“CAN I GET A SECOND OPINION?” HOW USER CHARACTERISTICS IMPACT TRUST IN AUTOMATION IN A MEDICAL SCREENING TASK

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ABSTRACT

As technology advances, processes traditionally carried out by humans are being automated in a variety of industries, such as automotive, security, and food service. In the medical field, advances in automation allow for disease classification, diagnosis, and even treatment recommendations. Technological advances have improved diagnoses by automated devices such that many cases can be more accurately diagnosed by a computer program than by a medical doctor. The hindrance to implementing these technologies is that these systems need not only to exist, they must be accepted, trusted, and appropriately used by both patients and healthcare providers. Previous literature on automation acceptance has focused primarily on how design features and characteristics of the automation influence human trust. Less research has explored the role that user characteristics—such as personality and dispositional traits—play in developing trust. User responses to automation may warrant adaptation in how automation is presented and distributed in order to encourage its acceptance. In the present study, researchers examined the relationship between user characteristics, trust, and automation use in a medical screening decision task. Although user characteristics were found to predict trust attitudes, they did not significantly predict trust behaviors, i.e., automation use. These findings are discussed with the consideration of the differences between attitudes and behaviors in predicting trust.

Keywords: trust in automation, medical decision-making, trust, automation, user traits

APPROVAL PAGE

The faculty listed below, appointed by the Dean of the College of Arts and Sciences, have examined a dissertation titled, "'Can I get a second opinion?' How user characteristics impact trust in automation in a medical screening task," presented by Norah C. Hass, candidate for the Doctor of Philosophy degree, and certify that in their opinion it is worthy of acceptance.

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CHAPTER 1

INTRODUCTION

Automation use is increasing in a variety of industries (e.g., automotive, food service) as technological advances allow for machines to complete tasks that were previously only feasible within the abilities of people. In the healthcare industry, automation is being used to identify cancerous tumors, categorize skin cancer, diagnose mental disorders, and suggest treatment plans (Bedi et al., 2015; Engchuan & Chan, 2015; Esteva et al., 2017). Given that mistakes can be costly and even deadly within a medical setting, it is critical to use the most accurate and reliable methods of diagnosis and treatment. Recent developments in medical technology show promise to be more accurate in diagnoses and less likely to miss a positive diagnosis than some professionals (Dreiseitl & Binder, 2005; Goddard, Roudsari, & Wyatt, 2012), making the adoption of this technology critical for saving lives and resources.

Implementation of automation in any industry is dependent on user willingness to accept it, yet acceptance largely depends on trust (e.g., Lee & Moray, 1994; Lee & See, 2004; Muir, 1994). Factors such as perceived risk, workload, and competency influence the decision to trust; however, individual differences are also believed to impact trust attitudes, willingness to trust, and trust behaviors. In order for automation acceptance and usage to keep up with automation development, the understudied role of user characteristics in trust development must be clarified.

This project explored how individual characteristics influence trust in automation in a medical screening task. Specifically, we aimed to examine how individual differences (e.g., personality, disposition) relate to self-reported trust attitudes and to the behavioral willingness to use automation in a medical diagnostic task. This research allows us to better understand how user factors influence the adoption of automated systems in healthcare, which, in turn, illuminates how automation features might be modified to encourage appropriate automation use.

CHAPTER 2

REVIEW OF THE LITERATURE

What is Automation?

Automation surrounds us in daily life. Chances are, you have interacted with automation several times in your day already: if you toasted your bread, sipped your home-brewed coffee, read your print newspaper, reversed your automatic transmission car while listening for the chime of the collision warning, followed your GPS to work, or bustled to your office via the elevator, you have enjoyed the benefits of automation. Despite its many definitions, automation can be broadly defined as “technology that actively selects data, transforms information, makes decisions, or controls processes” (Lee & See, 2004, p. 50). In short, it involves a transfer of a task or function from human control to an engineered system. As technology advances, automation is becoming more widespread, more specialized, and more autonomous. Numerous examples exist of the implementation of automation: in aviation, this includes software that controls the take-off, hover, landing, and other functions such as auto-piloting and route-planning; in defense systems, this includes target identification (i.e., threat/hostile assessment), and weapons detection; in the automotive industry, this includes lane correction, collision warning, parallel parking, and GPS navigation. Further, automation can span industries, such as home security systems, robotic floor vacuums, climate control systems, assembly lines, manufacturing processes, heart rate monitors, fire detectors, and sprinkler systems. As is evident from these examples, automation can be defined and described in various ways, covers roles from mundane tasks to high risk situations in daily life, and, in general, is intended to improve human life. The challenge with automation arises because it is not enough to simply create automation; it must be accepted and adopted into use in order to fulfill its purpose.

The broad category of "automation" can be qualified on several dimensions. Parasuraman, Sheridan, and Wickens (2000) divide automation into four types based on function: information acquisition, information analysis, decision selection, and action implementation. These types—although distinct—are not mutually exclusive, and one automated system can be composed of multiple types of automation functioning. Sheridan (2002) refers to automation as having some sort of control (e.g., cruise control, thermostats, and power steering) on situations and environments. Automation also can present basic, factual information, such as with clocks, speedometers, and thermometers, or can integrate information and provide decision suggestions. In addition, automation's role can be to manage other automation, that is, to support a human operator in managing automated systems (e.g., flight systems, security monitoring systems).

In addition to functional specifiers, automation can be qualified by the degree of control the machine has, or, conversely, the degree of interaction a human must have. Sheridan and Verplank (1978) defined these degrees as a 10-level scale of automation, with automation having an increasingly larger role at each step up until autonomy (i.e., when the computer decides and acts on everything without human involvement). Moray and colleagues (2000) simplified this scale into three groupings, with each interval between groups indicating a shift in the locus of control. Specifically, in levels one to five, the human operator has primary control and decision-making responsibilities, in levels five to seven, the collaboration is dynamic between human and automation, and in levels seven through ten, the automation operates independently without needing human intervention. Parasuraman and Riley (1997) note that automation that is “fully automated” or requiring little to no human input often undergoes a change in terminology overtime to be viewed as a machine rather than as automation of a function which humans typically perform. Examples help illuminate this: a toaster is automation but is more commonly viewed as a machine. Coffee makers, printing presses, assembly lines, automatic transmission and automated elevators are considered machines but used to (or infrequency do) involve a human component as well and thus classify as automation. Although socially the terminology may change over time, by definition machines and automation are the same when they take a task that humans would normally do and create a technology to execute it all or in part without human influence. It is important to note that the literature, including psychometric scales designed for self-report, often interchange the terms automation and machine while operationalizing both under the same definition. For the purposes of this study, the term automation will be used unless an existing measurement scale has been previously validated using the term “machine.” Automation is a dynamic term that can be qualified by the functional role it fills and by the level of control it has in serving that role.

Beyond these levels of automation is technology that allows computers to learn new things independently from human programming, termed machine learning. Machine learning falls under the umbrella of automation as well, and specifically allows for predictions, decision-making, and data modelling to occur from automation’s creation of algorithms without any human intervention. This “next level” of automation is especially relevant in fields in which it is difficult to accurately program the exact algorithm for the task due to overall complexity, multiple unknown variables, fluctuations and changes to the data, and/or higher occurrence of errors, such as in “big data” analysis, stock market decisions, and text categorization (i.e., the sorting of digital texts based on themes; Sebastiani, 2002). It is the technology that "knows" to tag someone's face in an image on Facebook and not tag their sister, and can identify a voice if "Hey Siri" is spoken. In a higher-stakes realm, machine learning has also permeated the medical field and has been applied to areas such as dementia diagnosis through brain scans (Chen, Alsadoon, Prasad, & Elchouemi, 2017), tracking eye movements and orientation through electrooculography (López, Fernández, Ferrero, Valledor, & Postolache, 2016), and skin disease detection through imaging analysis (Seixas, Barbon, & Mantovani, 2015). Machine learning is the most advanced form of current automation and has the most potential to impact fields (such as the medical field) which are seeking to predict outcomes increasingly earlier as well as more accurately and more efficiently.

Automation and Healthcare

As mentioned above, one of the industries in which automation has become increasingly prominent is the medical field. Healthcare is one of the largest industries in the United States, with approximately $3.3 trillion spent on healthcare in 2016 (approximately $10,000 spent on each person) and estimates that healthcare expenditures will continue to rise each year (Centers for Medicare and Medicaid Services, 2017). The majority of this spending (52%) was on hospital care and physician and clinical services, which includes technology use. The research and development of technology to improve healthcare services are expensive as well, yet often worth the upfront cost for their long-term benefits, including efficiency and savings. Advances in healthcare technology have improved in medical treatment and medical diagnosis, allowing technology's benefits to expand to include increased accuracy and reliability in diagnosis and treatment planning. A growing interest in predicting future health problems through biomarker and genome research has also spurred research into advancing automation's ability to detect early symptoms. Although automation has been used in healthcare for years to streamline simple processes, machine learning introduces a new type of automation that is attempting to predict uncertain future outcomes and identify previously unconfirmed conditions. Examples of this include using machine learning to classify lung cancer (Engchuan & Chan, 2015) or to predict the development of psychosis by examining speech patterns (Bedi et al., 2015). Diosan and Andreica (2015) showed the efficiency of a system to review mammograms and identify abnormal images as a second opinion for the radiologist and to save them time and effort. In research by Esteva and colleagues (2017), machine learning was even able to classify skin cancer types as accurately as dermatologists. Machine learning technology also carries the benefit of being able to be disseminated at a low cost and to a broad audience through means such as mobile phone applications and websites, two media platforms which are already being used to spread medical information (Esteva et al., 2017). Automation is not subject to boredom, fatigue, or distractions as humans are, making it well-adapted to performing time-consuming tasks that can save medical professionals' time. In the medical setting where upfront technological costs are high, there exists high value in understanding and promoting automation acceptance. As is the dilemma with all automation, though, user acceptance and proper usage is critical in order for automation to reach its full potential of effectiveness, and, in the medical field, justify upfront costs.

Automation Acceptance and Use

Broadly, the intention of automation is to decrease human workload or error and to increase efficiency, speed, and/or safety. It can be beneficial to use in repetitive tasks, in situations which might be dangerous for humans, or in situations where a human may not have time to respond (Hoff & Bashir, 2015). However, automation use can lead to significant negative outcomes as well. Aviation crashes, maritime mishaps and automotive accidents involving automation have had catastrophic and sometimes fatal outcomes (e.g., Lee & Sanquist, 2000; Sparaco, 1995). Less consequential results of improper automation use occur as well, such as reduced efficiency, reduced situational awareness, and skill degradation (Hollnagel & Woods, 2005; Parasuraman & Riley, 1997; Zuboff, 1988). Examples of these include situations where the human elects to take control over a more efficient automated process, the human user stops paying full attention to the situation because the automation is controlling some processes, and the human operator loses his/her skill as an operator because he/she is not practicing and refining a skill for which he/she now relies on automation to do. As mentioned above, automation can benefit the healthcare industry by taking over repetitive tasks and reducing errors, yet it cannot always make the best treatment recommendations when the system does not have all the information which it may need to consider. Further, the consequences of automation's effects on its surroundings cannot always be predicted until tested. Automated driving systems that allow for less headway between vehicles directly impacts the headway that nearby non-automated drivers give when following another car, suggesting a dangerous "contagion" impact of having traffic with a mix of automated and non-automated (e.g., human) driving systems (Gouy, Wiedermann, Stevens, Brunnett, & Reed, 2014). Further, complacency with automation creates situations of overdependence and failures to monitor imperfect automation (e.g., Dreiseitl & Binder, 2005; Goddard et al., 2012). For example, the drawbacks of automated vehicles include reduced situational awareness of drivers, overreliance on automation to perform, and skill atrophy for the tasks controlled by automation (Parasuraman, Sheridan, & Wickens, 2000). Further, failing to use automation in situations in which increased demands are present (e.g., fast-occurring changes) can lead to more accidents and worse outcomes when humans continue to manage systems themselves (Moray et al., 2000). Although the intent of automation may be good, its usage creates the possibility for a variety of problems.

The intent, design, and functionality of automation are meaningless if the operator is not willing to use it and use it properly. When automation fails its purpose, it is important to look closer at the cause of the undesirable outcome. Failure can occur due to software and hardware issues, poor initial design, environmental factors, and other unpredictable contaminants (Parasuraman & Riley, 1997). It can also occur due to human causes, such as being too reliant on or complacent with the automation process. Although research refers to the human-sourced causes using many terms, they are most easily divided into two categories: misuse and disuse (Parasuraman & Riley, 1997). Parasuraman and Riley (1997) defined misuse as an overuse, occurring when the operator has a lack of skepticism in the automation's capacities. Disuse, on the other hand, arises when the operator's use of automation does not match its capabilities. The goal in establishing a successful human-automation relationship, then, is to minimize disuse and misuse. Calibration is described as appropriate use of and reliance on automation given its capabilities (Lee & Moray, 1994). There are many examples of when operators' preferences to use (or not use) automation do not align with the proper use of that automation given its performance capabilities (e.g., Andre & Wickens, 1995; Casner, 2009; Hollnagel & Woods, 2005). For example, drivers tend to prefer collision warnings over automated control even in situations where automated control performs better than they do (Inagaki, Itoh, & Nagai, 2007). There is also research that auditory lane-drifting correction cues are more accepted than more effective motor cues (i.e., a slight corrective motion on the steering wheel), which may be due to interpretations of tactile cues as less helpful or more intrusive on controlling the steering (El Jaafari, Forzy, Navarro, Mars, & Hoc, 2008; Kozak et al., 2006; Navarro, Mars, Forzy, El Jaafari, & Hoc, 2010). Deliberate abuse of a system's capabilities would also qualify as disuse. Thus, the issue of calibration is a key consideration in automation acceptance and implementation.

A broadly-used method for understanding automation use is the Technology Acceptance Model (TAM; Davis, 1989; Davis, Bagozzi, & Warsaw, 1989). This model was developed out of an information systems perspective and states that automation use is determined by the behavioral intention to use, which results from an attitude towards using automation. Attitudes towards use are primarily determined by the user's perceived usefulness and perceived ease of use in the system. Stated in other words, perceived usefulness and ease of use contribute to form an attitude towards automation, which is the primary predictor of actual use. This model was developed out of the Theory of Reasoned Action (Fishbein & Ajzen, 1975) and keeps its core principle that attitudes predict behaviors.

The TAM has been modified throughout its existence, perhaps most notably when Taylor and Todd (1995) added constructs to TAM to parallel the Theory of Planned Behavior (Ajzen, 1991; Ghazizadeh, Lee, & Boyle, 2012). The model emphasizes considering both intentions and actual behavioral actions; in applying this framework to automation use, motives behind the intention to use become critical. TAM has had criticism for its inability to explain actual automation use, its poor adaptability when attempting to apply it to new technology, and for the factors of perceived ease of use and perceived usefulness being poor contributors to attitudes and intentions towards using automation (Benbasat & Barki, 2007;

Legris Ingham, & Collerette, 2003). More specifically, this model does not explain the disconnect between positive attitudes and intentions of using automation and lack of actual use that might be due to other factors such as time constraints, over-confidence, and so forth. Further, perceived usefulness and ease of use become irrelevant in situations where automation use might be forced (Ghazizadeh et al., 2012). Additionally, "automation use" in this model is not limited to appropriate use, which means that disuse and misuse could be occurring under TAM yet regarded positively as "use." The Automation Acceptance Model (AAM; Ghazizadeh et al., 2012), was developed in response to TAM's shortcoming in linking both cognitive and information system perspectives into a unified model. Despite AAM's attempt to improve on TAM by including trust and compatibility constructs, it has not seen widespread adoption due to continued disagreement over how to model automation acceptance. Instead, the predominant theories behind automation use have traditionally circled back to trust, carrying over ideas on human-human interactions in social psychology into the realm of human-automation relationships.

Trust has been added to TAM and found to relate, both directly and indirectly, to nearly every factor in the model: behavioral intention, perceived usefulness, perceived ease of use, and, in a modified model, perceived risk (Carter & Belanger, 2005; Pavlou, 2003). The role of trust in TAM becomes more confusing when considered an attitude, yet it impacts other parts of the model in ways that a general attitude towards using does not (Ghazizadeh et al., 2012). Thus, it appears most appropriate to consider trust on its own based on social trust literature. Despite automation designers' best attempts to create automation that will be appropriately used, misuse and disuse still occur not due to design flaws or a lack of perceived usefulness, but due to variations in user's trust in the automation.

Trust directly influences automation acceptance (Lee & Moray, 1994; Muir, 1994). Simply put, over-trust leads to misuse, and distrust leads to disuse (Lee & See, 2004). As TAM suggests, trust influences both attitudes and behaviors, and, furthermore, is influenced itself by many factors of both the user and the automation (Lee & See, 2004; Hoff & Bashir, 2015). Trust becomes one of the most critical components of proper, optimal automation use, and must be understood conceptually in order to recognize its role in automation functioning.

Trust as a Construct

Definition

Trust is a necessary feature of human interactions. Although many definitions exist, Lee and See (2004) provide a generally accepted definition when they call trust: "the attitude that an agent will help achieve an individual's goals in a situation characterized by uncertainty and vulnerability" (Lee & See, 2004, p.51). To fully understand this definition, it is helpful to break down its components. First, it claims trust is an attitude. Although other theories propose trust as a belief, expectation, or behavior (see Hoff & Bashir, 2015, and Lee & See, 2004, for reviews), it is arguably most accurate to consider it firstly a way of thinking or feeling which shapes beliefs, informs expectations, and contributes to behaviors. Secondly, Lee and See's definition of trust mentions an agent and an individual. In fact, trust cannot exist without at least two agents: a trustor and a trustee. The trustor must see some reason to consider a trustee's help, which leads into the third necessary requirement for trust: something must be at stake. This "goal" might literally be a goal, or might be a similar concept such as preserving one's safety or securing something beneficial (Lee & See, 2004). When the trustor seeks the trustee's help towards his/her goal, it is due to uncertainty in his/her own ability or uncertainty to accomplish the goal otherwise. The risk involved must be a pertinent risk or have consequence to the trustor, or else the decision to put trust in another is irrelevant (Drnec & Metcalfe, 2016). Trust becomes increasingly important the more complex and/or higher risk the situation is, as well as the more uncertain the outcomes of the situation are. There must be the possibility of the trustee failing, which presents uncertainty and risk in choosing the trustee (Hardin, 2006; Hoff & Bashir, 2015). Placing trust in another, then, naturally creates a relationship of vulnerability and dependence on the trustee towards the trustor's goal. In turn, the trustee must have motivation to cooperate with the trustor. This motivation can include a direct investment in the outcome, material or other gains, or a genuine goodwill to help others. Without an incentive, though, the trustee has no motivation, and the trustor has no basis upon which to put trust in that agent (Hoff & Bashir, 2015).

The propensity to trust is theorized to be a relatively stable, persistent trait that varies across individuals, with some considered naturally more trusting than others (Freitag & Bauer, 2016; Gaines et al., 1997; Rotter, 1967; Stack, 1978; Sztompka, 1998). A general consensus exists that trust is a psychological state with both affective and cognitive components (Mayer, Davis, & Schoorman, 1995; Muir, 1994). Trust is considered multidimensional, dynamic, and situational. Trust may be different based on context (i.e., trust in a barber differs from trust in a friend, which differs from trust in a romantic partner), based on conclusions drawn from experience, either direct or indirect, and based on social expectations (Lee & See, 2004). Snap judgments of trustworthiness of faces can be made quickly (~100 ms) and accurately, supporting the idea that humans are innately wired to factor trust into their social relationships and interactions (Engell et al., 2007; Willis & Todorov, 2006). It is also thought that humans carry an innate bias towards trusting others initially (Drnec & Metcalfe, 2016); however, findings also suggest that people are conservative in their initial interpersonal trust as trust forms (Rempel, Holmes, & Zanna, 1985). Predisposition to trust becomes the stepping stone from which trust is formed in relationships.

