other collaborative efforts to identify potential solutions to the issues identified during the Measure and Analyze phases. Solutions should be evaluated based on their feasibility, impact on the process, and ability to meet the project's overall goals.

In conclusion, the Analyze phase of DFSS is a critical step in creating products and services that meet customer expectations. By carefully analyzing the data collected in the Measure phase and developing and testing hypotheses about the root causes of any issues identified, organizations can gain a deeper understanding of the process being developed and identify opportunities for improvement. In the case of SARs in hospitals, this phase involves analyzing nurse feedback and determining the factors influencing nurse satisfaction with SAR. The Analyze phase is an essential part of the overall DFSS process and plays a key role in achieving Six Sigma levels of quality and consistency.

Design

The Design phase is the fourth stage of the DFSS methodology. In this phase, a product or service is developed based on the customer's requirements and the data collected during the previous stages. The Design phase aims to create a product or service that meets or exceeds customer expectations while ensuring that it is reliable, cost-effective, and easy to manufacture or deliver (Chowdhury, 2002).

The Design phase typically involves several key steps. The first step is to identify the critical-to-quality characteristics (CTQs) of the product or service which are essential to the customer. These CTQs should be prioritized based on their importance and feasibility of achieving them. The second step is to generate multiple design concepts that meet these CTQs. These design concepts should be evaluated based on their feasibility, potential benefits, and risks. The third step is to select the best design concept and refine it further. This involves creating detailed design specifications and performing simulations, testing, and analysis to ensure the design meets the CTQs and other requirements. The design specifications should be comprehensive and communicate all requirements to the manufacturing or delivery team.

In conclusion, the Design phase of DFSS is a critical step in developing products or services that meet customer requirements and expectations. By identifying CTQs, generating multiple design concepts, and selecting the best design concept, organizations can create a reliable, cost-effective, and easy-to-manufacture or deliver product or service that meets or exceeds customer expectations. This design phase may involve designing new SAR social attributes or modifying existing ones to meet hospital nurses' needs better. The Design phase is an essential part of the overall DFSS process and plays a crucial role in achieving Six Sigma levels of quality and consistency.

Validate

The Validate phase is the final stage of the Design for Six Sigma (DFSS) methodology. In this phase, the product or service is validated to ensure that it meets all customer requirements and is ready for implementation (Chowdhury, 2002). The Validate phase is critical in ensuring that the final product or service is of high quality and will provide a positive customer experience (Antony & Coronado, 2002). The Validate phase typically involves several key steps. The first step is to verify that the product or service meets all the design specifications and requirements identified in the previous stages. This involves testing and analyzing the product or service to ensure that it meets all the critical-to-quality characteristics (CTQs) and other customer requirements.

The second step is to validate the manufacturing or delivery process to ensure that it is reliable and can consistently produce or deliver the product or service to meet customer expectations. The third step is to validate the entire supply chain and customer support system to ensure that it can effectively support the product or service. This includes testing and analyzing the product or service's packaging, delivery, and after-sales support to ensure that the customer experience is positive and meets all expectations.

In conclusion, the Validate phase of DFSS is a critical step in ensuring that the final product or service meets all customer requirements and expectations. By verifying that the product or service meets all design specifications and requirements, validating the manufacturing or delivery process, and validating the entire supply chain and customer support system, organizations can ensure that they are providing a high-quality product or service that will provide a positive customer experience. This may involve conducting further studies to test the effectiveness and safety of the SARs in hospitals and obtaining feedback from hospital nurses.

The results of the pilot studies can be used to refine the SAR design and improve the process further. The Validate phase is an essential part of the overall DFSS process and plays a key role in achieving Six Sigma levels of quality and consistency.

In conclusion, using SARs in hospitals can potentially improve patient outcomes and enhance the quality of care. However, successful implementation requires a rigorous approach that ensures the robot's effectiveness and safety. DFSS is a structured approach that can be used to effectively design and implement SARs in hospitals. Following the five phases of DFSS, hospitals can identify the root causes of nurses' inclination toward social attitudes toward robots based on their technology adoption, design effective solutions, and test the SARs' effectiveness and safety.

Conceptual Framework

Theories are the suppositions that we use to explain our observations. A conceptual framework is a type of analytical instrument that exists in various forms and can be applied in different situations. Its purpose is to establish conceptual differences and structure concepts. Effective conceptual frameworks accurately represent something tangible and accomplish this in a manner that is simple to recall, communicate, and use as a mental model. Conceptual frameworks all the time whenever we try to make sense of something, to explain it or predict what will happen, we are using a conceptual framework. A good conceptual framework should do four things (Passey, 2020):

1. It should be simple.
2. It should be easy to remember.
3. It should be easy to communicate.
4. It should capture something real.

To understand the conceptual framework of the study researcher will address the below theories:

- The Diffusion of Innovations Theory
- The Unified Theory of Acceptance and Use of Technology
- The Technology Acceptance Model
- Technology Readiness Index

The Diffusion of Innovations Theory

The theory of diffusion of innovations (DOI), as introduced by Rogers in 1995, has been applied across various disciplines to elucidate the process through which new ideas and technologies permeate society. The theory's basic premise is that there are four main groups of people within any given population: innovators, early adopters, early majority, and late majority. Each group has distinct characteristics that affect how quickly they adopt new ideas. Innovators are individuals who are the initial adopters of novel ideas, and they usually possess a significant degree of inquisitiveness and a propensity for risk-taking. Early adopters are next in line and often opinion leaders within their social groups. The early majority are those who adopt new ideas before most people do, but they are not as quick to act as innovators or early adopters. Finally, most individuals are more skeptical of change and tend only to adopt new ideas once they have been widely accepted by society. The diffusion of innovation theory helps to explain why some people are more likely to adopt new technologies than others. It can also be used to predict how quickly new technology will spread through a population. The diffusion of innovations theory has been used extensively in marketing (Trinidad, 2020), and it can be applied to other areas as well. For example, the theory can be used to understand why some people are more likely to adopt a new diet or exercise regimen than others. It can also be used to explain why some people are more likely to vote for a particular candidate in an election.

SARs are a type of robot designed to help humans with various tasks. These robots can assist with activities of daily living, such as personal care, home chores, and even social interactions (Feil-Seife & Mataric, 2005). SARs can potentially improve the quality of life for people of all ages, but SARs are still in the early phases of evolution and diffusion. As SARs become more advanced, they will likely diffuse into more homes and workplaces. The diffusion of innovation theory can help us understand how and why particular technologies spread. There are four primary components to this theory: innovation, channels of communication, time, and social system. The potential adopters need to perceive the innovation as both new and beneficial. The communication channels must reach the likely adopters. The time aspect refers to how long the innovation takes to diffuse. Finally, the social system refers to the group of people interacting with each other and adopting innovation.

For SARs to diffuse, they must first be perceived as new and valuable by potential adopters. This may not be comfortable to accomplish because SARs are still in the initial stages of development and many people are unfamiliar with them. However, as SARs become more advanced and their capabilities increase, they are likely to be seen as more practical and thus diffused into more homes and workplaces.

The subsequent component of the diffusion of innovation theory is communication channels (Kaminski, 2011). For an innovation to be diffused, the potential adopters must be able to receive information about it. Information can be done through various channels, such as advertising, oral communication, and personal interactions. For SARs, informal communication might be the most essential channel of communication as it is probable that individuals who have previous experience with SARs would be the most passionate about them and, therefore, more capable of persuading others to embrace them.

Time is the third component of the diffusion of innovation theory (Sahin, 2006). It takes time for an innovation to diffuse into a population. This is because people must first learn about the creation and decide whether to adopt it. In the case of SARs, they will likely be diffused into the population slowly at first, but as more people learn about them and their benefits, they are likely to be adopted more quickly.

The fourth and final section of the diffusion of innovation theory is the social system. (Lundblad, 2003). The social system refers to the group of people interacting with each other and adopting innovation. In order for an invention to diffuse, it must first be accepted by the social system. SARs are likely to diffuse into the population slowly at first because they are still in the early stages of development and many people are unfamiliar with them. However, as more people learn about them and their benefits, they will likely be accepted by the social system and diffused into the population more quickly.

The Unified Theory of Acceptance and Use of Technology

The Unified Theory of Acceptance and Use of Technology (UTAUT) helps explain how people accept and use new technologies (Passey, 2020; Venkatesh et al., 2016). The model is based on four main factors that affect a person's decision to adopt new technology. The factors identified in UTAUT are performance expectancy, effort expectancy, social influence, and facilitating conditions. The concept of performance expectancy refers to the extent to which an someone perceives that utilizing a specific technology will assist them in attaining their desired objectives. For example, if someone believes that using a new software program will help them be more productive, their performance expectancy for that technology is high. Effort expectancy refers to an individual's perception of the level of exertion required to use a specific technology.

For example, if someone believes that using a new software program will be very complicated and time-consuming, then their effort expectancy for that technology is low.

Social influence is the degree to which a person's friends or peers use a particular technology (Williams et al., 2015). For example, if someone's friends are using a new social networking site, that person is likely to feel some social pressure to use the site. Facilitating conditions encompass the external factors that can either simplify or complicate an individual's use of a specific technology. For example, suppose a person has access to high-speed Internet and a computer compatible with the new software program. In that case, their facilitating conditions for using the technology are promising. The UTAUT has been found to be a valuable tool for predicting a person's likelihood of adopting new technology. The model is capable of determining the key factors that significantly impact an individual's choice to embrace novel technology. By understanding the factors that impact the adoption of emerging technologies, businesses can devise strategies to promote its acceptance.

According to the UTAUT model, people will use technology when they believe it will help them achieve their goals (Venkatesh et al., 2016). In the case of SARs, users must believe that the robot will be able to assist them in some way. For example, if a SAR is designed to help older adults with activities of daily living, then users must believe that the robot can perform these tasks. In addition, users must also believe that using the robot will require less effort than not using the robot. For example, if a SAR is intended to help with laundry, then users must believe that it would be easier to use the robot to do their laundry than to do it themselves. Finally, social influence plays a role in determining whether or not people will use technology. If other people use technology and perceive it to be beneficial, it will increase the likelihood that others will also use it.

The UTAUT model can explain why people hesitate to use SARs (Alaiad & Zhou, 2013). For people to adopt and use SARs, they must believe that the robots can assist them and that using the robot will require less effort than not using the robot. In addition, social influence is also an important factor in determining whether or not people will use SARs. If other people are not using SARs, then this stands to decrease the likelihood that others will use them as well.

There are various ways to increase the adoption and use of SARs. One way is to improve performance expectancy by demonstrating the robot's capabilities. Another way is to reduce effort expectancy by making it easier for people to use the robot. Finally, social influence can be increased by providing positive social proof of the benefits of using SARs.

The Technology Acceptance Model

The Technology Acceptance Model (TAM) was first applied to help understand how new users accept and intend to use new technology (Davis, 1985). The model is widely used in information technology and has been extended to other areas such as health care, accounting, and marketing. TAM suggests that two key factors influence a user's acceptance of technology: perceived usefulness and perceived ease of use. Perceived usefulness explains how users believe using a particular system will enhance their job performance. Perceived ease of use describes why users believe using a specific system is free from effort. End users are more likely to accept and use technology if they perceive it to be valuable and easy to use. The TAM has been used to explain end-user adoption of technologies such as computer systems, websites, and mobile apps.

Socially assistive robots are a kind of technology that has been shown to be beneficial for users in various ways. One study found that socially assistive robots can help improve mood and reduce user stress levels, while another found that they can promote social interaction and reduce loneliness (Bemelmans et al., 2012). In addition, TAM is a useful model for predicting user acceptance of socially assistive robots. Specifically, it has been found that the perceived usefulness and perceived ease of use of socially assistive robots are significant predictors of user acceptance.

Given the potential advantages of socially assistive robots and the evidence that TAM is a valuable model for understanding user acceptance of this type of technology, it is clear that further research on this topic is warranted. In particular, future research should focus on investigating the impact of different kinds of socially assistive robots on users and the potential moderating role of individual differences (such as age, gender, and personality) in determining user acceptance. Ultimately, this research may provide valuable insights into how socially assistive robots can be used to enhance the lives of users.

Technology Readiness Index

The Technology Readiness Index (TRI) is a multiple-item scale that measures an individual's readiness to embrace new technologies (Parasuraman, 2000). The TRI consists of three subscales: perceived benefits, perceived risks, and perceived ease of use. The TRI has been shown to be a reliable and valid measure of technology readiness. Perceived benefits refer to the extent to which an individual believes that using new technology will result in positive outcomes. Perceived risks refer to the extent to which an individual believes that using new technology will result in negative outcomes. Perceived ease of use refers to the extent to which an individual believes that using a new technology is easy to use. See Figure 3 for the conceptual framework for the study. Details regarding each variable used in conceptual framework is mentioned in Table 1.

Figure 3

Conceptual Framework

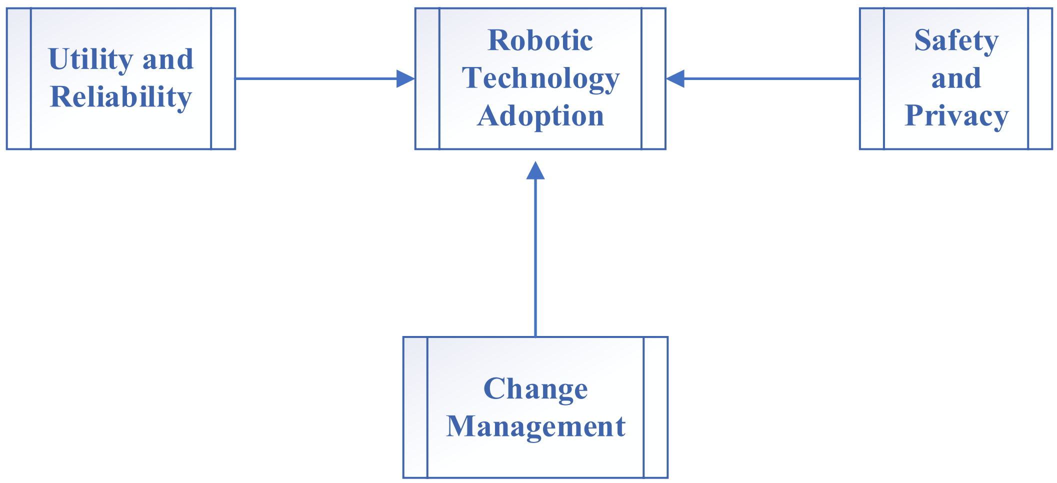


Table 1

Conceptual Framework Parameters

Utility and Reliability	**Safety and Privacy**	**Change Management**
• Performance expectancy (UTAT) • Effort expectancy (UTAT) • Perceived usefulness (TAM) • Perceived ease of use (TAM) • Optimism (TAPI) • Proficiency (TAPI) • Innovation (DOI) • Perceived ease of use (TRI) • Perceived benefit (TRI) • Warmth (RoSAS) • Competence (RoSAS)	Perceived risks (TRI) Dependence (TAPI) Vulnerability (TAPI) Discomfort (RoSAS)	Social influence (UATAT) Facilitating conditions (UTAT) Communication Channels (DOI) Time (DOI) Social System (DOI)

Utility and Reliability	**Safety and Privacy**	**Change Management**
DOI=The Diffusion of Innovations Theory (Rogers, 1995) RoSAS= Robot Social Attributes Scale (Carpinella et al., 2017) TAM= The Technology Acceptance Model (Davis, 1985) TAPI= Technology Adoption Propensity Index (Ratchford & Barnhart, 2012) TRI= Technology Readiness Index (Parasuraman, 2000). UTAT=The Unified Theory of Acceptance and Use of Technology (Venkatesh et al., 2016)		

Utility and Reliability

Based on different theories and models (Carpinella et al., 2017; Davis, 1985; Parasuraman, 2000; Ratchford & Barnhart, 2012; Rogers, 1995; Venkatesh et al., 2016), this study defines utility and reliability based on performance expectancy, effort expectancy, Perceived usefulness, Perceived ease of use , optimism, proficiency, innovation, perceived ease of use, benefit, warmth, and competence. Utility and reliability are positive factors that increase robotic technology adoption (Carpinella et al., 2017; Davis, 1985; Parasuraman, 2000; Ratchford & Barnhart, 2012; Rogers, 1995; Venkatesh et al., 2016). Performance expectancy is the breadth to which a person believes that using a particular technology will help them to achieve their desired outcomes (Venkatesh et al., 2016). Effort expectancy is the extent to which a person believes using a specific technology will require much effort (Venkatesh et al., 2016). Perceived usefulness explains how users believe using a particular system will enhance their job performance. Perceived ease of use describes why users believe using a specific system is free from effort (Davis, 1985).

Optimism entails the belief that technology offers enhanced control and flexibility in life, and Proficiency indicates confidence in swiftly learning to use new technologies and feeling technologically competent (Ratchford & Barnhart, 2012, p.1212). The innovation must be perceived as new and useful by the potential adopters (Rogers, 1995). Perceived benefits refer to the extent to which an individual believes that using new technology will result in positive outcomes, and perceived ease of use refers to the extent to which an individual believes that using new technology is easy to use (Parasuraman, 2000). "When people are evaluated as warm and competent, they are seen more favorably and experience more positive interactions" (Carpinella et al., 2017, p.257).

Safety and Reliability

Based on different theories and models (Carpinella et al., 2017; Parasuraman, 2000; Ratchford & Barnhart, 2012; Rogers, 1995; Venkatesh et al., 2016), this study defines safety and privacy based on perceived risks, dependence, vulnerability, and discomfort. Safety and reliability concerns section discusses the factors that discourage robotic technology adoption. Perceived risks refer to the extent to which an individual believes that using new technology will result in negative outcomes (Parasuraman, 2000). Dependence implies an excessive reliance on and a feeling of being controlled by technology. Vulnerability relates to the belief that technology raises the risk of being exploited by criminals or businesses (Ratchford & Barnhart, 2012, p.1212). Discomfort relates to "awkwardness" regarding robotic technology (Carpinella, et al., 2017, p. 257).

Change Management

Change management involves the external factors enabling robotic technology adoption. Based on different theories and models (Carpinella et al., 2017; Parasuraman, 2000; Ratchford & Barnhart, 2012; Rogers, 1995; Venkatesh et al., 2016), this study defines change management based on social influence, facilitating conditions, communication channels, time, and social

System. Social influence is the degree to which a person's friends or peers use a particular technology (Williams et al., 2015). Facilitating conditions increase technology adoption, including but not limited to need, resources, trialability, compatibility, and observability. The next constituent of the diffusion of innovation theory is communication channels (Kaminski, 2011). For an innovation to be diffused, the potential adopters must be able to receive information about it. Information can be done through various channels, such as advertising, word-of-mouth, and personal interactions.

Time is the third component of the diffusion of innovation theory (Sahin, 2006). It takes time for an innovation to diffuse into a population. This is because people must first learn about the creation and decide whether to adopt it. The fourth and final element of the diffusion of innovation theory is the social system (Lundblad, 2003). It refers to people interacting with each other and adopting innovation.

In summary, change management component of the conceptual framework provide a comprehensive framework for understanding the challenges and opportunities related to the adoption of Socially Assistive Robots. These theories help to identify the factors that influence individuals and organizations as they consider incorporating SARs into their operations and daily lives. By considering social influence, facilitating conditions, communication channels, time, and the social system, stakeholders can develop strategies to effectively manage the process of SARs adoption and ensure successful integration.

Positionality

When writing this paper, I have more than 18 years of experience in the US healthcare industry as an executive advisor in data analysis and reporting. I have an engineering degree in Electronics and Communication from Cochin University of Science and Technology, India, and a dual MBA from Pepperdine University in General Management and Digital Innovation and Information Systems. I am certified in the Six Sigma Black Belt and am also completing my PhD program in Global Leadership and Change from Pepperdine University. My education and experience have helped me to understand the technology in detail and its significant practical applications.

Chapter 2: Literature Review

Introduction to the Types of Robots

Manufacturing Robots

Manufacturing robots are used to assist in the production process (Bragança et al., 2019). These robots can be used to help assemble products or to move materials from one area to another. Manufacturing robots are usually large and expensive. However, they can save a company a lot of money in labor costs over time. Undoubtedly, the utilization of manufacturing robots yields numerous benefits as these machines facilitate more efficient production systems by assisting employees with both physical and mental tasks.

Industrial Robots

Industrial robots are used in various industries for welding, painting, assembly, and packaging (Hägele et al., 2016). Industrial robots are usually large and expensive, but they can significantly increase productivity in a manufacturing settingThe most significant use of robotics technology in the commercial sector currently is in industrial robotics, with approximately 1.5 million units installed in 2014, and the industry's yearly revenue estimated to be $32 billion USD.

Healthcare Robots

Healthcare robots are being used to help care for patients in hospitals and nursing homes (Robinson et al., 2014). The main challenges that elderly individuals encounter include deterioration in physical and cognitive abilities, managing their health, and coping with psychosocial problems. These robots can help with bathing, feeding, and providing companionship. Healthcare robots are becoming increasingly sophisticated and can offer more and more care for patients.

Retail Robots

Retail robots are used in stores to assist customers with tasks such as finding items, answering questions, and providing directions (Niemelä et al., 2019). Retail robots are usually smaller and less expensive than other types of robots. They can be a great way for stores to improve customer service. The MuMMER project investigated the opinions and worries of mall customers, store managers, and mall managers regarding a shopping mall robot. The study found that two important factors that could lead to the acceptance of social robots are the ability of the robot to be entertaining and helpful, and its capability to hold a conversation, which was considered to be especially important.

Home Robots and Service Robots

Home robots are becoming more popular as they become more affordable. Home robots can vacuum your floors, mow your lawn, and even entertain your pets while the owners are away. Home robots are a great way to make daily life easier (Asafa et al., 2018). Service robots are being used in an assortment of settings to assist people. Service robots can serve as tour guides, help with security, or provide information at an event. Service robot technology is constantly evolving, and new ways to use service robots are always found. Service robots are designed to interact with humans and provide a service. Common examples of service robots include vacuum cleaners, floor scrubbers, and lawnmowers. Service robots are becoming increasingly common in homes and businesses as they become more affordable.

Companion Robots

Companion robots are aimed to offer companionship and emotional support. They are commonly outfitted with sensors and AI capabilities to react to human emotions. Some companion robots even can learn and remember faces and names. Robots have the potential to provide functional and emotional support for older adults. There are concerns that robots may take the place of human caregivers or trick older individuals into forming connections with them (Lazar et al., 2016).

Therapeutic Robots

One type of robot that is becoming increasingly popular in healthcare settings is the therapeutic robot. These robots are designed to provide patients with physical or occupational therapy and emotional support (Shibata & Wada, 2011). For example, Paro the seal is a therapeutic robot that has been shown to reduce stress and anxiety in patients in hospitals and nursing homes. Oska Wellness is another company that makes therapeutic robots designed to help people with chronic pain conditions such as fibromyalgia.

Social Robots

Social robots are another type of robot used more and more in healthcare settings (Salem et al., 2015). These robots are designed to provide social interaction and support for patients who may be isolated or lonely. For example, Mabu is a social robot that has been developed to provide personalized health coaching for patients with established conditions such as diabetes (Johnson et al., 2020).

Care Robots

Care robots are perhaps the most common type of robot used in healthcare today (Huston, 2013). These robots are designed to assist nurses and aides with lifting and transferring patients, delivering medications, and even providing primary patient care such as bathing and grooming. One example of a care robot is the Henn-na Hotel Robot, developed to assist guests with luggage delivery and room service (Reis et al., 2020). Another example is the AmeoBot, specifically designed to help nurses with tasks such as lifting and transferring patients.

Robots in Schools

Robots are also beginning to be used in educational settings to help students with special needs (Eguchi, 2010). For example, robot assistants can now be used in classrooms to provide one-on-one assistance to students with autism or other learning disabilities. These robots can be programmed to remind the student when it's time to transition between activities or complete a task, and they can even provide verbal encouragement when needed. Another type of robot that is being used in schools is known as a social robot. These machines are designed to work with students in a way that helps them develop social skills (Lorusso et al., 2018). For example, some social robots can be used in group settings to help teach children how to take turns or share toys. And because they're so interactive, children tend to respond very well to them.

The Current State of SAR Development

Social robots are robots that are designed for interactions with humans (Hegel et al., 2009). These interactions can be physical (like shaking hands or giving a hug) or verbal (like carrying on a conversation). Social robots are currently being created for a wide range of uses, including customer service and healthcare. Given that they will be in close collaboration with humans, they must possess the capability to comprehend and react to human emotions. Researchers are still working on refining the design of social robots; however, it is clear that their success will depend on their ability to communicate effectively with humans. This means that the robot's face must be designed in a way that conveys emotions and its voice must be able to give tone and inflection. The robot's movements must also be fluid and naturalistic, as not to startle or intimidate people.

One of the earliest examples of a SAR was Kismet (Breazeal, 2003), a robot developed at MIT in the early 2000s. Kismet was designed to interact with humans in a way that emulated nonverbal communication cues like facial expressions and body language. While Kismet was primarily used for research purposes, it laid the groundwork for future SARs by demonstrating the feasibility of building robots that could effectively communicate with humans.

Since the debut of Kismet, SARs have come a long way. The progress made in artificial intelligence (AI) and robotics technology has led to the creation of advanced SARs that offer a wider variety of services. This newer generation of SARs is being used in healthcare settings to support and assist patients recovering from injury or illness. In education, SARs are being used as teaching assistants and tutors. In business, SARs are being used to help with customer service, sales, and marketing tasks.

As these machines become more advanced and affordable, we'll likely see them become more common in homes and workplaces worldwide. SARs use a combination of AI, sensors, and actuators to interact with people (Cooper et al., 2020). AI gives SARs the ability to understand human emotions and respond accordingly. Sensors allow SARs to detect things like movement, temperature, and light. Actuators provide SARs the ability to move and make sounds. All together, these capabilities allow SARs to act as an extension of their human companions.

SARs have the prospective to change the way we live and interact with each other. They could help us age gracefully in our hospitals and homes, provide much-needed companionship for isolated people (Feil-Seifer & Matarić, 2011), and even serve as educational assistants in classrooms. In short, socially assistive robots have the potential to make our lives easier and improve our well-being. SARs designed to help people with disabilities or chronic illnesses. SARs are often used in rehabilitation and therapy settings. SARs have many benefits for people with disabilities or chronic illnesses. Some of these benefits include:

- Improved physical functioning

- Increased social interaction
- Improved mental health
- Increased independence
- Increased motivation
- Lowered stress levels

Social robots come equipped with sensors and artificial intelligence to react to human emotions and behaviors. For example, a socially assistive robot might be used to help an older adult with dementia perform everyday tasks or to provide companionship to someone who is isolated due to a chronic illness. There are several potential benefits of using socially assistive robots. First, they have the capability to improve compliance with treatment regimens. For instance, if a patient with diabetes is reluctant to take their insulin injections, a socially assistive robot could be used to remind them and provide encouragement (Robaczewski et al., 2021). Second, they can help reduce stress and anxiety levels. For example, a socially assistive robot might be used as a distraction during painful medical procedures such as cancer treatment. Third, they can promote social interaction and reduce loneliness and isolation. This is particularly beneficial for people who are confined to their homes due to disability or illness.

The Future of Socially Assistive Robots

One central area of interest for SAR developers is healthcare. These machines have several potential applications in hospitals, nursing homes, and even people's homes. For example, SARs can be used to support patients with therapy after an injury or to provide social interaction for elderly patients who may be suffering from loneliness (Feil-Seifer & Matarić, 2011). Additionally, SARs could be used as part of mental health treatment plans or to monitor patients with chronic diseases.

Due to their potential usefulness, there has been a lot of interest in developing SARs over the past few years. However, many challenges still need to be overcome before these machines can be widely used. For example, one major challenge is programming robots to recognize and respond appropriately to human emotions (Langer et al., 2019). This isn't necessarily easy because emotional states can be conveyed through verbal and nonverbal cues (e.g., body language). Additionally, humans often do not act rationally when emotional, making it hard for machines to predict human behavior. As such, considerable effort is still required to develop algorithms that allow SARs to interact with humans on an emotional level effectively.

Although there are obstacles that require resolution, envisioning a future where SARs play a vital part in our lives, especially in the healthcare sector, is achievable. These machines have the potential to provide invaluable assistance to patients and caregivers alike. Additionally, as the technology continues to develop, it is possible that SARs will become increasingly sophisticated and nearly indistinguishable from their human counterparts.

Social Robot Cost

There are a variety of SARs on the market, ranging in price from a few hundred dollars to several thousand dollars (Dickstein-Fischer., 2018; Koutentakis et al., 2020). Compared to other types of assistive technology, SARs are relatively new, and thus, their price point reflects this. However, as SARs become more popular and widely available, their price will likely decrease.

Social robots can be used for various tasks and purposes, making them a great option for people who need assistance with everyday tasks. In comparison, other types of assistive technologies can be much more expensive. For example, powered wheelchairs can cost upwards of $5,000. Cochlear implants, which are surgically implanted devices that provide a sense of hearing for people who are deaf or hard of hearing, can cost up to $50,000. There are a variety of social robots available on the market today. Additionally, companies like Tesla who are in the forefront of innovation are developing humanoid robots with advanced skills that can cost $20k. Based on a recent Goldman Sachs report, humanoid robots' business could reach $150 billion by 2037 (Lambert, 2022).

Helping People with Special Needs

Robots are increasingly used in healthcare facilities and schools to help people with special needs. They assist with everything from physical therapy to communication. Here are three ways that robots help people with special needs.

Physical Therapy

Robots are being used in physical therapy to help people with mobility issues regain movement. For example, the humanoid robot NAO is frequently used in rehabilitation centers (Robaczewski et al., 2021). NAO can be programmed to help patients with a range of motion exercises and balance training. The robot's sensors provide feedback to therapists so they can see how a patient is progressing.

Communication

Robots are also being used to help people with communication disorders. One example is a robot called Ozobot, which helps children with autism spectrum disorder (ASD) learn social cues and communication skills. Ozobot can be programmed to display different emotions on its screen, which allows children with ASD to understand how emotions affect social interactions (Tengler et al., 2020). The robot also responds to touch, sound, and color, which helps children learn about cause-and-effect relationships.

Activities of Daily Living

Another way that robots are helping people with special needs is by assisting them with activities of daily living (ADLs). For example, a robot called the Laundroid can sort laundry, fold clothes, and even put away folded laundry into cupboards or drawers (J. Lee, 2018). This is a massive help for people who have difficulty doing these things independently. Some robots can prepare food and help with grocery shopping. These ADL-assisting robots greatly improve the quality of life for many people with special needs.

Robots in Healthcare Facilities

One of the most common ways that robots are being used to help people with special needs are in healthcare facilities. For example, robots are now being used to transport patients from their beds to wheelchairs or bathrooms. These machines can be programmed to move at different speeds and even stop if they sense an obstruction in their path, making them much safer than human caregivers.

One type of robot that is being used is known as a Telebot. Telebots are remotely operated and can transport medications and supplies to patients' rooms, collect hazardous waste, and even deliver meals (Alsamhi & B. Lee, 2020). They boast many features that make them ideal for use in a hospital setting, including UV sterilization capabilities and the ability to disinfect themselves automatically. In addition, Telebots can be equipped with cameras and monitors so that doctors can check in on patients without having to enter their rooms in person.

During COVID-19 pandemic, healthcare facilities were struggling to keep up with the demand for care across the globe (Alsamhi & B. Lee, 2020). Hospitals were overwhelmed with patients Healthcare facilities used robots to help patients with therapy and rehabilitation. One type of robot, the Robot-Assisted Rehabilitation Device (RARD), is used to help people who have had a stroke or other neurological injury regain movement in their affected limbs (Zimmerli et al., 2012). The RARD is a wearable device that attaches to the affected limb and provides electrical stimulation to help the muscles contract and move.