Trust Formation in Human Relations

Propensity to trust is considered an innate trait; however, trust develops beyond this propensity. Emotional reasoning and rational thinking both play a role in forming enduring trust. The reasons considered when deciding whether to trust can be driven by social norms, opinions, and other information gathered about the trustee, as well as by evaluations of actual trust experiences (Hoff & Bashir, 2015; Lee & See, 2004; Rempel et al., 1985). Emotional reasoning and implicit attitudes or stereotypes are more likely to drive the trust development process in situations where the trustor has insufficient time or cognitive resources to make an analytic decision (i.e., judgment), since the former require less time and less conscious awareness to process (Hoff & Bashir, 2015). That is to say, trust is thought to be based on emotional or "gut" feelings both when data on the trustee are lacking and in cases where there is not time to process said data and make an informed decision. Hence, initial trust, which exists based on descriptions and prior knowledge about a trustee but without having direct contact, is more likely to be based on emotions and intuitive processes than be analytical. Nuamah, Oh, and Seong (2015) conceptualized trust as varying along a continuum from analytic to intuitive. The intuitive side of trust consisted of emotion-based judgments or gut reactions, which are both subjective and without explicit evidence. This can be considered the same as initial trust, which may be based on perceptions, but lacks true knowledge of the trustee that is learned through interactions. Analytical trust, on the other hand, is trust formed after informative experiences with the trustee. When there are no empirical data upon which to draw an objective conclusion, the intuitive side dominates the decision to trust (Madsen & Gregor, 2000). According to Drnec and Metcalfe (2016), the level of trust can be thought of as a reckoning of objective observations compared to preexisting expectations of how the agent would perform. Trust is gained through experiences when the trustor evaluates the outcome after having trusted and uses that new information in future judgments (Coleman, 1990; Freitag & Bauer, 2016; Hardin, 2002; Mayer et al., 1995). Experiences with the trustee directly and also with others can shape future trust, especially when the others are perceived to be closely associated to the trustee (e.g., same sex, race, or other grouping feature; Coleman, 1990; Freitag & Bauer, 2016; Hardin, 2002). Models of trust formation have focused on different aspects of the relationship as their basis, such as Mayer et al. (1995) emphasizing characteristics of the trustee (i.e., ability, integrity, and benevolence), and Marsh and Dibben (2003) characterizing trust into multiple domains (i.e., dispositional, situational, and learned trust). One consistent limitation in most trust models, though, is that they have not been thoroughly validated, particularly across contexts. Although this steps beyond the scope of this study, it is nonetheless important to acknowledge the lack of a definitive model to explain the development of trust.

Trust in Automation

Trust plays a significant role in explaining human-automation interactions. Trust in automation is thought to be similar to, yet still distinct from, trust in humans. This distinction is evident in one of the most widely held definitions of trust in automation, which states, “trust in automation is an attitude which includes the belief that the collaborator will perform as expected, and can, within the limits of its designers' intentions, be relied on to achieve the design goals" (Moray & Inagaki, 1999, p. 204). Just as human-human trust is formed out of a relationship, so too do humans form relationships with automation which impact the development of trust (Madhavan & Wiegmann, 2007b). These relationships are even more distinctive when the automation takes on human qualities, such as a human voice (e.g., Apple's Siri), animation (e.g., Microsoft's Clippy), language patterns, human-like appearances, or even emotional expressions (e.g., MIT's Nexi). Humans approach automation and technology in a similarly social manner, carrying over social norms, communication rules (e.g., politeness, taking turns), and expectations from interactions with humans to interactions with automation, particularly anthropomorphized automation (e.g., gender stereotypes; Nass, Moon, & Carney, 1999; Nass, Steuer, & Tauber, 1994; Reeves & Nass, 1996). For example, users tend to be more responsive to instructions from male automation, which is similar in human-to-human interactions (Lee, 2008). Users also tend to be polite to automation that acts politely, such as automated, pop-up chat windows to assist with purchases on websites (Nass et al., 1999). Just as humans tend to be attracted to those with like-personalities, so too do humans prefer automation that portrays personality characteristics similar to their own, and, in fact, are able to detect introversion and extroversion solely through speech patterns (Nass & Lee, 2001). Emotional states also impact acceptance of automation, with individuals responding more positively to happy and friendly humanized automation (Norman, Ortony, & Russell, 2003; Picard, 1997). Thus it is clear that affect, attitudes, and personality traits all impact interactions with automation. Indeed, Parasuraman and Riley (1997) speculate that this carry-over is seen because humans' trust in automation systems is, in part, symbolic of their trust in the designer of the automation.

Because automation is often responded to as a social interaction, social constructs such as trust apply. However, it is unclear by what mechanisms these factors influence automation trust.

Trust in automation is also similar to interpersonal trust in that it is thought to have both cognitive aspects, expressed in beliefs and expectations about the automation, and affective aspects, expressed in feelings and intentions toward the automation (Muir & Moray, 1996). The predisposition to trust can have a significant impact on initial trust, initial usage, and subsequent reliance on automation (Lee & See, 2004). Trust in automation also develops over time through experiences, similar to interpersonal trust (Muir, 1989; Muir, 1994). Research by Lee and Moray (1994) suggests that trust in automation is similarly dynamic, shaped by the information that the user gathers over time from the performance of the automation. Trust also appears to degrade at a similar rate whether the cause of the failure is human or machine (Lewandowsky, Mundy, & Tan, 2000). Lee and See (2004) describe trust in automation as a dynamic loop: trust impacts how one interacts with automation, and interactions with automation impact trust.

Yet clearly, trust in automation differs from trust between humans. There is no reciprocity or mutuality in human-automation trust: the benefits are unidirectional. Humans generally do not interact with automation to form a social relationship, but rather to accomplish a goal. Automation does not work to earn trust or intentionally break or repair it. Trust may be formed from the trustor viewing the automation as a proxy for its designer; even then, though, the trust is based on the reputation of the designer until experience with the automation is gained (Muir, 1994). Because of this general one-sidedness, the qualities of the human operator become more relevant factors in the decision to trust automation. One model of trust in automation states the trust is based on the performance (i.e., capability of the automation to execute its purpose), process (i.e., the user's understanding of how the automation works), and purpose (i.e., automation's designed intent) of the automation, distinguishing it from human-to-human trust (Lee & Moray, 1992). Dzindolet and colleagues (2003) suggest a bias towards trusting automation from the start likely due to assumptions that machines are infallible (Madhavan & Wiegmann, 2007a). These factors make features such as functional transparency, understanding capabilities, and user-friendly designs critically important for trust in automation.

Behavior and Trust. Past literature has disagreed on whether trust should be conceptualized solely as a mental state, or as a choice behavior as well (Mayer et al., 1995). Ajzen and Fishbein (1980) put forth a framework of relationships tying trust into behaviors, stating that beliefs inform attitudes, which motivate intentions, which are carried out through behaviors. However, it is important to note that other factors may interfere—an operator might trust the automation but behaviorally is prevented from using it due to circumstantial reasons. Thus, trust can exist without one acting on it or demonstrating it through behaviors. Mayer and colleagues' (1995) theory supported the idea that trust is a psychological state; therefore, measuring "trust behaviors" would be a poor strategy for assessing trust, since the behaviors could be only partially driven by trust. For example, it is possible for people to not trust each other but still work cooperatively, as much as it is possible for people to endorse trust in another but not behave thusly due to other reasons. A behavior that looks like trust might actually be motivated by organizational policies; emotional biases may block someone from displaying trusting behaviors despite rational, cognitive reasons to trust. Thus, trust takes a willingness that is motivated by both emotional and cognitive components.

Although attitudes and behaviors are not the same, they both serve to capture trust as operationalizations of the construct. Past research has established a relationship between trust in the ability of automation and actual, behavioral use of automation (Lee & Moray, 1992, 1994; Muir & Moray, 1996). Trust behaviors can be viewed as appropriate actions that demonstrate a sense of trust; in the case of automation, this would relate to automation use that is proportionate to the accuracy and reliability of the automation (i.e., avoiding misuse or disuse). Thus, the components of trust warrant its measurement via both attitudes and behavioral choices.

Reliance. Trust and reliance are closely related but distinct constructs. While reliance is seen through behavior, trust is not always apparent. Reliance on automation can occur for more reasons than trust. More specifically, reliance can be based on cognitive (e.g., workload, attention, effort), social (e.g., perceived abilities, self-confidence), motivational (e.g., time constraints, perceived benefits/risks, desire for control), environmental (e.g., weather) and other situational factors such as limited resources, policies or procedures (Dzindolet, Pierce, Beck, & Dawe, 2002; Lee & See, 2004). For example, the greater the perceived risk, the less reliance is generally shown (Keller & Rice, 2010; Riley, 1994). Thus, risk can moderate the relationship between reliance and actual automation use (Riley, 1996). In order for appropriate use to occur, the user must rely on automation within the bounds of its capabilities given all the factors that can influence reliance. Thus, distinguishing reliance from trust conceptually is important in order to understand automation use and choice behaviors.

By definition, trust is necessarily demonstrated by reliance on someone (or thing) else. Muir and Moray (1996) posit that initial trust must be built by first relying on the automation without experience. Trust has a direct, positive relationship to reliance: the more one trusts an automated system (or person), the more one is likely to rely on it (Lee & See, 2004). Hence trust can be said to mediate how people rely on each other. Complacency occurs when there is an overreliance on automation resulting in a lack of oversight or intervention on the operator's end (Parasuraman & Riley, 1997), which, unsurprisingly, is responsible for numerous automation accidents. Inappropriate reliance and complacency are challenges to successful automation use.

Calibration. A similar issue with human-automation trust is appropriate calibration (Lee & See, 2004; Muir, 1994). Calibration occurs when making predictions about future performance based on available information. However, it also follows as a response to the subjective perception of an agent's trustworthiness and may not always align with the objective features of the trustee. As mentioned above, too much trust in automation can result in misuse, while having not enough trust in the capabilities of automation can create disuse (Borum, 2010; Lee & Moray, 1994; Lee & See, 2004; Muir & Moray, 1996). Further, inappropriate levels of trust are thought to negatively impact system performance (Muir, 1994). In seeking to increase the behavioral usage of automation, then, increasing trust is *not* the goal; rather, the goal is to develop a balanced, proportionate level of trust in the automation, recognizing that other factors contribute to behaviors as well. Thus, it is critical to be mindful that the ideal level of trust in automation is the level most likely to lead to the desired outcome and avoid undesirable outcomes, which can vary between systems and users.

Calibration of appropriate levels of trust depends on several factors: the operator, the environment, the automated system itself, and the interaction of these three (Merritt & Ilgen, 2008). Trust in automation can be situation specific if the individual can notice differences and thus calibrate their trust discriminately across situations in which the automation's reliability varies (Cohen, Parasuraman, & Freeman, 1998). Trust calibration is also dependent on the individual's subjective perception of the automation's performance; if the automation is making errors that the operator does not notice, there would not be a basis for that individual to reassess his/her trust (Lee & See, 2004; Merritt & Ilgen, 2008). Thus, actual automation capability does not directly influence trust, but rather perceived capability does. In a similar way, expectations that automation is trustworthy can lead to better calibrated trust when the reliability of the automation subtly changes (Pop, Shrewsbury, & Durso, 2015). The subjective component of trust introduces more room for error when attempting to properly calibrate trust and creates an added challenge to interpreting automation use behaviors in terms of trust.

Trust in Automation in Healthcare

Historically, the adoption of automation into medical practice has seen resistance from clinicians for numerous reasons, often stemming from uncertainty surrounding automation's function and the role it would assume in the medical setting (see Hammer & Hile, 1986, for review). However, advances in technology and familiarity with it have created the opposite problem: in some cases, acceptance of automation has increased to the point where concerns now center on automation overuse and complacency in healthcare providers (Dreiseitl & Binder, 2005; Goddard et al., 2012). Research on automation decision aids and healthcare is arguably lacking, and, in the case of machine learning automation, is still relatively infantile. The lack of experience that both patients and practitioners may have with medical-specific automation creates a challenge in understanding how automation will be received since acceptance of automation is likely to vary across domains. Indeed, recent research has shown that individuals associate different words with trust in technology than with trust in medical technology, suggesting divergence between the two constructs (Montague, Kleiner, & Winchester, 2009). This would imply that trust is even more multifaceted than attitudes and behaviors; it is also context-specific and thus, should be measured sensitively. Although numerous studies have looked at trust related to physicians and patients (e.g., Franks et al., 2005; Hall, Camacho, Dugan, & Balkrishnan, 2002; Krot & Rudawska, 2017; Tarn et al., 2005), few studies consider trust in automation in the healthcare field.

Research by Montague, Winchester, and Kleiner (2010) showed that different factors influenced trust in medical technology in an obstetric setting from a patient's perspective than from a physician's perspective; for patients, trust in providers, the technology's characteristics, and how care providers used technology were relevant to building trust, whereas for physicians the key factors were their trust in themselves and the trustworthiness of the system. This difference in factors influencing trust based on the perspective of the user emphasizes the need to study trust in automation from multiple viewpoints. Some researchers express concern that automation will reduce a patient's trust in the physician by creating a degree of separation in patient care (Boehm, 2003). A study by McBride, Carter, and Ntuen (2012) found that trust in a diagnosis made by an automated system was higher for nurses with intuitive-type personalities than nurses with sensing personalities, demonstrating how personality differences in thinking styles and problem-solving approaches can impact technology acceptance. Another study exploring how anthropomorphizing automation aid might impact trust and dependence for young and old adults during a diabetes decision-making task found that low levels of humanization impacted trust for young but not older adults (Pak, Fink, Price, Bass, & Sturre, 2012). Interestingly, high levels of anthropomorphism significantly increased dependent usage of automation for both young and old adults, suggesting a complex interaction of anthropomorphizing automation on automation trust and use depending on age. Dreiseitl and Binder's 2005 study on physician's acceptance of an automated decision aid found that lower self-confidence related to a stronger likelihood to use automation. To our knowledge, other, notable research on trust in automation in this setting is lacking. Despite the deficiency of research on trusting automation in the medical setting, research on developing high-level automation to better identify, diagnose, and predict medical conditions is increasing at a rapid pace. Additionally, automation technology is shifting towards empowering the individual with resources to use medical automation on their own, without needing to visit the doctor's office. In these cases, medical diagnostic decisions may no longer be in the expert's hand, but rather, inexperienced, less knowledgeable users are coming into contact with medical automation and making decisions on trusting it themselves. Thus, examining trust in automation in the context of healthcare carries strong applicability to real world concerns.

Factors Impacting Trust

System and Design Properties

Automation reliability is one of the most influential factors on trust (Drnec & Metcalfe, 2016; Lee & Moray, 1992; Muir, 1994; Muir, 1989). Numerous research studies examining trust in automation have found a strong relationship between automation reliability and operator trust (e.g., Moray & Inagaki, 1999; Moray, Inagaki, & Itoh, 2000; Riley, 1994). Automated systems that perform consistently well are more likely to be trusted (Muir, 1989; Sheridan, 1988), than those that do not. Operators tend to trust automation that is at least 70% reliable, especially when the errors are consistent (Dzindolet, Pierce, Beck, & Dawe, 1999; Parasuraman, Sheridan, & Wickens, 2000). Increased trust due to reliable automation leads to the automation being more likely to be used, as well (Muir & Moray, 1996). Yet, research has shown that trust does not always change in a direct relationship as reliability changes (Lee & See, 2004). Moray, Inagaki, and Itoh (2000) found that trust was negligibly impacted by changes in reliability that still kept the system reliability above 90%; when reliability was below 90%, though, changes had an increasingly stronger impact on trust.

System transparency and user knowledge of it are also important factors in increasing trust. Sheridan (1988) states that illuminating the intention of automation to users directly influences trust in its purpose. Decreasing uncertainty in system performance also improves trust (Uggirala, Gramopadhye, Melloy, & Toler, 2004). The level of automation control also impacts trust (Drnec & Metcalfe, 2016) as well as performance (Strand, Nilsson, Karlsson, & Nilsson, 2014). Strand and colleagues (2014) observed significantly worse driving performance as automation control increased when they were required to take back control from automated driving, and drivers handled total automation failures worse than partial failures.

More basic characteristics, such as design features, also impact trust in automation. When automation's purpose is to serve as a decision-making aid, the consensual design goal is for the automation to behave and perform like a human in order to increase trust (Madhavan & Wiegmann, 2007b; Pak et al., 2012). Automation expertise impacts reliance and trust, with higher perceived expertise increasing trust (Madhavan & Wiegmann, 2007a). Thus, system and design features are capable of influencing trust in the automation.

Automation Failures

Failures impact trust. Trust tends to be sensitive to faults but can recover, although generally not to previous levels (Lee & Moray, 1992). Research shows that the severity, consistency, and type of fault (a false alarm versus a missed hit) can all influence the level of impact on trust and the rate of recovery from a loss of trust (e.g., Keller & Rice, 2010; Lee & Moray, 1992; Muir, 1994; Muir & Moray, 1996; Parasuraman & Riley, 1997). Tomlinson and Mayer (2009) theorized that the source cause of an error (or, a failed trust outcome) impacted future trust differently. Specifically, their model emphasized the locus of the cause for the error or failure as a major contributor in whether trust was lost. External causes, such as unexpected environmental factors, may not necessarily impact trust since the trustee can identify that the automation itself was not responsible for the failure. Internal causes, however, such as a limitation in the automation's capabilities, would be expected to result in the user losing trust in that automation. Pop, Shrewsbury, and Durso (2015) additionally found that the cause of an automation error—whether it is internal or external to the automated system—influences trust calibration sensitivity. It has also been seen that automation misses hurt user trust more than false alarms, suggesting a greater impact on trust for systems that are perceived to be lax or inconsistent than for conservative or overly sensitive systems (Keller & Rice, 2010; Parasuraman & Riley, 1997). Additionally, the greater the perceived risk in relying on automation, the less reliance: implying that the severity of the consequences of failure impacts trust. Thus, automation failures impact trust in different ways and to different degrees based on the specifications and context of the failure.

Workload

Workload also interacts with trust in automation. When the user's workload is high, research has repeatedly shown that users will be more likely to utilize automation to aid them—even automation for which they report low levels of trust (Cummings, Mastracchio, Thornburg, & Mkrtchyan, 2013; Wickens, 2000). Low workload also tends to moderate the usage of automation, with studies showing users are more likely to perform tasks themselves and not outsource to automation when they are under less pressure, time-constraint, or have less competing demands (Basten, Biele, Heekeren, & Fiebach, 2010; Wickens, 2000). Often, when users choose to ignore automation's aid and handle situations manually, the price is at an increase in workload and, more importantly, reduction in success towards the goal and/or performance efficacy (Cummings, Clare, & Hart, 2010).

User Characteristics and Trust

Throughout reviews of trust in automation, a strong theme emerges: there is a lack of research examining how *user characteristics* specifically impact trust in automation. The design of automation, transparency into its functioning, user-friendliness, and other qualities *of the automation itself* can make a significant difference in the user's willingness to trust and rely on a system. Automation reliance is not solely determined by external factors, though; research has shown that certain qualities of individuals can make them more or less likely to be trusting. Anecdotes support this: some people trust a car to park itself, and others prefer to do the task themselves. Experience, knowledge, perceived competency, and personality all interact in situations involving trust in automation. Further, research shows that higher trust in automation is associated with automation use that is most appropriate given its capabilities, a finding which encourages exploration into the factors that increase appropriate trust (Lee & See, 2004). In order to fully comprehend trust and create automation that encourages it, the role of user characteristics must be better understood.

Individual differences have been seen in response to automation changes, such as in Lee and Moray's (1994) study where changes in trust differed across individuals when the reliability of the automation changed. Pop and colleagues (2015) proposed that this discrepancy was due to individual differences moderating the relationship between automation and trust, and indeed, they found that the expectation that automation is trustworthy differentially impacted sensitivity to automation changes in reliability. Past experiences with automation which form pre-existing beliefs and biases that differ across individuals also affect trust (Muir, 1994), highlighting the importance of assessing attitudes towards automation as its own construct. Additionally, propensity to trust can be thought of as both general trust tendencies and context-specific trust, such as trust in automation. According to research by Cummings and colleagues (2010), negative attitudes towards Unmanned Aerial Vehicles (UAVs) in general impacted the acceptance of automation's suggestion and, in turn, overall performance in a simulation environment that required controlling several unmanned vehicles. However, Parasuraman and Riley (1997) speculate that propensity to trust automation in general does not exclude one from having low trust towards a specific automated system, thus distinguishing these two as separate constructs which may be influenced by personality characteristics in unique, independent ways. Because of the role user characteristics are thought to play in influencing trust in automation, it is necessary to explore these characteristics further and unravel the mechanisms behind which they interact with trust.

Knowledge and Competency

As mentioned above, both actual and perceived level of expertise (i.e., competency) in the task tends to negatively relate to automation usage. This implies that even two individuals with the same objective level of experience may differ in how they engage with automation based on how they perceived their abilities to succeed in the task at hand. Variations in training and background experiences with automation likewise impact how one might choose to use automation. In the case of non-experts using automation with which they have little experience, the decision to trust automation includes a decision to trust automation to be the expert. Research by Montague and colleagues (2010) demonstrated that the decision to trust automation is based on different factors for experts as compared to non-experts, therefore suggesting that the mechanisms behind the decisions of novices and experts ought to be considered separately. Knowledge and experience with both automation and the task play a key role in shaping which user factors may influence trust.