Another type of robot used in healthcare is the Rehabilitation Gaming System (RGS). This video game system helps people with physical disabilities improve their range of motion and hand-eye coordination (Cameirao et al., 2009). The RGS can be used for people with conditions such as cerebral palsy, multiple sclerosis, and Parkinson's disease. Robots are also being used to assist nurses and doctors in hospitals. One example is the Telesurgery System, a remote surgery system that allows surgeons to operate on patients from different locations (Lum et al., 2009). This system has been used for procedures such as removing tumors and placing stitches.

Finally, some hospitals use robots to deliver medicine and supplies to patients' rooms Alsamhi & B. Lee, 2020). These autonomous mobile robots navigate the hospital using sensors and artificial intelligence, and they can avoid obstacles and find their way around people and objects.

In healthcare facilities, robots are used in various ways to help patients with special needs. For example, hospitals are using robots to dispense medication (Volpe et al., 2012). This can be more efficient than having a human staff member do it and eliminates the risk of human error. Robots are also being used to transport medicines and supplies between different parts of the hospital. This also can help free up nurses and other hospital staff to focus on providing direct patient care.

Why Do We Study Social Robots

We study social robots because we want to figure out how to make them safe and reliable (Peter & Kühne, 2018). For example, imagine you are in a hospital room, and you see a robot come into the room carrying a tray of medications. Will you trust the robot to give you the proper medication in the right dosage? For people to trust social robots, we need to understand how they perceive and process information about the world around them. We also need to design algorithms allowing robots to make decisions in ambiguous situations. Another reason why we study social robots is that we want to figure out how best to design them so that they can interact seamlessly with humans. As mentioned before, this includes everything from the robot's facial expressions to its body language. But it also extends to more technical aspects, like what sensors the robot should have and how it should process human speech. All of this research is essential if we want social robots to become a regular part of our lives in the future.

One area of research is focused on how to make social robots more realistic and lifelike (Onyeulo & Gandhi, 2020). This includes work on aspects such as appearance, locomotion, and behavior. Researchers want to create robots that are not only physically realistic but also behave in natural and believable ways. This work is important so that people can interact with social robots as they would with other human beings.

Another area of research focuses on making social robots more efficient and effective at completing tasks (Alterovitz et al., 2016). This includes work on social robot navigation, task allocation, and human-robot teaming. Researchers want to create robots that can navigate their environment without getting lost, allocate tasks between themselves and humans efficiently, and work together with humans effectively as part of a team. This work is important, so social robots can be deployed in numerous settings, such as homes, hospitals, and offices.

Another application for social robots is their use as companions for children with autism spectrum disorder (ASD). In a study conducted by researchers at Yale (Weir, 2018), children diagnosed with autism spectrum disorder exhibited noteworthy advancements in their social skills after participating in robot-guided activities for 30 minutes each day for 30 days. The robots were programmed to demonstrate social behaviors such as eye contact. They guided the children through tasks to improve skills such as emotional understanding, perspective-taking, and taking turns. Parents/grandparents reported improved communication and eye contact, and clinicians' data also supported this finding, both with or without the robots present. The social robots were intentionally designed to adapt to an individual's learning level and interact with humans. While previous studies have demonstrated the efficacy of social robots for children with autism, this research showed their effectiveness beyond controlled laboratory settings.

Challenges Before Social Robots Can Become Commonplace In Society

The term "social robot" might conjure up images of humanoid machines that can walk and talk like humans. However, social robots are not just limited to humanoids. They can take any form, from simple machines to complex AI systems. Whatever their form, social robots all have one thing in common: they are aimed to intermingle with humans on a social level. However, a few challenges must be addressed before social robots can become commonplace in society. Below are the main challenges faced by social robots today.

Lack of Trust

One of the biggest challenges faced by social robots is a lack of trust. Humans are naturally suspicious of anything new and different, and social robots qualify as both new and different. For social robots to become accepted members of society, they must gain the trust of the people they interact with.

Uncanny Valley Effect

The uncanny valley effect is a phenomenon that occurs when people encounter something that looks and acts almost like a human but not quite (Brink & Wellman, 2017). When this happens, people tend to feel uneasy or even scared. The uneasiness comes from feeling something is "off," but you can't quite put your finger on what it is. This unease is often strong enough to prevent people from wanting to interact with the thing that triggered it. And since social robots are designed to interact with humans, the uncanny valley effect is a challenge that must be overcome.

Privacy Concerns

Another challenge faced by social robots is privacy concerns (Lutz & Tamó-Larrieux, 2020). Imagine conversing with a social robot and telling it your deepest, darkest secrets. Now imagine that conversation being overheard by someone who then uses that information against you. This is a real concern regarding social robots because they often have access to sensitive information about the people they interact with. For social robots to become accepted members of society, privacy concerns will need to be addressed so that people feel comfortable trusting them with their personal information.

Developing Robots That Can Understand and Respond to Human Emotions

A significant challenge lies in connecting basic automation with robots that can interact with humans naturally and empathetically (Fearon, 2020). However, there has been notable advancement in this area over the past few years. Studies on social robots have indicated that emotion-responsive machines can benefit the most susceptible members of society, such as the elderly and children, and could potentially increase the societal acceptance of robots.

Robots that assist in caregiving are often pioneers in emotional interaction. One example is Milo, a robot designed by RoboKind to function both as a teacher and a student. Milo aims to aid children with autism spectrum disorders in developing their emotional expression and empathy while gathering data on their progress to customize their learning and treatment. With its amicable countenance, Milo is easily approachable, and the children can analyze its facial expressions without feeling socially anxious (Fearon, 2020).

Making Robots That Are Socially and Physically Acceptable

Another challenge facing social robot developers is making machines that are both socially and physically acceptable to humans. In terms of social acceptability, robots will need to learn how to behave in a way that is appropriate for different situations. For instance, a robot working as a waitress in a restaurant would need to know how to take orders and serve food without being too intrusive or making customers uncomfortable. In terms of physical acceptability, humans need to be reassured that social robots will not pose a threat to their safety. This means having fail-safes to prevent robots from harming people accidentally or deliberately such as a control or a kill switch in case of emergency (Kottasova, 2017).

Ensuring That Social Robots Benefit Society as a Whole

A final challenge facing social robot developers is ensuring that these machines will benefit society and not just create new problems or exacerbate existing ones (Boada et al., 2021). For example, one worry is that social robots could take jobs away from human workers such as careers or service staff. A related concern is that robots could be used for nefarious purposes, such as spying on people. It will be crucial for developers to create ethical frameworks for social robotics that minimize these risks while still allowing the technology to flourish. One of the main challenges of social robots is that they can be expensive. For example, the humanoid robot

Pepper costs around $20,000 for universities and businesses (Moon, 2021). This price tag might be too expensive for some people, which could limit the number of people who have access to these types of robots.

The Advantages and Disadvantages of SARS

It's no secret that robots are increasingly becoming a staple in society. From industrial and commercial applications to personal assistants, there seems to be a robot for almost everything. One of the latest trends in robotics is the development of so-called "socially assistive robots" (SARs), which are designed to help people with various tasks such as communication, social interaction, and even physical therapy. But are SARs a good thing? Are there any potential risks or concerns that come along with using them? Are there any concerns about using such robots and their impact on human relationships and communication skills development?

The Advantages of SARs

One of the biggest advantages of SARs is that they have the potential to provide much-needed assistance to people with disabilities. For example, SARs are being developed specifically for children with autism that can help teach them social skills and communication techniques (Weir, 2018). There are also SARs being designed for senior citizens who may need help with things like groceries or getting around the house. In other words, SARs have the potential to improve quality of life for many people who may otherwise struggle with everyday tasks.

Another advantage of SARs is that they can help give human caregivers time. For example, if a senior citizen has a SAR that helps them with things like getting dressed or bathed, it frees up time for their caregiver to do other things, like run errands or take care of other patients. This can not only improve efficiency but also help reduce caregiver burnout.

The Disadvantages of SARs

One potential downside of SARs is that they could further isolate certain individuals (Broadbent et al., 2009; Feil-Seifer & Matarić, 2011). For example, if a child with autism only interacts with their SAR and not others, it could limit their opportunities to make real-world connections and find friends their age. Additionally, if seniors only interact with their SARs and not others, it could exacerbate feelings of loneliness and isolation. Another concern is that SARs could lead to the loss of jobs for human caregivers (Eubanks & Mateescu, 2021). While this likely won't happen overnight, it's possible that as SAR technology continues to improve, there will be less need for human caregivers in the future. This could lead to mass unemployment in certain sectors, such as healthcare.

One of the worries with sustained use of social robots is that it might lead to decreased opportunities for humans to interact with each other directly. As humans increasingly rely on SARs for tasks such as companionship, there might be less incentive for us to interact with each other face-to-face. This could potentially lead to decreased social skills development opportunities and increased loneliness and isolation.

Another concern is that the use of SARs could reduce empathy. If people become accustomed to emotional support from robots, they may be less likely to turn to other humans for comfort and assistance. This could lead to a decrease in empathy and compassion among people. Another concern is that people could become too dependent upon SARs. If people come to rely on SARs for tasks such as companionship or emotional support, they may have difficulty developing or maintaining relationships with other humans. Additionally, if people become too reliant on SARs, they may lose essential life skills such as cooking or cleaning.

Human-Robot Interaction

Human-robot interaction (HRI) is an emerging area of research that centers on the interaction between humans and robots. (Sheridan, 2016). HRI encompasses aspects of psychology and engineering, and its goal is to create robotic systems that can effectively interact with and assist humans. Additionally, the purpose of HRI is to develop robots that are more efficient, safer, and easier to use. To achieve this goal, HRI studies how humans interact with technology so that the same principles can be applied to robots. HRI has become increasingly important as robots have expanded beyond traditional industrial applications into homes, hospitals, schools, and other settings. As robots become more ubiquitous, it is essential to understand how humans and robots can best work together.

Humans and robots have been interacting for centuries, but HRI researchers have only recently started studying these interactions in depth (Breuer & Takanishi, 2009). One of the earliest examples of HRI can be found in the myth of Pygmalion, in which a sculptor falls in love with a statue he has created (Trovato et al., 2018). While this may seem like a far-fetched story, HRI researchers are intertied in knowing why someone will fall in love with a painting or a robot. it highlights some of the key issues that we still face regarding HRI—namely, how will engineers develop a lifelike robot to elicit an emotional response from a human?

As technology has evolved, so has the ability to create ever more realistic robots. This has led to increased studies focusing on HRI as researchers attempt to understand how humans and robots can best work together (Sheridan, 2016). For example, HRI research has looked at issues such as how humans can effectively communicate with robots, how to design safe and easy robots, and how to make sure that humans maintain control over robotic systems. These HRI focus areas are important to research. e.g., What happens if we lose control of robotic systems? Why is this important? Unless robots are designed safe bad actors can take control of these systems and cause harm to the healthcare workers and patients.

What HRI Involves

HRI research deals with all aspects of the human-robot relationship, from how robots should move and behave to design principles for robot builders (Murphy at al., 2010). Additionally, this field looks at social, cultural, ethical, and legal issues when robots are introduced into society (Riek & Howard, 2014). For example, financial institutions are increasingly using chatbots to help customers with their banking needs. However, there are concerns about chatbots being able to detect and accurately respond to human emotions like sarcasm. Other ethical concerns include things like sex robots and robots in the military.

There are legal, moral, and ethical implications of creating sex robots that look and act like children. Algorithms can be created to make robots learn from experience, raising the question of whether we predict with reasonable certainty what the robot will learn by experience. Additionally, In the military, some soldiers already report being attached to the robot that saved their lives (Lin et al, 2006). These are a few ethical concerns of robots in the military that HRI researchers need to address. Researchers in the field of HRI seek solutions to these problems so that humans and robots can coexist peacefully.

Applications of HRI

One key area of HRI research is human-robot teamwork (Wolf & Stock-Homburg, 2022). This involves designing robotic systems collaborate effectively with humans to accomplish tasks such as search and rescue, disaster relief, and manufacturing. For example, imagine a team of firefighters working alongside a robotic firefighting assistant. The robot might be equipped with sensors that allow it to see through smoke and identify victims, or it might be able to transport supplies upstairs more quickly and safely than a human could. The ability of humans and robots to work together would significantly improve the team's effectiveness.

Another area of research in HRI focuses on social interaction between humans and robots (Tapus et al., 2007). This includes understanding how humans perceive and respond to robots and designing robots capable of interacting socially with humans. For example, one application of this study is the development of socially assistive robots, i.e., robots that can provide assistance and companionship to people who are elderly or have disabilities. These robots are being deployed increasingly in hospitals and nursing homes, and their ability to provide social interaction has improved patients' mental health and well-being.

Types of Research in HRI

Fundamental research in HRI focuses on how humans interact with technology in general. This type of research is essential to understanding the basic principles of human-robot interaction. For example, one principle might be that people are more likely to trust a robot if it has a face (Wolf & Stock-Homburg, 2022). Another principle might be that individuals are extra likely to obey a robot's commands if given in a clear, concise manner. Applied research in HRI takes the principles learned from fundamental analysis and applies them to specific tasks or situations. For example, applied research might study how best to design a robot nurse that will care for elderly patients (Silva et al., 2017). This type of research considers not only how humans interact with technology but also how they interact with other humans.

Evaluation research in HRI assesses the usefulness of human-robot interaction by comparing it to other methods of performing the same task. For example, evaluation research might reach the point of using a robot cleaner in an office versus a traditional vacuum cleaner.

This type of research is essential to determine whether investing in HRI is worth the time and money.

The Importance of HRI

There are several reasons why HRI is essential. First, robots are becoming increasingly common in our society. It's estimated that around 3 million robots will be in use by 2023 (Bliznovska, 2022). This means that it's increasingly likely that people will have to interact with robots daily. Additionally, it is expected that there will be 20 million robots by 2030. Surgical robots market value by 2025 will be 12.6 billion (Bliznovska, 2022).

Second, as robots become more advanced, they are being used in various settings, including healthcare, education, manufacturing, and even consumer homes (Tapus et al, 2007). This means that there is a growing need for research on how to design safe and effective robots for use in these different settings. Finally, HRI allows researchers to study human behavior by observing interactions between people and robots. By studying these interactions, researchers can gain insight into various aspects of human cognitive processing, social interaction, and emotions.

Challenges Associated with HRI

Though HRI is a promising research area, many challenges are still associated with it (Tapus et al., 2007). One challenge is that robots are often designed for specific tasks and environments. This means they may not be able to adapt to new tasks or environments unless they are specifically programmed to do so. Another challenge is that humans are often unpredictable when interacting with robots. This can make it difficult for researchers to study human behavior using HRI methodologies. Finally, Robots also have limitations in their ability to communicate and interact with humans effectively. This can sometimes lead to confusing or frustrating interactions between people and robots.

Utility and Reliability Regarding Robot Technology

In the utility and reliability section of the literature review, optimism, proficiency, warmth, and competence regarding technology and robot technology will be discussed. Optimism is the belief that technology offers greater control and flexibility in life, while Proficiency is the confidence in swiftly learning and using new technologies, along with a feeling of technological competence (Ratchford & Barnhart, 2012, p. 1212). "When people are evaluated as warm and competent, they are seen more favorably and experience more positive interactions" (Carpinella et al., 2017, p. 257).

The Importance of Performance Expectancy

In today's world, technology is everywhere. Technology is used to communicate, work, study, and even relax. It's hard to imagine a world without it! Performance expectancy is the belief that using a particular technology or method will, to some extent, be advantageous or performance-enhancing (Li, 2010). This means that it is expected technology to make our lives easier in some way.

When you use new technology, you usually try to achieve a specific goal. You want to accomplish something faster, better, or more efficiently than you could without using that technology. Naturally, expectation of the technology to help meet our goal. If it doesn't, there will be disappointment and may not continue using it. But suppose the technology does help you meet your goal (and hopefully exceed your expectations). You're more likely to keep using it and may even tell others about your positive experience (Oh et al., 2009).

Thus, it's clear that performance expectancy is a key factor in whether we adopt and continue using new technologies (Oh et al., 2009), but there are other factors to consider as well. To fully adopt new technology, we need to believe it is usable (usability) and will fit into our lifestyle (relatively free of disruption).

Performance expectancy measures how much effort users will put into using a given system (Im et al., 2011). In other words, it measures how much value users believe they will get from using the system. For example, if a user acknowledges that a given system will save them a lot of time and effort, they will be more likely to use it than if they believe the system is too complicated or time-consuming.

The concepts of "user experience" (UX) and "human-centered design" (HCD) are essential in many aspects of life but are especially relevant regarding technology (Hornbæk & Hertzum, 2017; Kluge & Termer, 2017). Good UX/HCD considers the user's performance expectancy when designing systems. If a system is designed to be easy to use and provides value to the user, the user will be more likely to use it. On the other hand, if a system is designed in such a way that it is difficult to use or provides little value to the user, the user will be less likely to use it. In short, good UX/HCD focuses on ensuring that users get what they want and need out of a given system. By considering performance expectancy, designers can create designs that users want to use instead of unused systems because they're too difficult or time-consuming.

Importance of Perceived Benefit in Technology

When technology is discussed, what comes to mind? For most people, it's probably their smartphones, laptops, and other gadgets. But technology isn't just about gadgets and devices—it's also about the systems and processes that we use to make our lives easier. And those systems and processes are always changing and evolving, thanks to the power of technological optimism.

Technological optimism is the belief that technology can be used to improve the world. It's the hope that new inventions and innovations will make life better for everyone, not just a select few. And it's the idea that we can use technology to resolve most of the world's most demanding issues, from climate change to poverty and to improve healthcare. Below are the key advantages of technology and optimism that technology can make our life easier.

Increased Efficiency

Technology can help us do more with less time and effort. For example, consider how online shopping has made it possible to buy things without ever leaving our homes. Additionally, in manufacturing sector adoption of new technology has improved technical efficiency (Hwang & Kim, 2022).

Greater Accessibility

Technology can also help us overcome physical limitations and access things we wouldn't be able to otherwise. For instance, virtual reality headsets allow people with disabilities to experience something they otherwise couldn't, and 3D printing is opening up new possibilities for prosthetics and other medical devices. Additionally, research has shown using technology in classroom can remove cultural limitations (Abeer, 2013)

Enhanced Safety

In many cases, technology can help keep us safe from harm (Eby et al., 2016). For example, blind spot detection and the automatic emergency braking are making cars safer than ever. Similarly, biometric security measures like fingerprint scanners are helping keep our personal information safe from hackers.

Improved Quality of Life

Many technological optimists believe that technology will improve our quality of life (Park & Jayaraman, 2003). They point to things like extended lifespans (thanks to advances in medicine) and increased leisure time (due to automation) as evidence that life in the future will be better than it is today.

The Importance of Ease of Use

Technology has become a staple in our everyday lives. We rely on it for entertainment, communication, work, and so much more. However, one technology element that is often overlooked is the ease of use. For people to fully benefit from what technology has to offer, it must be easy to use (Lederer et al., 1998).

Ease of Use Equals Greater Accessibility

The primary rationale for the significance of user-friendliness is its potential to enhance accessibility. When technology is uncomplicated to operate, a broader range of people can utilize it, which is particularly critical for disadvantaged communities who might not have otherwise had access to certain technologies. (Philippe Le Houérou & Schulman, 2018). For example, assistive technologies like screen readers or text-to-speech software can help people with visual impairments or reading disabilities access information they otherwise would not be able to. In this way, ease of use can help level the playing field and provide opportunities for everyone.

Ease of Use Equals Increased Productivity

Another reason why ease of use is essential is that it can lead to increased productivity. When technology is complex and challenging to use, it takes up valuable time that could be spent doing other things. This can lead to frustration and decreased motivation. However, when technology is easy to use, people can accomplish tasks more quickly and with less effort

(Brynjolfsson & Yang, 1996). This leaves them with more time and energy to devote to other areas of their life.

Safety and Privacy Regarding Robot Technology

In the safety and Privacy section of the literature review, dependence, vulnerability and discomfort regarding technology and robot technology will be discussed. Dependence denotes an excessive reliance on and feeling of being controlled by technology. Vulnerability pertains to the belief that technology heightens the risk of being exploited by criminals or companies (Ratchford & Barnhart, 2012, p. 1212). Discomfort relates to "awkwardness" regarding robotic technology (Carpinella et al., 2017, p. 257)

Perceived Risks

There are dangers of becoming too reliant on technology. We've seen the stories about people who can't put down their phones, get in car accidents because they're texting, and become isolated from the world around them. While these are all valid concerns, there are even more significant risks with our dependence on technology. Here are three of the most significant dangers of technology that you should be aware of.

Cybersecurity Risks

As more and more businesses move online, cybersecurity risks are becoming a significant concern (Conteh & Schmick, 2016). Hackers are constantly finding new ways to gain access to sensitive information, and if your business is compromised, the consequences can be severe. From financial losses to reputational damage, there's a lot at stake when it comes to cybersecurity. That's why it's important to ensure that a business has robust security measures in place. The existence of security weaknesses in robots is a major cause for concern, particularly in areas that demand sensitivity such as healthcare, and may pose risks for those who engage with them (Fosch-Villaronga & Mahler, 2021).

Outages and Downtime

Other risks of relying on technology are outages and downtime. Even the most well-designed systems can experience problems from time to time, and when that happens, it can majorly impact the business (Kashiwagi et al., 2017). Valuable customers and revenue is lost if your website or app go down. That's why it's crucial to have a plan in place for dealing with outages and ensuring that you can quickly get your systems up and running again.

Employee Training and Development

Finally, one of technology's most often overlooked risks is the need for employee training and development. As new technologies are introduced, employees need to be properly trained on how to use them (Lukowski et al., 2021). Otherwise, they won't be able to take advantage of all the benefits these technologies offer. Additionally, employees need to be given time to develop their skills to keep up with the ever-changing landscape of technology.

While there are many risks that come with our dependence on technology, there are also many ways to mitigate those risks. By being aware of the dangers and taking steps to protect your business, you can make sure that you're able to take advantage of all the benefits that technology has to offer without putting your business at risk.

Technology Dependence

Overuse of Technology Causes Distraction

You're trying to focus on something important, but your mind keeps wandering off to think about that Snapchat you just got or the Facebook notification that popped up. When we're constantly tethered to our devices, it's hard to disconnect and focus on the task at hand. Thus the distraction due to overuse of technology can have impact on life satisfaction and depression (Roberts & David, 2016).

Overuse of Technology Causes Anxiety

It's no secret that social media can be a breeding ground for anxiety and depression. Constantly comparing ourselves to the "perfect" lives, we see our friends living online can seriously affect our mental health. And when we're always attached to our devices, it's hard to give our brains a break from all the harmful noise. Additionally, research has also found that overdependency on wireless technology device can cause anxiety when the device is not present with the user (Cheever et al., 2014).

Overuse of Any Technology Will Lead to Addiction

Just like anything else in life, moderation is key when it comes to technology use. But some people have an unhealthy dependence on their gadgets. for some people, it's straightforward to develop an unhealthy dependence on their gadgets. If you cannot go more than an hour without checking your phone or start getting anxious when you can't access the internet, then it might be time to consider cutting back on your tech use (Cheever et al., 2014).

Too Much Reliance on Technology Will Lead to Being Self-Centered

In the age of social media and selfies, it's easy to be wrapped up and forget about the people around us. People become obsessed with documenting our their every behavior (or something like this, more formal than “move”) online, therefore they neglect living in the moment enjoying experiences for what they are—meaningful interactions with real people in the real world. Certain scholars propose that the increasing prevalence of mental health problems might be attributed to technologies that intensify our self-awareness. For instance, Facebook emphasizes expressing our opinions, Pinterest allows us to organize our preferences, and LinkedIn focuses on showcasing our accomplishments (Davis, 2018).

Overuse of Technology Ruins Relationships

The concept of technology ruining relationships might be controversial, but research shows that overuse of technology can ruin relationships (Roberts & David, 2016). For example, technology can sometimes do more harm than good in romantic relationships if we are not careful about how we use it. Whether it's "ghosting" someone after a date or texting each other more than talking face-to-face, relying too much on technology in our relationships can lead to severe interpersonal issues down the line.

Technology Vulnerability

The Dangers of Technology Overreliance

In today's world, it's hard to imagine life without technology. We use it to stay connected with our friends and family, get work done, and even entertain ourselves. But what happens when we become too reliant on technology? What are the dangers of overreliance on technology?

Become Less Productive

A company can experience less productivity if technology is invested in and implemented ineffectively. When companies invest and implement technology ineffectively, it can lead to less productivity (Stratopoulos & Dehning, 2000). Additionally, contrary to the belief that technology can increase productivity, the reality is that overuse of technology can lead to less productivity. When we're constantly checking our phones, refreshing our social media feeds, and responding to emails, we're not focusing on one specific task. Therefore, providing less effective attention that can lead to mistakes, errors, and subpar work (Sharma & Gupta, 2004).

We Miss Out on Important Moments

The current culture makes it easy to get wrapped up in our phone screens and zone out when we're supposed to pay attention to the people and things around us. As a result, we miss out on opportunities to connect with the people we care about and experiences that could enrich our lives (Sharma & Gupta, 2004).

We Become More Vulnerable to Cybercrime

More frequent use of technology provides more opportunities for cybercriminals to access personal information and wreak havoc in our lives (Gordon & Ford, 2006). From identity theft to financial fraud, there are several ways that cybercrime can negatively impact us if we are not careful about protecting our online identities.

Technology is an essential part of our lives, but it's important to be aware of the dangers associated with an overreliance on technology. Being mindful of how much time we spend online and taking steps to protect our online identities can minimize the risks associated with technology use and enjoy all the benefits it offers without risk.

Discomfort Around Robots

Many people feel a sense of unease when they think about robots. In part, this is because we don't fully understand them. We know they can vacuum our floors or build our cars, but we don't see how they work or their limitations. This lack of understanding can lead to fear, particularly when we think about how robots might eventually replace us in the workforce.

The Fear Factor

One of the reasons we might be afraid of robots is that often they are portrayed as evil in movies and television (Liang & S. Lee, 2017). For example, The Terminator, The Matrix, and Ex Machina all have these stories about robots who become self-aware and attempt to destroy humans.. Although this is just fiction, but it's easy to see how it could make people afraid of robots in real life. Another reason for our discomfort is that robots are becoming more sophisticated (Torresen, 2018). Robots can walk and talk like humans; some even have facial expressions. The level of realism can make it hard to remember that robots are not alive. As a result, we might start to view them as a threat to our existence.

Are Robots a Threat

It's important to remember that robots cannot harm us. They are machines programmed to do specific tasks (Javaid et al., 2021). They might eventually replace us in the workforce (Smids et al., 2020), but that doesn't mean they'll kill us all! Robots can be helpful. For example, they can help us with dangerous or challenging tasks like diffusing bombs or exploring other planets.

There is no need to be afraid of robots! While feeling uneasy around robots is understandable, there is no reason to believe that they will harm us in any way. Robots can be helpful, especially when doing dangerous or complex tasks. So next time you see a robot, don't run away screaming! Instead, take a closer look and try to understand how the robot works.

Change Management

In the previous literature review positive reasons for robotic technology adoption, such as sections on utility and reliability, optimism, proficiency, warmth, and competence, were discussed. The safety and privacy section of the literature review discussed dependence, vulnerability, and discomfort regarding robotic technology, which are negative reasons. The change management section of the literature review discusses the conditions that facilitate robotic technology adoption. These change conditions encourage the adoption of robotic technology and act as an enabler.

Social Influence and Facilitating Conditions Influence Technology Adoption

When it comes to technology adoption, there are many factors. Some people adapt easily and become innovators, some wait until the product is more refined Some people follow the lead of their friends and family. A social model that considers technology adoption is known as the social influence model (Fulk et al.,1990; Tanford & Penrod, 1984). The Innovation Diffusion Theory (Rogers, 1995) introduced the model, which has been employed to investigate several decisions related to adoption. Accordingly, the social influence model can be applied to technology adoption decisions. The next section will further explore the five main factors that influence an individual's decision to adopt new technology; which include relative advantage, compatibility, complexity, risk, and observability (Al-Jabri & Sohail, 2012; Kolodinsky et al., 2004; Rijsdijk & Hultink, 2009; Tanford & Penrod, 1984; Teo et al., 1995). The next section will further explore each factor.

Relative Advantage

This refers to how much improvement an individual perceives in new technology compared to the existing. To willfully switch to a new technology, an individual needs to understand that the new technology is significantly better than what they are currently using (Al-Jabri & Sohail, 2012; Kolodinsky et al., 2004; Rijsdijk & Hultink, 2009; Tanford & Penrod, 1984; Teo et al., 1995). For example, when HDTV first came out, it offered a much higher quality picture than standard definition TV. As a result, people were willing to switch to HDTV even though it was more expensive than standard-definition TV.

Compatibility

Compatibility refers to how well the new technology fits with an individual's lifestyle and values (Al-Jabri & Sohail, 2012; Kolodinsky et al., 2004; Rijsdijk & Hultink, 2009; Tanford &

Penrod, 1984; Teo et al., 1995). For example, if you're attached to your current phone and don't like change, you're less likely to switch to a new phone, even if it offers significant improvements. On the other hand, if you're always looking for the latest and greatest gadgets, you're more likely to switch to a new phone, even if it means learning how to use a new interface.

Complexity

Complexity refers to how difficult it is to use new technology (Al-Jabri & Sohail, 2012; Kolodinsky et al., 2004; Rijsdijk & Hultink, 2009; Tanford & Penrod, 1984; Teo et al., 1995). Generally, people are more likely to adopt new technology if it is easy to use. For example, Apple products are often lauded for their ease of use compared to other products on the market. As a result, people are more likely to switch from their PC to an Apple product, even if they're not particularly tech-savvy.

Risk

This refers to how an individual perceives risk associated with adopting the new technology (Al-Jabri & Sohail, 2012; Kolodinsky et al., 2004; Rijsdijk & Hultink, 2009; Tanford & Penrod, 1984; Teo et al., 1995). For example, people might be hesitant to switch to 5G because they've heard it's not as reliable as 4G. However, if 5G offers faster speeds and more excellent coverage, people may decide that the risk is worth it. The observability component shows how noticeable the adoption of a new technology can be. It is when Someone else adopts the new technology. One of the reasons why the iPhone was so successful was because people could immediately see the difference between it and other smartphones on the market. The iPhone was also much easier to use than other phones, so more and more people began to switch.

The social influence model helps us understand why people adopt or don't adopt new technologies. When considering a switch to new technology, individuals will weigh all these factors before deciding. To get someone to switch to a new technology, emphasize its relative advantage over existing technologies, its compatibility with lifestyles and values, its ease of use, and its low risk.

The Role of Communication Channels

The diffusion of innovation is the process by which members of a social system adopt a new form of technology (or other synonym for innovation) innovation (Rogers, 1995). The speed of adoption depends on numerous factors, including the nature of the invention itself and the communication channels through which it spreads. There are two communication channels: mass media and interpersonal (Lin & Burt, 1975). Mass media channels reach large numbers of people at, such as television, radio, and newspapers. Interpersonal channels involve one-on-one or small group interactions, such as word-of-mouth, face-to-face conversation, and online social networks.

Both mass media and interpersonal channels play an essential role in the diffusion of innovation. Mass media channels provide exposure to a wide audience, which can help to create awareness of innovation. Interpersonal channels offer a more personal touch, which can help to generate interest in innovation and build trust in its source. A company might use television or YouTube advertising to generate awareness of a new product, followed by face-to-face sales presentations to create interest and word-of-mouth marketing to build trust (Lillie, 2008). By using a mix of communication channels, companies can reach a larger number of people with their message and increase the likelihood that their innovation will be adopted.

The diffusion of innovation is an important process that determines how quickly members of a social system adopt new products and ideas. The speed of adoption depends on numerous factors, including the nature of the innovation itself and the communication channels through which it spreads. By using a mix of mass media and interpersonal channels, companies can reach a larger number of people with their message and increase the likelihood that their innovation will be adopted.

Effects of Time

It takes time for an innovation to diffuse throughout a population. The role of time in the diffusion of innovation is critical. The speed of diffusion is affected by several factors, including the type of innovation, the size of the population, and the social networks within that population. A small, tight-knit community will likely adopt a new idea much faster than a large, heterogeneous population (Tanford & Penrod, 1984; Fulk,1990). However, even in large populations, early adopters will always try out a new idea as soon as it emerges (Rogers, 1995).

As an innovation diffuses throughout a population, it goes through the following stages:

1. Introduction: This is the stage where the innovation is first introduced. At this point, only a small number of people are aware of it.

2. Growth: As word spreads about innovation, more and more people start to adopt it.

3. Maturity: At this stage, most people have adopted the innovation, and it has become part of the status quo.

4. Decline: Finally, there comes a time when the innovation falls out of favor and is replaced by something new.

The diffusion of innovation is a complex process that is affected by many factors. Time plays a crucial role in this process; the longer an invention has been around, the more likely it is to be adopted by a more significant proportion of people. Therefore, when promoting a new idea, don't expect everyone to jump on board immediately.

The Role of Social Systems

The diffusion of innovation is the process by which a new idea or product is introduced and adopted by a market. This process can be tricky to navigate but understanding social systems' role in the diffusion of innovation can help you position your product or service for success. Here's what you need to know. Four key characteristics of social systems affect the diffusion of innovation: size, density, centralization, and formalization (Fulk,1990; Tanford & Penrod, 1984).

The social system characteristic, size, refers to the number of people in each system. Larger systems tend to diffuse innovation slower than smaller ones because more people need to be reached and convinced new product's value or idea. In contrast, small systems diffuse innovation quickly because there are less people to convince. Density is a measure of how interconnected the members of a system are. A system with high density (i.e., its members are highly connected) will diffuse innovation faster than a system with low density (i.e., its members are less interconnected). The difference in innovation diffusion is due to rapid flow of information can have through dense systems, thus allowing ease for people to become aware of and adopt new ideas.

Centralization refers to the characteristic that shows how much power is concentrated in a few individuals within a system. Highly centralized systems tend to be less effective at diffusing innovation because decisions about adopting wat new products or ideas are made by only a few people. In contrast, decentralized systems diffuse innovation more quickly because many people make decisions about adoption.

Lastly, formalization is a measure of how rules-based a social system is. Formalized systems have many rules and regulations about how things should be done, while informalized systems have few rules and regulations. Formalized systems diffuse innovation slower than informalized ones because rules in a system make it challenging to implement new ideas and products. On the contrary, informal systems diffuse innovation faster because information can spread freely without having to adhere to strict guidelines. Social systems have a significant role in the diffusion of innovation. Therefore, understanding how a social system's size, density, centralization, and formalization can affect the diffusion process can benefit the process of implementing the new the product or service.

The World is Facing a Delice in Birth Rate

It's no secret that the world is facing a baby shortage. In developed countries, birth rates have been declining for years and the trend does not appear to be slowing down anytime soon. There are several reasons the world is experiencing falling birth rates. One of the most significant factors is the cost of raising a child. In developed countries, the cost of living is high, therefore many couples delay starting a family until they are financially secure. Additionally, more women are pursuing careers instead of starting a family. Consequently, the declining birth rate also has implications for the future. Due to less babies, the world's population will experience an increase of older adults compared to young people. The change in population will strain social security and healthcare systems due to increased support needed by the aging population. support an aging population. Additionally, it could lead to labor shortages in specific industries as fewer young people are available to fill jobs.

Japan and South Korea are examples of countries that are experiencing a pronounced decline in births. Therefore, the population lacks the amount of young people needed to support the increasing number of retirees. This results in higher taxes and cuts to government benefits. If the decrease in babies persists, it will only get worse.

The world is facing a baby shortage, which has severe implications for the future. Although there are several reasons behind the falling birth rate, the most significant factor appears to be the high cost of living in developed countries. In addition, as women pursue careers instead of starting families, the pool of potential mothers shrinks even further. With fewer babies being born, eventually, there will be more older adults than young people. This will strain social security and healthcare systems as they try to support an aging population., The falling birth rate is a cause for concern due to less young people available for jobs, therefore leading to labor shortages.

In the Manufacturing Sector. Furthermore, the manufacturing sector has been hit hard by the labor shortage. To remain competitive, manufacturers are turning to collaborative robots, or "cobots." Cobots are designed to work alongside human employees, assisting them with tasks such as lifting heavy objects or performing repetitive motions. By using cobots, manufacturers can increase production without putting their workers at risk of injury.

In the Healthcare Sector. The healthcare sector is another area robots are starting to make a significant impact. Hospital staff members are often overworked and underpaid, which contributes to high turnover rates. But by using robots to perform specific tasks—such as transporting supplies or cleaning rooms—hospitals can free up nurses and doctors allowing them to focus on patient care. Additionally, robotic assistants can provide personalized care to elderly patients who live alone, helping them to stay healthy and independent for longer.

Robots can be used for many tasks, from assembly line work to complex industrial processes like 3D printing or CNC milling. Robots can work 24/7 and don't need breaks, vacations, or benefits like human employees. Additionally, They get tired or require the same level of supervision needed by humans. Robots are appealing to businesses because they can help increase production and efficiency while minimizing costs.

Robots are also very precise and are able to repeat the same motion over and over with accuracy. This makes them ideal for tasks requiring detail-oriented work like assembly or packaging. Many businesses have already started utilizing robots in their production processes to reduce costs and increase efficiency. Robots can also help reduce workplace injuries by taking on jobs that would otherwise put human workers at risk. For example, robots can be used to perform dangerous tasks like painting or welding in hazardous environments. Robotics can also help reduce workplace fatigue by taking on mundane, repetitive tasks that would otherwise require human labor.

Overall, robots offer a viable solution to the global labor shortage crisis by reducing costs, increasing efficiency and keeping workers safe from harm. With the right investment, businesses can use robots to increase production and free up their employees for more creative and meaningful work. In this way, robotics can be a key part of any business's long-term strategy. While there is no doubt that robots offer many advantages over human labor, it is essential to remember that they should be used to supplement human labor, not replace it. Robots can help businesses reduce costs and increase efficiency, but human workers are still invaluable to any successful organization. By finding the right balance between automation and human efforts, businesses can make the most out of both technologies to create a thriving work environment for everyone involved.

In conclusion, robots can be a valuable tool to help businesses reduce labor shortages while keeping costs and production levels up. However, companies should remember to use robots in tandem with human workers instead of replacing them completely. A joint workforce of humans and robots will ensure that everyone benefits from the increased efficiency and reduced risk that robotics-based solutions offer. Businesses can use robots strategically to maximize their potential and create a safe, productive work environment.

Need For Human Robot Connection and Trust

Similar to all types of perception, social perception is shaped by evolutionary forces. When interacting with members of their own species, social animals must rapidly determine whether the other animal is a friend or foe and whether they possess the capability to carry out their intentions, whether they are good or bad. Evidence verifies the existence of these two fundamental components of social cognition: warmth and competence (Fiske et al., 2007). These components have developed to ensure survival and give rise to essential social structure answers about competition and status. Individuals who are perceived as warm and competent are met with generally positive emotions and behaviors, while those who lack warmth and competence are met with uniformly negative reactions. Those classified as having high warmth and low competence, or vice versa, elicit predictable, varied emotional and behavioral responses. These universal components can be applied to both interpersonal and intergroup social cognition.

People are already interacting with robots that resemble the behavior of humans when they go to stores. For example, it is becoming more common to see robots that resemble human behavior in stores. These robots are designed to perform a variety of tasks, such as greeting customers, providing information about products, and even assisting with sales transactions. These interactions can have both advantages and disadvantages for people and companies. Research show that when people interact with these robots, they act differently than when they interact with human employees. They buy more expensive things, try to be friends with the robot, or order more food (Mende et al., 2019). Researchers have investigated why people act differently with robots and found that robots make people uncomfortable. People have reported feeling “creeped out” or like the robot threatens their identity. Additionally, the conditions that reduce the impact of the humanoid robot include when the person thinks they belong with other people, when the food is perceived as healthier, and when the robot looks more like a machine than a person (Mende et al., 2019)

Researchers previously used physical signals from human bodies to measure how we feel when interacting with robots (Kulic & Croft, 2005). The robots were programmed to do some regular movements, and study participants reported how they felt while researchers measured their physical reactions. The motion paths were created using a classic potential field planner and a safe motion planner. The safe motion planner makes it so there is less chance of hitting something along the path. The fuzzy inference engine was created to predict how people will respond to different things based on data from experiments. The study shows that people feel more anxious and surprised when they use the unsafe planner for robots at high speeds (Kulic & Croft, 2005).

Li et al. (2010) have also examined have also examined how the culture, the robot looks, and the robot's tasks (teaching, guiding, entertainment, and security guard) affect how people interact with the robot. The cultures analyzed were Chinese, Korean, and German. The looks analyzed in the study were anthropomorphic, zoomorphic, and machine-like. The study also investigated people's active involvement with the robot, their level of trust, and overall satisfaction. The study found that people from various cultures have dissimilar opinions about how much they like, trust, and are satisfied with something.

There need to be better ways to measure how people feel about robots. To advance, it is necessary to have the ability to contrast findings from diverse studies. Researchers looked at how five key concepts (a) anthropomorphism, (b) animacy, (c) likeability, (d) perceived intelligence, and (e) perceived safety are measured in studies about human-robot interaction. Bartneck et al. (2009) discovered five questionnaires that utilized semantic differential scales consistently and instruments for the Anthropomorphism, Animacy, Likeability, Perceived Intelligence, and Perceived Safety of Robots. Robot developers can use these questionnaires to monitor their progress.

K. Lee et al. (2005) investigated how prolonged artificial development of a robot impacts users' social presence and response towards the robot. The research consisted of a 2 x 2 between-subjects experiment, where 40 participants interacted with Sony's robotic dog, AIBO, for a month. The study testing two factors: developmental capability (developmental versus fully matured) and number of participants (individual versus group). The findings suggest that the ability to learn and develop had a noteworthy and favorable effect on how participants viewed AIBO as being realistic, their sense of interacting with a social entity, and their reactions towards the robot. However, the number of participants only affected parasocial relationships and buying intentions. No interaction between the two factors was found. Path analyses revealed that feelings of social presence facilitate participants' social reactions towards AIBO. The potential consequences of the study are examined concerning the interaction between humans and robots, the paradigm of computers as social actors (CASA), and research on (tele)presence.

As machines become more common, people worry about whether robots can be trusted to drive cars or take care of children (Waddell, 2019). Calibrating a human's trust in a machine's capability is critical; however, the challenge is measuring that level of trust is an inexact process.

Trust cannot be as easily measured like heart rate. On the contrary, researchers examine people's behavior for evidence of trust. Purdue University discovered additional accurate indicators by examining people's brain signals and skin reactions (Brouk, 2021). To measure trust researchers experimented using sensors to measure people's brain activity and skin response when they saw a virtual self-driving car with faulty sensors.

If researchers understand how people feel about robots, the robots can be changed accordingly, for example, autonomous vehicles could give skeptical drivers more time before reaching obstacles, industrial robots could reveal the reasoning behind the decision, etc. Hu et al. (2019) found that demographic factors influence human trust. Additionally, national culture and gender have a significant impact on trust. For instance, participants from the United States demonstrated a lower level of trust and were more sensitive to errors than participants from India.

According to Snow (2018), people can classify robots with human-like characteristics, such as a face or eyes, into racial categories. The study involved taking photographs of individuals from various ethnicities and a humanoid robot called Nao, whose exterior was altered to resemble different human skin tones. The experiment used a technique called "shooter bias," where participants were asked to decide whether to use their firearm when presented with images of a person or Nao holding a weapon or a harmless object, while being placed in the role of a police officer. The results disclosed that participants were faster to shoot black robots than white robots. The individuals who conducted the study were mostly white and responded faster at not shooting unarmed white humans and robots than unarmed black figures. The researchers believe that if predominantly white robots are used in roles like teachers, friends, or care providers, it could worsen racism. Is it ethical to use robots in law enforcement? AI systems can make mistakes because of how they are programmed, or the data sets used (Pacific Standard Staff, 2016). The Dallas Police Department employed a tactical robot from Northrop Grumman to neutralize Micah Johnson, the shooter responsible for the deaths of five officers during a Black Lives Matter protest. In 2015, North Dakota made history as the first state to permit the use of armed drones by law enforcement. This incident might set a model for other law enforcement organizations. Robots are imperfect and must be monitored when used by law enforcement agencies.

Acceptance for Humanoid Robots

In Kuchenbrandt et al.'s (2011) study, they employed a minimal-group approach to examine whether labeling the NAO humanoid robot as either an in-group or out-group member, based on non-social characteristics, would lead to greater anthropomorphism and favorable assessments of the robot. The minimal group paradigm is a method that researchers use to study how people act in groups. The minimal condition for group biases, or feeling more favorable towards your group and feeling less favorable towards other groups, is simply being a group member (Minimal Group Paradigm, n.d.) The experimenters wanted to know if people would consider robot as more human-like and have better opinions if they thought it was part of their group. An implicit measurement procedure was utilized to assess anthropomorphism. When people thought of the robot as part of their group, they tended to like it more and saw it as more human-like. People who saw NAO as part of their group said they would be more likely to interact with robots in general compared to those who did not see it that way.

Additionally, the way a robot looks affects how much people like it. The type of task performed by a robot affects how participants respond and how engaged they are with the robot (Li et al., 2010). Furthermore, taking into account both cultural background and the nature of the task suggests that individuals from cultures with low-context communication (where social interactions are less emphasized) may experience a notable decrease in engagement when the task's social aspects are reduced. Li et al. (2010) also found significant and positive connections between the quality of interaction and the likability, trust, and satisfaction levels in human-robot interactions.

Walters et al. (2008) have also studied how people feel about robots that look different ways and act differently (Walters et al., 2008). The study looked at what kind of robot people like the best and why. People tended to like robots that looked more like humans, but there were some differences depending on the person's personality (Walters et al., 2008). Introverts and participants with lower emotional resilience tend to like the mechanical-looking build more than other participants (Walters et al., 2008). These results suggest no perfect design or behavior when creating an engaging robot. Instead, people's individual preferences and personalities should be considered when designing a robot.

Additionally, empathy is essential for the emotional interaction between a human and robots (Kwak et al., 2013). Kwak et al. (2013) have investigated the design factors that influence human empathy toward robots. Participants were made to interact with either a mediated robot or a simulated robot. The mediated robot showed the emotions of a person who was not there, which is referred to as a "remote user". The second robot displayed its programmed feelings. The people in the study felt more empathy for the robot that was there in person than for the simulated robot.

Thus, the results show that it is better to have an actual robot present during emotional interactions between people. The study also examined human interaction with physically embodied robots or disembodied robots. The findings indicated that individuals exhibited greater empathy towards a robot that possessed a physical body compared to a robot that lacked a physical body (Kwak et al., 2013). These results also indicate that having a physical body seems to affect how much empathy people feel.

Bartneck et al. (2007) experimented with investigating how people perceive different robot embodiments. In this study, two robots, iCat and Robovie II, were utilized, with robot type functioning as the independent variable and the perceived animacy and intelligence of the robot as the dependent variables. The findings revealed that a robot's perceived intelligence was linked to its animacy, with this association being more pronounced in the iCat embodiment. Furthermore, the outcomes indicated that when the robots made eye contact, human participants tended to perceive them as more animated. (Bartneck et al., 2007).

Additionally, van Pinxteren et al. (2019) have used a humanoid service robot in an experimental field study to display gaze cues and static eye color. The study examined how people trust technology that looks like a person or an animal in order to better understand how people might be more likely to use self-service technology. Additionally, the study looked at how people see technology that is designed to help them. It also explored how much people trust this technology The robot exhibited greater social behavior that resembled that of humans (not human like in appearance) in one condition, with the other focusing on human-like appearance. Self-reported information was gathered from 114 participants regarding their observations of trust, anthropomorphism, interaction comfort, enjoyment, and intention to use. van Pinxteren et al. (2019) indicates the impact of gaze cues on anthropomorphism is influenced by the level of interaction comfort. The use of gaze cues increases the anthropomorphism to a robot when the level of comfort is low but reduces it when the level of comfort is high. Anthropomorphism plays a significant role in building trust, intention to use, and enjoyment.

Research has also examined how a robot's face might affect how people see it (Eyssel & Hegel, 2012). In a past study, researchers looked at how people might see robots differently if the robot has a male or female face. Results indicate people think a robot is more like a man if it has short hair and more like a woman if it has long hair. People also believe that male robots are better at doing things that are typically seen as "male" tasks and vice versa for female tasks (Eyssel & Hegel, 2012). These results mean that people transfer their social perceptions of humans onto robots. We discuss what this could mean for design decisions related to robots in the future.

Humanoid Robots at Work

AI is changing how service works by doing different jobs. This could mean that machines might replace some jobs that people do presently (Huang & Rust, 2018). Huang & Rust (2018) have identified four types of intelligence needed for service tasks such as mechanical, analytical, intuitive, and empathetic. This classification can help companies decide if they should use humans or machines to do a particular job. AI develops from lower intelligence (mechanical) to higher intelligence (empathetic), replacing specific tasks with automation instead of entire job positions. As AI takes over more analytical tasks, analytical skills will become less critical while "softer" skills such as intuition or empathy gain importance in human employment opportunities.

A robot that looks like a person was made to make drinks for people in a social setting (Foster et al., 2012). The system used different types of software for things like seeing, processing language, managing what the robot does, and controlling the robot. Thirty-one people were asked to try to get a drink from the bartender in different conditions. The majority of customers were able to obtain a beverage from the bartender, and task success and dialogue efficiency significantly impacted personal satisfaction levels among users (Foster et al., 2012).

Eventually, AI may be able to take over all aspects of a given task, which could lead to an increase in unemployment. Tussyadiah and Park (2018) conducted two studies to see how people would react to hotel robot. The first study was an online survey, and the second was in a laboratory using sensors. Researchers asked people what they thought about two kinds of robots, NAO designed for hotel check-in and Relay intended for room delivery. Tussyadiah and Park (2018) found that reasons for consumers' intentions for adoption differed based on the type of robot used. The first study found NAO's adoption depends on people thinking it is like a person and feel safe around it. Relay's adoption depends on people thinking it is brilliant and how essential service robots are in hotel experiences. The second study using sensors also reiterated the same finding as the first study.

The impact of robotic service on the hotel experience was also investigated by Chan and Tung (2019). The study investigated how guest evaluations of hotel brand experience are affected by different levels of robotic service quality. The study also further explores the moderating effects of the hotel segment on brand (budget, midscale, or luxury). Chan and Tung (2019) found that people staying in midscale and budget hotels would have a better experience if the hotels used robotic technology. In general, the utilization of robotic service may not enhance brand experience as influenced by the controlling role of the hotel segment.

Robots are becoming more common in the hotel industry, but some people may not want to use them. In 2016–2017, Russian consumers were asked about their thoughts on robots in hotels (Ivanov et al., 2018). According to the results, men and individuals who were already favorable towards service industries were more inclined to welcome robots in hotels compared to women. (Ivanov et al., 2018). Additionally, young Russian adults may support introducing service robots into the hotel industry. The research reveals that there is no notable distinction in how guests perceive service robots based on their continent of origin. Ivanov et al. (2018) argue that the data that emerged from the survey reveals that robots are desired in the hospitality industry.

Furthermore, Lu et al. (2019) have created a Service Robot Integration Willingness (SRIW) Scale that comprises various dimensions to identify the significant factors that indicate customers' willingness to adopt service robots and artificial intelligence in routine service interactions. The SRIW measurement tool is composed of 36 items that are categorized into six domains, including performance effectiveness, inherent drive, anthropomorphism, social impact, enabling factors, and emotions. These factors define how well the robot does the task, if the robot is easy to use, if the robot is like a person, what other people think if there are good conditions for using the robot, and how the person feels about it. The study also found that these things are important across different industries where service robots might be used (e.g., restaurants, hotels, airlines, and retail stores). This information can help companies make better robots that people will want to use.

Humanoid Robots for Elder Care

Čaić et al. (2018) have looked into how service robots can help older adults in value networks from an older person's perspective. The six robot roles in the value network are the (a) enabler, (b) intruder, (c) ally, (d) replacement, (e) extended self, and (f) deactivator. Čaić et al. (2018) found these roles were linked to three health-supporting functions: safeguarding, social contact, and cognitive support. The findings can help service scholars and managers understand how to design robots that avoid value destruction while also creating value for older adults.

As we age, more and more people who need help taking care of themselves. Social robots have been suggested to help people stay healthy and safe in their homes without needing someone to take care of them all the time. However, even though there is a need for these robots, and some have been successful, other robots have not been received well (Broadbent et al., 2009). Broadbent et al. (2009) have analyzed why people do or do not like healthcare robots which include making sure the robot can do what the person needs and making the robot look and act like it will be helpful. Another way to encourage people to accept healthcare robots may be to change what people expect the robot will be able to do (Broadbent et al., 2009).

More and more older people are feeling lonely. Robots are being used to help care for them, but there are not enough robots for everyone who needs one (Leng Leng Thang, 2018). Programs exist in which young people volunteer to visit retirement homes and long-term care facilities. They spend time with the elderly residents, teaching them how to use social media or doing graffiti art together. Even though robots can provide a technical solution for caring for older adults, it may be better if society adopts a more human approach.

For its part, Honda has decided to stop making its humanoid robot, Asimo (Ackerman, 2018). The company is now focusing on creating robots that can be more useful and practical in the real world instead of just for demonstrations. Honda intends to concentrate on elder care and disaster robots instead of improving its iconic humanoid. In July 2013, Honda began developing a Disaster Response Robot based on ASIMO technology. The Fukushima disaster played a role in this change as Japanese robots were criticized for being too sophisticated yet not helpful when needed most.

Technology's ability to engage customers on a social level is a critical advancement of technology infusions. The connection between ASP and service outcomes may be influenced by social cognition and psychological ownership. The way technology is evolving is quickly altering the characteristics of service, the way customers interact with service providers, and their overall experiences at the service frontlines. The expectation is that by 2025, technology will be integrated into various service experiences. Although technology is becoming more proficient at performing tasks that are repetitive and mundane, there are certain human traits that may prove challenging for technology to substitute.

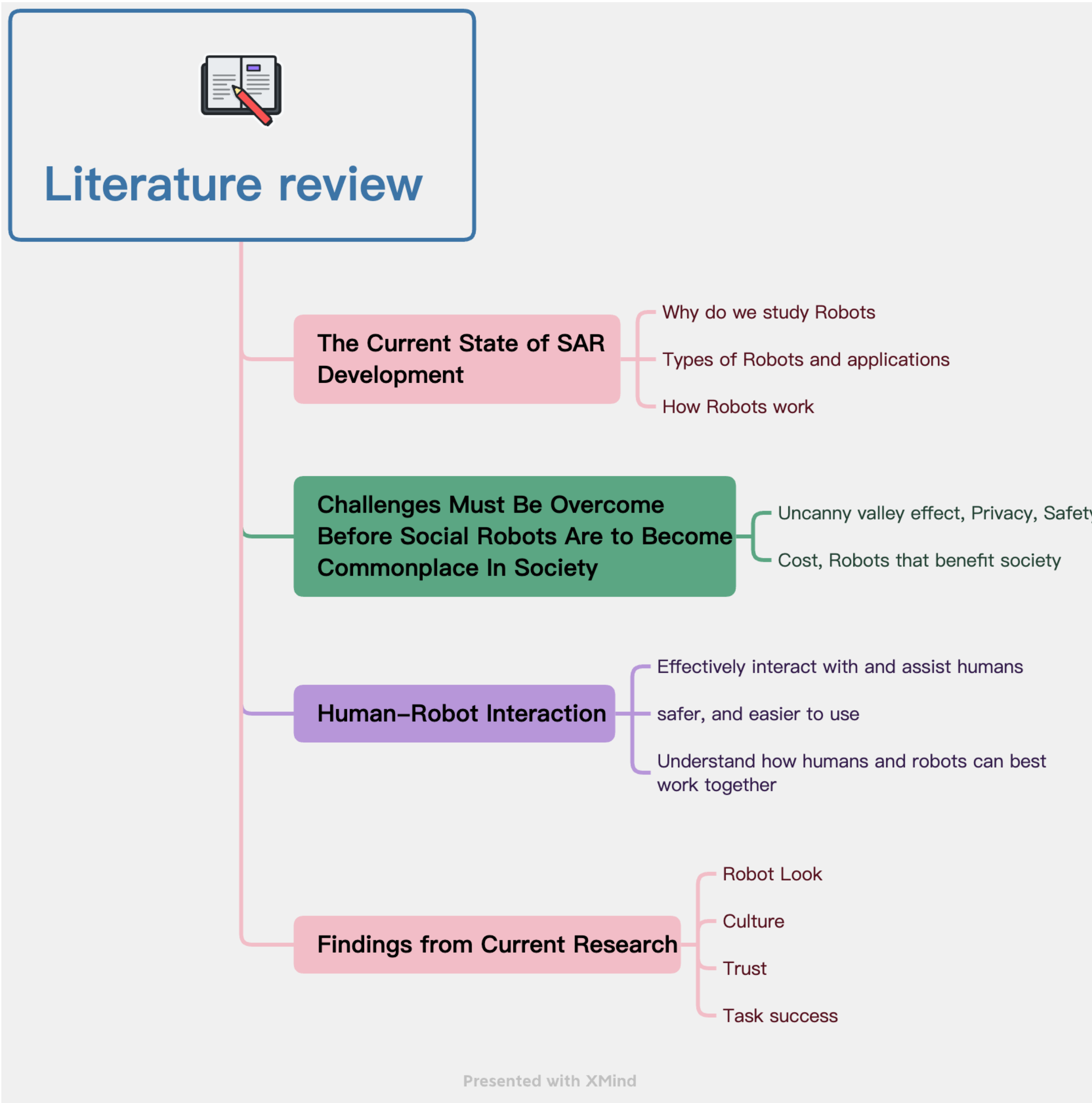
Literature Review Summary Findings

The literature review analyzed the current state of development in SAR. It provided detailed information on topics such as the reasons for studying robots, the different types of robots and their applications, and how robots function. The review then shifted its focus to the challenges that must be addressed before SAR becomes widely accepted in society. This discussion covered issues such as the uncanny valley effect, privacy concerns, the benefits and risks of using robots, and their costs.

The literature review also delved into Human-Robot Interaction, exploring how robots can effectively interact with and assist humans, how to build safer and user-friendly robots and the different theories on technology adoption. Finally, the review included current findings from studies on how humans perceive robots based on their features. Two important conclusions of the literature review relevant to the present study include the importance of robotic feature attributes towards its likeness and acceptance — also the utility, reliability, safety, privacy, and change management factors towards its adoption. The literature review summary finding is shown in Figure 4.

Figure 4

Literature Review Summary Findings



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Chapter 3: Research Design

Research Design and Rationale

The research approach for this study is quantitative and predictive. The study is non-experimental. Additionally, the study will employ the use of two self-report surveys. All variables collected in the study are scored at the interval level of measurement. To understand and describe the demographics of the targeted population of study (hospital nurses) their age, gender, educational level, years of experience in nursing, race, and socioeconomic status were collected. But these demographic characteristics will not be analyzed in the study. Rather, they were collected for the sake of describing the characteristics of its participants. The Amazon Mechanical Turk (MTurk ; https://www.mturk.com) and Prolific online human labor platform (www.prolific.co) were used to recruit participants and distribute the survey, with questionnaires being hosted on Qualtrics for their completion. The survey was cross-sectional, collecting data on Warmth, Competence, and Discomfort regarding the SARs. Additionally, the self-report measures obtained Optimism, Proficiency, Dependence, and Vulnerability regarding Technology adoption.

Optimism, Proficiency, Dependence, and Vulnerability are the four aspects of the propensity for adopting new technology. Optimism involves the belief that technology enhances control and flexibility in life, while Proficiency indicates confidence in swiftly learning and using new technologies, reflecting technological competence. Dependence refers to excessive reliance and feeling enslaved by technology. Vulnerability relates to the belief that technology heightens the risk of exploitation by criminals or companies (Ratchford & Barnhart, 2012). Warmth, competence, and Discomfort are common social attitudes that elder adults have toward hybrid assistive robotic caretakers. "When people are evaluated as warm and competent, they are seen more favorably and experience more positive interactions." Discomfort relates to "awkwardness" (Carpinella, et al., 2017, p.257)

The survey instruments used in the study were selected because they both provide robust ways to identify data in an interval level of measurement to identify means and standard deviations and perform inferential statistical analysis. The data collection timeframe of two weeks allowed ample time for participants to complete the survey with meaningful responses and not rush the response process.

Measures

The Technology Adoption Propensity Index

The Technology Adoption Propensity Index (TAP) scale was created by taking 17 items from the Technology Readiness Index (TRI) scale (Parasuraman, 2000) and adding 30 additional items (Ratchford & Barnhart, 2012). After factor analysis, 14 questions were retained in the survey. The TAP includes four subscales Optimism, Proficiency, Dependence, and Vulnerability. Optimism and Proficiency are contributing factors to ability to adopt new technology (or something like that) Whereas, Dependence, and Vulnerability are inhibiting factors for the customer's TAP (Ratchford & Barnhart, 2012).

The TAP's questions are sectioned based on the four contributing factors for technology adoption. Items 1-4 questions represent Technology Optimism, items 5-8 represent Technology proficiency, items 9-11 represent Technology Dependence, and items 12-14 represent Technology Vulnerability. Each of the 14 questions are scored between 1 and 5, and subscale scores are determined by averaging the respective items. Inhibiting factor questions 9-14 are reverse scored. The mean and standard deviation for each subscale reported by Ratchford &

Barnhart (2012), along with thresholds for determining scores as low and high, are provided in Table 2.

Table 2

Means, Standard Deviations, and Low and High Subscale Thresholds For the TAP

	Mean	Std. Dev.	Low	High
Optimism	3.95	0.92	<3.03	>4.87
Proficiency	3.46	1.17	<2.29	>4.63
Dependence	2.7	1.12	<1.58	>3.82
Vulnerability	3.41	1.14	<2.27	>4.55

Reliability

The Cronbach's alpha reliabilities reported by Ratchford & Barnhart (2012) for Optimism, Proficiency, Dependence, and Vulnerability were .87, .87, .78, and .73, respectively. Quantitative measures are conventionally considered to have modest but sufficient evidence of internal consistency reliability if their scales and/or subscales alpha reliability coefficients are 0.70. The Optimism, Proficiency, Dependence, and Vulnerability subscales have a Cronbach alpha greater than .70, therefore they are considered sufficiently reliable (Nunnally, 1978).

Validity

Ratchford & Barnhart (2012) used three separate data samples (named DS1, DS2, and DS3) to arrive at the TAP instrument. In their first study, Ratchford & Barnhart (2012) used exploratory factor analysis comparing 3 to 6-factor structures before finalizing the four-factor solution to measure the Technology adoption propensity. Ratchford & Barnhart (2012) also performed a Confirmatory Factor Analysis (CFA) on three samples (Studies 1, 2, and 3). Respectively, Tables 3, 4, and 5 show results of CFA with interpretation of the relevant parameters (Cohen, 1988).