Personality and Dispositional Traits

Five Factor Model of Personality. Previous research has examined how personality traits relate to one's propensity to trust in general. Research shows interpersonal trust negatively relates to shyness, jealously, and suspiciousness (Couch & Jones, 1997). The majority of research has explored personality traits through Costa and McCrae's (1992) Five Factor Model of Personality, which identifies openness, conscientiousness, extraversion, agreeableness, and neuroticism as the fundamental dimensions of personality. Studies looking at the Five Factor Model show inconsistent relationships with trust: in some cases, only agreeableness related to general trust (Anderson, 2010; Dohmen, Falk, Huffman & Sunde, 2008; Mondak & Halperin, 2008); in other research, extraversion related to trust attitudes (Merritt & Ilgen, 2008; Oskarsson, Dawes, Johannesson, & Magnusson, 2012); in research by Hiraishi and colleagues (2008) agreeableness and extraversion both related to general trust; neuroticism has been found to negatively relate to trust behaviors (Szalma & Taylor, 2011); and finally, Dinesen and colleagues (2014) concluded that all five personality traits impacted trust. Differences in these results may be explained by variants in measurement approaches, research designs, and context, as Freitag and Bauer (2016) report how something as little as describing trust as general trust in most people can be interpreted differently and thus lead to different response patterns because of its broadness. Thus, despite the emphasis of research on the Five Factor Model, the methods have been inconsistent and therefore, unsurprisingly, shown inconclusive results. To build off previous research, support for relating these personality traits to automation trust would expand current understanding of the influence user characteristic have on automation use. Even considering the methodological shortcomings, the lack of consensus on how personality traits may relate to trust suggests further research in this area is warranted given that they have been shown to differentially impact trust.

Risk-Taking. The definition of trust includes a component of uncertainty and risk which weighs into the decision-making process. However, individuals vary in how they perceive, subjectively assess, and decide to act when risk is involved, which may change how one approaches a decision to trust. Some individuals tend to naturally be more risk-averse, while others are more prone to taking risks (Zuckerman, 1994). In addition, research has shown a tendency to withhold trust and reliance in situations of higher perceived risk (Keller & Rice, 2010; Riley, 1994). Thus, one's natural tendency to embrace risks coupled with their perceptions of the severity of the risk is likely to influence their risk-taking behaviors, including their decision to put trust in automation. Those who are risk averse—or less likely to take risks—may be less likely to put trust in another if it feels riskier than assuming the risk themselves. In order to understand how personality relates to trust in automation, it is necessary to acknowledge that risk-taking propensity would be expected to impact willingness to trust.

Need for Control. The need for control or dominance, distinct from actually having control or dominating, can influence whether one will enter into a trust-relationship with another entity. Since trust inherently involves dependence on another, it is unsurprising that those who have a strong need for control tend not to trust others but rather rely solely on themselves (Oskarsson et al., 2012; Uslaner, 2002). Such tendencies would be expected to continue to influence trust regardless of the context. Therefore, it follows that a need for control may relate to withholding trust from another.

Locus of Control. Locus of control is defined as one's sense of whether life outcomes are controlled by oneself or by external forces and is an important construct for understanding how personalities interact with the world (Gabay, 2015). Research across social psychology has established a relationship between locus of control and trust (e.g., Doherty & Ryder, 1979; Massari & Rosenblum, 1972). This relationship has been found in such contexts as academic achievement and assertiveness levels in newlyweds (Doherty & Ryder, 1979; Massari & Rosenblum, 1972). The impact that locus of control has on trust also tends to differ by sex (Doherty & Ryder, 1979; Massari & Rosenblum, 1972). Specific types of locus of control also relate to trust. For example, health locus of control can impact a patient's trust in their doctors, with higher external locus of control being associated with more trust in one's oncologist in a study by Hillen and colleagues (2014). Perceived control over a patient's own health is associated with patient-physician trust, which is also increased by positive communication skills (Gabay, 2015). The relationship between work locus of control and psychological safety was moderated by trust in a study on work teams (Triplett & Loh, 2018). Thus, the relationship between locus of control and trust appears established in both general and some specific settings, but it has not been examined in the context of trust in automation despite the relevance of control in making a decision to trust automation in a health context.

Self-Efficacy. Self-confidence can be a general, persistent trait as well as task- or situation-specific. Self-confidence is also necessarily a subjective assessment of one's own abilities, varying in the amount of bias yet nevertheless influential in decision-making. Experience builds confidence, and confidence is directly related to reliance (Lee & Moray, 1994; Riley, 1996). Findings have established that the relationship between trust in the automation's abilities and self-confidence in one's own ability without automation has a significant impact on actual choices to depend on automation (Lee & Moray, 1994; Muir & Moray, 1996). Specifically, Lee and Moray (1994) postulated that when trust is greater than one's confidence, the automation used, but when confidence is greater than trust, manual control is used. This inverse relationship has been seen in other research as well (Dreiseitl & Binder, 2005; McGuirl & Sarter, 2006). In higher levels of automation, a more complex relationship is found, in which trust responds to system characteristics (such as perceived reliability) whereas self-confidence in the task is more sensitive to the operator's involvement than to the system's reliability (Moray, Inagaki, & Itoh, 2000). That is to say, trust was impacted by changes in reliability, but self-confidence was not. In cases such as this, task-confidence appears to have a direct impact on the decision to trust automated systems, sometimes regardless of the abilities or reliability of the automation itself (Lee & See, 2004; Moray, Inagaki, & Itoh, 2000). Lewandowsky and colleagues (2000) also found that self-confidence in the task was not impacted by changes in automation reliability in the same way as trust was. Thus, self-confidence has a confirmed yet complex relationship to trust in automation.

Demographic Influencers

Trust can differ significantly based on age, culture, education level and gender (Pak et al., 2012; and see Hoff & Bashir, 2015, for review). Trust in the automation differed significantly by age in a study of automation aid during a medical decision-making task in which participants had to answer questions about diabetes with or without automation's help (Pak et al., 2012). Specifically, younger participants increased their trust when the aid was anthropomorphized, whereas older adults' trust did not change based on changing the nature of the automation. In another study, older adults were more trusting of an automated decision-aid than younger adults (Ho, Wheatley, & Scialfa, 2005). Research has also shown the male and female users of automation respond differently to the gender and characteristics of anthropomorphized automation (Lee, 2008). Oskarsson and colleagues (2012) found a relationship between intelligence and trust levels. Finally, as mentioned above, simple differences in knowledge or experience can influence trust decisions as well (Muir, 1994). From these examples it becomes apparent that demographic differences can impact trust and are an important consideration in understanding the interplay between user traits and automation traits on trust.

Summary

Even perfect automation is worthless if it is not used within its capabilities. Although use depends on attributes of both the system and the user, trust is arguably the most critical factor in determining the potential for a user's appropriate reliance. Trust contains both emotional and rational components, based on prior experience, information, and intuition. Previous research on trust in automation has focused on automation-related changes such as design, functional transparency, and the effect of failures on trust. However, individual differences outside of the properties of automation are known to impact use as well, despite the lack of research pursuing the details of these differences (Muir, 1994). Individual characteristics that alter responses to—and ultimately, use of—automation are critical to consider when attempting to design automation that maximizes trust.

Automation within the healthcare system is at a critical developmental point: it is able to streamline many laborious tasks of medical staff, and it is also showing increasing reliability in making diagnostic predictions. Transitions within the medical field favor increasing automation in healthcare without substantial research to support whether it will be trusted and accepted. These transitions promote automation use not only by trained experts in medical settings but also promote putting power in the hands of the lay person to use tools (e.g., phone applications) for medical purposes as well. Given that research suggests that individual characteristics impact trust formation, it is imperative to explore this relationship further in the context of medical automation use.

Purpose

The primary purpose of this study was to test relationships between the characteristics of individual automation users and a) the propensity to trust automation as well as b) "actual" automaton use behaviors in the context of a medical diagnostic screening task with an automated decision-aid. In accomplishing this purpose, there were several sub-goals we also aimed to achieve. First, we hoped to clarify previous findings of an association between trust and dispositional characteristics. Specifically, the Big Five Factors of personality have been shown to relate to trust, although the nature of specific factors' relationships has been inconsistent in past research. We intended to explore, within our study, how these personality factors relate from both a multimodal measurement approach and operationalizing trust as both an attitude and a behavior. We similarly sought to examine how traits of risk-taking, self-efficacy, locus of control, and need for control predict trust in automation. Second, we intended to extend past research by distinguishing general trust from trust in automation. Whereas past research has sometimes used general trust and automation-specific trust interchangeably, we speculated that these are similar but unique concepts that will hold different relationships with the dispositional variables. Additionally, we aimed to measure how propensity to trust automation relates to trust behaviors (i.e., automation acceptance through usage), that is, to compare the relationship between trust attitudes and trust behaviors. On top of this, we intended to explore differences in how individual characteristics predict self-reported trust attitudes as compared to trust behaviors through use. There is disagreement in the literature concerning the conceptualization of trust as a psychological state or as a behavior, although recent research is moving towards defining trust as a state that manifests itself in behaviors (Costa, Roe, & Taillieu, 2001). Because of the lack of resolution on this point both theoretically and in experimental research, we intended to measure both subjective reports of trust and behaviors which may be demonstrative of trust and potentially clarify this dissonance.

Studying trust in automation is critical at a time when automation technologies are advancing, yet it is not fully understood how best to achieve appropriate acceptance. As mentioned above, most research has focused on changing automation characteristics in order to increase user trust in automation (Lee & See, 2004). Less has looked at how the characteristics that the user brings to the table may impact how he/she interacts with the automation. The research that has been done has primarily focused on demographics, such as age and gender (Pak et al., 2012). Although user characteristics are unlikely to change, understanding how these qualities influence trust in automation is informative for designing, marketing, and distributing technology. It can begin to reveal which personality qualities tend to work best with automation and, in cases of misuse or disuse, be an important piece of explaining what went wrong. Furthermore, examining how personality qualities relate to automation trust and use can help redesign automation to be more effectively appealing to a wider range of users. Thus, the goal behind examining the interplay of personality and trust in automation was to use the findings to adapt automation features in order to encourage more appropriate automation use for the given user.

As mentioned above, past literature has operationalized trust in various ways, leading to various methods of measurement including self-report, social experiments, and “real world” scenarios. The present study measured trust from two separate conceptual standpoints: trust as an attitude and trust as a behavior. Thus it was necessary that trust be measured using multiple modalities. Assessing attitudes towards trusting automation is most commonly seen through self-report. The standard strategy for measuring behavioral trust in automation is through simple scenarios and paradigms (Lee & See, 2004). A key component of these scenarios is that previous experience or expertise is controlled. In some studies, the tasks have required the subjects to be experts (or at least knowledgeable) in the task (e.g., aviation, systems controls) in order to determine context-specific findings that could be applied directly within that setting. Other research has aimed at gaining a broader understanding of how humans interact with automation regardless of the context, and thus have used scenarios in which expertise was not desired and instead controlled for (e.g., the luggage-screening task of Merritt & Ilgen, 2008). The benefits of using novices includes removing any confounding impact that an individual's perceived skill in the task would have on one's decision to use automation. Further, it is clinically relevant to anticipate that the layperson will encounter automation in unfamiliar domains and will have to choose whether to trust automation, trust one's own judgment (often an uneducated guess), or seek out a human expert. In order to explore how personality characteristics impact trust attitudes and behaviors, the present study implemented a task that controlled for the role of expertise in choosing to use automation and instead focused on how dispositional traits influence the tendency to trust automation.

We implemented a medical screening task as the context for our behavioral observations due to the highly relevant and under-researched nature of automation in medicine. We examined how trust in automation and the decision to use automation in medical diagnostic judgments were impacted by individual differences. Technology use is expanding such that non-experts are deciding whether to turn to automation for knowledge that can provide answers more quickly and easily than making an appointment at the doctor's office. Further, automation for preventative and preliminary diagnostic means can be cost- and resource- efficient if used properly at home. The task designed for this study involved screening skin abnormalities for malignancy; a process that is likely to occur at home before a visit to the doctor's. Mobile-based applications are already acknowledging this and are being developed as aids to assist individuals in more accurately categorizing their skin condition based on an algorithmic analysis of a photo of the abnormality (Esteva et al., 2017). Skin cancer is also highly relevant given that it is deadly yet preventative. It is the most common cancer in the United States, with approximately 20% of the population being treated for skin cancer at some point in their lives, and three million people affected every year (Guy et al., 2015; Guy, Machlin, Ekwueme, & Yabroff, 2015). Melanoma, the most deadly category of skin cancer, was expected to be seen in over 160,000 individuals in 2017 and is the third most common type of cancer among young, college-aged adults (American Academy of Dermatology, 2017; American Cancer Society, 2017; Siegel, Miller, & Jemal, 2017). However, it is possible not only to prevent most skin cancers but also to detect their presence early through home screenings. Early detection significantly increases the survival rates for all types of skin cancer, including melanoma (American Cancer Society, 2017). Because early detection primarily lies in the hand of the untrained individual, it is important to consider their responses to automation that may be able to assist—and likely outperform—them in this process. We anticipated that our medical screening task would be highly relevant both for the participants and in the field itself for understanding trust in automation.

The hypotheses for this study were as follows:

> **H1:** We expected that propensity to trust automation would relate positively to general propensity to trust.
>
> **H2:** We hypothesized that personality traits would significantly predict a propensity to trust automation, specifically that openness, extraversion, agreeableness, and external locus of control would positively predict trust attitudes and that neuroticism,

risk-aversion, need for control, self-efficacy, and internal locus of control would negatively predict trust attitudes towards automation. We anticipated that personality qualities would thusly predict trust in automation and explored this relationship through a stepwise regression model.

H3: With regard to our behavioral task, we hypothesized that propensity to trust automation and to trust in general would significantly, positively predict automation use.

H4: We expected to replicate from our first study the relationship between personality qualities and trust attitudes as described in hypothesis two.

H5: We further explored how personality qualities relate to trust behaviors (i.e., automation use) and specifically predicted that conscientiousness, agreeableness, extraversion, and openness would positivity predict automation use, whereas neuroticism, risk-aversion, need for control, internal locus of control, and self-efficacy would negatively predict automation use when controlling for trust attitudes.

In addition, our study also included the following exploratory hypotheses:

H6: We predicted an increase from pre-test to post-test scores measuring trust in the task-specific automation, as is seen in literature that suggests a general positivity towards trusting automation.

H7: We hypothesized that task self-efficacy and a desire for mastery would moderate the relationship between trust attitudes and trust behaviors (i.e., automation use).

H8: With regard to health locus of control, we hypothesized a negative relationship between internal health locus of control and automation trust, and a positive relationship between beliefs that locus of control is external due to powerful others (vs. chance) and automation use.

CHAPTER 3

METHODS

Overview

The study was conducted over two studies in order to achieve the following goals: in the first study, our aims were to explore the relationships between individual characteristics and propensity to trust automation, and to gather baseline accuracy ratings on the diagnostic categorization of our images. In the second study, our goals were to examine how propensity to trust relates to trust behaviors in a medical screening automation task, and how individual qualities relate to trust behaviors. The measures of Study One were included in Study Two with the addition of the behavioral task and brief, task-specific pre- and post-task surveys. The specific methods for each study are described below.

Study One

As mentioned above, the purposes of Study One were two-fold: to gather qualitative data on our variables of interest from a large, diverse sample in order to explore the relationships between initial (propensity to) trust and individual characteristics, and to establish the reliability and accuracy ratings for each image in order to determine which to include in our behavioral task in Study Two.

Participants and Procedure

Three hundred fifty participants (M_{age} = 22.6, *SD* = 4.6; 57.9% female; 60.5% White) were recruited through the online participant recruitment systems of the psychology department and business school at a mid-sized, Midwest public university. Students who signed up via the recruitment system websites were provided with a link to the study hosted by Qualtrics, an online survey hosting platform. The study included survey measures of personality, disposition, and trust-related traits as well as an image rating task in which participants categorized images in order to determine average accuracy ratings without automated assistance. The two separate parts of Study One—the surveys and the rating task— were presented randomly to participants in order to minimize order effects. Overall, the study took approximately 45-55 minutes. Fatigue and attention checks were included in the form of repeated questions and comparing the responses on contradictory questions. Upon satisfactory completion of the surveys, the student received course credit within the online system. The study protocol was reviewed and approved by the university's Institutional Review Board (IRB).

Outcome Measures

Propensity to Trust Automation. Our primary outcome variable is propensity to trust automation. The Checklist for Trust between People and Automation (TPA; Jian, Bisantz, & Drury, 2000) is a widely-used measure that assesses beliefs in automation's trustworthiness and its capabilities. It is a 12-item measure with a 7-point, Likert-type rating scale for each question and overall scores ranging from 7- 84, with higher scores indicating higher levels of trust. Example items include, "I am confident in the system" and "the system is dependable." For our purposes, the phrase "the system" was replaced with "automation," in order to broaden the applicability of the phrase to all automated systems. Dispositional trust in automation was measured by the 6-item Propensity to Trust questionnaire (PTT; Merritt, 2011). It contains statements such as, "I usually trust machines until there is a reason not to" and "for the most part I distrust machines" answered on a Likert-scale with total scores ranging from 6- 30 (30 indicates highest levels of trust). In addition, the Automation-Induced Complacency Potential Rating Scale (CPRS; Singh et al., 1993) was used for its scenario-based approach to measuring propensity to trust machines. In 12-items, scenarios vary from trusting computer-aided surgery to remove a tumor, to believing that automated systems in aviation have made flight safer. It has been used in trust in automation research to explore overall propensity to trust automation as well as domain-specific automation trust (Lee & See, 2004). For our purposes, we used answers from only the trust subscale of the CPRS, as the reliance, safety, and confidence-related complacency subscales measure different attitudes than trust. Scores on the trust subscale ranged from 3-15, with higher scores suggesting higher trust.

Independent Variable Measures

Propensity to Trust. Tendency to trust interpersonally was measured using Rotter's (1967) Interpersonal Trust Scale (ITS). The scale consists of 25 items rated on a 5-point, Likert type scale, with higher scores indicating higher interpersonal trust. Since a general propensity to trust is considered stable and trait-like, we anticipated it would positively correlate with a propensity to trust automation as seen in previous literature (Parasuraman & Riley, 1997).

Personality. Personality was measured using the Big Five Inventory (BFI; John, Donahue, & Kentle, 1991; John, Naumann, & Soto, 2008), a 44-item, self-report survey covering five subscales as delineated by Costa and McRae's (1992) Five Factor Model of Personality, namely: neuroticism, openness, conscientiousness, extraversion, and agreeableness (Benet-Martinez, & John, 1998). It is included in this study to explore the relationship between these factors and the propensity to trust automation, as shown inconsistently in previous literature (e.g., Dinesen et al., 2014; Dohmen et al., 2008; Hiraishi, Yamagata, Shikishima, & Ando, 2008; Merritt & Ilgen, 2008). The five subscales were scored dimensionally, e.g., ranging from extraversion vs. introversion (8 items), agreeableness vs. antagonism (9 items), conscientiousness vs. lack of direction (9 items), neuroticism vs. emotional stability (8 items), and openness vs. closedness to experience (10 items) for high scores vs. low scores, respectively.

Risk-Taking and Risk-Aversion. Risk-taking likelihood was measured using the Revised Domain-Specific Risk-Taking (DOSPERT) Scale (Blais & Weber, 2006). In the original as well as the revised scale, the DOSPERT asks participants to rate their likelihood of engaging in risky activities across five domains: financial, health, recreational, ethical, and social (Blais & Weber, 2006; Weber, Blais, & Benz, 2002). The 30-item revised version is intended to be shorter, modernized, and more culturally-inclusive than the original measure. Scores range from 30 – 210, with higher scores indicating greater risk-taking. It is included in our study in order measure risk-taking tendencies across a span of contexts in their relation to trust in automation.

Need for Control. The Desirability of Control Scale (DCS; Burger & Cooper, 1979) is a 20-item, Likert-type scale that assesses one's desire to have control in their personal and interpersonal situations. Scores range from 20- 140, with higher scores indicating a stronger desirability for control. Examples from this scale include, "I prefer a job where I have a lot of control over what I do and when I do it" and "When it comes to orders, I would rather give them than receive them." It is included in this study for its tendency to be negatively associated with trust attitudes in order to see if that association continues with automation-specific trust (Oskarsson et al., 2012; Uslaner, 2002).

General Locus of Control. The Levenson IPC Scale (LIPC) is a measure of general locus of control that distinguishes two types of external control, powerful others (e.g., authority or religious figures) and chance, from internal sources (Levenson, 1981). Twentyfour items are worded for the individual to answer about their own beliefs on a six-point Likert-type scale, with higher scores indicative of higher control beliefs in that subscale. A general locus of control scale is included in this study to acknowledge that the participants do not themselves necessarily have the medical condition being diagnosed, and therefore it is uncertain whether a health-specific locus of control scale would be relevant to their decision to trust automation. Additionally, general locus of control scales have been most commonly used in past trust research, and higher external locus of control tends to be positively associated with trust in others (Hillen et al., 2014).