Table 3

CFA on Study 1 and Interpretation

Parameter	**Values**	**Interpretation**
SRMR	0.049	Values less than 0.05, suggest good model fit to the data.
RMSEA	0.061	Values less than 0.05 indicate good model fit to the data.
CFI	0.96	Values greater than 0.95 indicate good model fit to the data.
TLI	0.95	Values between 0.90 and 0.95 indicate acceptable model fit to the data.

Table 4

CFA on Study 2 and Interpretation

Parameter	**Values**	**Interpretation**
SRMR	0.057	Values between 0.05 and 0.08 indicate acceptable model fit to the data.

Parameter	Values	Interpretation
RMSEA	0.059	Values between 0.05 and 0.08 suggest reasonable model fit to the data.
CFI	0.96	Values greater than 0.95 indicate good model fit to the data.
TLI	0.95	Values between 0.90 and 0.95 indicate acceptable model fit to the data.

Table 5

CFA on Study 3 and Interpretation

Parameter	Values	Interpretation
SRMR	0.056	Values between 0.05 and 0.08 indicate acceptable model fit to the data.
RMSEA	0.052	Values between 0.05 and 0.08 suggest reasonable model fit to the data.
CFI	0.94	Values between 0.90 and 0.95 indicate acceptable model fit to the data.
TLI	0.92	Values between 0.90 and 0.95 indicate acceptable model fit to the data.

71% of the variance of TAP scores was explained by four factors. The minimal amount of variance that should be explained by a model of a data set is 50% (Streiner, 1994). Hence, TAP has sufficient evidence of validity.

The Robotic Social Attribute (RoSAS)

The Robotic Social Attribute (RoSAS; Carpinella, et al., 2017) measures people's judgment of the social attributes of robots. The RoSAS scale is developed from the Godspeed Scale (Bartneck et al., 2009) which measures users' perceptions of robots, and is comprised of 18 questions. Each question is scored in 9 points Likert scale from 1 = definitely not associated to 9 = definitely associated. The first six items comprise the "Warmth" factor of the RoSAS. the next six items comprise the "Competence" factor of the RoSAS the last six items comprise the "Discomfort" factor of the RoSAS. Scores are based on averaging items within each subscale, with values ranging from 1.0 to 9.0.

Mean, and standard deviation scores are not provided in the article. Hence based on the actual survey data obtained in this study, the mean and standard deviation is calculated. Values below one-half is this correct standard deviation from mean is considered low, and values above one-half standard deviation from mean is considered as high, with those in between considered average.

Reliability

Quantitative measures are conventionally considered to have modest but sufficient evidence of internal consistency reliability if their scales and/or subscales alpha reliability coefficients are 0.70 or greater, though Nunnally (1978) indicates that coefficients of 0.80 or greater may be necessary depending on the research setting (Lance et al., 2006). The original authors of the RoSAS reported high reliability for the three subscales. The Warmth subscale had a reliability coefficient of .91, indicating that the items on this subscale consistently measured the construct of warmth. Similarly, the Competence subscale had a reliability coefficient of .84, suggesting that the items on this subscale were reliable in measuring competence. Finally, the Discomfort subscale had a reliability coefficient of .82, indicating that the items on this subscale were also reliable in measuring discomfort. These high-reliability coefficients suggest that the measures used in this study consistently calculate the constructs they intended to measure.

Validity

Based on factor loadings and factor scores, an item needs to load on a factor at .40 or above (though some make the threshold lower, such as .30, or higher, such as .50). Items in all the three factors have a factor loading score of .5 or higher. Hence RoSAS demonstrates satisfactory construct validity based on factor loadings and factor scores.

The minimal amount of variance that should be explained by a model of a data set is 50% (Streiner, 1994). However, the RoSAS is only able explain the variance of 44% in robot evaluation. Hence, based on the percentage (or proportion) of variance explained by the model, the scale does not satisfy this minimum threshold.

Nevertheless, eigenvalues values for Warmth, Competence and Discomfort were 22.031, 9.336 and 5.047 respectively. The number of eigenvalues over 1.0 is an indication of the number for factors measured by the questionnaire. Thus, the RoSAS obtained three Eigenvalues over this threshold.

Participants

The total population for this study was nurses in the United States and Canada. Convenience sampling method was used to identify the required sample. The inclusion criteria for the participants for the survey was nurses working hospitals in United States and Canada.

MTurk and Prolific was used to identify participants. MTurk and Prolific premium qualifications was used to identify nurses aged 18 years and older in these countries. The survey was created in Qualtrics, with survey recruitment executed through MTurk and Prolific. Comparison of data obtained through MTrurk and Prolific is shown in Appendix A.

The study has four predictor variables (Optimism, Proficiency, Dependence, and Vulnerability from TAP) and three outcome variables (Warmth, Competence, and Discomfort from RoSAS). In order to detect a moderate effect of $f^2 = 0.0625$ with a significance level of 0.05 and a power of 0.80, an a priori power analysis indicates that the minimal sample size necessary to carry out a MANOVA is 97. To create a balanced design, in which there is an equal number of members in each of the 12 group, sample size was increased to 108, with 9 (108/12) subjects per group. There will be at least 9 respondents each in the “low”, “average” or “high” categorizations of Optimism, Proficiency, Dependence, and Vulnerability on the TAP. Thus, the predictor variable will be categorized as “low”, “average” or “high” based on the mean +/.5 standard deviation from the data obtained.

Additionally, to ensure a minimum sample size for each group is obtained and to account for the potential for low-quality data obtained from some participants, which needs to be excluded, the data was sought from at least 200 respondents. The survey was available for responses from May 25th to June 4th, 2023, as per the researcher's decision. No follow-up was made with non-respondents or those who do not complete all items in the survey instrument used in the study.

Human Subjects Protections

No site permission was necessary as data had been collected through MTurk and Prolific. However, Pepperdine University's IRB approval was obtained before conducting the survey.

Pepperdine IRB approval is provided in Appendix B. On the survey's landing page, consent information was presented to inform participants that their participation was voluntary. Participants were given the option to choose not to participate or to withdraw at any point during the survey. It was communicated to participants that their responses would be kept confidential, involving reporting data in aggregate rather than by participant name. Furthermore, reporting would not include any other personally identifying information.

Participants were also notified that the study's purpose was solely for the Ph.D. dissertation at Pepperdine University, and that the risks were minimal, such as potential fatigue or boredom while answering survey questions. While there were no immediate benefits for participants completing the survey, the findings might contribute to the future development of robotics technologies beneficial for hospital nurses. MTurk participants who completed the final survey received a compensation of $0.25, while Prolific participants received $1.07.

As signed consent wasn't feasible for online data collection, alternative methods were utilized to ensure participants actively consented prior to participating. The surveys began with the presentation of this consent information, and respondents who clicked the "Accept" button were considered as consenting, whereas those clicking the "Decline" button were regarded as non-consenting. The latter group was exited from the survey and thanked for their interest.

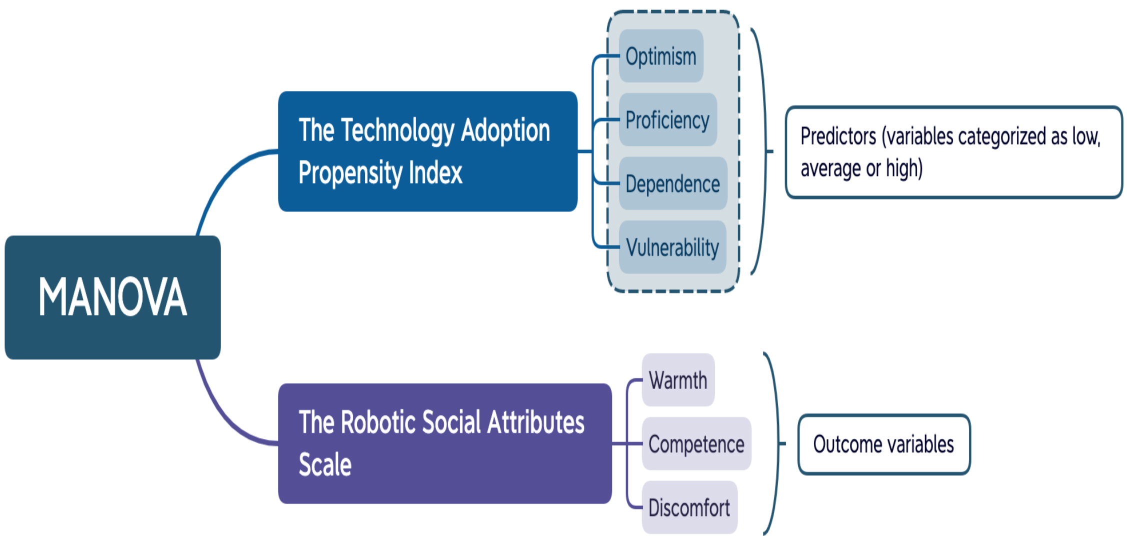
Data was maintained electronically, stored as password-secured files, and will be deleted after three years. Both surveys used for data collection can be employed for academic purposes, eliminating the need for additional copyright clearance and/or licensing.

Analytic Techniques

The alternate hypothesis is that four aspects of the propensity for adopting technology predicts three aspects of social attitudes towards hybrid assistive robotic caretakers among hospital nurses. Table 6 below shows a summary of the alternative hypothesis and constituent variables. Optimism, Proficiency, Dependence, and Vulnerability from the Technology Adoption Propensity Index survey (TAP Index; Ratchford & Barnhart, 2012) are predictor variables. Warmth, Competence, and Discomfort the Robotic Social Attributes Scale (RoSAS; Carpinella, et al., 2017) are the outcomes involved in this study. All variables will be captured and used in the analysis as continuous variables. is shown in See Figure 5 for Analytic technique visualization.

Figure 5

Analytic Technique Visualization



See Table 6 for a comprehensive overview of the alternative hypotheses, variable names, variable types, measurement names, and levels of measurement considered in the research study.

The Table 6 presents the foundation upon which the study's hypotheses are built and operationalized.

Table 6

Alternate Hypothesizes and Variables Summary

Alternative Hypothesis	Variable Name	Variable type	Measurement Name	Level of Measurement
Ha: - It is hypothesized that four aspects of the propensity for adopting technology predicts three aspects of social attitudes towards hybrid assistive robotic caretakers among nurses.	a: Optimism b: Proficiency c: Dependence d: Vulnerability e: Warmth. f: Competence. g: Discomfort	a-d: Predictor e-g: Outcome	a to d: The Technology Adoption Propensity Index survey (TAP Index; Ratchford & Barnhart, 2012) e to g: The Robotic Social Attributes Scale (RoSAS; Carpinella, et al., 2017)	continuous, with predictor variables converted to categorical (low, average, high)

Data Collection Procedures

The survey was available for responses from May 25th to June 4th, 2023. After the data collection window closed, the raw data was exported from Qualtrics. The data was then input into an Excel spreadsheet. After deleting survey metadata (e.g. Recorded Date, IP Address, etc.) from columns and rows, the file was re-saved in .csv format. Missing data, if present, were deleted case-wise. The researcher used Intellectus Statistics (intellectusstatistics.com) for descriptive and inferential data analysis.

The number of complete cases, along with the mean, median, and standard deviation of variables collected through the survey (Optimism, Proficiency, Dependence, Vulnerability, Warmth, Competence, and Discomfort), were reported in Chapter 4. Histograms and boxplots of each variable (Optimism, Proficiency, Dependence, Vulnerability, Warmth, Competence, and Discomfort), also presented in Chapter 4, were inspected to assess the distribution of the data and to identify potential outliers, respectively.

To identify the relationship between four aspects of the propensity for adopting technology and three aspects of social attitudes towards hybrid assistive robotic caretakers among elderly adults, MANOVA was used, since there were three continuous outcome variables and four continuous predictor variables categorized as “low,” “average,” and “high.” MANOVA required converting data on the predictor variables, yielding continuous-level data based on the survey into categorical ones. To run the MANOVA, the outcome variables (Warmth, Competence, and Discomfort) needed to have no more than a small-to-moderate correlation ($r = 0.10$ to 0.50). The input data needed to be normally distributed and also needed to satisfy the homogeneity of variance assumption. The data were tested for normality using the Shapiro-Wilk test, and were transformed as necessary to best approximate a normal distribution if the test was not satisfied. Each outcome variable (Warmth, Competence, and Discomfort) also needed to satisfy the homogeneity of variance to run the MANOVA. Levene's test was conducted to check the homogeneity of variance among each outcome variable (Warmth, Competence, and Discomfort) prior to inferential analysis.

The significance level of 0.05 was used in all inferential tests. Exact p-values and 95% confidence intervals obtained were reported to three decimal places. The researcher used partial eta-squared ($\eta p2$) statistics to determine the effect size. Values from 0.01 to less than 0.06 were considered small, values from 0.06 to less than 0.15 were considered medium, and values greater than 0.15 were considered large.

Chapter 4: Findings

Overview

This chapter provides a summary of the purpose and hypotheses of this study, as well as the findings of data collected using the methods highlighted in the previous chapter.

Description of Sample

The data collection process for this study involved utilizing two platforms, namely MTurk and Prolific, to gather information from nurses. However, it is worth noting that the researcher did not obtain the minimum sample size required to conduct the MNOVA analysis from the Prolific platform alone. However, sufficient data was obtained from the Amazon MTurk platform, which met the minimum sample size requirement. Hence data from the MTurk platform is used for this study.

The researcher also conducted two statistical tests to ensure the reliability and comparability of the data collected from both platforms: the Two-Tailed Independent Samples t Test and the Two-Tailed Mann-Whitney Rank Sum Test. These tests aimed to determine if there were any significant differences between the data obtained from MTurk and Prolific sources. The results of these tests indicated that out of the four predictor variables (Optimism, Proficiency, Dependence, and Vulnerability from TAP) examined in the study, only the mean of Dependence exhibited a significant difference between the MTurk and Prolific categories of the data source. Conversely, the mean differences for the other three variables (Optimism, Proficiency, and Vulnerability) were not found to be statistically significant. This comparison between the two platforms was crucial in assessing the reliability of the data collected from MTurk, which is used in the study. Two-Tailed Independent Samples tTests and Two-Tailed Mann-Whitney Rank Sum Tests are reported in Appendix A.

Descriptive Statistics

The researchers examined the demographic composition of the targeted population of nurses and explored several key variables to gain a comprehensive understanding of the participants' backgrounds. These variables encompassed age, gender, educational level, years of experience in the nursing field, race, and socioeconomic status. To shed light on the distribution within each category, the study presented frequencies and corresponding percentages for these variables. By delving into these demographic factors, the researchers aimed to acquire valuable insights into the characteristics and diversity of the nurse population under investigation. The total sample size obtained in this study was 137.

The most frequently observed category of gender was Female (*n* = 92, 67.15%). Frequencies and percentages are presented in Table 7.

Table 7

Frequency Table for Gender

Variable	*n*	%
gender		
Male	45	32.85
Female	92	67.15
Missing	0	0.00

Note. Due to rounding errors, percentages may not equal 100%.

The most frequently observed category of education was 4-year degree (*n* = 97, 70.80%). Frequencies and percentages are presented in Table 8.

Table 8

Frequency Table for Education

Variable	*n*	%
Education		
High school graduate	3	2.19
Some college	8	5.84
2 year degree	7	5.11
4 year degree	97	70.80
Professional degree	22	16.06
Missing	0	0.00

Note. Due to rounding errors, percentages may not equal 100%.

The most frequently observed category of income was \$50,000 - \$59,999 (n = 55, 40.15%). Frequencies and percentages are presented in Table 9.

Table 9

Frequency Table for Income

Variable	*n*	%
Income		
Less than \$10,000	5	3.65
\$10,000 - \$19,999	3	2.19
\$20,000 - \$29,999	4	2.92
\$30,000 - \$39,999	8	5.84
\$40,000 - \$49,999	5	3.65
\$50,000 - \$59,999	55	40.15
\$60,000 - \$69,999	9	6.57
\$70,000 - \$79,999	21	15.33
\$80,000 - \$89,999	3	2.19
\$90,000 - \$99,999	20	14.60
\$100,000 - \$149,999	2	1.46
More than \$150,000	2	1.46
Missing	0	0.00

Note. Due to rounding errors, percentages may not equal 100%.

The White ethnicity category was the most common, observed 130 times, accounting for 94.89% of the total. Detailed frequencies and corresponding percentages are provided in Table 10.

Table 10

Frequency Table for Ethnicity

Variable	*n*	%
Ethnicity		
White	130	94.89
Black or African American	1	0.73
American Indian or Alaska Native	3	2.19
Asian	2	1.46
Other	1	0.73
Missing	0	0.00

Note. Due to rounding errors, percentages may not equal 100%.

The most frequently observed category of years of experience was 1-5 years (n = 61, 44.53%). Frequencies and percentages are presented in Table 11.

Table 11

Frequency Table for Years of Experience

Variable	*n*	%
Years of Experience		
Less than 1 year	3	2.19
1-5 years	61	44.53
6-10 years	30	21.90
11-15 years	28	20.44
16-20 years	9	6.57
More than 20 years	6	4.38
Missing	0	0.00

Note. Due to rounding errors, percentages may not equal 100%.

The most frequently observed category of position was Mid-level/Experienced (n = 67, 48.91%). Frequencies and percentages are presented in Table 12.

Table 12

Frequency Table for Position

Variable	n	%
Position		
Entry-level/Junior	6	4.38
Mid-level/Experienced	67	48.91
Senior-level/Manager	49	35.77
Executive-level/Leadership	14	10.22
Other	1	0.73
Missing	0	0.00

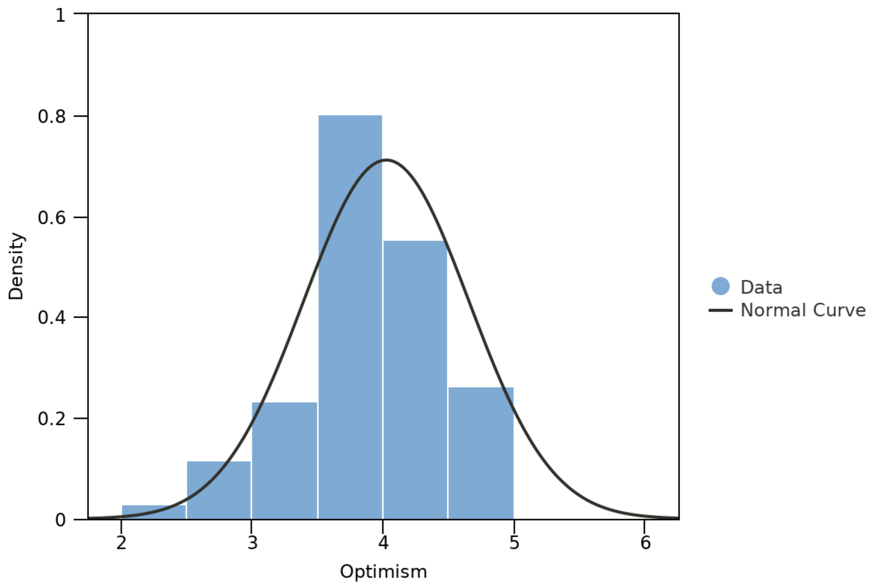
Note. Due to rounding errors, percentages may not equal 100%.

In the forthcoming section of the research study, the histograms of both the predictor variables (Optimism, Proficiency, Dependence, and Vulnerability from TAP) and the outcome variables (Warmth, Competence, and Discomfort from RoSAS) will be presented.

Optimism displays a distribution that deviates significantly from a normal distribution. The histogram indicates a slightly negatively skewed distribution with a relatively moderate level of peakedness compared to a normal distribution. Histogram of Optimism is shown in Figure 6 below.

Figure 6

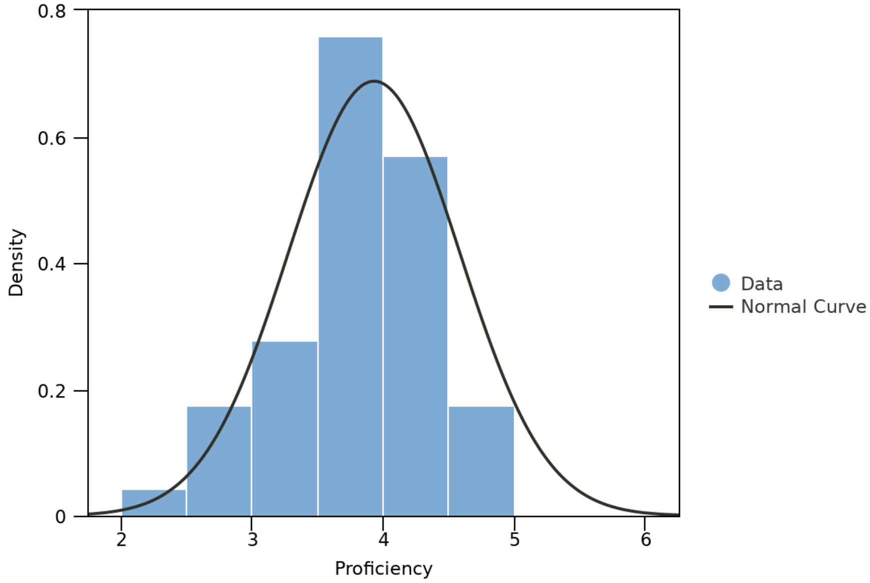
Histogram of Optimism



The histogram for Proficiency reveals a distribution that is notably different from a normal distribution. These values suggest a slightly negatively skewed distribution with a flatter shape compared to a normal distribution. Histogram of Proficiency is shown in Figure 7.

Figure 7

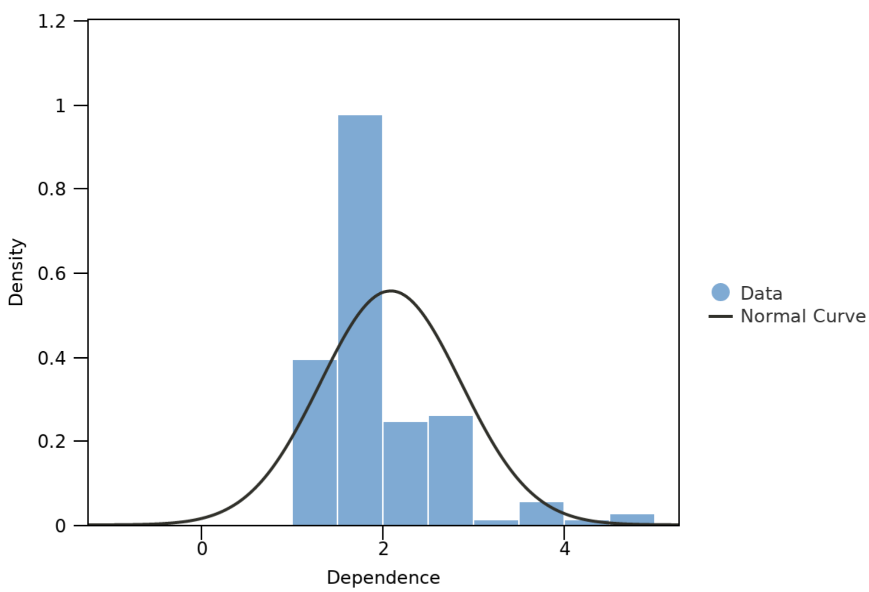
Histogram of Proficiency



The histogram for Dependence illustrates a distribution that significantly departs from normality. These values indicate a positively skewed distribution with heavy tails, suggesting that the data might exhibit outliers and a relatively higher peak compared to a normal distribution. Histogram of Dependence is shown in Figure 8.

Figure 8

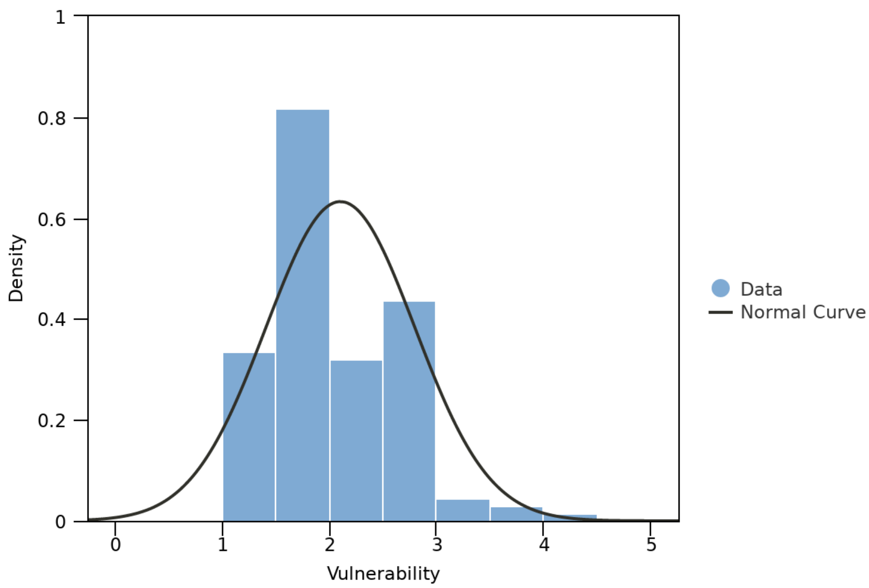
Histogram of Dependence



The histogram for Vulnerability presents a distribution that significantly differs from a normal distribution. These values suggest a slightly positively skewed distribution with a moderate level of peakedness compared to a normal distribution. Histogram of Vulnerability is shown in Figure 9.

Figure 9

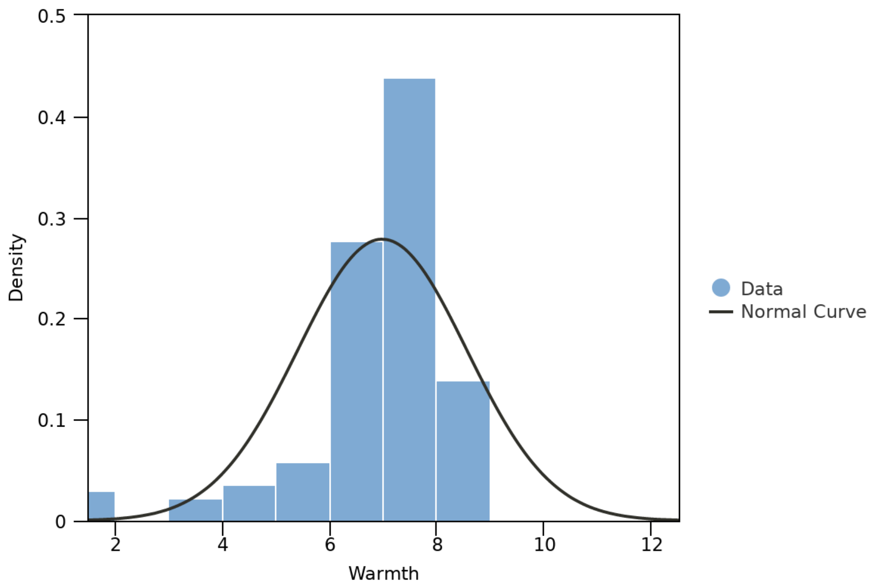
Histogram of Vulnerability



The histogram for Warmth showcases a distribution that significantly deviates from normality. These values indicate a highly negatively skewed distribution with heavy tails and a substantial level of peakedness compared to a normal distribution. Histogram of Warmth is shown in Figure 10.

Figure 10

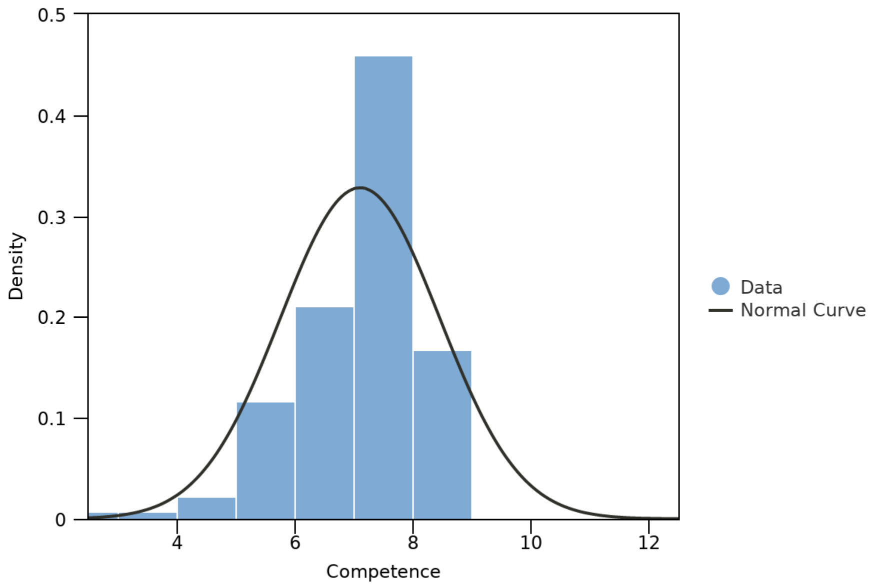
Histogram of Warmth



The histogram for Competence displays a distribution that significantly differs from normality. These values suggest a negatively skewed distribution with heavy tails and a relatively high peak compared to a normal distribution. Histogram of Competence is shown in Figure 11.

Figure 11

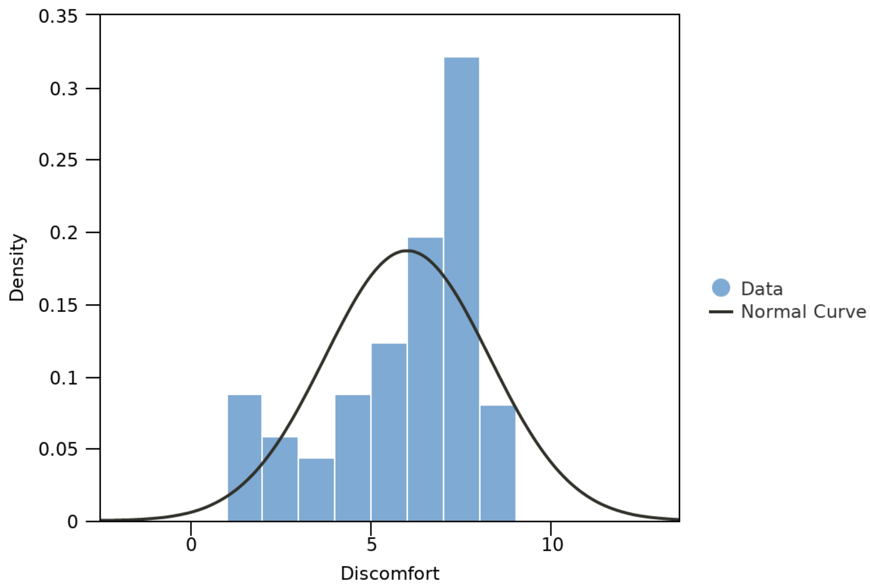
Histogram of Competence



The histogram for Discomfort exhibits a distribution that significantly departs from normality. These values indicate a slightly negatively skewed distribution with a flatter shape and a lower peak compared to a normal distribution. Histogram of Discomfort is shown in Figure 12.

Figure 12

Histogram of Discomfort

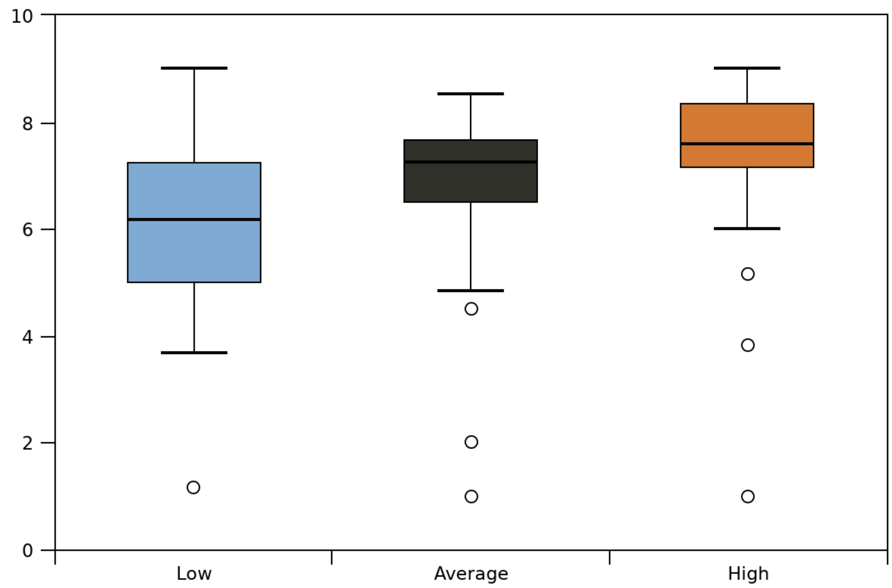


In the following section of the research study, box plots will be presented to illustrate the relationship between each outcome variable (Warmth, Competence, and Discomfort from RoSAS) and the predictor variables (Optimism, Proficiency, Dependence, and Vulnerability from TAP).

The boxplot suggests notable variations in "Warmth" scores among individuals with differing Optimism levels. It visually confirms that the perceived "Warmth" is not uniformly distributed across all Optimism groups. Given the distinct separation of the boxplots, Optimism levels impact how individuals perceive "Warmth." See Figure 13 for Boxplot of Warmth by Low, Average and High Optimism Scores.

Figure 13

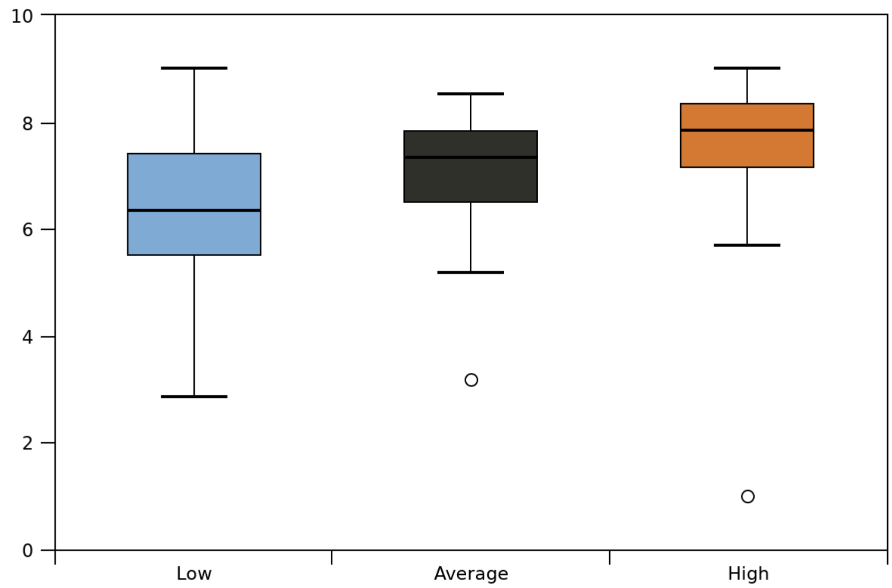
Boxplot of Warmth by Low, Average and High Optimism Scores



The boxplot suggests notable variations in "Competence" scores among individuals with differing Optimism levels. It visually confirms that the perceived " Competence " is not uniformly distributed across all Optimism groups. Given the distinct separation of the boxplots, Optimism levels impact how individuals perceive " Competence." See Figure 14 for Boxplot of Competence by Low, Average and High Optimism Scores.

Figure 14

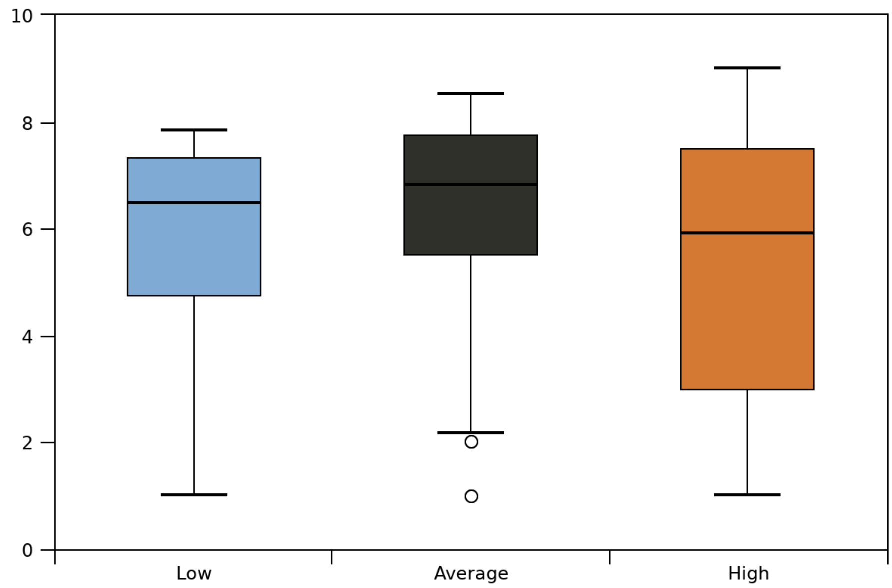
Boxplot of Competence by Low, Average and High Optimism Scores



The boxplot suggests notable variations in "Discomfort" scores among individuals with differing Optimism levels. It visually confirms that the perceived " Discomfort " is not uniformly distributed across all Optimism groups. Given the distinct separation of the boxplots, Optimism levels impact how individuals perceive " Discomfort." See Figure 15 for Boxplot of Discomfort by Low, Average and High Optimism Scores.

Figure 15

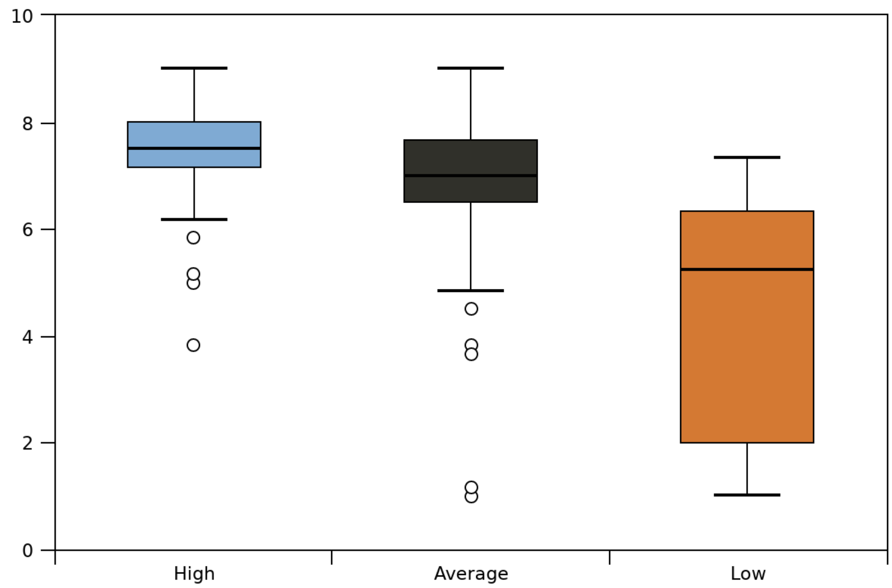
Boxplot of Discomfort by Low, Average and High Optimism Scores



The boxplot suggests notable variations in "Warmth" scores among individuals with differing Proficiency levels. It visually confirms that the perceived " Competence " is not uniformly distributed across all Proficiency groups. Given the distinct separation of the boxplots, Proficiency levels impact how individuals perceive " Competence." See Figure 16 for Boxplot of Warmth by Low, Average and High Proficiency Scores.

Figure 16

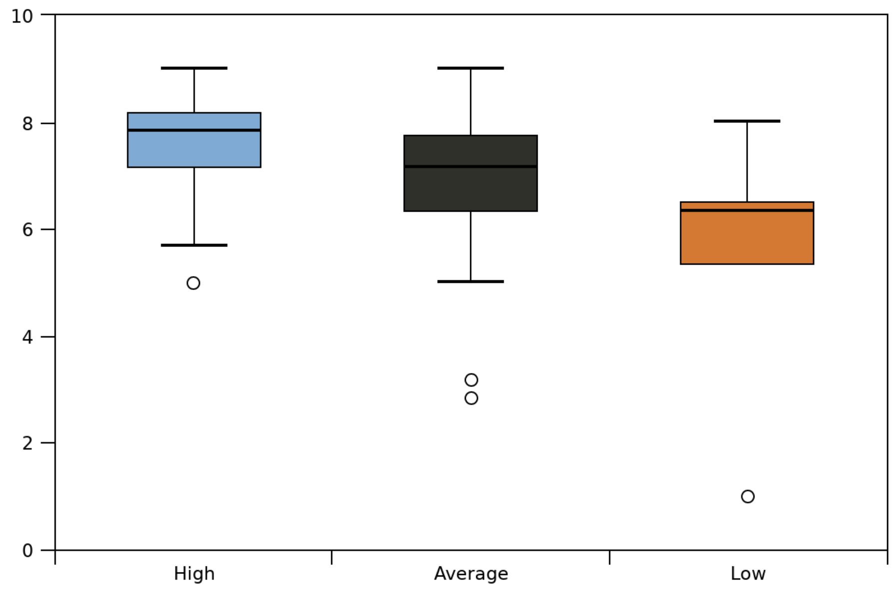
Boxplot of Warmth by Low, Average and High Proficiency Scores



The boxplot suggests notable variations in "Competence" scores among individuals with differing Proficiency levels. It visually confirms that the perceived " Competence " is not uniformly distributed across all Proficiency groups. Given the distinct separation of the boxplots, Proficiency levels impact how individuals perceive " Competence." See Figure 17 for Boxplot of Competence by Low, Average and High Proficiency Scores.

Figure 17

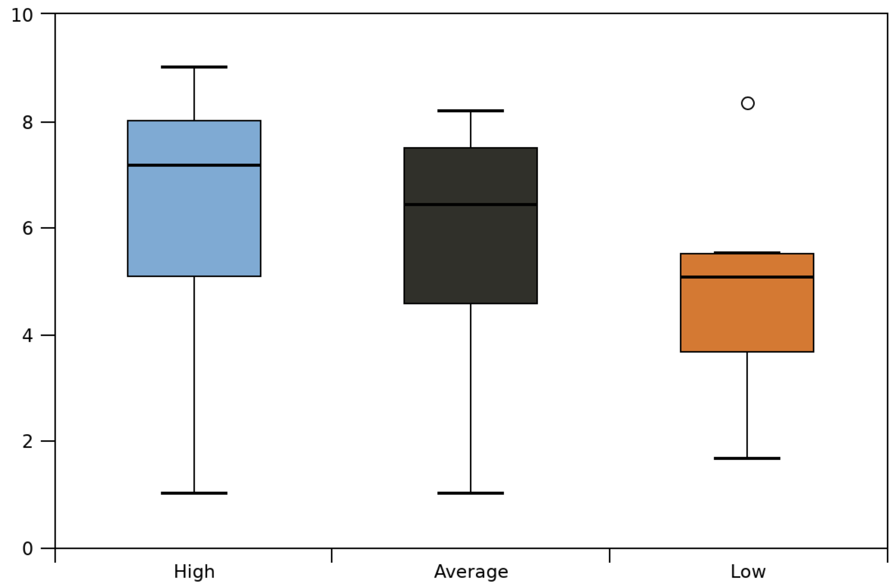
Boxplot of Competence by Low, Average and High Proficiency Scores



The boxplot suggests notable variations in "Discomfort" scores among individuals with differing Proficiency levels. It visually confirms that the perceived " Discomfort " is not uniformly distributed across all Proficiency groups. Given the distinct separation of the boxplots, Proficiency levels impact how individuals perceive " Discomfort." See Figure 18 for Boxplot of Discomfort by Low, Average and High Proficiency Scores.

Figure 18

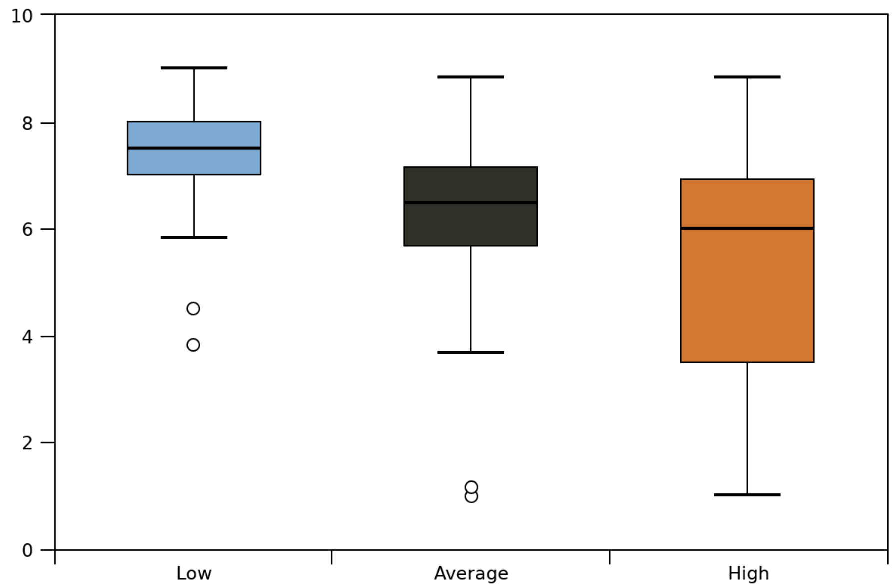
Boxplot of Discomfort by Low, Average and High Proficiency Scores



The boxplot suggests notable variations in "Warmth" scores among individuals with differing Dependence levels. It visually confirms that the perceived " Warmth " is not uniformly distributed across all Dependence groups. Given the distinct separation of the boxplots, Dependence levels impact how individuals perceive " Warmth." See Figure 19 for Boxplot of Warmth by Low, Average and High Dependence Scores.

Figure 19

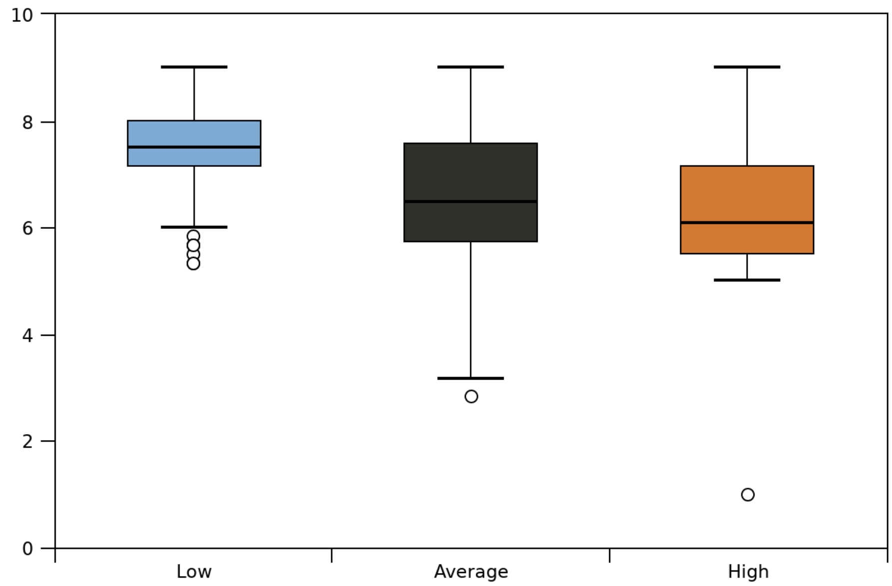
Boxplot of Warmth by Low, Average and High Dependence Scores



The boxplot suggests notable variations in "Competence" scores among individuals with differing Dependence levels. It visually confirms that the perceived " Competence " is not uniformly distributed across all Dependence groups. Given the distinct separation of the boxplots, Dependence levels impact how individuals perceive " Competence." See Figure 20 for Boxplot of Competence by Low, Average and High Dependence Scores.

Figure 20

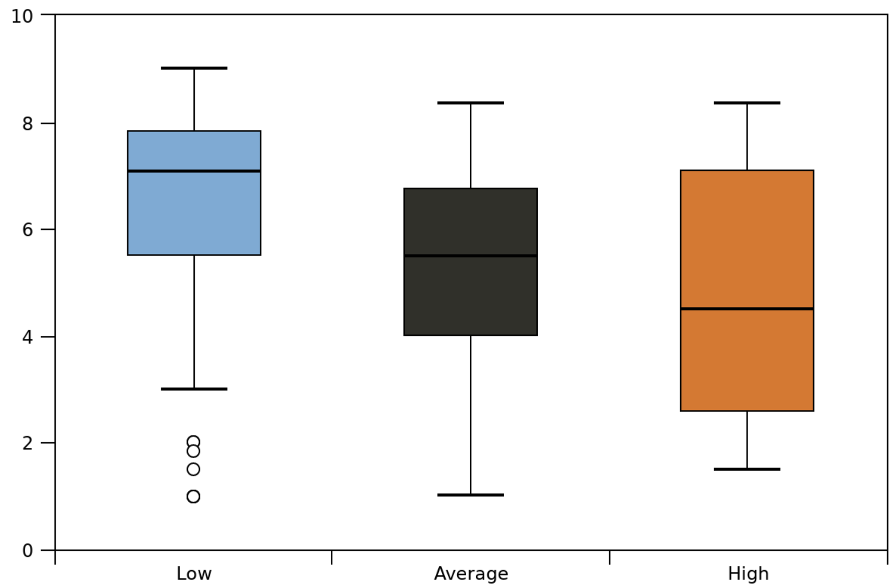
Boxplot of Competence by Low, Average and High Dependence Scores



The boxplot suggests notable variations in "Discomfort" scores among individuals with differing Dependence levels. It visually confirms that the perceived " Discomfort " is not uniformly distributed across all Dependence groups. Given the distinct separation of the boxplots, Dependence levels impact how individuals perceive " Discomfort." See Figure 21 for Boxplot of Discomfort by Low, Average and High Dependence Scores.

Figure 21

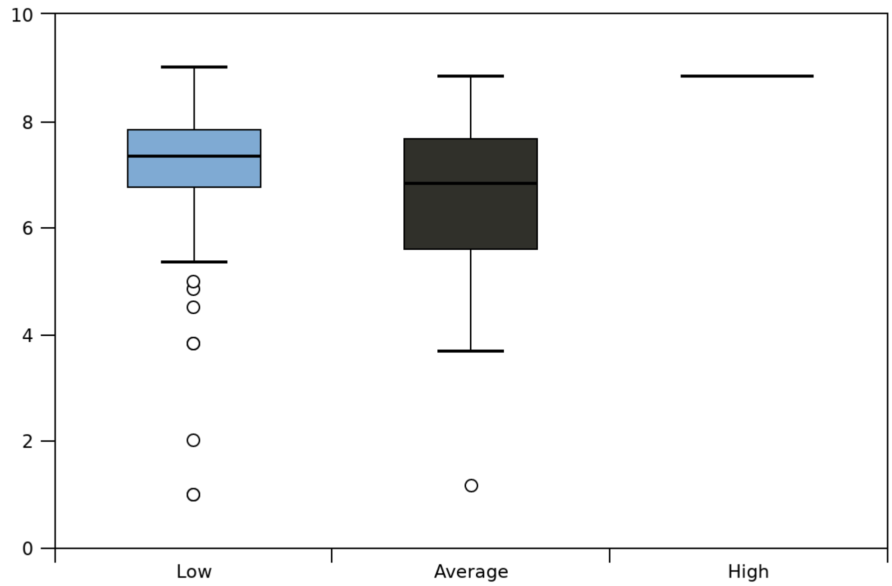
Boxplot of Discomfort by Low, Average and High Dependence Scores



The boxplot suggests notable variations in "Warmth" scores among individuals with differing Vulnerability levels. It visually confirms that the perceived " Warmth " is not uniformly distributed across all Vulnerability groups. Given the distinct separation of the boxplots, Vulnerability levels impact how individuals perceive " Warmth.". See Figure 22 for Boxplot of Warmth by Low, Average and High Vulnerability Scores.

Figure 22

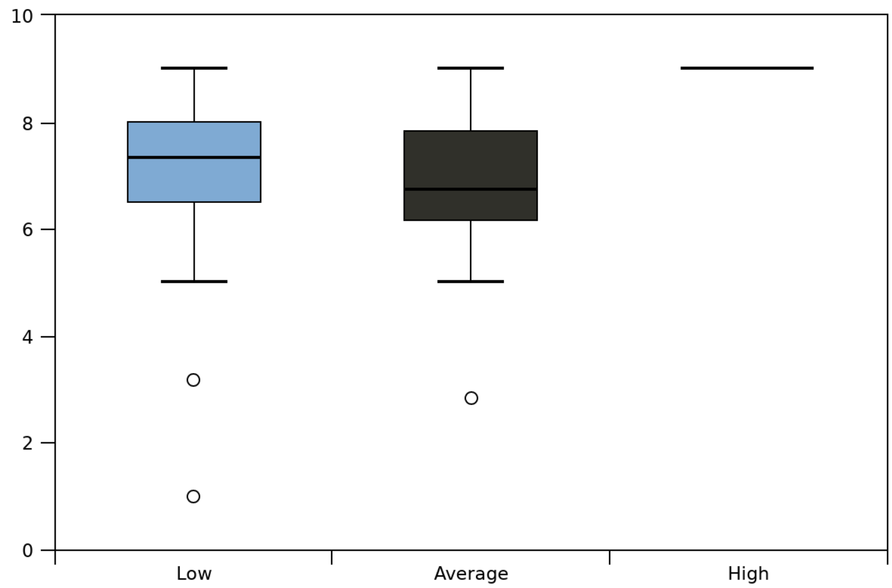
Boxplot of Warmth by Low, Average and High Vulnerability Scores



The boxplot suggests notable variations in "Competence" scores among individuals with differing Vulnerability levels. It visually confirms that the perceived " Competence " is not uniformly distributed across all Vulnerability groups. Given the distinct separation of the boxplots, Vulnerability levels impact how individuals perceive " Competence." See Figure 23 for Boxplot of Competence by Low, Average and High Vulnerability Scores.

Figure 23

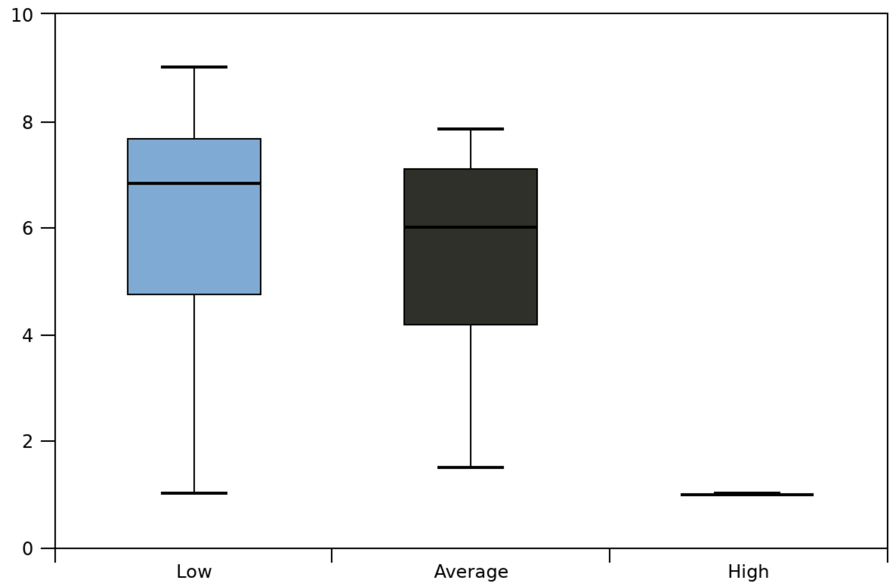
Boxplot of Competence by Low, Average and High Vulnerability Scores



The boxplot suggests notable variations in "Discomfort" scores among individuals with differing Vulnerability levels. It visually confirms that the perceived " Discomfort " is not uniformly distributed across all Vulnerability groups. Given the distinct separation of the boxplots, Vulnerability levels impact how individuals perceive " Discomfort." See Figure 24 for Boxplot of Discomfort by Low, Average and High Vulnerability Scores.

Figure 24

Boxplot of Discomfort by Low, Average and High Vulnerability Scores



Descriptive statistics were computed for Optimism, Proficiency, Dependence, and Vulnerability. Optimism scores averaged 4.02 (*SD* = 0.56, *SEM* = 0.05, Min = 2.25, Max = 5.00, Skewness = -0.47, Kurtosis = 0.32). Proficiency scores had a mean of 3.93 (*SD* = 0.58, *SEM* = 0.05, Min = 2.25, Max = 5.00, Skewness = -0.40, Kurtosis = 0.04). Dependence scores averaged 2.07 (*SD* = 0.72, *SEM* = 0.06, Min = 1.00, Max = 5.00, Skewness = 1.48, Kurtosis = 3.51). Vulnerability scores had an average of 2.13 (*SD* = 0.63, *SEM* = 0.05, Min = 1.00, Max = 4.33, Skewness = 0.44, Kurtosis = 0.25). Skewness values greater than 2 in absolute terms indicate asymmetry, and kurtosis values equal to or exceeding 3 signify a departure from a normal distribution, indicating a tendency to produce outliers (Westfall & Henning, 2013). Detailed summary statistics are available in Table 13.

Table 13

Summary Statistics Table for Interval and Ratio Variables

Variable	M	SD	n	SE_M	Min	Max	Skewness	Kurtosis
Optimism	4.02	0.56	137	0.05	2.25	5.00	-0.47	0.32
Proficiency	3.93	0.58	137	0.05	2.25	5.00	-0.40	0.04
Dependence	2.07	0.72	137	0.06	1.00	5.00	1.48	3.51
Vulnerability	2.13	0.63	137	0.05	1.00	4.33	0.44	0.25

Note. '-' indicates the statistic is undefined due to constant data or an insufficient sample size.

Descriptive statistics were computed for Warmth, Competence, and Discomfort. Warmth scores had a mean of 6.97 (*SD* = 1.43, *SEM* = 0.12, Min = 1.00, Max = 9.00, Skewness = -2.06, Kurtosis = 5.66). Competence scores averaged 7.14 (*SD* = 1.22, *SEM* = 0.10, Min = 1.00, Max = 9.00, Skewness = -1.59, Kurtosis = 4.83). Discomfort scores had an average of 5.95 (*SD* = 2.13, *SEM* = 0.18, Min = 1.00, Max = 9.00, Skewness = -0.91, Kurtosis = -0.24). Skewness values greater than 2 in absolute terms indicate asymmetry, while kurtosis values equal to or exceeding 3 signify a deviation from a normal distribution, indicating a tendency to produce outliers (Westfall & Henning, 2013). Detailed summary statistics are available in Table 14.

Table 14

Summary Statistics Table for Interval and Ratio Variables

Variable	M	SD	n	SE_M	Min	Max	Skewness	Kurtosis
Warmth	6.97	1.43	137	0.12	1.00	9.00	-2.06	5.66
Competence	7.14	1.22	137	0.10	1.00	9.00	-1.59	4.83
Discomfort	5.95	2.13	137	0.18	1.00	9.00	-0.91	-0.24

Note. '-' indicates the statistic is undefined due to constant data or an insufficient sample size.

Data Validation

Cronbach's Alpha

A Cronbach alpha coefficient was calculated for the Optimism scale, consisting of items 1-4 of the TAP. The Cronbach's alpha coefficient was evaluated using the guidelines suggested by George and Mallery (2018) where > .9 excellent, > .8 good, > .7 acceptable, > .6 questionable, > .5 poor, and ≤ .5 unacceptable.

The items for Optimism had a Cronbach's alpha coefficient of .63, indicating questionable reliability. Table 15 presents the results of the reliability analysis.

Table 15

Reliability Table for Optimism

Scale	No. of Items	α	Lower Bound	Upper Bound
Optimism	4	.63	.55	.72

Note. The lower and upper bounds of Cronbach's α were calculated using a 95.00% confidence interval.

A Cronbach's alpha coefficient for the Proficiency scale, encompassing items 5-8 of the TAP questionnaire was computed. The evaluation followed the criteria outlined by George and Mallery (2018), where values > .9 are excellent, > .8 are good, > .7 are acceptable, > .6 are questionable, > .5 are poor, and ≤ .5 are considered unacceptable.

For the Proficiency items, the Cronbach's alpha coefficient was .58, indicating poor reliability. Details of the reliability analysis can be found in Table 16.

Table 16

Reliability Table for Proficiency

Scale	No. of Items	α	Lower Bound	Upper Bound
Proficiency	4	.58	.48	.67

Note. The lower and upper bounds of Cronbach's α were calculated using a 95.00% confidence interval.

A Cronbach's alpha coefficient for the Dependence scale, comprising items 9-11 of the TAP questionnaire was computed. The assessment was done according to George and Mallery's (2018) guidelines, where values > .9 are excellent, > .8 are good, > .7 are acceptable, > .6 are questionable, > .5 are poor, and ≤ .5 are deemed unacceptable.

For the Dependence items, the Cronbach's alpha coefficient was .68, indicating questionable reliability. The results of the reliability analysis are displayed in Table 17.

Table 17

Reliability Table for Dependence

Scale	No. of Items	α	Lower Bound	Upper Bound
Dependence	3	.68	.61	.76

Note. The lower and upper bounds of Cronbach's α were calculated using a 95.00% confidence interval.

A Cronbach's alpha coefficient for the Vulnerability scale, encompassing items 12-14 of the TAP questionnaire was computed. The assessment followed the criteria outlined by George and Mallery (2018), where values > .9 are excellent, > .8 are good, > .7 are acceptable, > .6 are questionable, > .5 are poor, and ≤ .5 are considered unacceptable.

For the Vulnerability items, the Cronbach's alpha coefficient was .55, indicating poor reliability. Details of the reliability analysis are presented in Table 18.

Table 18

Reliability Table for Vulnerability

Scale	No. of Items	α	Lower Bound	Upper Bound
Vulnerability	3	.55	.44	.66

Note. The lower and upper bounds of Cronbach's α were calculated using a 95.00% confidence interval.

A Cronbach alpha coefficient was calculated for the Warmth scale, consisting of items 1-6 of the RoSAS. The Cronbach's alpha coefficient was evaluated using the guidelines suggested by George and Mallery (2018) where > .9 excellent, > .8 good, > .7 acceptable, > .6 questionable, > .5 poor, and ≤ .5 unacceptable.

The items for Warmth had a Cronbach's alpha coefficient of .92, indicating excellent reliability. Table 19 presents the results of the reliability analysis.

Table 19

Reliability Table for Warmth

Scale	No. of Items	α	Lower Bound	Upper Bound
Warmth	6	.92	.90	.94

Note. The lower and upper bounds of Cronbach's α were calculated using a 95.00% confidence interval.

A Cronbach's alpha coefficient for the Competence scale, which included items 7-12 of the RoSAS questionnaire was computed. The assessment adhered to the criteria set by George and Mallery (2018), where values > .9 are excellent, > .8 are good, > .7 are acceptable, > .6 are questionable, > .5 are poor, and ≤ .5 are deemed unacceptable.