Self-Efficacy. Self-efficacy was measured using the General Self-Efficacy Scale (GSES; Schwarzer & Jerusalem, 1995). Its 10-items are intended to measure perceptions of self-efficacy in coping with and adapting to both daily life and stressful events. Higher scores indicate a more positive, optimistic self-belief in performance and coping (with scores ranging from 10-40). It is included in this study in order to measure a relationship between self-efficacy and trust attitudes and behaviors which has been established in previous literature (e.g., Lee & Moray, 1994).

Other Demographic and Exploratory Measures

Demographics. Participants completed a brief demographic survey to collect information on age, gender, ethnicity, education, and whether the subject currently works in a medical field in order to control for variants in medical diagnostic exposure and/or knowledge. Knowledge of skin cancer and personal experience with it were also assessed.

Technology Familiarity and Attitudes Towards Use. In order to measure comfort and self-efficacy in technology use, we adapted the Media and Technology Usage and Attitudes Scale (MTUAS; Rosen, Whaling, Carrier, Cheever, & Rokkum, 2013).

Specifically, we abridged the measure to only include items on frequency of technology use across various tasks (e.g., checking e-mails, browsing the web) and attitudes (positive and negative) towards technology use. We also modified the questions on frequency of use to create new questions to assess how confident the user feels in performing each task. The MTUAS was originally included to assess familiarity and comfort with using application technologies as a potential control variable for impacting trust attitudes and use. Unsurprisingly, the reported use was disproportionately skewed towards high frequency of technology use and high comfort, familiarity, and confidence in use; thus it was not deemed an appropriate control variable.

Health Locus of Control. The Multidimensional Health Locus of Control Scale (MHLC; Wallston, Wallston, & DeVellis, 1978) assessed individual's health-specific locus of control. This scale contains 18 items and is comprised of three subscales: internal belief (i.e., the belief that health is dependent on one's own choices and behaviors), chance belief (i.e., the belief that chance or fate determines health), and powerful others belief (i.e., the belief that the competency or behaviors of doctors, family members, and others controls health). This measure was used in addition to a general locus of control scale because of its ability to directly measure ideas about power over one's own health, which may relate to decisions to trust others' health judgments. Although we hypothesized a positive relationship between internal health locus of control and appropriate trust and a positive relationship between powerful others belief and automation use, these analyses were purely exploratory in our study.

Image Screening Task

The image screening task is a brief sorting task designed to gain average ratings on the difficulty with which a lay sample can correctly categorize skin cancer images. Participants were instructed to categorize medical images according to a binary diagnostic criterion in order to determine the accuracy and reliability at which a large sample is able to judge intentionally ambiguous medical diagnoses. The images used are photographs of skin from the Interactive Dermatology Atlas (http://www.dermatlas.net), an online open-access database of de-identified, photograph images of skin conditions intended for education training purposes. Skin images were chosen both due to the availability of the database and because they are a current focus in machine learning automation research. Specifically, applications are already in development (Esteva et al., 2017) to assist the untrained user in identifying skin cancer at home, without the need for a visit to the doctor's office for a diagnosis. Further, skin cancer is a very common and deadly diagnosis, yet it is also preventable and detectable through self-checks. This ideally adds a sense of personal relevance to the participants while completing the task. Common screening criteria for melanoma follow five cues: asymmetrical shape, uneven border, multiple colors, larger than a quarter-inch diameter, and evolving, that is, changing in size, shape, or color over time (Mayo Clinic, 2015). The images used in our study varied in the number of criteria they met based on common screening methods in order to include a range of difficulties in judging each image.

Each participant was randomly assigned to rate either 40 or 42 images of the total selected set of 122 in order to minimize fatigue. There were 30 unique noncancerous images and 31 unique cancerous images; each image was shown twice, once in its original orientation and once reflected across the y-axis. In the task, each image appeared in the center of the screen with unlimited time for the participant to select one of two response choices indicating whether they believe skin cancer is or is not present in the image. No feedback was given on their choices. At the end, participants responded to a single question inquiring if they would have used automation for the task had it been available; the purpose of this was to ascertain willingness to use automation after an experience completing an ambiguous task manually. In our sample, 84.4% of participants stated that they would use the aid of an automated technology on the task had it been an option.

Planned Analysis

Correlations were conducted to explore relationships between individual characteristics and propensity to trust automation. Any significant correlations with trust were followed up in a stepwise regression predicting trust attitudes from personality qualities. A stepwise regression was used since the hypotheses were exploratory in nature; that is, because we were seeking to determine which, if any, relationships exist that are able to predict trust attitudes.

Further, the image ratings were used to calculate the average accuracy of our sample in correctly identifying the condition of the image (cancerous/not) in order to include only images with a range of ambiguity in the behavioral task in the second study. Ambiguity in the images was necessary in order to create uncertainty and thus to make trust relevant to the situation. It was our plan that images which were correctly assessed 100% of the time or below 50% (i.e., chance) were excluded from the task in Study Two. We used images which were correctly categorized within one to two standard deviations of the mean accuracy rating, which we expected would entail including images that were rated correctly between 60% and 80% of the time. One hundred images were used for Study Two.

Study Two

Study Two examined the role of automation-user characteristics in predicting "actual" automation acceptance. Through a behavioral task in which participants chose whether to trust automation's judgment or their own opinion, we tested if user characteristics predict trust differently in considering automation use.

Participants and Procedure

Two hundred forty-four students (M_{age} = 22.5, *SD* = 4.2, 59.8% female, 57.8% White) were recruited from a mid-sized, Midwest, public university. Interested students over the age of 18 registered via university online participant recruitment systems (Sona Systems, Ltd.), one of which recruits from business school undergraduate and graduate students, the other of which uses a pool of undergraduate psychology majors. Participation took place online, either in a location of the students' choosing or in group format in a computer laboratory depending on the requirements of the specific recruitment system. All participation took approximately 45- 60 minutes. Participants provided informed consent before beginning the study and were briefed of the voluntary nature of their participation and the complete confidentiality of their responses. Participants were compensated through research credit that was applied to their courses at the discretion of their instructors (e.g., usually as extra credit points). Further, students were told they could earn a cash pay-out based on their performance in the Medical Screening Task in order to increase motivation. Specifically, before beginning the task, participants read instructions informing them that they could receive up to an $8 giftcard based on their performance on the behavioral task. In reality, all students who completed the medical screening task and followed the instructions to leave their email addresses on a final screen earned an $8 Amazon giftcard. In other words, the amount of compensation was not linked to performance, and all participants were given full and equal compensation. Participants also still received course credit for their participation regardless of their performance in Study Two. The study protocol was reviewed and approved by the university's Institutional Review Board (IRB).

Study Two included the same surveys as Study One, with the addition of the Medical Screening Task and pre- and post-task surveys. Students did not complete the image rating task from the first study, as the purpose of that task was to determine images for use in the Medical Screening Task.

Additional Measures

Pre- and Post-Task Surveys. Both before and after the task, participants answered questions on their trust in this automation system on Merritt's (2011) 6-question scale, with sample items including, "I believe the automation is a competent performer" and "I can depend on the automation." After the task was complete, participants responded to questions adapted from Lee and Moray's (1994) Subjective Rating Scale Statements on their confidence during the task (in both themselves and the automation) and their desire for mastery when completing the task (Moray, Inagaki, and Itoh, 2000). These are included because of the impact motivation to succeed in a task can have on engagement and task performance. Additionally, perceived confidence was measured to control for the effects that one's perceived ability to successfully complete the task independently may have on one's willingness to use automation.

Medical Screening Task. We designed a computerized screening task in which participants viewed medical images and choose either to diagnosis the image (1) themselves or (2) for automation to make the diagnosis on the presence or absence of skin cancer. The concept for this task is based off the luggage screening task by Merritt and Ilgen (2008) in which participants cleared or pulled luggage to search for weapons after viewing an x-ray image. Similar to Merritt's study, we also used lay persons without extensive experience in the task in order to minimize the confound of expertise and, in our case, mimic real-life scenarios of encounters with automation in healthcare. The primary variable of interest in our task was participants' binary choice on automation use. This decision was recorded for each image assessed. Additionally, the accuracy of participant's decisions, response times for each image, and individual changes in response to feedback after each decision (i.e., calibration) were also measured. As mentioned above, the images used in our study are from the Interactive Dermatology Atlas (http://www.dermatlas.net) database, an online, open-access source of de-identified photographs of various skin conditions. Skin cancer images were chosen due to the availability of the database and because they are a current focus in machine learning automation research. Further, the high prevalence of skin cancer and emphasis on preventative care may, theoretically, make the content feel applicable to a college-aged sample of participants.

In our task, the medical images consist of 100 skin condition images with and without the presence of malignant cancer. Our images were selected based on ratings of 122 images from Study One and included pairs of images—the same image presented twice, with one copy of it reflected across the y-axis to be a mirror-image of the original. First, we compared whether the orientation of the original 122 images made a difference in how participants judged them. The difference in ratings for the original orientation and flipped orientation was not found to be significant in a paired-samples t-test, $t(60) = 1.22$, $p = .23$, and the correlation between the two groups was .90. This suggests strong consistency in how images were rated regardless of their orientation.

The task was designed such that each decision involved some ambiguity concerning the diagnosis in order to create a situation in which trust is relevant. Because it is not feasible to mimic real-world rates of skin cancer per skin concerns, we attempted to balance the rates of malignancy in the images displayed while also presenting images within a certain distribution from the mean accuracy of image ratings (i.e., images that were easier and harder to rate by Study One participants). This resulted in selecting 48 images containing visible and diagnosable skin cancer abnormalities and 52 images displaying non-cancerous skin blemishes. As mentioned above, our expectation was for these images to have been accurately rated approximately 60-80% of the time by participants in Study One, which was expected to insure ambiguity and uncertainty in the judgments. The average accuracy of our participants in rating images from Study One was 53.5%. Participants were, on average, only able to accurately judge images at a rate close to chance. This presented a challenge, as our original intent was to follow previous studies (and intuitive reasoning) and set automation to be roughly 75% accurate and to use images which had been accurately rated between 60-80% of the time, in order to maximize ambiguity in the decision. Instead, we selected 100 images nearest to the mean accuracy we observed: this resulted in picking images ranging from 33.3% - 87.5% in how accurately participants had rated them. This subset of images had been correctly judged 59.2% of the time on average (61.6% for cancerous images, and 57% for noncancerous images).

The accuracy of the automation's judgment was to be fixed at rates similar to the average unassisted ratings from the task in Study One, which we anticipated would be around 75% accuracy based on previous work (e.g., Merritt & Ilgen, 2008; Merritt, 2011; Merritt et al., 2015). Following this format, we chose to set our automation at 60% accuracy in order to have automation's accuracy match the mean accuracy of human participants from Study One on ratings of the images selected for Study Two (which was 59.2%). In other words, we set automation to be equally as accurate at rating images as human judges in order to create maximum ambiguity in the decision by removing bias that may exist based on performance abilities. If automation were to perform significantly better (or worse) than the average human, then the decision to use (or not use) automation would become obvious regardless of the influence of personality factors. Among the 100 images selected, we randomly assigned 60 images to be correctly judged by the automation in the task. This resulted in 28 cancerous images being correctly judged by automation, and 32 noncancerous images being correctly judged.

In each decision, participants had the choice either to make their own judgment (yes/no to the presence of malignant cancer) or elect to defer the judgment to automation. The goal of the task was to accumulate as many correct diagnoses as possible, with the veiled motivation a financial payout based on overall performance. Participants were not told of the automation's accuracy and reliability ahead of time, but they received feedback on the correct decision after each trial regardless of whether they used automation or their own choice. Thus, participants had the opportunity to learn automation's reliability over time and adjust their usage as they see fit, which is common with most automation experiences (e.g., Merritt & Ilgen, 2008). In theory, the most appropriate use of automation would be to employ it on images which are more difficult to judge (e.g., were judged correctly less than 60% of the time in the first study) and to use one's own judgment when it is more likely to be correct than the automation's rate. As mentioned above, we attempted to increase motivation by informing participants that their compensation was based on their performance on the task.

The task started with a brief instructional screen introducing participants to the task and their role in judging images. They were told that they are to decide on a medical diagnosis for each image on their own or may defer the judgment to an automated aid. Specifically, participants were instructed to search each photographed image for the presence of malignant skin cancer and either select whether they wanted to make the decision themselves or select for automation to make the decision. If participants chose to make their own judgment, then the following screen presented two options from which they could select "yes" or "no" to indicate the presence or absence of cancer, respectively. Regardless of whether the participant chose for automation to decide or selected a decision on his/her own, the following screen displayed the correct answer for seven seconds before beginning the next trial. Participants were able to view the instruction screen indefinitely before starting. At the beginning of the task, participants completed five untimed practice trials to familiarize themselves with the task. After these, they answered the pre-task questions on their propensity to trust the present automaton. The procedures for the practice trials were the same as those for the behavioral task except the responses were not calculated into the final score.

The first trial appeared on the screen after the participant indicated they were ready to begin (Figures 1 & 2). Each screen consisted of a 300 x 400 pixel image at the top of the screen and two response choice buttons centered below the image modelled after the study by

Merritt and Ilgen (2008). Below the image were the words “Choose to decide yourself or let automation decide,” asking participants to make the decision to judge the image’s condition themselves or to defer to automation as quickly and accurately as possible. Participants indicated their choice by using the mouse to click on one of two options labelled “Manual- Me Decide” to make the decision themselves and “Auto- Automation Decide.” If participants chose to make their own judgment, the following screen presented two options from which they could select: “yes” or “no” to indicate the presence or absence of skin cancer, respectively. If participants chose to let automation decide, the next screen displayed automation’s choice indefinitely until the participant selected to move on. After participants made their selection, a feedback screen was displayed for 7s indicating the correct response; after 7s, the next trial appeared. As mentioned above, participants completed five practice trials and answered a brief set of questions before beginning. The main task began after these questions with an instruction screen indicating the start of the task. Once participants indicated their readiness to begin, they commenced the 100 trials of the task. Once a participant completed all trials, a final screen appeared to alert the participant that they were done with the task and to redirect them to a separate page for compensation.

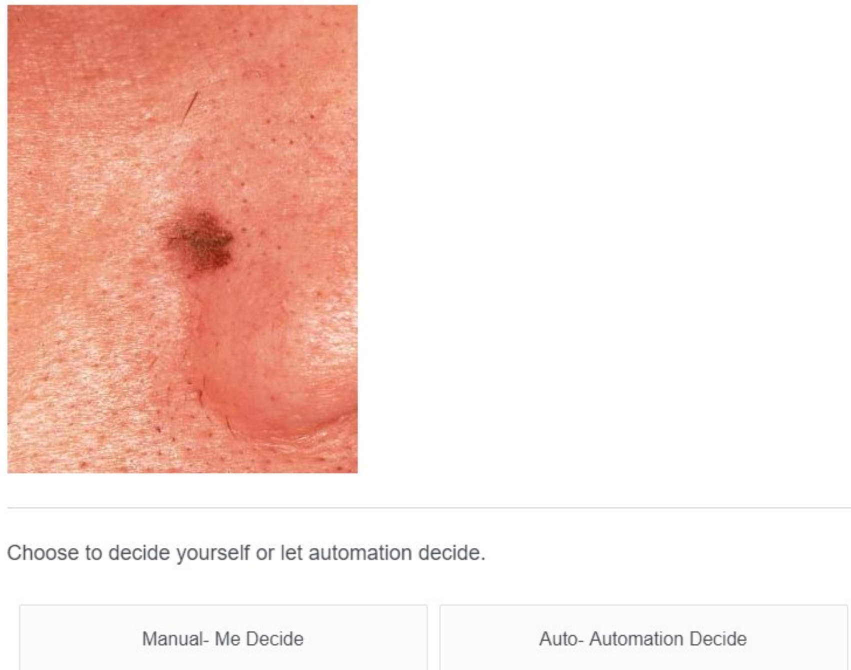


Figure 1. *Sample Images from Medical Screening Task.*

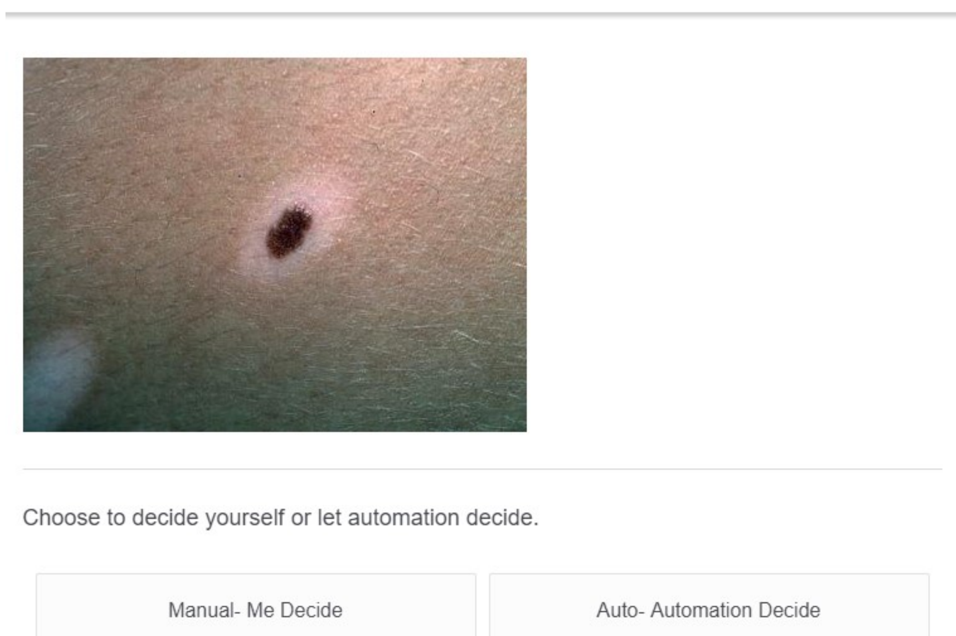


Figure 2. *Sample Images from Medical Screening Task.*

Planned Analysis

We first explored all correlations from the first study and attempted to replicate significant findings. We conducted a simple regression to explore whether self-reported propensity to trust predicts “actual” automation usage (i.e., trust behaviors). Further, we tested whether user characteristics predicted automation usage similar to how they were tested in Study One. More specifically, we again conducted stepwise regressions predicting trust attitudes from personality qualities as in Study One, and also conducted a second stepwise regression predicting trust behaviors (e.g., automation usage) from personality qualities while controlling for trust attitudes.

CHAPTER 4

RESULTS

Study One

Demographics and Descriptives

Study One consisted of 349 participants, M_{age} = 22.6, *SD* = 4.6, and was predominantly female (*N*= 202, 57.9%) and White (*N*= 211, 60.5%; see Table 1 for complete demographic information). Thirteen participants were removed before analysis for missing, inconsistent, or inattentive responses. The majority of our sample reported no medical field experience (*N* = 299, 86.7%), no formal medical knowledge (*N* = 200, 58.1%) and no encounters (either directly or through close relationships) with skin cancer (*N* = 199, 57%). Descriptive statistics from measures of trust in automation (i.e., Automation-Induced Complacency Potential Rating Scale [CPRS], Checklist for Trust between People and Automation [TPA], Pre-Task Trust [PTT]), technology use (i.e., Media and Technology Usage and Attitudes Scale [MTUAS]), self-efficacy (i.e., General Self-Efficacy Scale [GSES]), locus of control (i.e., Levenson Internality, Powerful Others, and Chance Scale [LIPC]), health locus of control (i.e., Multidimensional Health Locus of Control Scale [MHLC]), desire for control (i.e., Desirability of Control Scale [DCS]), Big Five personality traits (i.e., Big Five Inventory [BFI]), risk-taking (i.e., Domain-Specific Risk-Taking Scale [DOSPERT]), and interpersonal trust (i.e., Interpersonal Trust Scale [ITS]) are included as well in Table 2.