For the Competence items, the Cronbach's alpha coefficient was .89, indicating good reliability. The results of the reliability analysis can be found in Table 20.

Table 20

Reliability Table for Competence

Scale	No. of Items	α	Lower Bound	Upper Bound
Competence	6	.89	.87	.92

Note. The lower and upper bounds of Cronbach's α were calculated using a 95.00% confidence interval.

Cronbach's Alpha

A Cronbach's alpha coefficient for the Discomfort scale, which involved items 13-18 of the RoSAS questionnaire was computed. The evaluation followed George and Mallery's (2018) guidelines, where values > .9 are excellent, > .8 are good, > .7 are acceptable, > .6 are questionable, > .5 are poor, and ≤ .5 are considered unacceptable.

For the Discomfort items, the Cronbach's alpha coefficient was .96, signifying excellent reliability. Detailed results of the reliability analysis are shown in Table 21.

Table 21

Reliability Table for Discomfort

Scale	No. of Items	α	Lower Bound	Upper Bound
Discomfort	6	.96	.95	.97

Note. The lower and upper bounds of Cronbach's α were calculated using a 95.00% confidence interval.

Tests of Statistical Assumptions

Pearson Correlation Analysis

Introduction

A Pearson correlation analysis was performed to examine the relationships between Warmth, Competence, and Discomfort. Cohen's criteria were employed to assess the strength of these relationships: coefficients between .10 and .29 denoted a small effect size, coefficients between .30 and .49 indicated a moderate effect size, and coefficients exceeding .50 were considered as a large effect size (Cohen, 1988).

Assumptions

Linearity. A Pearson correlation necessitates a linear relationship between each pair of variables (Conover & Iman, 1981. This assumption is compromised if there is curvature among the points on the scatterplot for any variable pair. Scatterplots illustrating the correlations are displayed in Figures 25 and 26, with a regression line included to aid interpretation.

Figure 25

Scatterplots with Regression Line Added For Warmth and Competence (Left), Warmth and Discomfort (Right)

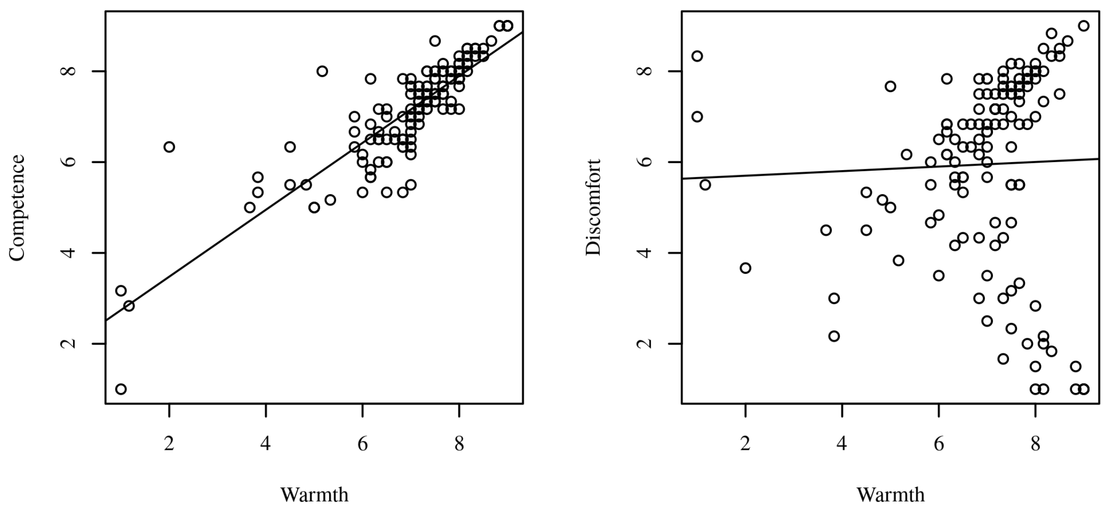
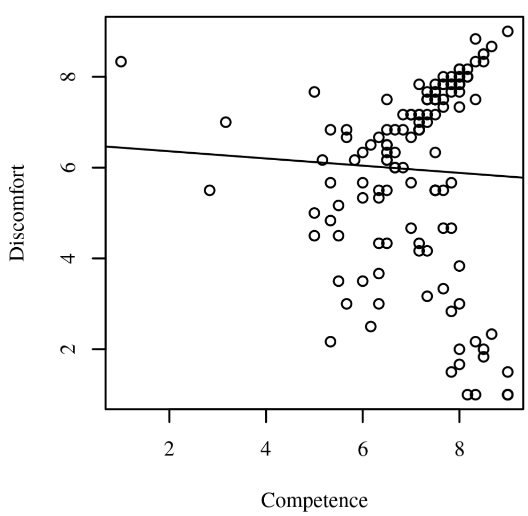


Figure 26

Scatterplots with the regression line added for Competence and Discomfort



Results

The result of the correlations was examined using the Holm correction to adjust for multiple comparisons based on an alpha value of .05. A significant positive correlation was observed between Warmth and Competence, with a correlation of .87, indicating a large effect size ($p < .001$, 95.00% CI = [.82, .90]). This suggests that as Warmth increases, Competence tends to increase. No other significant correlations were found. Table 22 presents the results of the correlations.

Table 22

Pearson Correlation Results Among Warmth, Competence, and Discomfort

Combination	*r*	95.00% CI	*n*	*p*
Warmth-Competence	.87	[.82, .90]	137	< .001
Warmth-Discomfort	.03	[-.13, .20]	137	1.000
Competence-Discomfort	-.05	[-.21, .12]	137	1.000

Note. p-values adjusted using the Holm correction.

Shapiro-Wilk Test

Results

Shapiro-Wilk tests were conducted in order to determine whether the distributions of Optimism, Proficiency, Dependence, Vulnerability, Warmth, Competence, and Discomfort were significantly different from a normal distribution. The following variables had distributions which significantly differed from normality based on an alpha of .05: Optimism ($W = 0.96$, $p < .001$), Proficiency ($W = 0.96$, $p < .001$), Dependence ($W = 0.87$, $p < .001$), Vulnerability ($W = 0.96$, $p < .001$), Warmth ($W = 0.82$, $p < .001$), Competence ($W = 0.89$, $p < .001$), and Discomfort ($W = 0.89$, $p < .001$). The results are presented in Table 23.

Table 23

Shapiro-Wilk Test Results

Variable	*W*	*p*
Optimism	0.96	< .001
Proficiency	0.96	< .001
Dependence	0.87	< .001
Vulnerability	0.96	< .001
Warmth	0.82	< .001
Competence	0.89	< .001
Discomfort	0.89	< .001

Levene's Test

Introduction

Levene's test was conducted for Warmth, Competence, and Discomfort by Low, Average and High Optimism Scores, Low, Average and High Proficiency Scores, Low, Average and High Dependence Scores, and Low, Average and High Vulnerability Scores. Levene's test, which is typically employed to evaluate the fulfillment of the homogeneity of variance assumption, was utilized in this analysis, following the method introduced by Levene in 1960. The homogeneity of variance assumption posits that the variance of the dependent variable should be roughly uniform across all groups. The calculations involved median centering, and an alpha level of 0.05 was employed for interpretation.

Results

The outcomes of Levene's tests for Warmth, Competence, and Discomfort were not statistically significant, as evidenced by F (25, 111) = 1.10, p = .353 for Warmth, F (25, 111) = 0.81, p = .726 for Competence, and F (25, 111) = 1.23, p = .230 for Discomfort. These results indicate that the assumption of homogeneity of variance was satisfied for all three variables.

Inferential Results

MANOVA

Introduction

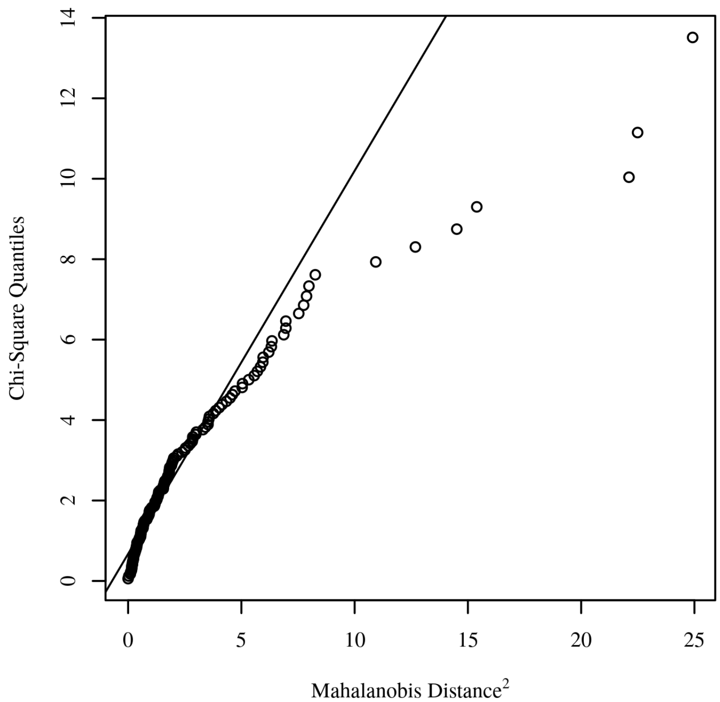
A multivariate analysis of variance (MANOVA) was conducted to assess if there were significant differences in the linear combination of Warmth, Competence, and Discomfort between the levels of Low, Average and High Optimism Scores, Low, Average and High Proficiency Scores, Low, Average and High Dependence Scores, and Low, Average and High Vulnerability Scores.

Assumptions

Multivariate Normality. In order to assess the multivariate normality assumption, calculated the squared Mahalanobis distances for the residuals of the model and plotted them against the quantiles of a Chi-square distribution, as per the methods outlined by DeCarlo (1997) and Field (2017). In the scatterplot, the solid line represented the expected quantiles of a normal distribution. A relatively straight line formed by the points would indicate that multivariate normality could be assumed. However, significant deviations suggested potential unreliable parameter estimates, indicating a violation of the multivariate normality assumption. The scatterplot illustrating normality is shown in Figure 27.

Figure 27

Chi-Square Q-Q Plot for Squared Mahalanobis Distances of Model Residuals to Test Multivariate Normality



Homogeneity of Covariance Matrices. Due to specific characteristics of the data, it was not possible to calculate some of the covariance matrices. Consequently, Box's M test could not be performed.

Multivariate Outliers. To pinpoint influential data points in the model residuals, Mahalanobis distances were computed and compared against a $\chi2$ distribution, following the approach outlined by Newton and Rudestam (2012). An outlier was identified as any Mahalanobis distance surpassing 16.27, corresponding to the 0.999 quantile of a $\chi2$ distribution with 3 degrees of freedom, as per Kline (2015). In total, 3 observations were identified as outliers.

Absence of Multicollinearity. A correlation matrix to assess potential multicollinearity among the dependent variables was computed. For all variable combinations, the correlations were below 0.9 in absolute value. This suggests that the study results are unlikely to be substantially affected by multicollinearity. Detailed correlations can be found in Table 24.

Table 24

Correlations Between Dependent Variables

Variable	1	2	3
1. Warmth	-		
2. Competence	.87	-	
3. Discomfort	.03	-.05	-

Results

The main effect for Low, Average and High Optimism Scores was significant, $F(6, 254) = 3.25$, $p = .004$, $\eta^2_p = 0.07$, suggesting the linear combination of Warmth, Competence, and Discomfort was significantly different among the levels of Low, Average and High Optimism Scores. The main effect for Low, Average and High Proficiency Scores was significant, $F(6, 254) = 4.03$, $p < .001$, $\eta^2_p = 0.09$, suggesting the linear combination of Warmth, Competence, and Discomfort was significantly different among the levels of Low, Average and High Proficiency Scores. The main effect for Low, Average and High Dependence Scores was significant, $F(6, 254) = 3.72$, $p = .001$, $\eta^2_p = 0.08$, suggesting the linear combination of Warmth, Competence, and Discomfort was significantly different among the levels of Low, Average and High Dependence Scores. The main effect for Low, Average and High Vulnerability Scores was not significant, $F(6, 254) = 1.35$, $p = .235$, $\eta^2_p = 0.03$, suggesting the linear combination of

Warmth, Competence, and Discomfort was similar for each level of Low, Average and High Vulnerability Scores. The MANOVA results are presented in Table 25.

Table 25

MANOVA Results for Warmth, Competence, and Discomfort by Low, Average and High Optimism Scores, Low, Average and High Proficiency Scores, Low, Average and High Dependence Scores, and Low, Average and High Vulnerability Scores

Variable	Pillai	F	df	Residual df	p	η_p^2
Low, Average and High Optimism Scores	0.14	3.25	6	254	.004	0.07
Low, Average and High Proficiency Scores	0.17	4.03	6	254	< .001	0.09
Low, Average and High Dependence Scores	0.16	3.72	6	254	.001	0.08
Low, Average and High Vulnerability Scores	0.06	1.35	6	254	.235	0.03

Posthocs. To further examine the effects of Low, Average and High Optimism Scores, Low, Average and High Proficiency Scores, Low, Average and High Dependence Scores, and Low, Average and High Vulnerability Scores on Warmth, Competence, and Discomfort, an analysis of variance (ANOVA) was conducted for each dependent variable.

ANOVA

An analysis of variance (ANOVA) was conducted to determine whether there were significant differences in Warmth by Low, Average and High Optimism Scores, Low, Average and High Proficiency Scores, Low, Average and High Dependence Scores, and Low, Average and High Vulnerability Scores.

The ANOVA was examined based on an alpha value of .05. The results of the ANOVA were significant, $F(8, 128) = 7.73$, $p < .001$, indicating there were significant differences in Warmth among the levels of Low, Average and High Optimism Scores, Low, Average and High Proficiency Scores, Low, Average and High Dependence Scores, and Low, Average and High

Vulnerability Scores (Table 34). The main effect, Low, Average and High Optimism Scores was significant, $F(2, 128) = 4.13$, $p = .018$, $\eta_p^2 = 0.06$, indicating there were significant differences in Warmth by Low, Average and High Optimism Scores levels. The main effect, Low, Average and High Proficiency Scores was significant, $F(2, 128) = 4.77$, $p = .010$, $\eta_p^2 = 0.07$, indicating there were significant differences in Warmth by Low, Average and High Proficiency Scores levels. The main effect, Low, Average and High Dependence Scores was significant, $F(2, 128) = 7.96$, $p < .001$, $\eta_p^2 = 0.11$, indicating there were significant differences in Warmth by Low, Average and High Dependence Scores levels. The main effect, Low, Average and High Vulnerability Scores was not significant, $F(2, 128) = 1.54$, $p = .219$, indicating there were no significant differences of Warmth by Low, Average and High Vulnerability Scores levels. The means and standard deviations are presented in Table 26. A bar plot of the means is presented in Figure 28 -Figure 30.

Table 26

Analysis of Variance Table for Warmth by Low, Average and High Optimism Scores, Low, Average and High Proficiency Scores, Low, Average and High Dependence Scores, and Low, Average and High Vulnerability Scores

Term	*SS*	*df*	*F*	*p*	η_p^2
Low, Average and High Optimism Scores	12.14	2	4.13	.018	0.06
Low, Average and High Proficiency Scores	14.03	2	4.77	.010	0.07
Low, Average and High Dependence Scores	23.41	2	7.96	< .001	0.11
Low, Average and High Vulnerability Scores	4.52	2	1.54	.219	0.02
Residuals	188.30	128			

Figure 28

Means of Warmth by Low, Average and High Optimism Scores with 95.00% CI Error Bars

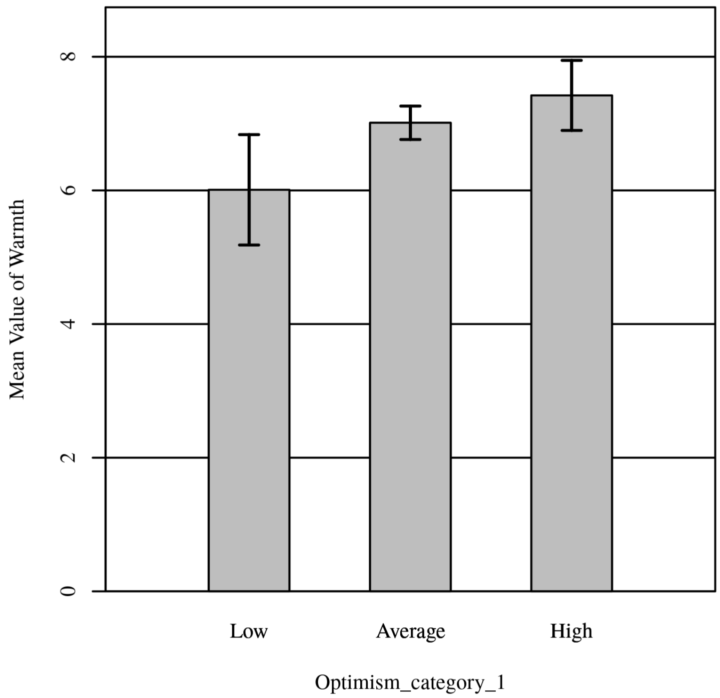


Figure 29

Means of Warmth by Low, Average and High Proficiency Scores with 95.00% CI Error Bars

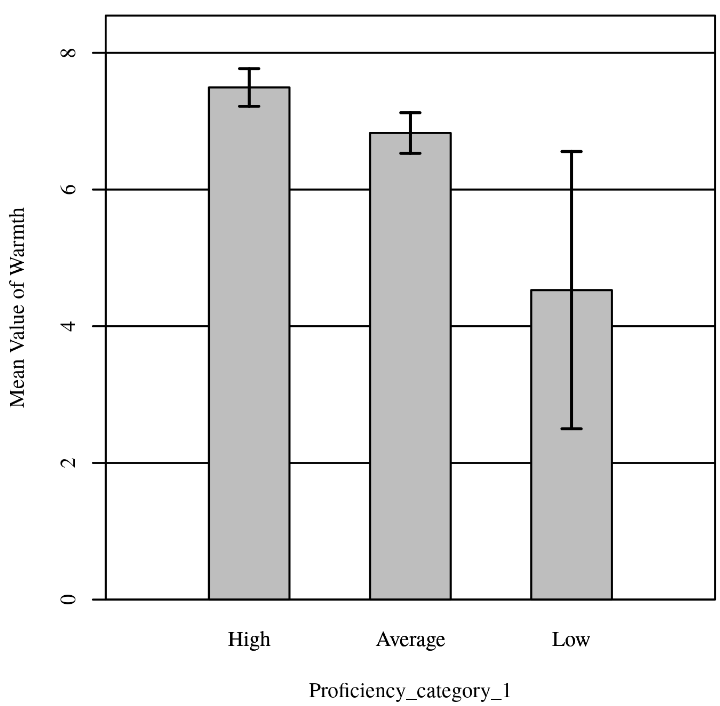
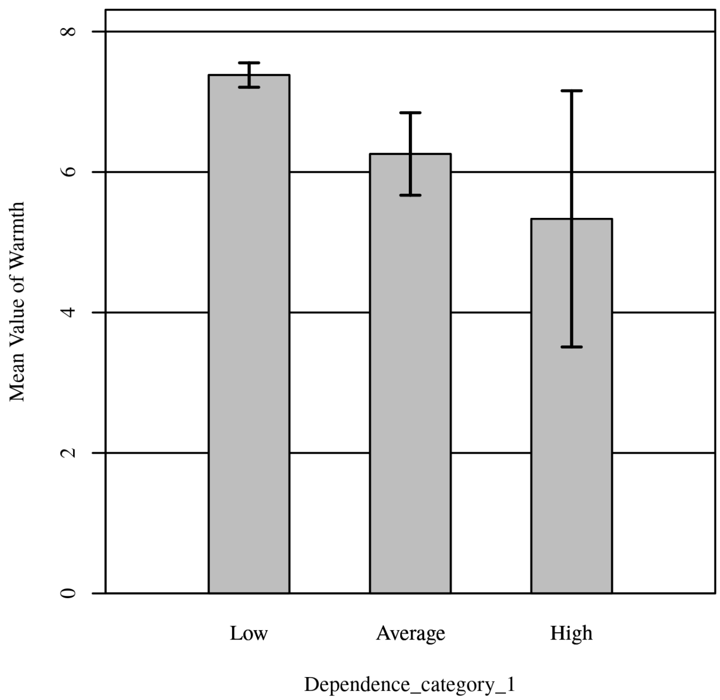


Figure 30

Means of Warmth by Low, Average and High Dependence Scores with 95.00% CI Error Bars



An analysis of variance (ANOVA) was conducted to determine whether there were significant differences in Competence by Low, Average and High Optimism Scores, Low, Average and High Proficiency Scores, Low, Average and High Dependence Scores, and Low, Average and High Vulnerability Scores.

The ANOVA was examined based on an alpha value of .05. The results of the ANOVA were significant, $F(8, 128) = 6.40$, $p < .001$, indicating there were significant differences in Competence among the levels of Low, Average and High Optimism Scores, Low, Average and High Proficiency Scores, Low, Average and High Dependence Scores, and Low, Average and High Vulnerability Scores (Table 35). The main effect, Low, Average and High Optimism Scores was significant, $F(2, 128) = 3.14$, $p = .047$, $\eta_p^2 = 0.05$, indicating there were significant differences in Competence by Low, Average and High Optimism Scores levels. The main effect, Low, Average and High Proficiency Scores was significant, $F(2, 128) = 3.17$, $p = .045$, $\eta_p^2 = 0.05$, indicating there were significant differences in Competence by Low, Average and High Proficiency Scores levels. The main effect, Low, Average and High Dependence Scores was significant, $F(2, 128) = 7.03$, $p = .001$, $\eta_p^2 = 0.10$, indicating there were significant differences in Competence by Low, Average and High Dependence Scores levels. The main effect, Low, Average and High Vulnerability Scores was not significant, $F(2, 128) = 2.34$, $p = .100$, indicating there were no significant differences of Competence by Low, Average and High Vulnerability Scores levels. The means and standard deviations are presented in Table 27. A bar plot of the means is presented in Figure 31 - Figure 33.

Table 27

Analysis of Variance Table for Competence by Low, Average and High Optimism Scores, Low, Average and High Proficiency Scores, Low, Average and High Dependence Scores, and Low, Average and High Vulnerability Scores

Term	*SS*	*df*	*F*	*p*	η_p^2
Low, Average and High Optimism Scores	7.05	2	3.14	.047	0.05
Low, Average and High Proficiency Scores	7.13	2	3.17	.045	0.05
Low, Average and High Dependence Scores	15.80	2	7.03	.001	0.10
Vulnerability_category_1Low, Average and High Vulnerability Scores	5.26	2	2.34	.100	0.04
Residuals	143.79	128			

Figure 31

Means of Competence by Low, Average and High Optimism Scores with 95.00% CI Error Bars

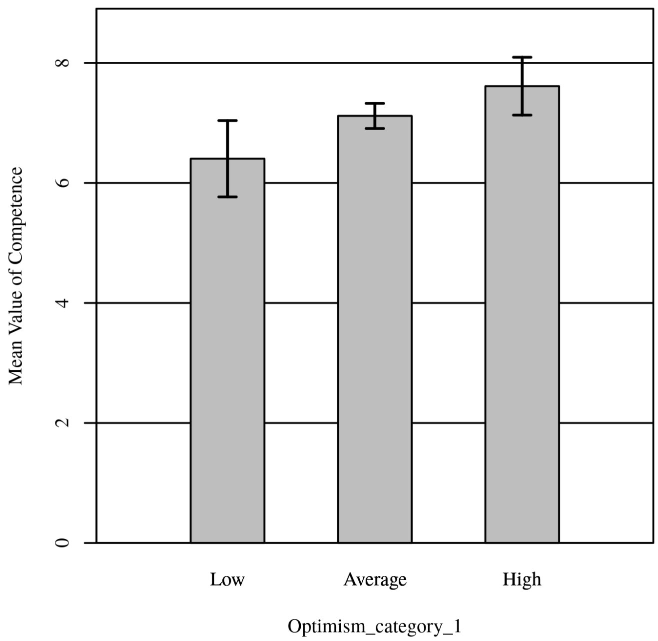


Figure 32

Means of Competence by Low, Average and High Proficiency Scores with 95.00% CI Error Bars

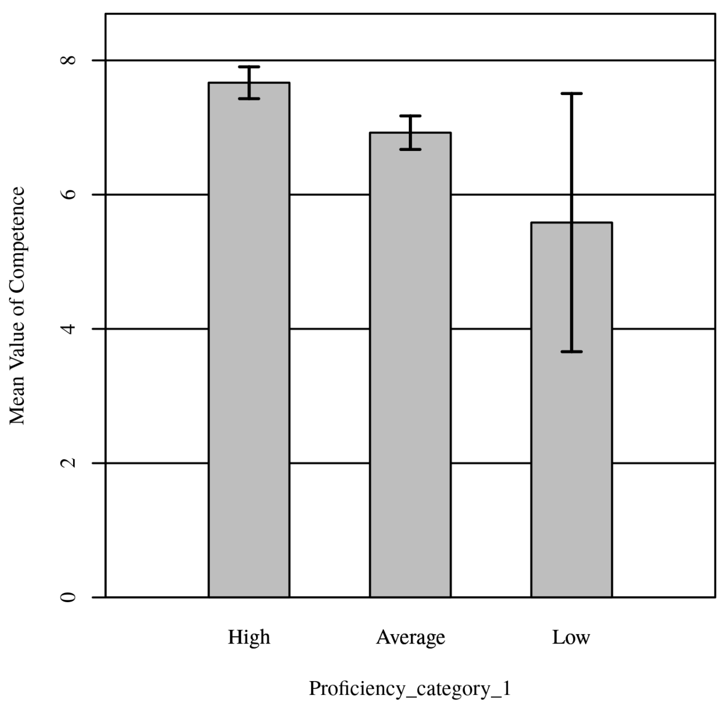
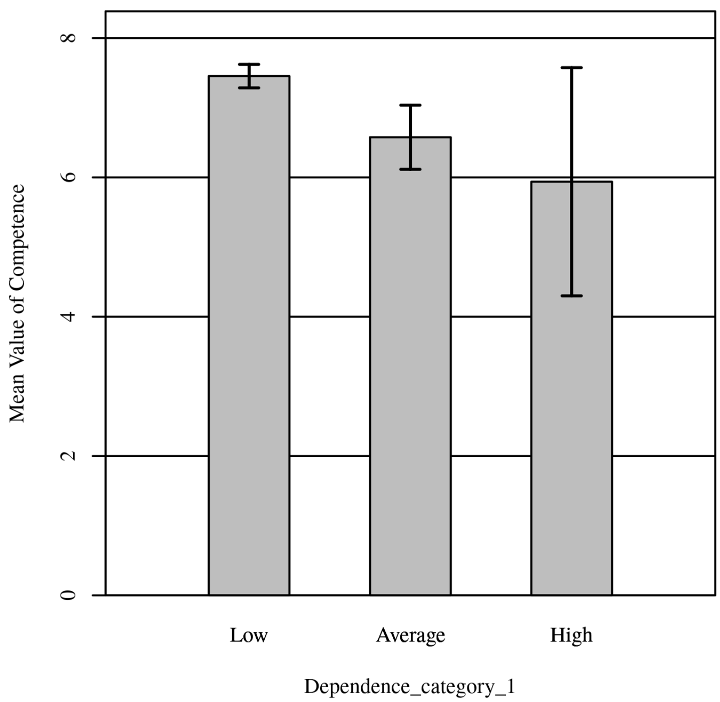


Figure 33

Means of Competence by Low, Average and High Dependence Scores with 95.00% CI Error Bars



An analysis of variance (ANOVA) was conducted to determine whether there were significant differences in Discomfort by Low, Average and High Optimism Scores, Low, Average and High Proficiency Scores, Low, Average and High Dependence Scores, and Low, Average and High Vulnerability Scores.

The ANOVA was examined based on an alpha value of .05. The results of the ANOVA were significant, $F(8, 128) = 3.61$, $p < .001$, indicating there were significant differences in Discomfort among the levels of Low, Average and High Optimism Scores, Low, Average and High Proficiency Scores, Low, Average and High Dependence Scores, and Low, Average and High Vulnerability Scores (Table 24). The main effect, Low, Average and High Optimism

Scores was significant, $F(2, 128) = 5.83$, $p = .004$, $\eta_p^2 = 0.08$, indicating there were significant differences in Discomfort by Low, Average and High Optimism Scores levels. The main effect, Low, Average and High Proficiency Scores was significant, $F(2, 128) = 3.72$, $p = .027$, $\eta_p^2 = 0.05$, indicating there were significant differences in Discomfort by Low, Average and High Proficiency Scores levels. The main effect, Low, Average and High Dependence Scores was not significant, $F(2, 128) = 2.73$, $p = .069$, indicating there were no significant differences of Discomfort by Low, Average and High Dependence Scores levels. The main effect, Low, Average and High Vulnerability Scores was not significant, $F(2, 128) = 1.75$, $p = .178$, indicating there were no significant differences of Discomfort by Low, Average and High Vulnerability Scores levels. The means and standard deviations are presented in Table 28. A bar plot of the means is presented in Figure 34 and Figure 35.

Table 28

Analysis of Variance Table for Discomfort by Low, Average and High Optimism Scores, Low, Average and High Proficiency Scores, Low, Average and High Dependence Scores, and Low, Average and High Vulnerability Scores

Term	*SS*	*df*	*F*	*p*	η_p^2
Low, Average and High Optimism Scores	46.01	2	5.83	.004	0.08
Low, Average and High Proficiency Scores	29.40	2	3.72	.027	0.05
Low, Average and High Dependence Scores	21.54	2	2.73	.069	0.04
Low, Average and High Vulnerability Scores	13.81	2	1.75	.178	0.03
Residuals	505.37	128			

Figure 34

Means of Discomfort by Low, Average and High Optimism Scores with 95.00% CI Error Bars

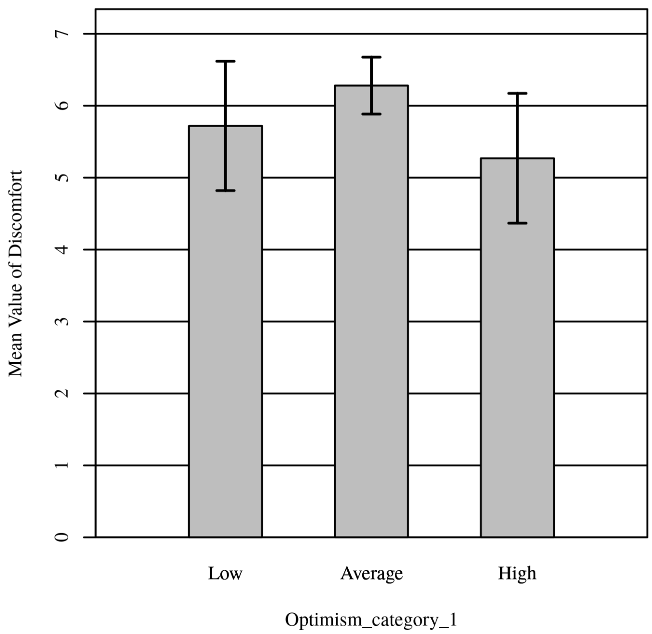
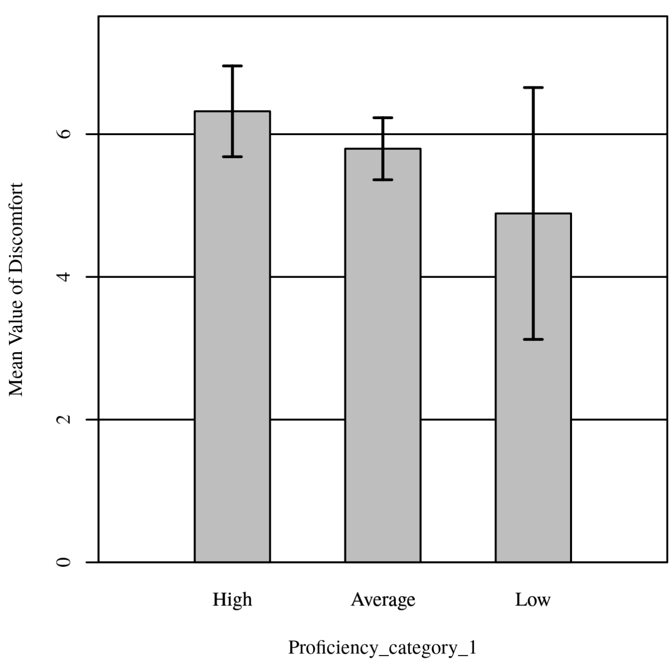


Figure 35

Means of Discomfort by Low, Average and High Proficiency Scores with 95.00% CI Error Bars



Findings Summary

The study found significant main effects for Optimism, Proficiency, and Dependence but not for Vulnerability. The main effect of Optimism was significant ($F = 3.25$, $p = .004$, η2p = 0.07), indicating that the combined scores of Warmth, Competence, and Discomfort differed significantly among the different levels of Optimism. Similarly, the main effect of Proficiency was significant ($F = 4.03$, $p < .001$, η2p = 0.09), suggesting that the combined scores varied significantly across the Proficiency levels. Additionally, the main effect of Dependence was significant ($F = 3.72$, $p = .001$, η2p = 0.08), indicating significant differences in the combined scores among the levels of Dependence. However, the main effect of Vulnerability was not significant ($F = 1.35$, $p = .235$, η2p = 0.03), suggesting that the combined scores of Warmth, Competence, and Discomfort were similar across each level of Vulnerability. These results demonstrate that Optimism, Proficiency, and Dependence significantly impact the perception of Warmth, Competence, and Discomfort, while Vulnerability does not significantly influence these perceptions.