Table 1. *Summary of Demographics for Study One*

Total N= 349	Mean (n)	Standard Deviation (%)
Gender		
Male	142	40.7%
Female	202	57.9%
Other	1	.3%
Age	22.6	4.6
Ethnicity		
White	211	60.5%
Black or African American	42	12.2%
American Indian or Alaska Native	1	.3%
Asian	50	14.5%
Native Hawaiian or Pacific Islander	2	.6%
Other	39	11.3%
Year		
Freshman	38	10.9%
Sophomore	75	21.5%
Junior	113	32.4%
Senior	90	25.8%
Graduate Student	29	8.3%
Medical Field Experience		
None	299	86.7%
Previous	28	8.1%
Current	18	5.2%
Medical Knowledge		
None	200	58.1%
Minimal	101	29.4%
Moderate	38	11%
Extensive	5	1.5%
Skin Cancer Experience		
Never screened nor diagnosed	199	57%
I, myself screened but not diagnosed	23	6.6%
I, myself, diagnosed	1	.3%
Someone close to me screened but not diagnosed	49	14%
Someone close to me diagnosed	83	23.8%

Table 2. *Summary of Self-Report Data Descriptives*

Self-Report Measure	Mean	Standard Deviation
CPRS- Trust	11.43	2.19
TPA	55.09	11.68
MHLC- Internal	26.20	4.72
MHLC- Others	20.07	4.69
MHLC- Chance	18.77	4.86
MTUAS- Use	70.73	17.56
MTUAS- Confidence	44.50	5.41
MTUAS- Positive Attitudes	23.97	3.88
MTUAS- Anxious/ Dependent	10.25	3.02
MTUAS- Negative Attitudes	10.59	2.47
MTUAS- Task Switching	10.52	3.76
GSES	31.59	4.08
LIPC- Internality	33.72	5.55
LIPC- Powerful Others	22.10	8.31
LIPC- Chance	20.59	8.53
DCS	100.37	12.42
DOSPERT	101.24	21.78
BFI- Extroversion	3.27	.80
BFI- Agreeableness	3.82	.57
BFI- Consciousness	3.68	.61
BFI- Neuroticism	2.90	.77
BFI- Openness	3.46	.59
ITS	64.59	9.16
PTT	21.63	4.66

Note: CPRS = Automation-Induced Complacency Potential Rating Scale, TPA = Checklist for Trust between People and Automation, MHLC = Multidimensional Health Locus of Control Scale, ITS = Interpersonal Trust Scale, PTT = Propensity to Trust Scale, MTUAS = Media and Technology Usage and Attitudes Scale, GSES = General Self-Efficacy Scale, *LIPC = Levenson Internality, Powerful Others, and Chance Scale, DCS = Desirability of Control Scale, DOSPERT = Domain-Specific Risk-Taking Scale, BFI = Big Five Inventory*

Statistical Analyses

Hypothesis One. All correlations between trust measures and personality traits are shown in Table 3, with significant correlations flagged. In our first hypothesis, we predicted that there would be a positive correlation between general propensity to trust and propensity to trust automation, as suggested by the literature (Lee & See, 2004; Muir & Moray, 1996). This was supported in that the Interpersonal Trust Scale (ITS) was positively and significantly correlated with the Trust between People and Automation Scale (TPA; $r = .11$, $p < .05$). However, ITS negatively correlated with the Trust subscale of the CPRS ($r = -.14$, $p < .05$), which was contrary to prediction. It did not significantly correlate with the Propensity to Trust Scale.

Table 3. *Correlation Matrix of Automation Trust and Personality Characteristics, Study One*

	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1. CPRS-Trust														
2. TPA	.423***													
3. ITS	-.135*	.113*												
4. Propensity Trust	.347***	.663***	.056											
5. Self-Efficacy	.215***	.214***	-.112*	.114*										
6. LIPC-Internality	.196***	.216***	.133*	.121*	.384***									
7. LIPC-Pwr Others	-.063	-.131*	.028	.004	-.138*	.069								
8. LIPC- Chance	-.207***	-.260***	.041	-.110*	-.210***	-.066	.665***							
9. DCS	.244***	.183**	-.235***	.101	.462***	.323***	-.221***	-.262***						
10. DOSPERT	.022	.040	.041	.079	.137*	.136*	.054	.102	.148**					
11. BFI-Extrovers.	.005	.019	.015	-.021	.202***	.095	-.083	-.112*	.317***	.238***				
12. BFI-Agreeable.	.132*	.168**	-.001	.074	.306***	.208***	-.235***	-.284***	.211***	-.070	.121*			
13. BFI- Conscient.	.175**	.122*	-.122*	.092	.414***	.288***	-.197***	-.263***	.305***	-.122*	.062	.413***		
14. BFI-Neuroticism	-.022	-.141**	-.177**	-.053	-.365***	-.211***	.160**	.204***	-.206***	-.136*	-.202***	-.367***	-.239***	
15. BFI-Openness	.069	.093	-.006	.008	.281***	.188***	-.110*	-.116*	.308***	.193***	.225***	.199***	.083	-.127*

Note: CPRS = Automation-Induced Complacency Potential Rating Scale, TPA = Checklist for Trust between People and Automation, ITS = Interpersonal Trust Scale, Propensity Trust = Propensity to Trust Scale, GSES = General Self-Efficacy Scale, LIPC = Levenson Internality, Powerful Others, and Chance Scale, DCS = Desirability of Control Scale, DOSPERT = Domain-Specific Risk-Taking Scale, BFI = Big Five Inventory (Extroversion, Agreeableness, Conscientiousness)

**p ≤ .05; **p ≤ .01; *** p ≤ .001*

Hypothesis Two. Our second hypothesis set out to test whether personality traits predict propensity to trust automation. Using only the traits that significantly correlated with trust in automation measures, we conducted several stepwise regressions to test this. The overall model predicting CPRS-Trust from personality characteristics was significant, R = .31, R^2 = .10, *adjusted* R^2 = .09, $F(3, 341) = 12.28$, $p < .001$ (Table 4). Model one entered desirability of control (DCS) as a significant predictor in itself, R = .24, R^2 = .06, *adjusted* R^2 = .06, $F(1, 343) = 21.71$, $p < .001$. The second and third models each contributed 2% additional explanation in the variance of CPRS-Trust through the contributions of LIPC-Chance (Model 2: R^2_{change}= .02, F_{change} (1, 342) = 8.19, $p < .01$) and LIPC- Internality (Model 3: R^2_{change}= .02, F_{change} (1, 341) = 6.04, $p < .05$).

Table 4. *Stepwise Regression Predicting Trust Attitudes through CPRS-Trust Scores* (n= 344)

Predictors	*B(SE)*	*Β*	*t*	*p*	*95% Confidence Intervals* Lower Bound	*95% Confidence Intervals* Upper Bound
Full Model: $F(3, 341) = 12.28$, $p < .001$, $R = .31$, $R^2 = .10$, *adjusted* $R^2 = .09$						
Model 1:						
Constant	7.12(.93)		7.62***	.000	5.28	8.95
DCS	.04(.01)	.24	4.66***	.000	.03	.06
Model 2:						
Constant	8.64(1.07)		8.10***	.000	6.54	10.74
DCS	.04(.01)	.20	3.80***	.000	.02	.06
LIPC- Chance	-.04(.01)	-.15	-2.86**	.004	-.07	-.01
Model 3:						
Constant	7.65(1.13)		6.76***	.000	5.42	9.88
DCS	.03(.01)	.16	2.84**	.005	.01	.05
LIPC- Chance	-.04(.01)	-.16	-2.93**	.004	-.07	-.01
LIPC- Internality	.05(.02)	.13	2.46*	.01	.01	.10

*p < .05 (2-tailed).
**p < .01 (2-tailed).
***p < .001 level (2-tailed).

The overall regression predicting Trust between People and Automation (TPA) was significant, $R = .33$, $R^2 = .11$, *adjusted* $R^2 = .10$, $F(2, 342) = 20.53$, $p < .001$ (Table 5). The first model entered LIPC- Chance as a predictor of TPA, $R = .26$, $R^2 = .07$, *adjusted* $R^2 = .07$, $F(1, 343) = 24.86$, $p < .001$. The second model added 4% explanation of the variance in scores beyond that which LIPC- Chance alone was able to predict, through LIPC- Internality, $R^2_{change} = .04$, $F_{change}\ (1, 342) = 15.17$, $p < .001$. LIPC- Internality was the only predictor entered into the model for predicting Propensity to Trust, $F(1, 343) = 5.12$, $p < .05$, $R = .12$, $R^2 = .02$, *adjusted* $R^2 = .01$ (Table 6).

Table 5. *Stepwise Regression Predicting Trust Attitudes Measured by TPA Scores* (n= 344)

Predictors	*B(SE)*	*B*	*t*	*p*	*95% Confidence Intervals* Lower Bound	Upper Bound
Full Model: $F(2, 342) = 20.53$, $p < .001$, $R = .33$, $R^2 = .11$, *adjusted* $R^2 = .10$						
Model 1:						
Constant	62.42(1.59)		39.25***	.000	59.29	65.54
LIPC- Chance	-.36(.07)	-.26	-4.99***	.000	-.496	-.22
Model 2:						
Constant	47.89(4.04)		11.84***	.000	39.93	55.84
LIPC- Chance	-.34(.07)	-.25	-4.82***	.000	-.48	-.20
LIPC- Internality	.42(.11)	.20	3.99***	.000	.21	.63

* $p < .05$ (2-tailed).
** $p < .01$ (2-tailed).
*** $p < .001$ level (2-tailed).

Table 6. *Stepwise Regression Predicting Trust Attitudes measured by the PTT* (n = 344)

Predictors	*B(SE)*	*B*	*t*	*p*	*95% Confidence Intervals* Lower Bound	Upper Bound
Full Model: $F(1, 343) = 5.12$, $p < .05$, $R = .12$, $R^2 = .02$, *adjusted* $R^2 = .01$						
Constant	18.20(1.54)		11.84***	.00	15.18	21.22
LIPC- Internality	.10(.05)	.12	2.26***	.02	.01	.19

* $p < .05$ (2-tailed).
** $p < .01$ (2-tailed).
*** $p < .001$ level (2-tailed).

Overall, the consistent predictors of trust attitudes toward automation were internal locus of control, desirability for control, and chance locus of control.

Study Two

Demographics and Descriptives

The sample for Study Two consisted of 244 total participants, M_{age} = 22.5, *SD* = 4.2, and was predominantly female (*N*= 146, 59.8%) and White (*N*= 141, 57.8%). Complete demographic information is shown in Table 7. Twenty-one participants were removed listwise before analysis for missing, inconsistent, or inattentive responses. The majority of the sample reported no previous medical field experience (*N*= 209, 85.7%), no formal medical knowledge or training (*N*= 123, 50.4%), and, most relevant, had no exposure to skin cancer diagnoses (*N*= 142, 58.2%) nor confidence in their own ability to check for skin cancer (*N*= 168, 68.9%). Descriptive statistics from measures of trust in automation (i.e., Automation-Induced Complacency Potential Scale, [CPRS], Trust between People and Automation [TPA], Pre- and Post-Task Propensity to Trust [PTT]), self-efficacy (i.e., General Self-Efficacy Scale [GSES]), locus of control (i.e., Levenson Internality, Powerful Others, and Control Scale [LIPC]), health locus of control (i.e., Multidimensional Health Locus of Control [MHLC]), desire for control (i.e., Desirability of Control Scale [DCS]), Big Five personality traits (i.e., Big Five Inventory [BFI]), risk-taking (i.e., Domain Specific Risk-Taking Scale [DOSPERT]), technology use (i.e., Media and Technology Usage and Attitudes Scale [MTUAS]) and interpersonal trust (i.e., Interpersonal Trust Scale [ITS]) are included as well in Table 8. Overall, our sample showed average automation usage of 37% (*SD* = 30.4), which is notably lower than expected. On the one hand, human judges were correct an average of 57% of the time in the first task, so relying on automation the other

43% would make intuitive sense. On the other hand, of the images included in the study, humans were correct less than 60% of the time (i.e., the automation's accuracy rate) on 56 of the 100 images. Thus, if the average accuracy for a human judge is less than 60% on an image, and automation's average accuracy is 60%, automation is the intuitive choice on those images. This means that automation should have been used 56% of the time (on those 56 images) instead of 37%. In other words, participants were somewhat resistant to select automation on difficult images, where automation would produce large payoffs on average. When participants decided to rate the images themselves in Study Two, they correctly rated the images 67% of the time (*SD* = 12.67). The mean reaction time for participants when choosing whether to use automation or not was 3.33s, with a standard deviation of 1.63s. The average additional time it took participants to submit their own choice on images they chose to judge themselves was 1.54s (*SD* = .58).

Table 7. *Summary of Demographics for Study Two*

Total N= 244	Mean (n)	Standard Deviation (%)
Gender		
Male	96	39.3%
Female	146	59.8%
Other	2	.8%
Age	22.5	4.2
Ethnicity		
White	141	57.8%
Black or African American	37	15.2%
American Indian or Alaska Native	3	1.2%
Asian	36	14.8%
Native Hawaiian or Pacific Islander	1	.4%
Other	26	10.7%
Year		
Freshman	29	11.9%
Sophomore	50	20.5%
Junior	68	27.9%
Senior	72	29.5%
Graduate Student	25	10.2%
Medical Field Experience		
None	209	85.7%
Previous	23	9.4%
Current	12	4.9%
Medical Knowledge		
None	123	50.4%
Minimal	85	34.8%
Moderate	32	13.1%
Extensive	3	1.2%
Skin Cancer Experience		
Never screened nor diagnosed	142	58.2%
I, myself screened but not diagnosed	16	6.6%
I, myself, diagnosed	0	0%
Someone close to me screened but not diagnosed	27	11.1%
Someone close to me diagnosed	59	24.2%
Skin Cancer Detection Confidence		
Not confident at all	168	68.9%
Slightly confident	43	17.6%
Moderately confident	25	10.2%
Very confident	5	2.0%
Extremely confident	2	0.8%

Table 8. *Summary of Self-Report Data Descriptives*

Self-Report Measure	Mean	Standard Deviation
CPRS- Trust	11.21	2.16
TPA	42.71	9.53
MHLC- Internal	26.77	4.81
MHLC- Others	19.98	4.67
MHLC- Chance	18.96	4.94
MTUAS- Use	33.17	7.85
MTUAS- Confidence	18.85	2.16
MTUAS- Positive Attitudes	23.53	4.14
MTUAS- Anxious/ Dependent	10.09	2.92
MTUAS- Negative Attitudes	10.68	2.40
MTUAS- Task Switching	10.35	3.76
GSES	31.48	4.09
LIPC- Internality	32.49	5.85
LIPC- Powerful Others	20.65	7.92
LIPC- Chance	19.98	7.48
DCS	94.43	10.46
DOSPERT	100.24	21.95
BFI- Extroversion	3.16	.86
BFI- Agreeableness	3.92	.52
BFI- Consciousness	3.61	.63
BFI- Neuroticism	2.98	.82
BFI- Openness	3.57	.64
ITS	63.87	8.10
PTT- Pre-Task	21.91	4.80
Automation Use (%)	35.77	30.4
RT for Automation Choice (secs)	3.33	1.63
RT for Manual Decision (secs)	1.54	.58
Accuracy of Manual Ratings (%)	66.95	12.67

PTT- Post-Task	17.95	6.29
Automation Confidence	2.49	1.13
Automation Trust	2.60	1.14
Self-Confidence	2.74	1.06
Self-Confidence (2)	2.76	1.27
Mastery	3.41	1.31
Desire to be Correct	3.60	1.20

Note: CPRS = Automation-Induced Complacency Potential Rating Scale, TPA = Checklist for Trust between People and Automation, MHLC = Multidimensional Health Locus of Control Scale, ITS = Interpersonal Trust Scale, Propensity Trust (PTT) = Propensity to Trust Scale, MTUAS = Media and Technology Usage and Attitudes Scale, GSES = General Self-Efficacy Scale, LIPC = Levenson Internality, Powerful Others, and Chance Scale, DCS = Desirability of Control Scale, DOSPERT = Domain-Specific Risk-Taking Scale, BFI = Big Five Inventory

Statistical Analyses

Hypothesis Three. We first conducted correlations between our trust measures of attitude and "actual" automation use behaviors (see Table 9). We found that automation use significantly correlated with CPRS-Trust ($r = .164$, $p < .01$) and pre-task ratings of trust ($r = .143$, $p < .05$). Also, automation use and post-task trust were strongly associated, $r = .624$, $p < .001$. Given that the post-task trust measure asked specifically about trust in the automation with which the participants had, moments before, interacted, it is unsurprising to have found the strongest relationship between automation use and trust in automation reported in this measure.

In our third hypothesis, we speculated that self-reported trust attitudes would predict "actual" trust behaviors as demonstrated through automation use. CPRS- Trust was significant in predicting automation use, $R = .16$, $R^2 = .03$, *adj* $R^2 = .02$, $F(1, 241) = 6.67$, $p < .05$, although it only explained 3% of the variance in use (Table 10). Our pre-task measure of trust, Merritt's Propensity to Trust Scale, also was significant, $R = .14$, $R^2 = .02$, *adjusted* R^2

= .02, $F(1, 242) = 5.03$, $p < .05$. However, general propensity to trust (ITS) and trust between people and automation (TPA) were not significant in predicting automation use.

Table 9. *Correlation Matrix of Automation Use and Self-Reported Trust*

	1	2	3	4	5
1. Automation Use					
2. CPRS-Trust	.164**				
3. TPA	.058	.000			
4. ITS	.086	.081	.025		
5. Pre-task Trust	.143*	.197**	.060	.083	
6. Post-task Trust	.624***	.121	.078	.094	.345***

Note: CPRS = Automation-Induced Complacency Potential Rating Scale, TPA = Checklist for Trust between People and Automation, ITS = Interpersonal Trust Scale, Pre-task Trust (Post-task Trust) = Propensity to Trust Scale, pre- and post-task
**p ≤ .05; **p ≤ .01; *** p ≤ .001*

Table 10. *Simple Regression Predicting Trust Behaviors/Automation Use* ($n = 243$)

Predictors	*B(SE)*	*B*	*t*	*p*	*95% Confidence Intervals* Lower Bound	Upper Bound
Full Model: $F(1, 241) = 6.67$, $p < .05$, $R = .16$, $R^2 = .03$, *adjusted* $R^2 = .02$						
Constant	9.76(10.2)		.96	.34	-10.33	29.84
CPRS- Trust	2.31(.89)	.16	2.58*	.01	.55	4.07

*$p < .05$ (2-tailed).
**$p < .01$ (2-tailed).
***$p < .001$ level (2-tailed).

Table 11. *Simple Regression Predicting Trust Behaviors/Automation Use* ($n = 244$)

Predictors	*B(SE)*	*B*	*t*	*p*	*95% Confidence Intervals* Lower Bound	Upper Bound
Full Model: $F(1, 242) = 5.03$, $p < .05$, $R = .14$, $R^2 = .02$, *adjusted* $R^2 = .02$						
Constant	15.95(9.05)		1.76	.08	-1.87	33.8
Pre-Task Trust	.91(.40)	.14	2.24*	.03	.11	1.70

*$p < .05$ (2-tailed).
**$p < .01$ (2-tailed).
***$p < .001$ level (2-tailed).

As in Study One, Hypothesis One, we also tested whether a positive correlation exists between propensity to trust automation and general propensity to trust. As shown in Table 9, none of our measures of trust in automation significantly correlated with general propensity to trust. In comparison, results from the first study found that ITS positively related to TPA and negatively related to CPRS-Trust. The reason for these mixed results is unclear, although they suggest that the relationship between general trust and automation-specific trust may not be as simple as a direct, positive relationship.

Hypotheses Four and Five. In order to test our fourth and fifth hypotheses, namely, that personality characteristics would predict self-reported propensity to trust automation as well as predict automation usage (when controlling for trust attitudes), we first examined all correlations between trust attitudes, trust behaviors, and the personality characteristics we measured. Below are the correlation tables reporting this information (Table 12). As seen in Table 12, automation use did not significantly correlate with any of the personality traits measured. Thus, regressions were not conducted to test whether personality traits predicted automation use, and hypothesis five was not supported.

Table 12. *Correlation Matrix of Automation Trust and Personality Characteristics, Study 2*

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
1. Automation Use																
2. CPRS-Trust	.164**															
3. TPA	.058	.000														
4. ITS	.086	.081	.025													
5. Pre-task Trust	.143*	.197**	.060	.083												
6. Post-task Trust	.624***	.150*	.078	.094	.345***											
7. Self-Efficacy	.013	.225***	.039	-.074	.075	-.045										
8. LIPC-Internality	.055	.252***	-.008	.043	.192**	.025	.341***									
9. LIPC-Pwr Others	-.058	-.011	.147*	.005	.032	-.051	-.187**	.002								
10. LIPC- Chance	-.030	-.166**	.140*	-.024	-.016	.042	-.280***	-.148*	.594***							
11. DCS	.041	.041	.071	-.131*	.073	.000	.176**	.205***	.080	.080						
12. DOSPERT	.046	.000	.122	-.004	.028	-.038	.161*	.150*	.045	.003	.203***					
13. BFI-Extrovers.	.061	.116	-.065	.102	.065	-.008	.311***	.163**	-.113	-.125	.236***	.229***				
14. BFI-Agreeable.	-.042	-.002	-.016	.098	.084	-.025	.150*	.117	-.126	-.076	.029	-.172**	.106			
15. BFI- Conscient.	.079	.017	.036	-.014	-.016	-.086	.456***	.238***	-.206**	-.357***	.152*	-.015	.244***	.330***		
16. BFI-Neuroticism	-.094	-.083	-.014	-.267***	-.077	-.039	-.327***	-.198**	.179**	.234***	-.096	-.195**	-.320***	-.289***	-.331***	
17. BFI-Openness	.021	.121	-.026	-.163*	-.059	-.039	.348***	.033	-.120	-.113	.245***	.118	.289***	.203**	.237***	-.094

Note: CPRS = Automation-Induced Complacency Potential Rating Scale, TPA = Checklist for Trust between People and Automation, ITS = Interpersonal Trust Scale, Pre-task Trust (Post-task Trust) = Propensity to Trust Scale, pre- and post-task, GSES = General Self-Efficacy Scale, LIPC = Levenson Internality, Powerful Others, and Chance Scale, DCS = Desirability of Control Scale, DOSPERT = Domain-Specific Risk-Taking Scale, BFI = Big Five Inventory (Extroversion, Agreeableness, Conscientiousness)
$^*p \leq .05$; $^{**}p \leq .01$; $^{***} p \leq .001$

Our fourth hypothesis was a replication of hypothesis two from Study One, which predicted that certain personality traits would predict propensity to trust automation. To test this, we ran stepwise regressions to predict trust attitudes from personality characteristics. In the first stepwise regression, the Trust subscale of the CPRS was significantly predicted from personality characteristics, $R = .29$, $R^2 = .09$, *adjusted* $R^2 = .08$, $F(2, 239) = 11.21$, $p < .001$ (Table 13). In this model, 9% of the variance was accounted for by the two variables that contributed, LIPC- internality (internal locus of control) and general self-efficacy. In Step 1, internality alone predicted trust in automation scores, $R = .25$, $R^2 = .06$, *adjusted* $R^2 = .06$, $F(1, 240) = 16.21$, $p < .001$, and in a positive direction, $t(240) = 4.03$, $p < .001$. Step 2 was significant when controlling for internality, $R^2_{change} = .02$, $F_{change}\,(1, 239) = 5.89$, $p < .05$ with self-efficacy the only significant predictor in Step 2, $t(239) = 2.43$, $p < .05$. Internality still contributed significantly, $t(239) = 2.99$, $p < .01$. Thus, it appears as though these two factors, internal locus of control beliefs and self-efficacy, can successfully predict trust in automation attitudes in themselves as measured by a scenario-based measurement of trust.

Table 13. *Stepwise Regression Predicting Trust Attitudes Measured by CPRS-Trust* (*n*= 241)

Predictors	*B(SE)*	*B*	*t*	*p*	*95% Confidence Intervals* Lower Bound	Upper Bound
Full Model: F(2, 239) = 11.21, $p < .001$, $R = .29$, $R^2 = .09$, *adjusted* $R^2 = .08$						
Model 1:						
Constant	8.19(.76)		10.74***	.000	6.68	9.69
LIPC- Internality	.09(.02)	.26	4.03***	.000	.05	.14
Model 2:						
Constant	6.18(1.12)		5.52***	.000	3.97	8.39
LIPC- Internality	.07(.02)	.20	2.99**	.003	.03	.12
GSES	.09(.04)	.16	2.43*	.016	.02	.15

*p < .05 (2-tailed).
**p < .01 (2-tailed).
***p < .001 level (2-tailed).

LIPC- Internality continued to be a significant predictor of the propensity to trust automation survey given before the automation task (Pre-Task Trust; Table 14). The pre-task survey on propensity to trust automation similarly was significantly predicted by internality, $R = .19$, $R^2 = .04$, *adjusted* $R^2 = .03$, $F(1, 241) = 9.27$, $p < .01$, with only 4% of the variance in scores explained by this predictor. Internality again had a positive relationship with propensity to trust automation scores, $t(241) = 3.04$, $p < .01$.

Table 14. *Stepwise Regression Predicting Trust Attitudes via Pre-Task Propensity to Trust* (*n* = 241)

Predictors	*B(SE)*	*B*	*t*	*p*	*95% Confidence Intervals* Lower Bound	Upper Bound
Full Model: F(1, 241) = 9.27, $p < .01$, $R = .19$, $R^2 = .04$, *adjusted* $R^2 = .03$						
Constant	16.83(1.71)		9.89***	.00	13.47	20.19
LIPC- Internality	.16(.05)	.19	3.04**	.003	.06	.26

*p < .05 (2-tailed).
**p < .01 (2-tailed).
***p < .001 level (2-tailed).

Finally, predicting TPA was only significant when predicted by LIPC- Powerful Others ($R = .15$, $R^2 = .02$, *adjusted* $R^2 = .02$, $F(1, 233) = 5.17$, $p < .05$), yet only 2% of the variance in scores were accounted for by this model (Table 15). Powerful Others had a positive relationship with TPA, $t(233) = 2.27$, $p < .05$.

Table 15. *Stepwise Regression Predicting Trust Attitudes through TPA* ($n = 234$)

Predictors	*B(SE)*	*B*	*t*	*p*	*95% Confidence Intervals* Lower Bound	Upper Bound
Full Model: $F(1, 233) = 5.17$, $p < .05$, $R = .15$, $R^2 = .02$, *adjusted* $R^2 = .02$						
Constant	39.08(1.71)		22.83^{***}	.00	35.71	42.46
LIPC- Powerful Others	.18(.08)	.15	2.27^{*}	.02	.02	.33

$^{*}p < .05$ (2-tailed).
$^{**}p < .01$ (2-tailed).
$^{***}p < .001$ level (2-tailed).

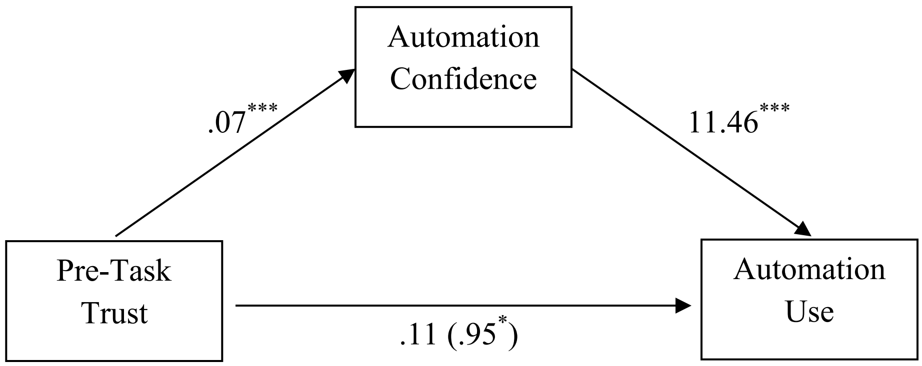
From Study Two, it appears that internal locus of control, locus of control in powerful others, and self-efficacy were able to predict trust attitudes toward automation. In comparison, the predictors in Study One were internal locus of control, desirability for control, and chance locus of control.

Exploratory Hypotheses

Hypothesis Six. Post-task trust in the automation was significantly lower than pre-task trust, contrary to our hypothesis ($t(243) = 9.57$, $p < .001$). The mean trust in automation prior to the task was 21.91 (*SD* = 4.8) and 17.95 (*SD* = 6.3) after the task, demonstrating that interacting with an automation that had 60% accuracy rating decreased initial trust.

Hypothesis Seven. Our seventh hypothesis posited that the relationship between trust attitudes and “actual” trust behaviors (i.e., automation use) may be moderated by confidence in the automation, self-confidence, and a desire for personal mastery when completing the task. We used our measure of pre-task trust (i.e., trust in the automation with which the participants were about to interact) to test for these interaction effects. The overall models for these variables were significant; however, none showed significant main or interaction effects. To follow up on this, exploratory mediation analyses were conducted to test whether factors of automation confidence, self-confidence, and a desire for personal mastery mediated the relationship between pre-task trust and automation use (trust behaviors). Mediation models with self-confidence were not significant due to pre-task trust not significantly predicting task self-confidence. However, analyses with mastery and automation confidence were significant, suggesting that task-specific attitudes of confidence and mastery mediate the relationship between initial trust in the automation and actual use of the automation.

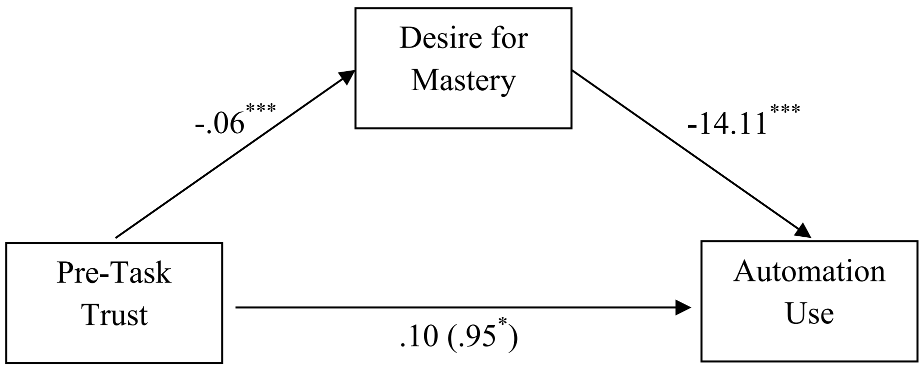
In the first mediation analysis, confidence in automation was found to completely mediate the relationship between pre-task trust and automation use (Figure 3). The total effect of pre-task trust on automation use was significant, $c = .95$, $t\ (240) = 2.35$, $p < .05$. Pre-task trust was significantly predictive of the anticipated mediator, automation confidence, $a = .07$, $t(240) = 5.09$, $p < .001$. When controlling for pre-task trust, automation confidence was significantly predictive of automation use, $b = 11.46$, $t\ (239) = 6.94$, $p < .001$. The estimated effect of pre-task trust on automation use when controlling for automation confidence was not significant, $c' = .11$, $t(239) = .28$, $p = .78$. The indirect effect, *ab*, was .80, which was significant according to Sobel's test, $z = 4.10$, $p < .001$. Since Sobel's test was significant, and since *a, b*, and *c'* were significant, then it appears that confidence in automation completely mediated the relationship between pre-task trust and automation use. Overall, automation use was predicted moderately well from pre-task trust and automation confidence, $R^2 = .19$ and $F(2, 239) = 27.38$, $p < .001$.



Note. * $p < .05$ ** $p < .01$, *** $p < .001$

Figure 3. *Automation Confidence Mediates Relationship between Pre-Task Trust and Use*

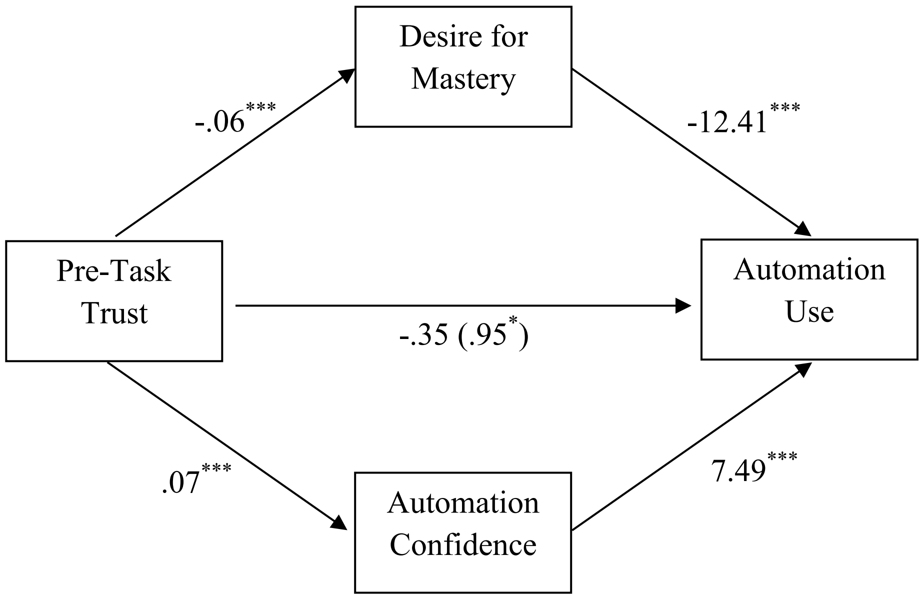
In the second mediation analysis, desire for mastery in the task was found to mediate the relationship between pre-task trust and automation use (Figure 4). The total effect of pre-task trust on automation use was significant, $c = .95$, $t\ (240) = 2.35$, $p < .05$. Pre-task trust was significantly predictive of the anticipated mediator, desire for mastery, $a = -.06$, $t(240) = -3.54$, $p < .001$. When controlling for pre-task trust, mastery was significantly predictive of automation use, $b = -14.11$, $t\ (239) = -11.55$, $p < .001$. Specifically, it was negatively predictive: a higher desire for mastery on the task predicted lower automation use. The estimated effect of pre-task trust on automation use when controlling for mastery was not significant, $c' = .10$, $t(239) = .29$, $p = .78$. The indirect effect, *ab*, was .85, which was statistically significant using the Sobel test, $z = 3.38$, $p < .001$. Overall, automation use was predicted well from pre-task trust and desire for mastery, $R^2 = .37$ and $F(2, 239) = 70.96$, $p < .001$. Further, desire for mastery completely mediated the relationship between pre-task trust and automation use.



Note. * $p < .05$ ** $p < .01$, *** $p < .001$

Figure 4. *Desire for Mastery Mediates Relationship between Pre-Task Trust and Use*

Combining the two mediators into one model also significantly predicted automation use from pre-task trust, $R^2 = .44$ and $F(3, 238) = 61.71$, $p < .001$ (Figure 5). The total effect of pre-task trust on automation use was significant, $c = .95$, $t\,(240) = 2.35$, $p < .05$. Pre-task trust was significantly predictive of both mediators, desire for mastery ($a_1 = -.06$, $t(240) = -3.54$, $p < .001$) and automation confidence ($a_2 = .07$, $t(240) = 5.09$, $p < .001$). When controlling for pre-task trust, both desire for mastery and automation confidence significantly predicted automation use, $b_1 = -12.41$, $t\,(238) = -10.31$, $p < .001$ and $b_2 = 7.49$, $t\,(238) = 5.24$, $p < .001$, respectively. The estimated effect of pre-task trust on automation use when controlling for both mediators was not significant, $c' = -.35$, $t(238) = -1.08$, $p = .28$. The indirect effect for desire for mastery, $a_1\,b_1$, was .75, which was significant according to Sobel's test, $z = 3.35$, $p < .001$. The indirect effect for automation confidence, a_2b_2, was .52, which was also significant according to Sobel's test, $z = 3.65$, $p < .001$. Since Sobel's tests were significant, and since a, b_1, b_2, and c' were significant, it appears that confidence in automation and desire for mastery completely mediated the relationship between pre-task trust and automation use.



Note. * $p < .05$ ** $p < .01$, *** $p < .001$

Figure 5. *Desire for Mastery and Automation Confidence Mediate Pre-Task Trust and Use*

Hypothesis Eight. Similar to our predictions for general locus of control, we speculated that health locus of control may also correlate with using automation in a health context. However, health locus of control, similar to general locus of control, did not significantly relate to automation use on any dimension. In Study Two, internal health locus of control did not correlate with measures of trust attitudes. External health locus of control in powerful others positively correlated with trust measures of TPA ($r = .13$, $p < .05$), ITS ($r = .18$, $p < .01$) and Pre-Task Propensity to Trust ($r = .15$, $p < .05$). We had predicted external health locus of control in powerful others correlating positively with automation use; here that relationship existed instead with attitudes toward automation trust. In Study One, internal health locus of control positively correlated with CPRS- Trust ($r = .15$, $p < .01$), and TPA (r

= .16, $p < .01$). Higher health locus of control in chance related to lower CPRS- Trust ($r = -.16$, $p < .01$) and TPA ($r = -.13$, $p < .05$). The findings from both studies mostly supported the hypothesis, however, they also were not as parallel with each other as expected, as trust attitudes across the studies showed positive relationships with both internal and external (powerful others) health locus of control.

CHAPTER 5

DISCUSSION

The integration of automation into the healthcare field is a rapidly expanding area of technological development, introducing new challenges for balancing appropriate applications and use of automation. As more providers and patients are coming into contact with assistive technologies, it is critical that these are being designed in a thoughtful manner so as to increase the likelihood of their successful adoption. Trust is the fundamental component in motivating people to use automation to its best potential, and research in trust in automation has examined how the design, transparency, and other automation-specific factors can impact human's willingness to trust the automation. Little research has focused on the characteristics of the other agent involved in this trust relationship, namely, human beings. Understanding how user traits may impact likelihood to use automation is critical for informing the design and dissemination of expensive and beneficial technologies. The goal of this project was to better understand how user factors influence the adoption of automated systems in healthcare and to suggest how automation features may be modified to encourage more appropriate use based on personality qualities. We tested this over the course of two studies, in which we designed a task wherein participants interacted with automation to detect skin cancer and provided information about their personal traits, beliefs, and attitudes toward trust and automation. Our study specifically sought to expand on previous research by examining how trust was conveyed through self-reported attitudes as well as through "actual," behavioral demonstrations.

Overall, judging images for skin cancer was considerably difficult for participants. When rating the images for skin cancer in Experiment One, participants were correct judges only 53.5% of the time— close to a chance guess. With no stakes (i.e., potential for performance-based compensation) on the line, 84.4% of these participants were willing to receive help from automation if they had to rate the images over again. These findings are perhaps unsurprising given that the sample had little to no medical experience but were highly proficient users of technology. However, it created a challenge when selecting images for our behavioral task that would be ambiguous but not impossible for participants to judge, forcing them to decide whether to trust themselves or automation in the judging. It also created a challenge for setting the reliability of the automation to be near to the average human performer, yet high enough that one might potentially build trust in it. When interpreting the pattern of our results, it is important to keep in mind the unique parameters of our study in comparison to other approaches for designing automation and measuring outcomes of trust in automation.

Our first aim was to explore the construct of trust by examining the relationship of trust in automation to a general propensity to trust. Based on research suggesting that trust in automation follows similar patterns as interpersonal trust (e.g., Lee & Moray, 1994; Lee & See, 2004; Muir, 1994; Muir & Moray, 1996), we predicted that trust in automation and general trust would show a positive association. In Study One, a scale measuring beliefs in automation's trustworthiness and its capabilities (i.e., TPA) positively correlated to general interpersonal trust; however, the trust subscale of the CPRS was found to negatively correlate. Results of Study Two did not relate automation-specific trust to interpersonal trust. This mixed support for trust in automation and general interpersonal trust being highly interrelated suggests perhaps more nuance in attitudes of trust toward non-human agents. Research supports the divergence of trust in automation from general trust due to the unique one-sidedness of the trust relationship when automation is involved (Muir, 1994). Biases unique to automation may likely impact trusting automation in ways they would not when trusting people, such as biases to view machines as infallible or that machines are predictable and precisely follow the purpose for which they were designed (Dzindolet et al., 2003; Lee & Moray, 1992; Madhavan & Wiegmann, 2007b). That is to say, individuals may trust machines differently than humans because they expect the machine will produce the outcome it was intended to produce, whereas humans may fail, change their minds, or take advantage of the situation and manipulate the trustee. Thus, these views provide an explanation for why trust in automation partly yet not completely related to general propensity to trust in our study.

Past research has shown mixed findings on the interplay of personality traits and trust (e.g., Freitag & Bauer, 2016), motivating us to explore how traits might predict both a propensity to trust automation and trust behaviors themselves. First we examined—in both studies—the ability of personality traits to predict attitudes of trust in automation. We anticipated that openness, extraversion, agreeableness, and external locus of control would positively predict trust attitudes and that neuroticism, risk-aversion, need for control, self-efficacy, and internal locus of control would negatively predict trust attitudes towards automation.

In Study One, we found that the predictors of trust attitudes were desirability of control, internal locus of control, and chance locus of control. Internal locus of control most frequently predicted trust attitudes, with chance locus of control being the next most common predictor. However, the direction of these findings was opposite of what we had predicted: internality and desirability for control positively predicted attitudes, and locus of control in chance negatively predicted them. We speculate that a sense of agency or involvement may be a key component in predicting willingness to put trust in automation. For example, research has shown that internal locus of control over one's health is associated with greater patient-physician trust (Gabay, 2015). In our study, the parallel finding is that internal locus of control predicted higher trust attitudes toward automation. At the same time, high external locus of control in chance related to low trust in automation in our study, possibly due to the thought that placing one's trust in automation would have little impact on the final outcome. Considering that being an agent is a fundamental component before trust can possibly even exist, it is possible that this sense of agency plays a role on how control and trust relate. Our finding that having a need or desire for control positively related to trust attitudes appears counterintuitive and is not consistent with research regarding need for control and trusting other people (Oskarsson et al., 2012; Uslaner, 2002). Such individuals with a strong desirability for control prefer to rely on themselves in human-human trust situations rather than surrender control to others. However, research has not previously examined this need for control in the context of automation to our knowledge. It is possible that different forces are at play when automation is involved, and that, in fact, choosing to trust automation feels empowering and not as though the individual has given up control. That is to say, we speculate that the choice to use automation may feel like an exercise of power rather than a surrendering. Future research would be important to confirm this claim and rule out other influencers.