The ANOVA results revealed significant differences in Warmth, Competence, and Discomfort among the levels of Optimism, Proficiency, and Dependence, but not for Vulnerability. The overall ANOVA was significant ($F = 7.73$, $p < .001$), indicating significant differences in Warmth among the levels of Optimism, Proficiency, Dependence, and Vulnerability. The main effect for Optimism was significant ($F = 4.13$, $p = .018$, ηp2 = 0.06), suggesting significant differences in Warmth based on different levels of Optimism. Similarly, the main effect for Proficiency was significant ($F = 4.77$, $p = .010$, ηp2 = 0.07), indicating significant differences in Warmth among the levels of Proficiency. Additionally, the main effect for Dependence was significant ($F = 7.96$, $p < .001$, ηp2 = 0.11), suggesting significant differences in Warmth based on different levels of Dependence. However, the main effect for Vulnerability was not significant (F = 1.54, p = .219, ηp2 = 0.03), indicating no significant differences in Warmth among the levels of Vulnerability.

Similarly, the ANOVA results for competence indicated significant differences among the levels of Optimism, Proficiency, Dependence, and Vulnerability (F = 6.40, p < .001). The main effect for Optimism was significant (F = 3.14, p = .047, ηp2 = 0.05), suggesting significant differences in competence based on different levels of Optimism. The main effect for Proficiency was also significant (F = 3.17, p = .045, ηp2 = 0.05), indicating significant differences in competence among the levels of Proficiency. Moreover, the main effect for Dependence was significant (F = 7.03, p = .001, ηp2 = 0.10), suggesting significant differences in competence based on different levels of Dependence. However, the main effect for Vulnerability was not significant (F = 2.34, p = .100, ηp2 = 0.04), indicating no significant differences in competence among the levels of Vulnerability.

Furthermore, the ANOVA results for Discomfort revealed significant differences among the levels of Optimism, Proficiency, Dependence, and Vulnerability (F = 3.61, p < .001). The main effect for Optimism was significant (F = 5.83, p = .004, ηp2 = 0.08), suggesting significant differences in Discomfort based on different levels of Optimism. The main effect for Proficiency was also significant (F = 3.72, p = .027, ηp2 = 0.05), indicating significant differences in Discomfort among the levels of Proficiency. However, the main effect for Dependence was not significant (F = 2.73, p = .069, ηp2 = 0.04), suggesting no significant differences in Discomfort based on different levels of Dependence. Similarly, the main effect for Vulnerability was not significant (F = 1.75, p = .178, ηp2 = 0.03), indicating no significant differences in Discomfort among the levels of Vulnerability.

Chapter 5: Interpretation of Findings

Summary of The Underlying Study Issue

Globally, the healthcare industry faces ongoing pressure to achieve more work with limited resources. As the aging population grows and the number of healthcare professionals remains insufficient, the demands for care options continue to rise. The lack of personalized care, long waiting times, and high readmission rates contribute to poor patient outcomes. SARs offer support and assistance to both patients and healthcare providers. By delivering personalized care, reducing waiting times, and preventing readmissions, SARs can potentially enhance patient care. However, the effectiveness of using SAR's in hospital settings lacks sufficient research. This study aims to contribute to the knowledge in this field by investigating the efficacy of SARs in hospitals.

SARs are autonomous machines equipped with sensors and software that enable them to interact socially with humans (Montaño-Serrano et al., 2021). Primarily used in healthcare settings, SARs provide patients with non-clinical support, such as conversation and emotional companionship (Aymerich-Franch & Ferrer, 2021). They can offer reminders, monitor vital signs, and provide educational information about health conditions or medications.

As technology progresses, we can anticipate even more remarkable applications of SARs in healthcare settings (Christoforou et al., 2020; Getson & Nejat, 2021). There are numerous potential benefits of SARs in healthcare, including reducing the workload for healthcare professionals (Christoforou et al., 2020). SARs can undertake routine tasks such as monitoring vital signs or issuing reminders, enabling nurses to focus on critical responsibilities. Furthermore, SARs can provide emotional support to patients and their families, an essential but often overlooked aspect of healthcare. SARs can also educate patients about their health conditions or medications, ensuring optimal care. When patients are discharged, SARs can deliver instructions, improving patient understanding and reducing errors (Getson & Nejat, 2021). The repetition of information and the ability to answer questions enhance patients' retention of crucial details.

One of the most exciting aspects of SARs is their capacity to be customized for each patient's needs. For example, some patients respond favorably to SARs with a human-like form, while others prefer more animal-like robots (Getson & Nejat, 2021). Human-like robots can even elicit a sense that they possess their own mind. The possibilities are vast. SARs are more cost-effective than hiring additional staff members and can provide care and support 24/7.

While there are numerous potential benefits, there are also drawbacks to using SARs in healthcare settings. One significant concern is the risk of cyber-attacks as more devices become connected to the internet, making them potential targets for hackers. Additionally, some individuals may feel uncomfortable interacting with robots and prefer human interaction. Lastly, there is a potential risk of patients becoming overly dependent on SARs and losing their ability to perform basic tasks independently.

Extensive research has been conducted on the applications of SARs. Previous studies have also explored the relationship between users' sociodemographic factors and their acceptance of SAR technology (Flandorfer, 2012). However, despite the advanced nature of SAR technology, no existing research has examined users' inclination to adopt technology and the specific features of SAR robots. Therefore, this quantitative study aims to investigate the nurses technology adoption propensity index of SAR users and the characteristics of SAR robots.

The study's research question is: To what extent, if at all, do four aspects of the propensity for adopting technology predict three aspects of social attitudes towards assistive robotic caretakers among hospital nurses. The alternative hypothesis (Ha) is that the four aspects of the propensity for adopting technology predict three aspects of social attitudes towards SARs among hospital nurses.

This quantitative study aims to understand the degree to which perceived Warmth, Competence, and Discomfort of SAR caretakers among hospital nurses is predicted by their Optimism, Proficiency, Dependence and Vulnerability regarding technology adoption propensity.

A Summary of the Underlying Conceptual/Theoretical Framework of the Study

The theoretical framework for this study incorporates systems theory and Design for Six Sigma (DFSS). Systems theory, which is commonly used in science and engineering, focuses on understanding complex systems and their collective behaviors (Von Bertalanffy, 1972). It has been applied to numerous fields, like mathematics, engineering, and biology. Recently, systems theory has been increasingly used to study human behavior, recognizing humans as complex systems. In the context of this study, systems theory provides a foundation for exploring the relationships between SAR characteristics and users' technology adoption propensity.

Applying systems theory within this study provides valuable insights into the likelihood of SAR adoption among hospital nurses. It recognizes that individual, social, and contextual factors influence nurses' attitudes and behaviors toward SAR adoption. By adopting a system thinking approach, researchers can gain insights that inform the development and implementation of SARs in healthcare settings. It facilitates proactive planning and mitigation of potential disruptions. Systems theory considers the complexity and interconnectedness of system components, offering a holistic framework for understanding SAR adoption. It supports the exploration of nurse acceptance, potential challenges, and opportunities related to SAR adoption.

Overall, systems theory enhances the understanding of SAR adoption within the healthcare system and aids in maximizing the likelihood of successful implementation among hospital nurses.

Design for Six Sigma (DFSS) is a comprehensive approach to designing products and services that fully meet customer expectations (Chowdhury, 2002). It involves understanding customer needs, identifying the root causes of problems, and developing effective solutions (Anbari, 2002). DFSS emphasizes gathering customer feedback, analyzing data, and engaging stakeholders to understand customer expectations deeply. The design phase of DFSS involves rigorous analysis and testing to identify the most effective solution that aligns with customer requirements (Francisco et al., 2020). Verification and validation ensure that the solution meets customer needs and is scalable.

By applying the DFSS framework, organizations can gain valuable insights into the likelihood of SAR adoption among hospital nurses. DFSS methodology strongly emphasizes understanding customer needs, which, in this case, would involve comprehending the specific requirements and expectations of hospital nurses regarding SAR. Additionally, DFSS provides a systematic approach to data analysis, enabling researchers to identify patterns and correlations between specific SAR features and nurses' technology adoption propensity. By analyzing the data, researchers can determine which characteristics of SARs appeal most to nurses, addressing their needs and improving their overall acceptance.

Summary of the Methodology and Methods Used

The methodology used in this study is quantitative and predictive. It employs a non-experimental research design and involves the administration of two self-report surveys to collect data from hospital nurses. The study focuses on understanding the likelihood of adopting

Socially Assistive Robots (SARs) among nurses in healthcare settings. To recruit participants, the study utilizes the Amazon Mechanical Turk (MTurk) and Prolific online platforms, which provide access to a diverse pool of potential participants. The surveys are hosted on the Qualtrics platform, allowing for convenient data collection and management.

The first survey instrument used is the Technology Adoption Propensity Index (TAP), which measures nurses' propensity for adopting new technology. The TAP consists of four subscales: *Optimism, Proficiency, Dependence*, and *Vulnerability*. Participants respond to a series of questions on a five-point Likert scale, and the subscale scores are computed by averaging the respective items.

The second survey instrument is the Robotic Social Attribute Scale (RoSAS), which assesses nurses' social attitudes towards hybrid assistive robotic caretakers. The RoSAS measures three aspects: *Warmth*, *Competence*, and *Discomfort*. Participants rate their agreement with specific statements on a nine-point Likert scale.

Data analysis involves descriptive and inferential statistics. Descriptive statistics, such as means, medians, and standard deviations, will be calculated to summarize the collected data. The distribution of variables will be assessed using histograms and boxplots to identify potential outliers. The inferential analysis will be conducted using Multivariate Analysis of Variance (MANOVA) to examine the relationships between the predictor variables (*Optimism*, *Proficiency*, *Dependence*, and *Vulnerability*) and the outcome variables (*Warmth*, *Competence*, and *Discomfort*). The data will be transformed and tested for normality and homogeneity of variance before conducting the MANOVA.

The significance level for all statistical tests will be set at 0.05, and exact p-values and 95% confidence intervals will be reported. Effect sizes will be determined using partial eta-squared (ηp2) statistics to assess the practical significance of the findings. This study employs a rigorous quantitative methodology, utilizing well-established survey instruments to collect data on nurses' technology adoption propensity and social attitudes towards SARs. The collected data will be analyzed using appropriate statistical techniques to examine the relationships between the variables of interest and provide insights into the likelihood of SAR adoption among hospital nurses.

Summary of Key Findings

This quantitative study investigated the relationship between hospital nurses' technology adoption propensity (*Optimism*, *Proficiency*, *Dependence*, and *Vulnerability*) and their perceived *Warmth, Competence, and Discomfort* with SAR. The goal was to determine how these factors predict nurses' perceptions of SAR.

The findings of this study revealed significant main effects for *Optimism*, *Proficiency*, and *Dependence*, indicating that these factors play a crucial role in shaping nurses' perceptions of *Warmth*, *Competence*, and *Discomfort* associated with SAR. The main effect of Optimism was found to be significant, indicating that the combined scores of *Warmth*, *Competence*, and *Discomfort* differed significantly among the different levels of *Optimism*. *Optimism* involves the conviction that technology enables enhanced command and adaptability in one's existence. In simpler terms, nurses with varying levels of *Optimism* had different perceptions of SAR regarding *Warmth*, *Competence*, and *Discomfort*.

Similarly, the main effect of proficiency was significant, suggesting that the combined scores varied significantly across different proficiency levels. Proficiency encompasses a sense of self-assurance in swiftly and effortlessly acquiring the skills to utilize novel technologies, along with a feeling of being skilled and knowledgeable in the technological realm. This means nurses with different proficiency levels displayed varying perceptions of warmth, competence, and discomfort related to SAR.

Furthermore, the main effect of dependence was found to be significant, indicating significant differences in the combined scores of warmth, competence, and discomfort among different levels of dependence.

Dependence entails a perception of excessive reliance on and a sensation of being captivated by technology, resulting in a loss of freedom. Nurses with different levels of dependence on technology had distinct perceptions of warmth, competence, and discomfort.

On the other hand, the main effect of vulnerability was not found to be significant. Vulnerability is the conviction that technology amplifies the likelihood of being exploited by both criminals and companies. This means that nurses' vulnerability, which refers to their perceived susceptibility to negative outcomes or difficulties associated with technology adoption, did not significantly impact their perceptions of warmth, competence, and discomfort with SAR. In simpler terms, regardless of their vulnerability levels, nurses had similar perceptions of SAR in terms of warmth, competence, and discomfort.

This study demonstrated that nurses' optimism, proficiency, and dependence significantly influenced their perceptions of warmth, competence, and discomfort with SAR. However, the vulnerability did not exert a considerable influence on these perceptions. These findings highlight the importance of nurses' characteristics and their level of technology adoption propensity shaping their perceptions and experiences with SAR.

Conclusion

This quantitative study explored the relationship between hospital nurses' technology adoption propensity using four key variables *Optimism*, *Proficiency*, *Dependence*, and

Vulnerability and their nurses' perceived *Warmth*, *Competence*, and *Discomfort* with SAR. The objective was to understand how these factors predicted nurses' perceptions of SAR.

Findings revealed significant main effects for *Optimism*, *Proficiency*, and *Dependence*, highlighting the influential role of these factors in shaping nurses' perceptions of warmth, competence, and discomfort associated with SAR. Optimism emerged as a significant predictor, indicating that nurses with different levels of optimism held distinct views regarding the warmth, competence, and discomfort associated with SAR. Optimistic nurses demonstrated a belief that technology enhances control and adaptability in their lives.

Similarly, proficiency played a significant role, with nurses at different proficiency levels displaying varying perceptions of warmth, competence, and discomfort concerning SAR. Proficiency encompassed nurses' confidence in swiftly acquiring and effectively utilizing new technologies, reflecting their knowledge and skills in the technological realm.

Furthermore, the study found that dependence on technology significantly influenced nurses' perceptions. Nurses with different levels of dependence on technology exhibited significant differences in their perceptions of warmth, competence, and discomfort regarding SAR. Dependence indicated the extent to which nurses relied on technology, and nurses' varying levels of dependence shaped their perspectives on the technology's warmth, competence, and discomfort.

However, our study did not find a significant effect of vulnerability on nurses' perceptions. Vulnerability, which relates to concerns about exploitation or negative consequences associated with technology adoption, did not significantly impact nurses' views on warmth, competence, and discomfort concerning SAR. This suggests that nurses' vulnerability levels did not influence their perceptions of the SAR.

In conclusion, this study highlights the significance of nurses' optimism, proficiency, and dependence in shaping their perceptions of warmth, competence, and discomfort with SAR. Understanding nurses' individual characteristics and their level of technology adoption propensity is crucial in comprehending their experiences and perspectives concerning SAR. These findings contribute to the field by shedding light on the factors that influence nurses' perceptions of SAR, providing valuable insights for technology implementation and support strategies in healthcare settings. Future research should continue to explore additional factors that may contribute to nurses' perceptions of SAR and expand the understanding of technology adoption in nursing practice.

Implications for Scholarship and Practice

The conclusions drawn from this quantitative study have important implications for the existing literature on technology adoption in healthcare, particularly in the context of SAR. The findings of this study align with several theoretical frameworks that have been previously explored in the literature.

Firstly, the significant main effects of optimism, proficiency, and dependence on nurses' perceptions of warmth, competence, and discomfort with SAR are consistent with the Unified Theory of Acceptance and Use of Technology (UTAUT). UTAUT posits that individual characteristics and beliefs, such as optimism, are critical in shaping technology acceptance and use (Passey, 2020; Venkatesh et al., 2016). The study findings support the idea that nurses' levels of optimism influence their perceptions of SAR, with optimistic nurses holding distinct views regarding warmth, competence, and discomfort. This connection with UTAUT reinforces the importance of considering individual characteristics in understanding technology adoption in healthcare settings.

Moreover, the significant role of proficiency in shaping nurses' perceptions of warmth, competence, and discomfort aligns with the Technology Acceptance Model (TAM) and the Technology Readiness Index (TRI). TAM and TRI emphasize the importance of individuals' perceived ease of use and self-efficacy in predicting technology adoption and attitudes (Davis, 1985; Parasuraman, 2000). The study's findings support these theories by demonstrating that nurses' proficiency levels influence their perceptions of SAR. Nurses more proficient in utilizing technology perceive SAR differently regarding warmth, competence, and discomfort.

The lack of a significant effect of vulnerability on nurses' perceptions of SAR is an interesting finding, considering the emphasis on vulnerability in the literature on technology adoption (Davis, 1985; Parasuraman, 2000; Passey, 2020; Venkatesh et al., 2016). This result suggests that vulnerability may not significantly influence nurses' perceptions of warmth, competence, and discomfort with SAR. However, it is important to note that this finding may differ from previous studies that have found vulnerability influential in technology adoption. Future research should continue exploring the role of vulnerability in the context of SAR adoption to understand its impact on nurses' perceptions.

Overall, the conclusions of this study contribute to the existing literature on technology adoption in healthcare, particularly in the field of human-robot interaction. The findings support the relevance of individual characteristics, such as optimism and proficiency, in shaping nurses' perceptions of SAR. This aligns with theoretical frameworks like UTAUT, TAM, and TRI, providing empirical evidence for their applicability in the context of SAR adoption. These findings have implications for technology implementation and support strategies in healthcare settings, emphasizing the importance of considering nurses' individual characteristics and technology adoption propensity when introducing SAR into practice.

To further advance the field, future research should explore additional factors that may contribute to nurses' perceptions of SAR. For instance, investigating the impact of organizational factors, such as leadership support and resources, on nurses' perceptions could provide valuable insights into the broader context of SAR adoption. Additionally, examining the role of user experience, emotional responses, and patient outcomes associated with SAR could enrich our understanding of the implications of technology adoption in nursing practice. Expanding the understanding of technology adoption in healthcare, particularly in the field of SAR, is essential for facilitating successful integration and maximizing the benefits of these technologies in improving patient care and nursing practice.

The conclusions of this study can also be discussed in relation to Systems Theory, which provides a broader perspective on the interaction between nurses, technology, and the healthcare system. Systems Theory emphasizes the interconnectedness of various components within a system and the dynamic relationships between these components.

In the context of technology adoption and nurses' perceptions of SAR, Systems Theory helps us understand the complexity of the healthcare system and how nurses' individual characteristics interact with the larger organizational context. The significant main effects of optimism, proficiency, and dependence in this study highlight the individual factors that influence nurses' perceptions of SAR. These individual factors can be seen as subsystems within the larger healthcare system.

Optimism, proficiency, and dependence represent individual subsystems that interact with other subsystems within the healthcare system, such as organizational policies, technological infrastructure, and workflow processes. The interactions between these individual subsystems and the broader system elements influence nurses' perceptions of warmth, competence, and discomfort with SAR.

Furthermore, Systems Theory emphasizes the importance of feedback loops and information flow within a system. In the context of technology adoption, nurses' perceptions of SAR provide feedback to the system regarding the effectiveness and usability of the technology. The significant main effects found in this study indicate that nurses' individual characteristics influence their perceptions, which, in turn, provide feedback to the healthcare system. This feedback can inform decisions related to technology implementation, training programs, and support strategies to enhance nurses' acceptance and utilization of SAR.

By considering Systems Theory, the conclusions of this study highlight the dynamic nature of technology adoption in healthcare and the interplay between individual factors and the larger organizational context. Systems Theory provides a framework for understanding the complexity of the healthcare system and the multiple factors that influence technology adoption and nurses' perceptions of SAR. Integrating Systems Theory into future research can help uncover additional factors and relationships within the system that contribute to the successful adoption and integration of SAR in nursing practice.

In summary, the findings of this study align with Systems Theory by emphasizing the interconnectedness and dynamic nature of technology adoption in healthcare. The significant main effects of optimism, proficiency, and dependence on nurses' perceptions of SAR highlight the individual subsystems that interact within the larger healthcare system. Understanding these interactions and incorporating Systems Theory into future research can provide valuable insights for improving technology adoption strategies, enhancing nursing practice, and optimizing patient care within the healthcare system.

In addition to the theoretical frameworks discussed earlier, such as the Unified Theory of Acceptance and Use of Technology, the Technology Acceptance Model, the Technology Readiness Index, Human-Robot Interaction, and Systems Theory, the conclusions of this study can also be connected to the concept of Design for Six Sigma (DFSS).

DFSS is a methodology that emphases on designing products or processes to meet customer needs and reduce flaws or errors. It emphasizes the importance of understanding customer requirements, gathering data, and utilizing statistical tools to optimize the design and implementation of a product or process.

In the context of technology adoption and nurses' perceptions of SAR, DFSS can provide insights into how to enhance the design and implementation of SAR systems to improve nurses' acceptance and experiences. By incorporating the significant factors identified in this study, such as optimism, proficiency, and dependence, into the design process, healthcare organizations can tailor the SAR systems to better align with nurses' needs and preferences.

For example, when designing SAR systems, organizations can consider features that promote a sense of control, adaptability, and confidence, which are associated with optimism and proficiency. This can include customizable interfaces, user-friendly functionalities, and comprehensive training programs that build nurses' skills and confidence in using the technology. Additionally, understanding the level of dependence nurses have on technology can inform the design of SAR systems to strike a balance between providing the necessary support and avoiding overreliance.

DFSS can also guide the collection and analysis of data to improve the design and implementation of SAR systems continuously. By gathering feedback from nurses, monitoring system performance, and utilizing statistical tools, organizations can identify areas for improvement, detect potential issues or bottlenecks, and make data-driven decisions to enhance the user experience and address any concerns related to warmth, competence, and discomfort.

Integrating DFSS principles into the development and deployment of SAR systems can contribute to the successful adoption and utilization of technology in nursing practice. It can help minimize implementation challenges, increase user satisfaction, and optimize the benefits of SAR in improving patient care outcomes.

1. In conclusion, the conclusions of this study can be connected to the concept of Design for Six Sigma, which highlights the importance of designing products and processes that meet customer needs and reduce issues. By incorporating factors such as optimism, proficiency, and dependence into the design and implementation of SAR systems, healthcare organizations can enhance nurses' acceptance and experiences. By utilizing DFSS methodologies, organizations can gather data, analyze feedback, and continuously improve the design and deployment of SAR systems to optimize nursing practice and improve patient care.

Study Limitations

While this quantitative study investigated the relationship between SAR robot features and technology adoption propensity among nurses in the United States and Canada, several limitations should be acknowledged. These limitations may affect the generalizability and interpretation of the study's findings.

Firstly, the study utilized a convenience sampling method to collect data. Convenience sampling may introduce biases and limit the representativeness of the sample. The participants were selected based on availability and accessibility, which may not accurately reflect the entire population of nurses in the United States and Canada, let alone nurses worldwide. Consequently, caution should be exercised when generalizing the findings beyond this study's specific sample and context.

The researcher aimed to increase the sample size to address the unequal representation of nurses' perspectives. By trying to ensure equal representation of nurses with a high, low, and average technological propensity, the goal was to obtain a more balanced and diverse sample. However, despite efforts to achieve a larger sample size and adequate representation, it is important to acknowledge that variations in characteristics and experiences among nurses may still exist, and the findings may not fully capture the breadth of perspectives within the nursing profession.

Another limitation of this study is the reliance on self-reported data. The data collection process involved participants reporting their own technology adoption propensity and perceptions of SAR robot features. Self-report assessments can be influenced by different biases, such as social desirability or memory recall biases, potentially affecting the accuracy and reliability of the gathered data. Future studies could consider incorporating objective measures or observational methods to supplement self-report data and provide a more comprehensive understanding of nurses' technology adoption behaviors and perceptions.

Furthermore, the study focused exclusively on United States and Canadian nurses. These countries' cultural, organizational, and technological contexts may differ from those in other regions. Thus, caution should be exercised when generalizing the findings to nursing populations in different countries or cultural contexts. Recognizing the potential influence of contextual factors that may shape nurses' technology adoption propensity and perceptions of SAR robot features is essential.

In summary, this study has several limitations to be considered when interpreting its findings. The use of convenience sampling and the focus on nurses in the United States and Canada may limit the generalizability of the results to broader nursing populations. Additionally, reliance on self-reported data and potential variations in sample sizes among technological propensity groups further impact the study's generalizability. Future research should address these limitations and expand the scope to include diverse samples from different regions, utilize objective measures, and conduct rigorous power analyses to enhance the validity and generalizability of the findings.

Recommendations for Future Research

Based on the findings and limitations of this quantitative study exploring the relationship between SAR robot features and technology adoption propensity among nurses, several recommendations for future research can be made. These recommendations aim to address the gaps in knowledge and provide avenues for further investigation in this field.

Diversify the Sample

To enhance the generalizability of the conclusions, potential research should include a more diverse and representative sample of nurses. This could involve expanding the study to include nurses from different countries and cultural backgrounds and considering a broader range of healthcare settings. By incorporating a more diverse sample, researchers can comprehensively understand the relationship between SAR robot features and technology adoption propensity across various contexts.

Longitudinal Studies

Conducting longitudinal studies would provide valuable insights into the changes and developments in nurses' technology adoption propensity and perceptions over time. By following nurses' experiences with SAR and technology adoption longitudinally, researchers can identify patterns, factors influencing change, and the long-term impact of technology on nurses' perceptions and practices. This would contribute to a deeper understanding of the dynamic nature of technology adoption in nursing.

Mixed-Methods Approach

Combining quantitative and qualitative methods in future studies can offer a more comprehensive exploration of nurses' technology adoption propensity and perceptions of SAR. Integrating qualitative data, such as interviews or focus groups, can provide rich insights into nurses' underlying motivations, experiences, and perceptions regarding SAR robot features and technology adoption. This mixed-methods approach would enable a more nuanced and holistic understanding of the factors influencing nurses' perspectives and behaviors.

Objective Measures

Incorporating objective measures of technology adoption propensity and perceptions of SAR would strengthen future research. Objective measures, such as behavioral observations or technology usage data, can provide a more accurate assessment of nurses' actual technology adoption behaviors and the impact of SAR on their practice. Combining self-report measures with objective data can enhance the validity and reliability of the findings.

Comparative Studies

Comparing nurses' perceptions and experiences using SAR with those using other forms of technology or traditional methods can offer valuable insights. Comparative studies can help identify the unique benefits and challenges of SAR adoption in healthcare settings.

Intervention Studies

Conducting intervention studies focused on promoting technology adoption and addressing barriers among nurses could inform best practices and strategies for successfully implementing SAR in healthcare settings. By designing and evaluating interventions to enhance nurses' technology adoption propensity and comfort with SAR, researchers can contribute to developing evidence-based approaches to support the integration of SAR in nursing practice.

Exploration of Ethical Considerations

Future research should also explore the ethical considerations associated with SAR adoption in nursing practice. Investigating the ethical implications of using SAR, such as patient privacy, data security, and potential disparities in access to technology, would contribute to SAR's responsible and ethical deployment in healthcare settings.

The recommendations outlined above provide directions for future research regarding SAR technology adoption among nurses. By expanding the sample, utilizing longitudinal and mixed methods approaches, incorporating objective measures, conducting comparative studies, implementing interventions, and addressing ethical considerations, researchers can advance our understanding of how SAR adoption influences nursing practice and patient outcomes. These recommendations aim to bridge the current gaps in knowledge and contribute to the effective integration of SAR in healthcare settings.

Include Demographic Factors

Consider including demographic factors in the analysis, either as covariates, as main effects on the predictors or the outcome variables, or both. This could provide a deeper understanding of how demographic characteristics influence nurses' technology adoption propensity and perceptions of SAR. Exploring demographic variables such as age, gender, years of experience, educational background, and cultural context could reveal nuanced insights into how these factors interact with the adoption of SAR technology. Understanding whether certain demographics are more predisposed to adopting SAR or have distinct perceptions could inform targeted strategies for enhancing technology adoption and tailoring training programs to meet specific needs.

Replicate Study with Different Participants

Replicating the study with different participant groups, such as patients, caregivers, and physicians, can enrich the understanding of how SAR adoption resonates with various stakeholders in healthcare settings. Examining how patients perceive and interact with SAR technology, how caregivers integrate it into their support roles, and how physicians view its impact on patient care would provide a holistic view of SAR's potential benefits and challenges. Comparing the perspectives of different participant groups could reveal synergies or disparities in perception, shedding light on areas that might require focused attention or customization when implementing SAR solutions across the healthcare spectrum.

Closing Comments

In conclusion, this quantitative study has provided valuable insights into the relationship between hospital nurses' technology adoption propensity and their perceptions of warmth, competence, and discomfort with SAR. The findings highlight the influential role of optimism, proficiency, and dependence in shaping nurses' perceptions of SAR. Optimism, reflecting a belief in technology's positive impact and proficiency, encompassing confidence and skills in utilizing technology, significantly influenced nurses' perceptions. Moreover, nurses' dependence on technology played a significant role in shaping their perceptions of SAR.

However, the study did not find a significant effect of vulnerability on nurses' perceptions. This suggests that nurses' concerns about exploitation or negative consequences associated with technology adoption did not significantly impact their views on warmth, competence, and discomfort concerning SAR.

These findings have important implications for healthcare organizations and policymakers. Understanding the factors that influence nurses' perceptions of SAR can guide the development of effective SAR implementation and support strategies. By fostering optimism, promoting proficiency, and addressing dependence on technology, healthcare organizations can enhance nurses' experiences with SAR and improve overall technology adoption.

It is important to note that this study has limitations, and further research is warranted. Future studies should explore additional factors contributing to nurses' perceptions of SAR, such as organizational support, training programs, and individual differences. By expanding our understanding of technology adoption in nursing practice, we can continue to enhance technology integration in healthcare settings and ultimately improve patient outcomes.