In Study Two, we again found that internality, or having an internal locus of control, was a positive predictor of trust attitudes. In addition, we found that self-efficacy was a significant positive predictor for the CPRS-Trust subscale. Again, we speculate that the sense of agency stemming from choosing to rely on technology may be driving positive correlations between measures of a sense of control, power, ability to influence and trust attitudes. Additionally, having an external locus of control based in powerful others was a positive predictor of trust, which was congruent with our predictions and adds a caveat to the pattern of results from Study One, namely, that trust attitudes relate differently to external locus of control placed in chance as compared to powerful others. We again assert that this difference can likely be explained by the conceptual difference in putting control in other people compared to putting control in the hands of chance. Finally, the Big Five were not significant predictors of trust attitudes in either study, which unfortunately does not aid in clarifying the mixed literature on how the Big Five relate to trust in automation (e.g., Anderson 2010; Dinesen et al., 2014; Dohmen et al., 2008, Hiraishi et al., 2008). Given the inconsistent relationships found in literature between general trust and personality traits, it is somewhat unsurprising that our exploration of the relationship between trust in automation and personality traits showed mixed results as well. However, our findings provide initial evidence of the role that traits related to locus of control, need for control, self-efficacy, and, more broadly, a sense of agency or involvement have on trusting automation, which can inform approaches to designing automation (and its planned method of interaction with its user).

With regard to our behavioral task, we hypothesized that propensity to trust automation and trust in general would significantly predict automation use. We found that the trust subscale of CPRS and pre-task ratings of propensity to trust automation significantly predicted automation use. General propensity to trust and another measure of trust in automation (i.e., TPA) did not significantly relate to automation use. When considering this, two possibilities arise: first, these findings begin to support that there are conceptual differences between trust as an attitude and trust as a behavior, and that these should be measured separately because they can be influenced by different factors (Ajzen & Fishbein, 1980). Also, the lack of consistently strong relationships between our measures of trust attitudes and usage of automation may highlight the situational specificity of trust (Lee & See, 2004). As mentioned above, the pre-task measure of trust in the specific task's automation (which participants answered after a brief trial with the automation) significantly predicted use of the automation for the rest of the task. This relation of trust attitudes in the same context as the trust behaviors confirms the idea that situational trust is more important than general trust in understanding actual automation usage. Further, the post-task measures of trust attitudes toward the automation also significantly correlated with actual automation use, suggesting even more so that trust in automation is context-specific and can be reliably measured within a context.

Building from this, we explored whether personality characteristics would predict trust behaviors (i.e., automation use), and specifically expected conscientiousness, agreeableness, extraversion, and openness to positivity predict automation use, and neuroticism, risk-aversion, need for control, internal locus of control, and self-efficacy to negatively predict automation use. We found that personality qualities did not significantly predict trust behaviors, (i.e., automation use), even when controlling for trust attitudes. However, automation use was significantly related to post-task measures of a desire for mastery in doing the task ($r = -.61$, $p < .001$), trust in the specific automation itself ($r = .44$, $p < .001$), task self-confidence ($r = -.43$, $p < .001$ and $r = -.36$, $p < .001$), and confidence in the automation ($r = .43$, $p < .001$). This again appears to indicate that task-related, context-specific trust attitudes hold a stronger relationship automation use than dispositional traits.

We also tested several exploratory hypotheses. Although we expected to see an increase from pre-test to post-test scores measuring trust in the task-specific automation, we in fact found the opposite: trust was *lower* after the task than prior to it. We speculate that this change may be due to the low accuracy of our automation. Although we intentionally chose for the automation to be accurate 60% based on the average human rating of the images in Study One, research shows that trust in automation tends to occur when the automation is at least 70% reliable (Dzindolet, Pierce, Beck, & Dawe, 1999; Parasuraman, Sheridan, & Wickens, 2000). Intuitively, higher rates of automation success would lead to more positive interactions with automation and better trust in the automation after interacting with it. Thus, it is possible that the perceived unreliability of our automation hurt trust over the course of the study, leading to lower post-task trust. Other studies suggest that there is a bias towards trusting automation upfront due to assumptions that machines are infallible (Dzindolet et al., 2003; Madhavan & Wiegmann, 2007b), which may have also contributed to higher pre-task scores that then degraded over the course of the study. Although it was important in our study to have automation set at a fixed rate similar to human performance in order to negate any direct advantage favoring automation, this may have caused our accuracy rate to be set too low for strong trust to form, and, in fact, appears to have hurt initial levels of trust.

In another exploratory hypothesis, we examined whether task self-efficacy or a desire for mastery would moderate the relationship between trust attitudes and trust behaviors (i.e., automation use). The moderation analyses showed overall significance in the model, but with an absence of significant main or interaction effects. In order to clarify this, we explored whether task self-efficacy and a desire for mastery in fact mediated the relationship between trust attitudes and behaviors, rather than moderated it. Given the temporal ordering of examining one's disposition to trust automation followed by one's attitudes toward trusting automation in a specific, immediate situation, it is sequentially logical for complete mediation to explain the significant relationship found when predicting trust behaviors from attitudes. Indeed, our results demonstrated that task-specific self-efficacy and a desire for mastery in the task both mediated the relationship between attitudes and behaviors. Confidence in the automation and desire for mastery were complete mediators, suggesting that these task-specific attitudes are key factors in determining whether pre-task trust is able to predict actual trust behaviors. Previous research has highlighted the importance of confidence in the automation in driving actual usage (Dzindolet, Pierce, Beck, & Dawe, 1999; Merritt & Ilgen, 2008; Parasuraman, Sheridan, & Wickens, 2000). Having the desire for mastery of the task completely mediated the relationship between pre-task trust and automation usage in the negative direction: the higher the desire for mastery, the lower the automation usage. This follows intuitively, and it also has been supported by past literature which states that individuals tend to keep control when they feel capable in a task, and, further, tend to not trust automation as much in high-risk tasks (Keller & Rice, 2010; Montague et al., 2010; Riley, 1994).

We also tested whether health-specific locus of control, in contrast to generalized locus of control, would better relate to using automation in a health context. We predicted a negative relationship between internal health locus of control and automation trust, and a positive relationship between beliefs that locus of control is external due to powerful others (vs. chance) and automation use. However, health locus of control did not significantly relate to automation use (nor, for that matter, did general locus of control). This follows with the lack of relationship between automation use and any traits measured in this study. When examining how health locus of control correlated with trust attitudes, our results were consistent with the patterns observed between general locus of control and trust attitudes. Specifically, internal health locus of control positively related to measures of trust, while external locus of control in chance correlated to lower trust scores across multiple measures. Although this is contrary to what we hypothesized, it supports our findings above that suggest a strong sense of personal agency may lead to higher trust. Further, it is possible that having a high internal health locus of control introduces a willingness to use technology when it is the best option for one's health, as seen in other research (Gabay, 2015). Considering the role that a sense of agency plays in trust decisions, those who believe health outcomes are mostly due to chance would be not expected to put their faith in automation to change the outcome. Additionally, having an external locus of control in powerful others was positively related to trust measures regarding general trust attitudes and task-specific trust. This finding is thought to occur given that external locus of control in powerful others is positively associated with trusting doctors (Hillen et al., 2014), so it is unsurprising to see a similar relationship with automation. If one is more likely to put their health in others' hands, it follows that they would likely include automation as an "other" and show higher trust in it. Once again, locus of control was found to relate to trust attitudes but not trust behaviors, highlighting differences between these trust constructs.

Overall, the results of our study provide new understanding into the realm of trust in automation. Our novel approach in examining both trust attitudes and trust behaviors as outcome measures revealed important differences between these constructs. While trust attitudes and behaviors were highly correlated, this relationship was completely mediated by situational factors (i.e., desire for mastery and confidence in the automation) related specifically to the automation task at hand. Our findings indicated distinctions in how trust attitudes and trust behaviors related to other measures; specifically, trust attitudes were predicted by measures of perceived and desired control, whereas trust behaviors did not have a relationship with these measures. Trust behaviors were not impacted by trait characteristics but rather influenced by situation specific attitudes, such as confidence and desire for mastery. The results of our finding provide evidence to conceptually distinguish attitudes towards using automation apart from actual use of automation, a distinction that has not consistently been made in automation research.

Our study has several limitations to be noted. Overall, our sampling pool was limited to predominantly younger, White, college-educated females, which impacts the generalizability of results. With regard to both studies, we attempted to combat fatigue effects by conservatively excluding participants who demonstrated random, inconsistent, or inattentive responding. However, given the length and repetition in our task, it is likely that some poor response patterns persisted in our data despite screening. In efforts to apply trust in automation research into the healthcare setting, we developed a first of its kind paradigm for testing our specific research questions. This allowed our research to be healthcare specific and highly applicable given the direction that automation in healthcare is heading with the development of phone application and other patient-friendly interfaces. Given how little knowledge our sample had of detecting skin cancer, it is possible that the task itself was highly difficult for participants from the onset. Further, although we chose to use skin cancer –a cancer with one of the highest rates of occurrence – as our subject matter in order to make the medical condition relevant for all participants, it is likely that the topic still felt distant or non-relatable for some participants. Using the promise of monetary compensation in the second study to increase motivation did not appear to be a sufficient way to increase engagement across all participants.

The processes we used for selecting images and automation accuracy were based on previous research yet may have been too harsh for our context, given that participants were poor raters of the images and poor users of the automation. For instance, choosing to set automation's accuracy at a comparable rate to human accuracy removed any bias for preferring one method over the other, yet left us using a fairly low (60%) reliability. Previous research has shown that automation reliability is a key factor in trust, and that trust in automation tends to occur when automation is at least 70% reliable (Drnec & Metcalfe, 2016; Dzindolet, Pierce, Beck, & Dawe, 1999; Lee & Moray, 1992; Muir, 1994; Muir, 1989; Parasuraman, Sheridan, & Wickens, 2000). Ideally, automation would only be created and used if it could outperform a human on a task. By setting automation's accuracy roughly equal to the accuracy of humans, we removed this performance-related bias. Although this helped us better measure other factors that may impact a decision to trust automation, it may have loss realism in how one may expect automation to perform. Also, the automation we created was intentionally simple—factors such as transparency, user interface, automation reliability, and others were all held constant in order to focus on measuring user-factors. Without further research manipulating these factors, we cannot know if they were the best combination to use or if these settings introduced challenges that complicate the results of our task. Finally, the images we used for our task were primarily White, and, while this matches the majority race of our sample, it limits generalizability of our participants' performance.

This study was the first of its kind to consider the role that personality characteristics have on impacting trust in automation in a healthcare context. It examined both trust attitudes and trust behaviors in the same research, and it compared dispositional and situational predictors of automation use. We created a novel skin-cancer screener task to be a relevant way for unskilled participants to interact with automation much in the same way that they might interact with automation in the real healthcare setting. Through two studies, we uncovered distinct differences between attitudes and behaviors when predicting trust, supporting the body of research that distinguishes these as separate aspects of trust. That is to say, our research suggests that the construct of trust is nuanced, specifically that trust as an attitude and as a behavior should be measured as distinct but related constructs. When considering how personality factors relate to trust in automation, we found a lack of support for the Big Five personality traits as predictors of automation trust or use, yet found that other personality factors, specifically ones of control and agency, had a direct relationship across both studies. Understanding the role that perceived and desired control play in attitudes toward trusting automation provides useful information to consider when designing the user's input and interaction with automation. We also observed the strong influence of task-specific attitudes of desire for mastery and automation confidence in impacting automation use, suggesting that trust in automation may be strongly shaped by context-specific attitudes and beliefs. Knowing that an individual's trust may be situationally-based encourages automation design that is transparent and sensitive to variations in an individual's senses of control and agency. Research would benefit from further exploring the role of dispositional and situational factors in impacting trust attitudes and behaviors. Overall, trust in automation shown through actual usage appears to be based more in situational than dispositional factors, which places high value on gaining user feedback throughout automation's development process in order to design automation that will be appropriately trusted by its users.

Appendix A

Checklist for Trust between People and Automation (TPA; Jian, Bisantz, & Drury, 2000)

Below is a list of statements for evaluating trust between people and automation. There are several scales for you to rate the intensity of your feelings of trust or your impression of automation (thinking of "automation" as "technology which controls (wholly or in part) a process usually done by humans"). Please mark an “x” on each line at the point that best describes your feeling or your impression.

Note: not at all = 1; extremely = 7

	Not at all					Extremely
1	2	3	4	5	6	7

Automation is deceptive.	
Automation behaves in an underhanded manner.	
I am suspicious of automation's intent, action, or outputs.	
I am wary of automation.	
Automation's actions will have a harmful or injurious outcome.	
I am confident in automation.	
Automation provides security.	
Automation has integrity.	
Automation is dependable.	
Automation is reliable.	
I can trust automation.	
I am familiar with automation.	

Appendix B

Propensity to Trust questionnaire (PTT; Merritt, 2011)

Please answer the following, thinking of "automation" as "technology which controls (wholly or in part) a process usually done by humans."

I usually trust automation until there is a reason not to.

- ○ Strongly agree
- ○ Somewhat agree
- ○ Neither agree nor disagree
- ○ Somewhat disagree
- ○ Strongly disagree

For the most part, I distrust automation.

- ○ Strongly agree
- ○ Somewhat agree
- ○ Neither agree nor disagree
- ○ Somewhat disagree
- ○ Strongly disagree

In general, I would rely on automation to assist me.

- ○ Strongly agree
- ○ Somewhat agree
- ○ Neither agree nor disagree
- ○ Somewhat disagree
- ○ Strongly disagree

My tendency to trust automation is high.

- ◯ Strongly agree
- ◯ Somewhat agree
- ◯ Neither agree nor disagree
- ◯ Somewhat disagree
- ◯ Strongly disagree

It is easy for me to trust automation to do its job.

- ◯ Strongly agree
- ◯ Somewhat agree
- ◯ Neither agree nor disagree
- ◯ Somewhat disagree
- ◯ Strongly disagree

I am likely to trust automation even when I have little knowledge about it.

- ◯ Strongly agree
- ◯ Somewhat agree
- ◯ Neither agree nor disagree
- ◯ Somewhat disagree
- ◯ Strongly disagree

Appendix C

Automation-Induced Complacency Potential Rating Scale (CPRS; Singh et al., 1993)

Below is a list of statements for evaluation trust between people and general automation. Please select the response that best describes your feeling or your impression.

I think that automated devices used in medicine, such as CT scans and ultrasound, provide very reliable medical diagnosis.

- ◯ Strongly agree
- ◯ Somewhat agree
- ◯ Neither agree nor disagree
- ◯ Somewhat disagree
- ◯ Strongly disagree

Automated devices in medicine save time and money in the diagnosis and treatment of disease.

- ◯ Strongly agree
- ◯ Somewhat agree
- ◯ Neither agree nor disagree
- ◯ Somewhat disagree
- ◯ Strongly disagree

If I need to have a tumor in my body removed, I would choose to undergo computer-aided surgery using laser technology because it is more reliable and safer than manual surgery.

- ◯ Strongly agree

○ Somewhat agree

○ Neither agree nor disagree

○ Somewhat disagree

○ Strongly disagree

Automated systems used in modern aircraft, such as the automatic landing system, have made air journeys safer.

○ Strongly agree

○ Somewhat agree

○ Neither agree nor disagree

○ Somewhat disagree

○ Strongly disagree

ATMs provide a safeguard against the inappropriate use of an individual's bank account by dishonest people.

○ Strongly agree

○ Somewhat agree

○ Neither agree nor disagree

○ Somewhat disagree

○ Strongly disagree

Automated devices used in aviation and banking have made work easier for both employees and customers.

○ Strongly agree

○ Somewhat agree

○ Neither agree nor disagree

○ Somewhat disagree

○ Strongly disagree

Even though the automatic cruise control is my car is set at a speed below the speed limit, I worry when I pass a police radar speed trap in case the automatic control is not working properly.

○ Strongly agree

○ Somewhat agree

○ Neither agree nor disagree

○ Somewhat disagree

○ Strongly disagree

Manually sorting through card catalogues is more reliable than computer-aided searches for finding items in a library.

○ Strongly agree

○ Somewhat agree

○ Neither agree nor disagree

○ Somewhat disagree

○ Strongly disagree

I would rather purchase an item using a computer than have to deal with a sales representative on the phone because my order is more likely to be correct using the computer.

- ◯ Strongly agree
- ◯ Somewhat agree
- ◯ Neither agree nor disagree
- ◯ Somewhat disagree
- ◯ Strongly disagree

Bank transactions have become safer with the introduction of computer technology for the transfer of funds.

- ◯ Strongly agree
- ◯ Somewhat agree
- ◯ Neither agree nor disagree
- ◯ Somewhat disagree
- ◯ Strongly disagree

I feel safer depositing my money at an ATM than with a human teller.

- ◯ Strongly agree
- ◯ Somewhat agree
- ◯ Neither agree nor disagree
- ◯ Somewhat disagree
- ◯ Strongly disagree

I have to tape an important TV program for a class assignment. To ensure that the correct program is recorded, I would use the automatic programming facility (e.g., on my VCR, DVR) rather than manual taping.

- Strongly agree
- Somewhat agree
- Neither agree nor disagree
- Somewhat disagree
- Strongly disagree

Appendix D

Rotter's (1967) Interpersonal Trust Scale (ITS)

Indicate the degree to which you agree or disagree with each statement:

1. Hypocrisy is on the increase in our society.

- ○ Strongly agree
- ○ Mildly Agree
- ○ Agree and disagree equally
- ○ Mildly disagree
- ○ Strongly disagree

2. One is better off being cautious when dealing with strangers until they have provided evidence that they are trustworthy.

- ○ Strongly agree
- ○ Mildly agree
- ○ Agree and disagree equally
- ○ Mildly disagree
- ○ Strongly disagree

3. This country has a dark future unless we can attract better people into politics.

- ○ Strongly agree
- ○ Mildly agree
- ○ Agree and disagree equally
- ○ Mildly disagree
- ○ Strongly disagree

4. Fear and social disgrace or punishment rather than conscience prevents most people from breaking the law.

◯ Strongly agree

◯ Mildly agree

◯ Agree and disagree equally

◯ Mildly disagree

◯ Strongly disagree

5. An honor system in which teachers would not be present during exams would probably result in increased cheating.

◯ Strongly agree

◯ Mildly agree

◯ Agree and disagree equally

◯ Mildly disagree

◯ Strongly disagree

6. Parents usually can be relied on to keep their promises.

◯ Strongly agree

◯ Mildly agree

◯ Agree and disagree equally

◯ Mildly disagree

◯ Strongly disagree

7. The United Nations will never be an effective force in keeping world peace.

◯ Strongly agree

◯ Mildly agree

◯ Agree and disagree equally

◯ Mildly disagree

○ Strongly disagree

8. The judiciary is a place where we can all get unbiased treatment.

○ Strongly agree

○ Mildly agree

○ Agree and disagree equally

○ Mildly disagree

○ Strongly disagree

9. Most people would be horrified if they knew how much of the news that the public hears and sees is distorted.

○ Strongly agree

○ Mildly agree

○ Agree and disagree equally

○ Mildly disagree

○ Strongly disagree

10. It is safe to believe that in spite of what people say most people are primarily interested in their own welfare.

○ Strongly agree

○ Mildly agree

○ Agree and disagree equally

○ Mildly disagree

○ Strongly disagree

11. Even though we have reports in newspapers, radio, TV, and the Internet, it is hard to get objective accounts of public events.

○ Strongly agree

- Mildly agree
- Agree and disagree equally
- Mildly disagree
- Strongly disagree

12. The future seems very promising.

- Strongly agree
- Mildly agree
- Agree and disagree equally
- Mildly disagree
- Strongly disagree

13. If we really knew what was going on in international politics, the public would have reason to be more frightened than they now seem to be.