This study provides valuable insights into the complex relationship between technology adoption propensity and nurses' perceptions of SAR. By considering nurses' individual characteristics and the factors that shape their perceptions, we can create a supportive environment that fosters the successful adoption and utilization of technology in healthcare.

Researcher Reflections

Several reflections have emerged while conducting this quantitative study on hospital nurses' technology adoption propensity and their perceived warmth, competence, and discomfort with SAR. These reflections shed light on the research process, the study's findings, and potential areas for future exploration.

First and foremost, the research process itself was a valuable learning experience. Designing and implementing a quantitative study requires careful planning and attention to detail. This study involved selecting appropriate measures, recruiting participants, collecting and analyzing data, and interpreting the results. It was a complex undertaking that required dedication and persistence. Throughout the process, I gained a deeper understanding of research methodologies and the importance of rigorous data analysis.

One reflection that stands out is the significance of optimism, proficiency, and dependence as influential factors in shaping nurses' perceptions of warmth, competence, and discomfort with SAR. The findings indicated that nurses' optimism, proficiency, and dependence levels significantly impacted their perceptions of SAR. These insights emphasize the importance of considering individual characteristics and technology adoption propensity when implementing and supporting technology in healthcare settings.

Another reflection pertains to the non-significant effect of vulnerability on nurses' perceptions of SAR. The findings revealed that nurses' vulnerability levels did not significantly influence their perceptions of warmth, competence, and discomfort. This raises interesting questions about the interplay between vulnerability and technology adoption in healthcare. Further exploration is warranted to better understand the factors contributing to nurses' vulnerability and its potential impact on their perceptions of SAR.

In retrospect, the study's limitations provide valuable insights for future research. One limitation was the reliance on self-report measures, which may introduce response biases. Future studies could incorporate observational or objective measures to complement self-report data. Additionally, the study focused on a specific population of hospital nurses, limiting the findings' generalizability. Including a more diverse sample of healthcare professionals, such as nurses from different specialties or healthcare settings, would provide a broader understanding of technology adoption in healthcare.

Moving forward, future research should explore additional factors that may influence nurses' perceptions of SAR. For instance, organizational support, training programs, and individual differences in technology readiness could be examined. Furthermore, qualitative studies could delve deeper into nurses' experiences and perspectives, providing rich insights into the nuances of technology adoption and its impact on nursing practice.

In conclusion, the researcher's reflections highlight the lessons learned from conducting this quantitative study on nurses' technology adoption propensity and their perceptions of SAR. The study's findings emphasize the significance of optimism, proficiency, and dependence in shaping nurses' perceptions, while vulnerability showed no significant impact. The research process provided valuable insights into research methodologies and the complexities of data analysis. As we move forward, building upon these findings and addressing the study's limitations is essential, ultimately enhancing our understanding of technology adoption in healthcare and its implications for nursing practice.

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APPENDIX A

Survey Source Comparison

Two-Tailed Independent Samples *t*-Test for Optimism

Introduction

A two-tailed independent samples *t*-test was conducted to examine whether the mean of Optimism was significantly different between the Prolific and Mturk categories of data source.

Assumptions

Normality. Shapiro-Wilk tests were conducted to determine whether Optimism could have been produced by a normal distribution for each category of online crowdsourced recruitment Source (Razali & Wah, 2011). The outcome of the Shapiro-Wilk test for Optimism within the Prolific category did not yield significant results with an alpha level of 0.05 ($W = 0.94$, $p = 0.371$). This indicates that the possibility of a normal distribution underlying Optimism in the Prolific category cannot be dismissed. Conversely, in the Mturk category, the Shapiro-Wilk test produced a significant result at the 0.05 alpha level ($W = 0.96$, $p < .001$), suggesting that Optimism in the Mturk category is unlikely to be derived from a normal distribution. Specifically, the Shapiro-Wilk test's significance for the Mturk category of Source indicates a violation of the normality assumption.

Homogeneity of Variance. Levene's test was performed to determine if the variability in Optimism was the same across different Source categories. The outcome of the test, conducted at a significance level of 0.05, showed a non-significant result: $F(1, 152) = 0.20$, $p = 0.652$. This implies that there is a chance that the variability in Optimism is consistent across all Source categories, confirming that the assumption of equal variance was met.

Results

The outcome of the independent samples t-test with a two-tailed analysis, conducted at a significance level of 0.05, yielded a non-significant result: $t(152) = 0.38$, $p = 0.702$. This indicates that the null hypothesis cannot be dismissed. In other words, there was no significant difference in the mean Optimism scores between the Prolific and Mturk categories of Source. Detailed results can be found in Table A1, and a visual representation of the means is depicted in Figure A1.

Table A1

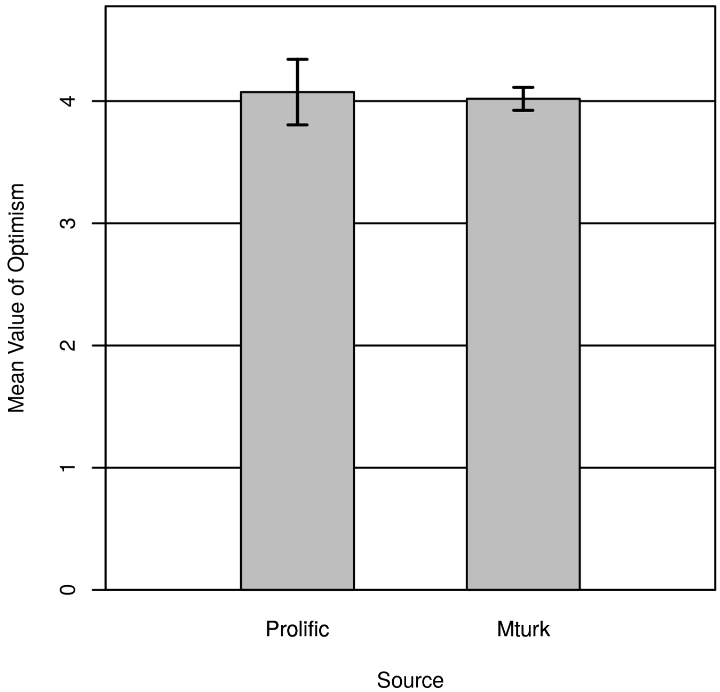
Two-Tailed Independent Samples t-Test for Optimism by Source

	Prolific			Mturk					
Variable	*M*	*SD*	*n*	*M*	*SD*	*n*	*t*	*p*	*d*
Optimism	4.07	0.56	17	4.02	0.56	137	0.38	.702	0.10

Note. N = 154. Degrees of Freedom for the *t*-statistic = 152. *d* represents Cohen's *d.*

Figure A1

The Mean of Optimism by Levels of Source with 95.00% CI Error Bars



Two-Tailed Mann-Whitney *U* Test for Optimism
Introduction

A two-tailed Mann-Whitney two-sample rank-sum test was performed to explore potential differences in Optimism across different data source levels. This test serves as an alternative to the independent samples t-test and does not rely on the same assumptions (Conover & Iman, 1981). The analysis involved 17 observations in the Prolific group and 137 observations in the Mturk group.

Results

The outcome of the two-tailed Mann-Whitney U test, conducted with a significance level of 0.05, was non-significant: $U = 1206$, $z = -0.24$, $p = 0.808$. The mean rank for the Prolific group was 79.94, and for the Mturk group, it was 77.20. This indicates that the distribution of Optimism in the Prolific group (Mdn = 4.00) did not significantly differ from the Optimism distribution in the Mturk group (Mdn = 4.00). The results of the Mann-Whitney U test are detailed in Table A2, and a visual representation of Optimism ranks by Source is provided in Figure A2.

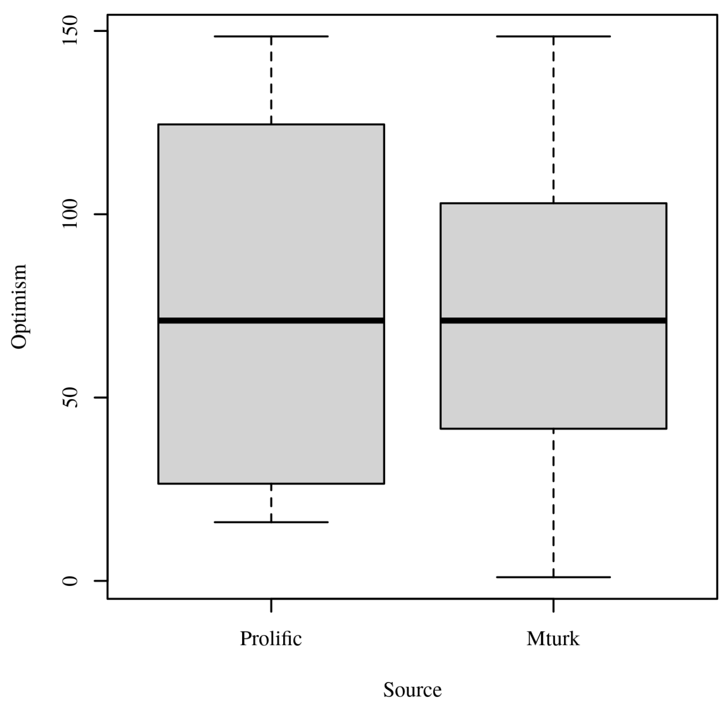
Table A2

Two-Tailed Mann-Whitney Test for Optimism by Source

	Prolific		Mturk				
Variable	Mean Rank	*n*	Mean Rank	*n*	*U*	*z*	*p*
Optimism	79.94	17	77.20	137	1,206.00	-0.24	.808

Figure A2

Ranks of Optimism by Source



Two-Tailed Independent Samples *t*-Test for Proficiency

Introduction

A two-tailed independent samples *t*-test was conducted to examine whether the mean of Proficiency was significantly different between the Prolific and Mturk categories of data source.

Assumptions

Normality. Shapiro-Wilk tests were performed to determine if Proficiency scores followed a normal distribution within each Source category (Razali & Wah, 2011). For the Prolific category, the Shapiro-Wilk test yielded a non-significant result at the 0.05 level, W = 0.92, p = 0.144, indicating that a normal distribution cannot be ruled out for Proficiency scores in this category. However, in the Mturk category, the Shapiro-Wilk test was significant at the 0.05 level, W = 0.96, p < 0.001, suggesting that Proficiency scores in the Mturk category likely do not adhere to a normal distribution. This violation of normality was specifically noted for the Mturk category.

Homogeneity of Variance. Levene's test was conducted to assess the equality of Proficiency variance across data source categories. The test yielded a significant result at the 0.05 level, F(1, 152) = 4.87, p = 0.029, indicating that the assumption of equal Proficiency variance across data source categories was unlikely. This result implies that the homogeneity of variance assumption was violated, suggesting that Proficiency variance differed between the data source categories

Results

Welch's t-test was used, which has higher statistical power than Student's t-test when the two samples have unequal variances and unequal sample sizes (Ruxton, 2006). The result of the two-tailed independent samples *t*-test was not significant based on an alpha value of 0.05, $t(18.20) = -1.08$, $p = 0.294$, indicating the null hypothesis cannot be rejected. This finding suggests the mean of Proficiency was not significantly different between the Prolific and Mturk categories of Source. The results are presented in Table A3. A bar plot of the means is presented in Figure A3.

Table A3

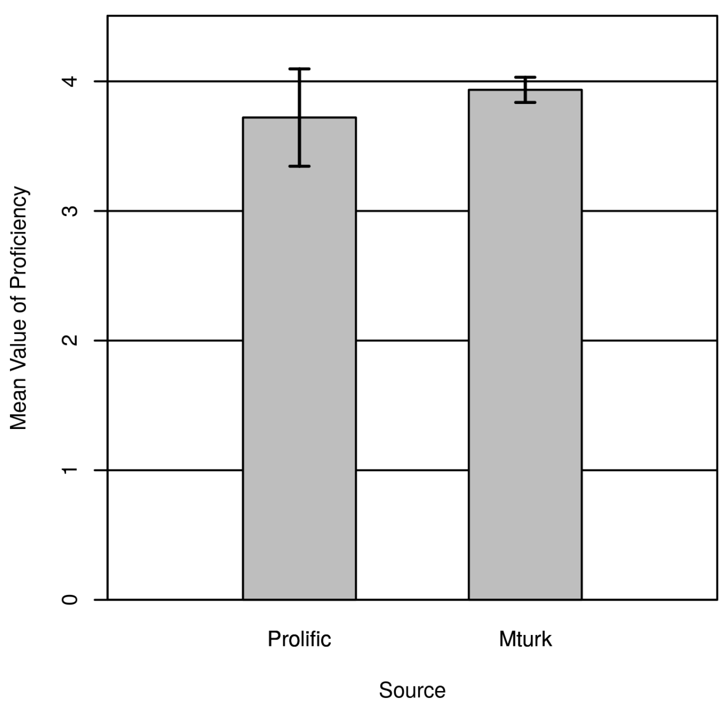
Two-Tailed Independent Samples t-Test for Proficiency by Source

	Prolific			Mturk					
Variable	*M*	*SD*	*n*	*M*	*SD*	*n*	*t*	*p*	*d*
Proficiency	3.72	0.79	17	3.93	0.58	137	-1.08	.294	0.31

Note. N = 154. Degrees of Freedom for the *t*-statistic = 18.20. *d* represents Cohen's *d*.

Figure A3

The Mean of Proficiency by levels of Source with 95.00% CI Error Bars



Two-Tailed Mann-Whitney *U* Test for Proficiency

Introduction

A two-tailed Mann-Whitney two-sample rank-sum test was carried out to investigate potential disparities in Proficiency across different Source levels. This test offers an alternative to the independent samples t-test and operates under different assumptions (Conover & Iman, 1981). The analysis involved 17 observations in the Prolific group and 137 observations in the Mturk group.

Results

The outcome of the two-tailed Mann-Whitney U test, conducted with a significance level of 0.05, was not significant: U = 1040, z = -0.73, p = 0.468. The mean rank for the Prolific group was 70.18, and for the Mturk group, it was 78.41. This indicates that the distribution of Proficiency in the Prolific group (Mdn = 4.00) did not significantly differ from the Proficiency distribution in the Mturk group (Mdn = 4.00). Detailed results of the Mann-Whitney U test are presented in Table A4, and a visual representation of Proficiency ranks by Source can be found in Figure A4.

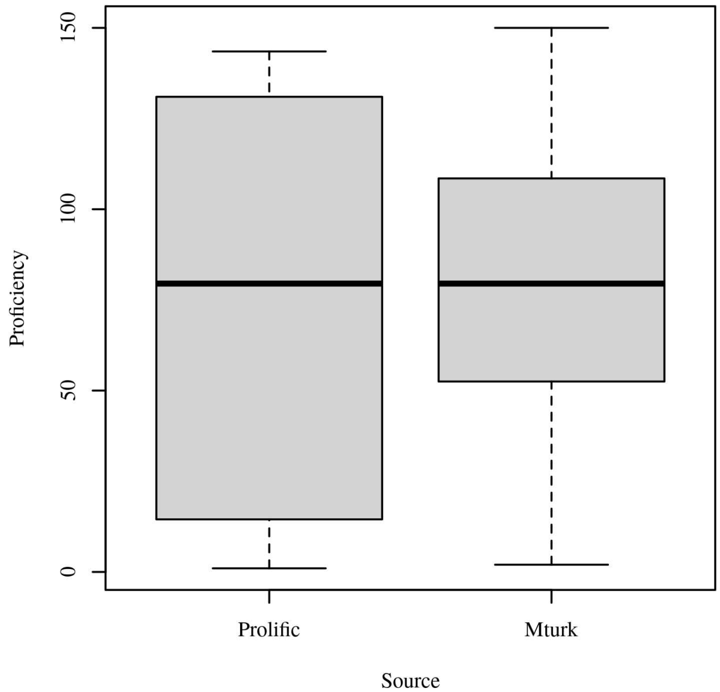
Table A4

Two-Tailed Mann-Whitney Test for Proficiency by Source

	Prolific		Mturk				
Variable	Mean Rank	*n*	Mean Rank	*n*	*U*	*z*	*p*
Proficiency	70.18	17	78.41	137	1,040.00	-0.73	.468

Figure A4

Ranks of Proficiency by Source



Two-Tailed Independent Samples *t*-Test for Dependence

Introduction

A two-tailed independent samples *t*-test was conducted to examine whether the mean of Dependence was significantly different between the Prolific and Mturk categories of Source.

Assumptions

Normality. Shapiro-Wilk tests were employed to determine if Dependence scores followed a normal distribution within each Source category (Razali & Wah, 2011). In the Prolific category, the Shapiro-Wilk test did not yield a significant result at the 0.05 level, $W = 0.91$, $p = 0.099$, suggesting that a normal distribution cannot be ruled out for Dependence scores in this category. However, for the Mturk category, the Shapiro-Wilk test was significant at the 0.05 level, $W = 0.87$, $p < 0.001$, indicating that Dependence scores in the Mturk category were unlikely to be derived from a normal distribution. This violation of normality was specifically noted for the Mturk category.

Homogeneity of Variance. Levene's test was conducted to assess the equality of Dependence variance across Source categories. The test yielded a significant result at the 0.05 level, $F(1, 152) = 5.31$, $p = 0.023$, suggesting that it was unlikely for the variance of Dependence to be equal across Source categories. This result indicates a violation of the assumption of homogeneity of variance, implying that Dependence variance differed between the Source categories.

Results

Welch's t-test, known for its heightened statistical power compared to Student's t-test, particularly when dealing with samples of unequal variances and varying sample sizes (Ruxton, 2006) was used. The result of the two-tailed independent samples t-test demonstrated significance at the 0.05 level, $t(18.23) = 4.69$, $p < 0.001$, allowing for the rejection of the null hypothesis. This outcome indicates a significant difference in the mean Dependence scores between the Prolific and Mturk categories of Source. Detailed results can be found in Table A5, and a graphical representation of the means is provided in Figure A5.

Table A5

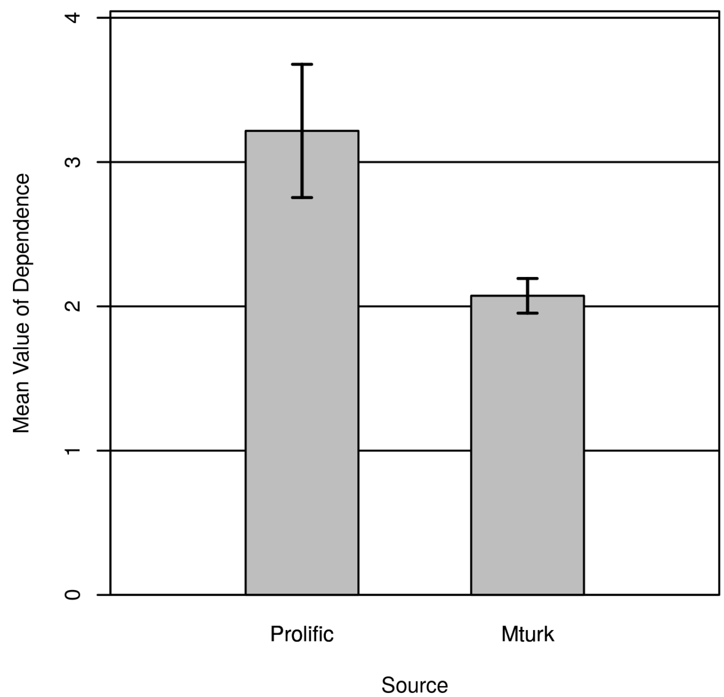
Two-Tailed Independent Samples t-Test for Dependence by Source

	Prolific			Mturk					
Variable	*M*	*SD*	*n*	*M*	*SD*	*n*	*t*	*p*	*d*
Dependence	3.22	0.97	17	2.07	0.72	137	4.69	< .001	1.34

Note. N = 154. Degrees of Freedom for the *t*-statistic = 18.23. *d* represents Cohen's *d.*

Figure A5

The Mean of Dependence by Levels of Source with 95.00% CI Error Bars



Two-Tailed Mann-Whitney *U* Test for Dependence

Introduction

A two-tailed Mann-Whitney two-sample rank-sum test was performed to explore potential differences in Dependence across different Source levels. This test serves as an alternative to the independent samples t-test and operates under distinct assumptions (Conover & Iman, 1981). The study encompassed 17 data points from the Prolific group and 137 data points from the Mturk group.

Results

The outcome of the two-tailed Mann-Whitney U test was significant at a significance level of 0.05, with U = 1906.5, z = -4.37, $p < 0.001$. The mean rank for the Prolific group was 121.15, whereas for the Mturk group, it was 72.08. This indicates that the distribution of Dependence in the Prolific group significantly differed from the distribution in the Mturk category. The median for Prolific (Mdn = 3.67) was significantly higher than the median for

Mturk (Mdn = 2.00). Details of the Mann-Whitney U test are presented in Table A6, and a graphical representation of Dependence ranks by Source can be found in Figure A6.

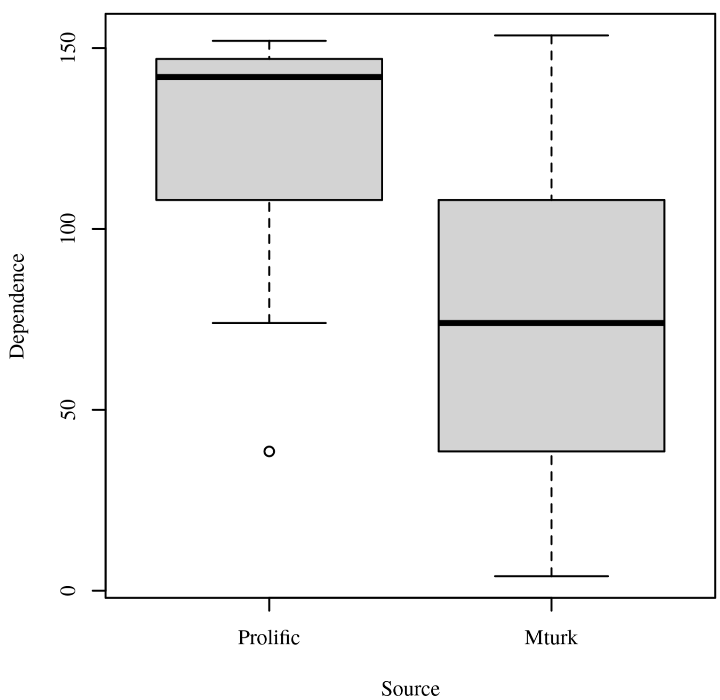
Table A6

Two-Tailed Mann-Whitney Test for Dependence by Source

	Prolific		Mturk				
Variable	Mean Rank	*n*	Mean Rank	*n*	*U*	*z*	*p*
Dependence	121.15	17	72.08	137	1,906.50	-4.37	< .001

Figure A6

Ranks of Dependence by Source



Two-Tailed Independent Samples *t*-Test for Vulnerability

Introduction

A two-tailed independent samples *t*-test was conducted to examine whether the mean of Vulnerability was significantly different between the Prolific and Mturk categories of Source.

Assumptions

Normality. Shapiro-Wilk tests were performed to ascertain whether Vulnerability data followed a normal distribution within each Source category (Razali & Wah, 2011). In the Prolific category, the Shapiro-Wilk test yielded a non-significant result at the 0.05 level, $W = 0.95$, $p = 0.449$, indicating that a normal distribution cannot be excluded as the underlying pattern for Vulnerability in this category. Conversely, in the Mturk category, the Shapiro-Wilk test was significant at the 0.05 level, $W = 0.96$, $p < 0.001$, suggesting that Vulnerability in the Mturk category likely did not conform to a normal distribution. This breach of normality was specifically noted for the Mturk category.

Homogeneity of Variance. Levene's test was utilized to evaluate whether the variance in Vulnerability was consistent across Source categories. The outcome of Levene's test for Vulnerability, conducted at a significance level of 0.05, was not significant: $F(1, 152) = 2.30$, $p = 0.131$. This implies that there is a chance that the variance in Vulnerability is uniform across all Source categories, indicating that the assumption of equal variance was satisfied.

Results

The outcome of the independent samples t-test with a two-tailed analysis, conducted at a significance level of 0.05, was non-significant: $t(152) = -0.45$, $p = 0.654$. This indicates that the null hypothesis cannot be dismissed. In other words, there was no significant difference in the mean Vulnerability scores between the Prolific and Mturk categories of Source. Detailed results can be found in Table A7, and a visual representation of the means is depicted in Figure A7.

Table A7

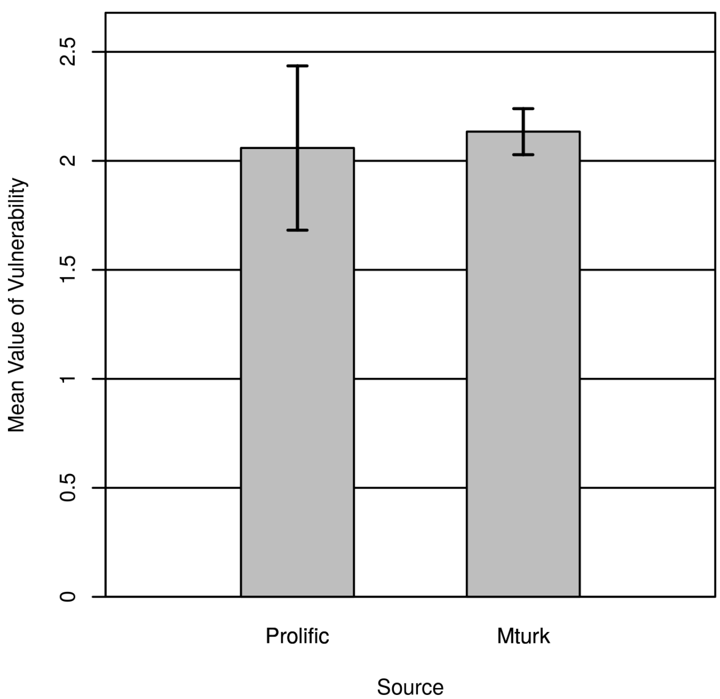
Two-Tailed Independent Samples t-Test for Vulnerability by Source

Variable	Prolific *M*	*SD*	*n*	Mturk *M*	*SD*	*n*	*t*	*p*	*d*
Vulnerability	2.06	0.79	17	2.13	0.63	137	-0.45	.654	0.10

Note. N = 154. Degrees of Freedom for the *t*-statistic = 152. *d* represents Cohen's *d.*

Figure A7

The Mean of Vulnerability by Levels of Source with 95.00% CI Error Bars



Two-Tailed Mann-Whitney *U* Test for Vulnerability

Introduction

A two-tailed Mann-Whitney two-sample rank-sum test was performed to investigate potential disparities in Vulnerability across different Source levels. This test serves as an alternative to the independent samples t-test and operates under distinct assumptions (Conover &

Iman, 1981). The analysis included 17 observations in the Prolific group and 137 observations in the Mturk group.

Results

The outcome of the two-tailed Mann-Whitney U test was not significant at a significance level of 0.05, with U = 1093.5, z = -0.42, p = 0.678. The mean rank for the Prolific group was 73.32, and for the Mturk group, it was 78.02. This suggests that the distribution of Vulnerability in the Prolific group (Mdn = 2.00) did not significantly differ from the Vulnerability distribution in the Mturk group (Mdn = 2.00). Detailed results of the Mann-Whitney U test are presented in Table A8, and a visual representation of Vulnerability ranks by Source can be found in Figure A8.

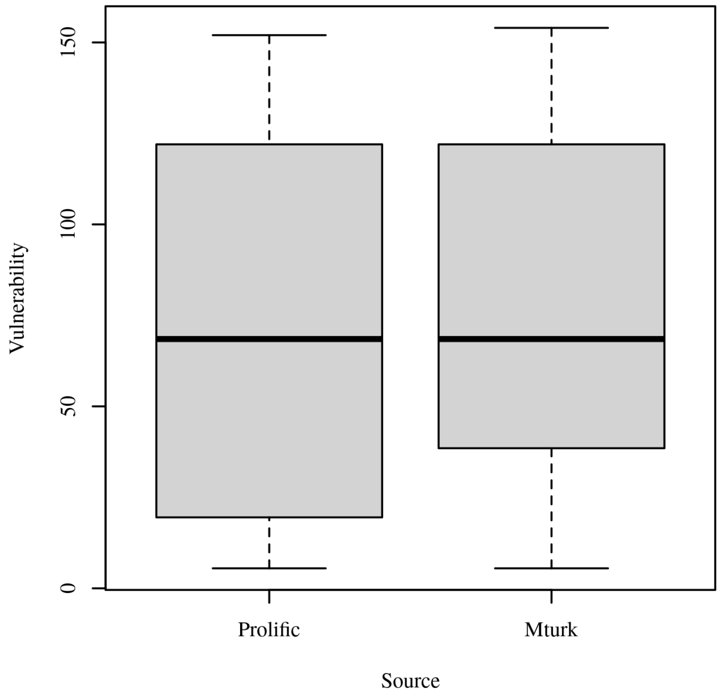
Table A8

Two-Tailed Mann-Whitney Test for Vulnerability by Source

	Prolific		Mturk				
Variable	Mean Rank	*n*	Mean Rank	*n*	*U*	*z*	*p*
Vulnerability	73.32	17	78.02	137	1,093.50	-0.42	.678

Figure A8

Ranks of Vulnerability by Source



150
100
50
0
Vulnerability
Prolific
Mturk
Source

APPENDIX B

IRB Approval

Pepperdine University
24255 Pacific Coast Highway
Malibu, CA 90263
TEL: 310-506-4000

NOTICE OF APPROVAL FOR HUMAN RESEARCH

Date: May 17, 2023

Protocol Investigator Name: Sooraj Sushama

Protocol #: 23-04-2143

Project Title: Initiating Change in Care: Socially Assistive Robots

School: Graduate School of Education and Psychology

Dear Sooraj Sushama:

Thank you for submitting your application for exempt review to Pepperdine University's Institutional Review Board (IRB). We appreciate the work you have done on your proposal. The IRB has reviewed your submitted IRB application and all ancillary materials. Upon review, the IRB has determined that the above entitled project meets the requirements for exemption under the federal regulations 45 CFR 46.101 that govern the protections of human subjects.

Your research must be conducted according to the proposal that was submitted to the IRB. If changes to the approved protocol occur, a revised protocol must be reviewed and approved by the IRB before implementation. For any proposed changes in your research protocol, please submit an amendment to the IRB. Since your study falls under exemption, there is no requirement for continuing IRB review of your project. Please be aware that changes to your protocol may prevent the research from qualifying for exemption from 45 CFR 46.101 and require submission of a new IRB application or other materials to the IRB.

A goal of the IRB is to prevent negative occurrences during any research study. However, despite the best intent, unforeseen circumstances or events may arise during the research. If an unexpected situation or adverse event happens during your investigation, please notify the IRB as soon as possible. We will ask for a complete written explanation of the event and your written response. Other actions also may be required depending on the nature of the event. Details regarding the timeframe in which adverse events must be reported to the IRB and documenting the adverse event can be found in the *Pepperdine University Protection of Human Participants in Research: Policies and Procedures Manual* at community.pepperdine.edu/irb.

Please refer to the protocol number denoted above in all communication or correspondence related to your application and this approval. Should you have additional questions or require clarification of the contents of this letter, please contact the IRB Office. On behalf of the IRB, I wish you success in this scholarly pursuit.

Sincerely,

Judy Ho, Ph.D., IRB Chair

cc: Mrs. Katy Carr, Assistant Provost for Research