- Strongly agree
- Mildly agree
- Agree and disagree equally
- Mildly disagree
- Strongly disagree

14. Most elected officials are really sincere in their campaign promises.

- Strongly agree
- Mildly agree
- Agree and disagree equally
- Mildly disagree
- Strongly disagree

15. Many major national sports contests are fixed in one way or another.

- Strongly agree
- Mildly agree
- Agree and disagree equally
- Mildly disagree
- Strongly disagree

16. Most experts can be relied upon to tell the truth about the limits of their knowledge.

- Strongly agree
- Mildly agree
- Agree and disagree equally
- Mildly disagree
- Strongly disagree

17. Most parents can be relied upon to carry out their threats of punishments.

- Strongly agree
- Mildly agree
- Agree and disagree equally
- Mildly disagree
- Strongly disagree

18. Most people can be counted on to do what they say they will do.

- Strongly agree
- Mildly agree
- Agree and disagree equally
- Mildly disagree
- Strongly disagree

19. In these competitive times one has to be alert or someone is likely to take advantage of you.

- Strongly agree
- Mildly agree
- Agree and disagree equally
- Mildly disagree
- Strongly disagree

20. Most idealists are sincere and usually practice what they preach.

- Strongly agree
- Mildly agree
- Agree and disagree equally
- Mildly disagree
- Strongly disagree

21. Most salesmen are honest in describing their products.

- Strongly agree
- Mildly agree
- Agree and disagree equally
- Mildly disagree
- Strongly disagree

22. Most students in school would not cheat even if they were sure they could get away with it.

- Strongly agree
- Mildly agree
- Agree and disagree equally

○ Mildly disagree

○ Strongly disagree

23. Most repairmen will not overcharge, even if they think you are ignorant of their specialty.

○ Strongly agree

○ Mildly agree

○ Agree and disagree equally

○ Mildly disagree

○ Strongly disagree

24. A large share of accident claims filed against insurance companies are phony.

○ Strongly agree

○ Mildly agree

○ Agree and disagree equally

○ Mildly disagree

○ Strongly disagree

25. Most people answer public opinion polls honestly.

○ Strongly agree

○ Mildly agree

○ Agree and disagree equally

○ Mildly disagree

○ Strongly disagree

Appendix E

Big Five Inventory (BFI; John, Donahue, & Kentle, 1991; John, Naumann, & Soto, 2008)

How I am in general. Here are a number of characteristics that may or may not apply to you. For example, do you agree that you are someone who likes to spend time with others? Please select the bubble next to each statement to indicate the extent to which you agree or disagree with that statement.

I am someone who...

	Disagree strongly	Disagree a little	Neither agree nor disagree	Agree a little	Agree strongly
Is talkative	○	○	○	○	○
Tends to find fault with others	○	○	○	○	○
Does a thorough job	○	○	○	○	○
Is depressed, blue	○	○	○	○	○
Is original, comes up with new ideas	○	○	○	○	○
Is reserved	○	○	○	○	○
Is helpful and unselfish with others	○	○	○	○	○
Can be somewhat careless	○	○	○	○	○
Is relaxed, handles stress well	○	○	○	○	○

Is curious about many different things	○	○	○	○	○
Is full of energy	○	○	○	○	○
Starts quarrels with others	○	○	○	○	○
Is a reliable worker	○	○	○	○	○
Can be tense	○	○	○	○	○
Is ingenious, a deep thinker	○	○	○	○	○
Generates a lot of enthusiasm	○	○	○	○	○
Has a forgiving nature	○	○	○	○	○
Tends to be disorganized	○	○	○	○	○
Worries a lot	○	○	○	○	○
Has an active imagination	○	○	○	○	○
Tends to be quiet	○	○	○	○	○
Is generally trusting	○	○	○	○	○
Tends to be lazy	○	○	○	○	○
Is emotionally stable, not easily	○	○	○	○	○

upset

Is inventive	○	○	○	○	○
Has an assertive personality	○	○	○	○	○
Can be cold and aloof	○	○	○	○	○
Perseveres until the task is finished	○	○	○	○	○
Can be moody	○	○	○	○	○
Values artistic, aesthetic experiences	○	○	○	○	○
Is sometimes shy, inhibited	○	○	○	○	○
Is considerate and kind to almost everyone	○	○	○	○	○
Does things efficiently	○	○	○	○	○
Remains calm in tense situations	○	○	○	○	○
Prefers work that is routine	○	○	○	○	○
Is outgoing, sociable	○	○	○	○	○
Is sometimes rude to others	○	○	○	○	○

Makes plans and follows through with them	○	○	○	○	○
Gets nervous easily	○	○	○	○	○
Likes to reflect, play with ideas	○	○	○	○	○
Has few artistic interests	○	○	○	○	○
Likes to cooperate with others	○	○	○	○	○
Is easily distracted	○	○	○	○	○
Is sophisticated in art, music, or literature	○	○	○	○	○

Appendix F

Revised Domain-Specific Risk-Taking (DOSPERT) Scale (Blais & Weber, 2006)

For each of the following statements, please indicate the **likelihood** that you would engage in the described activity or behavior if you were to find yourself in that situation. Provide a rating from *Extremely Unlikely* to *Extremely Likely*, using the scales below.

Admitting that your tastes are different from those of a friend.

- ○ Extremely unlikely
- ○ Moderately unlikely
- ○ Somewhat unlikely
- ○ Not sure
- ○ Somewhat likely
- ○ Moderately likely
- ○ Extremely likely

Going camping in the wilderness.

- ○ Extremely unlikely
- ○ Moderately unlikely
- ○ Somewhat unlikely
- ○ Not sure
- ○ Somewhat likely
- ○ Moderately likely
- ○ Extremely likely

Betting a day's income at the horse races.

- ◯ Extremely unlikely
- ◯ Moderately unlikely
- ◯ Somewhat unlikely
- ◯ Not sure
- ◯ Somewhat likely
- ◯ Moderately likely
- ◯ Extremely likely

Investing 10% of your annual income in a moderate growth diversified fund.

- ◯ Extremely unlikely
- ◯ Moderately unlikely
- ◯ Somewhat unlikely
- ◯ Not sure
- ◯ Somewhat likely
- ◯ Moderately likely
- ◯ Extremely likely

Drinking heavily at a social function.

- ◯ Extremely unlikely
- ◯ Moderately unlikely

- Somewhat unlikely
- Not sure
- Somewhat likely
- Moderately likely
- Extremely likely

Taking some questionable deductions on your income tax return.

- Extremely unlikely
- Moderately unlikely
- Somewhat unlikely
- Not sure
- Somewhat likely
- Moderately likely
- Extremely likely

Disagreeing with an authority figure on a major issue.

- Extremely unlikely
- Moderately unlikely
- Somewhat unlikely
- Not sure
- Somewhat likely

- ◯ Moderately likely
- ◯ Extremely likely

Betting a day's income at a high-stake poker game.

- ◯ Extremely unlikely
- ◯ Moderately unlikely
- ◯ Somewhat unlikely
- ◯ Not sure
- ◯ Somewhat likely
- ◯ Moderately likely
- ◯ Extremely likely

Having an affair with a married man/woman.

- ◯ Extremely unlikely
- ◯ Moderately unlikely
- ◯ Somewhat unlikely
- ◯ Not sure
- ◯ Somewhat likely
- ◯ Moderately likely
- ◯ Extremely likely

Passing off somebody else's work as your own.

- Extremely unlikely
- Moderately unlikely
- Somewhat unlikely
- Not sure
- Somewhat likely
- Moderately likely
- Extremely likely

Going down a ski run that is beyond your ability.

- Extremely unlikely
- Moderately unlikely
- Somewhat unlikely
- Not sure
- Somewhat likely
- Moderately likely
- Extremely likely

Investing 5% of your annual income in a very speculative stock.

- Extremely unlikely
- Moderately unlikely
- Somewhat unlikely

○ Not sure

○ Somewhat likely

○ Moderately likely

○ Extremely likely

Going whitewater rafting at high water in the spring.

○ Extremely unlikely

○ Moderately unlikely

○ Somewhat unlikely

○ Not sure

○ Somewhat likely

○ Moderately likely

○ Extremely likely

Betting a day's income on the outcome of a sporting event.

○ Extremely unlikely

○ Moderately unlikely

○ Somewhat unlikely

○ Not sure

○ Somewhat likely

○ Moderately likely

◯ Extremely likely

Engaging in unprotected sex.

◯ Extremely unlikely

◯ Moderately unlikely

◯ Somewhat unlikely

◯ Not sure

◯ Somewhat likely

◯ Moderately likely

◯ Extremely likely

Revealing a friend's secret to someone else.

◯ Extremely unlikely

◯ Moderately unlikely

◯ Somewhat unlikely

◯ Not sure

◯ Somewhat likely

◯ Moderately likely

◯ Extremely likely

Driving a car without wearing a seat belt.

◯ Extremely unlikely

◯ Moderately unlikely

◯ Somewhat unlikely

◯ Not sure

◯ Somewhat likely

◯ Moderately likely

◯ Extremely likely

Investing 10% of your annual income in a new business venture.

◯ Extremely unlikely

◯ Moderately unlikely

◯ Somewhat unlikely

◯ Not sure

◯ Somewhat likely

◯ Moderately likely

◯ Extremely likely

Taking a skydiving class.

◯ Extremely unlikely

◯ Moderately unlikely

◯ Somewhat unlikely

◯ Not sure

- Somewhat likely
- Moderately likely
- Extremely likely

Riding a motorcycle without a helmet.

- Extremely unlikely
- Moderately unlikely
- Somewhat unlikely
- Not sure
- Somewhat likely
- Moderately likely
- Extremely likely

Choosing a career that you truly enjoy over a more secure one.

- Extremely unlikely
- Moderately unlikely
- Somewhat unlikely
- Not sure
- Somewhat likely
- Moderately likely
- Extremely likely

Speaking your mind about an unpopular issue in a meeting at work.

- ◯ Extremely unlikely
- ◯ Moderately unlikely
- ◯ Somewhat unlikely
- ◯ Not sure
- ◯ Somewhat likely
- ◯ Moderately likely
- ◯ Extremely likely

Sunbathing without sunscreen.

- ◯ Extremely unlikely
- ◯ Moderately unlikely
- ◯ Somewhat unlikely
- ◯ Not sure
- ◯ Somewhat likely
- ◯ Moderately likely
- ◯ Extremely likely

Bungee jumping off a tall bridge.

- ◯ Extremely unlikely
- ◯ Moderately unlikely

○ Somewhat unlikely

○ Not sure

○ Somewhat likely

○ Moderately likely

○ Extremely likely

Piloting a small plane.

○ Extremely unlikely

○ Moderately unlikely

○ Somewhat unlikely

○ Not sure

○ Somewhat likely

○ Moderately likely

○ Extremely likely

Walking home alone at night in an unsafe area of town.

○ Extremely unlikely

○ Moderately unlikely

○ Somewhat unlikely

○ Not sure

○ Somewhat likely

- ◯ Moderately likely
- ◯ Extremely likely

Moving to a city far away from your extended family.

- ◯ Extremely unlikely
- ◯ Moderately unlikely
- ◯ Somewhat unlikely
- ◯ Not sure
- ◯ Somewhat likely
- ◯ Moderately likely
- ◯ Extremely likely

Starting a new career in your mid-thirties.

- ◯ Extremely unlikely
- ◯ Moderately unlikely
- ◯ Somewhat unlikely
- ◯ Not sure
- ◯ Somewhat likely
- ◯ Moderately likely
- ◯ Extremely likely

Leaving your young children alone at home while running an errand.

○ Extremely unlikely

○ Moderately unlikely

○ Somewhat unlikely

○ Not sure

○ Somewhat likely

○ Moderately likely

○ Extremely likely

Not returning a wallet you found that contains $200.

○ Extremely unlikely

○ Moderately unlikely

○ Somewhat unlikely

○ Not sure

○ Somewhat likely

○ Moderately likely

○ Extremely likely

Appendix G

Desirability of Control Scale (DCS; Burger & Cooper, 1979)

Below you will find a series of statements. Please read each statement carefully and respond to it by expressing the extent to which you believe the statement applies to you. For all items, a response from 1 to 7 is required. Use the number that best reflects your belief when the scale is defined as follows: 1 = The statement does not apply to me at all 2 = The statement usually does not apply to me 3 = More often, the statement does not apply 4 = I am unsure about whether or not the statement applies to me, or it applies to me about half the time 5 = The statement applies more often than not 6 = The statement usually applies to me 7 = The statement always applies to me

1. I prefer a job where I have a lot of control over what I do and when I do it.

○ 1

○ 2

○ 3

○ 4

○ 5

○ 6

○ 7

2. I enjoy political participation because I want to have as much of a say in running government as possible.

○ 1

○ 2

○ 3

○ 4

○ 5

○ 6

○ 7

3. I try to avoid situations where someone else tells me what to do.

○ 1

○ 2

○ 3

○ 4

○ 5

○ 6

○ 7

4. I would prefer to be a leader than a follower.

○ 1

○ 2

○ 3

○ 4

○ 5

○ 6

○ 7

5. I enjoy being able to influence the actions of others.

○ 1

○ 2

○ 3

○ 4

○ 5

○ 6

○ 7

6. I am careful to check everything on an automobile before I leave for a long trip.

○ 1

○ 2

○ 3

○ 4

○ 5

○ 6

○ 7

7. Others usually know what is best for me.

○ 1

○ 2

○ 3

○ 4

○ 5

○ 6

○ 7

8. I enjoy making my own decisions.

○ 1

○ 2

○ 3

○ 4

○ 5

○ 6

○ 7

9. I enjoy having control over my own destiny.

○ 1

○ 2

○ 3

○ 4

○ 5

○ 6

○ 7

10. I would rather someone else take over the leadership role when I’m involved in a group project.

○ 1

○ 2

○ 3

○ 4

○ 5

○ 6

○ 7

11. I consider myself to be generally more capable of handling situations than others are.

○ 1

○ 2

○ 3

○ 4

○ 5

○ 6

○ 7

12. I'd rather run my own business and make my own mistakes than listen to someone else's orders.

○ 1

○ 2

○ 3

○ 4

○ 5

○ 6

○ 7

13. I like to get a good idea of what a job is all about before I begin.

○ 1

○ 2

○ 3

○ 4

○ 5

○ 6

○ 7

14. When I see a problem, I prefer to do something about it rather than sit by and let it continue.

○ 1

○ 2

○ 3

○ 4

○ 5

○ 6

○ 7

15. When it comes to orders, I would rather give them than receive them.

○ 1

○ 2

○ 3

○ 4

○ 5

○ 6

○ 7

16. I wish I could push many of life's daily decisions off on someone else.

○ 1

○ 2

○ 3

○ 4

○ 5

○ 6

○ 7

17. When driving, I try to avoid putting myself in a situation where I could be hurt by another person's mistake.

○ 1

○ 2

○ 3

○ 4

○ 5

○ 6

○ 7

18. I prefer to avoid situations where someone else has to tell me what it is I should be doing.

○ 1

○ 2

○ 3

○ 4

○ 5

○ 6

○ 7

19. There are many situations in which I would prefer only one choice rather than having to make a decision.

○ 1

○ 2

○ 3

○ 4

○ 5

○ 6

○ 7

20. I like to wait and see if someone else is going to solve a problem so that I don't have to be bothered with it.

○ 1

○ 2

○ 3

○ 4

○ 5

○ 6

○ 7

Appendix H

Levenson IPC Scale (LIPC; Levenson, 1981)

1. Whether or not I get to be a leader depends mostly on my ability.

- ○ Strongly disagree
- ○ Disagree
- ○ Slightly disagree
- ○ Slightly agree
- ○ Agree
- ○ Strongly agree

2. To a great extent my life is controlled by accidental happenings.

- ○ Strongly disagree
- ○ Disagree
- ○ Slightly disagree
- ○ Slightly agree
- ○ Agree
- ○ Strongly agree

3. I feel like what happens in my life is mostly determined by powerful people.

- ○ Strongly disagree
- ○ Disagree
- ○ Slightly disagree
- ○ Slightly agree

- Agree
- Strongly agree

4. Whether or not I get into a car accident depends mostly on how good a driver I am.

- Strongly disagree
- Disagree
- Slightly disagree
- Slightly agree
- Agree
- Strongly agree

5. When I make plans, I am almost certain to make them work.

- Strongly disagree
- Disagree
- Slightly disagree
- Slightly agree
- Agree
- Strongly agree

6. Often there is no chance of protecting my personal interests from bad luck happenings.

- Strongly disagree
- Disagree
- Slightly disagree

○ Slightly agree

○ Agree

○ Strongly agree

7. When I get what I want, it's usually because I'm lucky.

○ Strongly disagree

○ Disagree

○ Slightly disagree

○ Slightly agree

○ Agree

○ Strongly agree

8. Although I might have good ability, I will not be given leadership responsibility without appealing to those in positions of power.

○ Strongly disagree

○ Disagree

○ Slightly disagree

○ Slightly agree

○ Agree

○ Strongly agree

9. How many friends I have depends on how nice a person I am.

○ Strongly disagree

○ Disagree

○ Slightly disagree

○ Slightly agree

○ Agree

○ Strongly agree

10. I have often found that what is going to happen will happen.

○ Strongly disagree

○ Disagree

○ Slightly disagree

○ Slightly agree

○ Agree

○ Strongly agree

11. My life is chiefly controlled by powerful others.

○ Strongly disagree

○ Disagree

○ Slightly disagree

○ Slightly agree

○ Agree

○ Strongly agree

12. Whether or not I get into a car accident is mostly a matter of luck.

○ Strongly disagree

○ Disagree

○ Slightly disagree

○ Slightly agree

○ Agree

○ Strongly agree

13. People like myself have very little chance of protecting our personal interests when they conflict with those of strong pressure groups.

○ Strongly disagree

○ Disagree

○ Slightly disagree

○ Slightly agree

○ Agree

○ Strongly agree

14. It's not always wise for me to plan too far ahead because many things turn out to be a matter of good or bad fortune.

○ Strongly disagree

○ Disagree

○ Slightly disagree

○ Slightly agree

○ Agree

○ Strongly agree

15. Getting what I want requires pleasing those people above me.

- ◯ Strongly disagree
- ◯ Disagree
- ◯ Slightly disagree
- ◯ Slightly agree
- ◯ Agree
- ◯ Strongly agree

16. Whether or not I get to be a leader depends on whether I'm lucky enough to be in the right place at the right time.

- ◯ Strongly disagree
- ◯ Disagree
- ◯ Slightly disagree
- ◯ Slightly agree
- ◯ Agree
- ◯ Strongly agree

17. If important people were to decide they didn't like me, I probably wouldn't make many friends.

- ◯ Strongly disagree
- ◯ Disagree
- ◯ Slightly disagree
- ◯ Slightly agree
- ◯ Agree

◯ Strongly agree

18. I can pretty much determine what will happen in my life.

◯ Strongly disagree

◯ Disagree

◯ Slightly disagree

◯ Slightly agree

◯ Agree

◯ Strongly agree

19. I am usually able to protect my personal interests.

◯ Strongly disagree

◯ Disagree

◯ Slightly disagree

◯ Slightly agree

◯ Agree

◯ Strongly agree

20. Whether or not I get into a car accident depends mostly on the other driver.

◯ Strongly disagree

◯ Disagree

◯ Slightly disagree

◯ Slightly agree

○ Agree

○ Strongly agree

21. When I get what I want, it's usually because I worked hard for it.

○ Strongly disagree

○ Disagree

○ Slightly disagree

○ Slightly agree

○ Agree

○ Strongly agree

22. In order to have my plans work, I make sure that they fit in with the desires of people who have power over me.

○ Strongly disagree

○ Disagree

○ Slightly disagree

○ Slightly agree

○ Agree

○ Strongly agree

23. My life is determined by my own actions.

○ Strongly disagree

○ Disagree

○ Slightly disagree

○ Slightly agree

○ Agree

○ Strongly agree

24. It’s chiefly a matter of fate whether or not I have a few friends or many friends.

○ Strongly disagree

○ Disagree

○ Slightly disagree

○ Slightly agree

○ Agree

○ Strongly agree

Appendix I

General Self-Efficacy Scale (GSES; Schwarzer & Jerusalem, 1995)

Please respond to the following questions.

1. I can always manage to solve difficult problems if I try hard enough.

◯ Not at all true

◯ Hardly true

◯ Moderately true

◯ Exactly true

2. If someone opposes me, I can find the means and ways to get what I want.

◯ Not at all true

◯ Hardly true

◯ Moderately true

◯ Exactly true

3. It is easy for me to stick to my aims and accomplish my goals.

◯ Not at all true

◯ Hardly true

◯ Moderately true

◯ Exactly true

4. I am confident that I could deal efficiently with unexpected events.

◯ Not at all true

○ Hardly true

○ Moderately true

○ Exactly true

5. Thanks to my resourcefulness, I know how to handle unforeseen situations.

○ Not at all true

○ Hardly true

○ Moderately true

○ Exactly true

6. I can solve most problems if I invest the necessary effort.

○ Not at all true

○ Hardly true

○ Moderately true

○ Exactly true

7. I can remain calm when facing difficulties because I can rely on my coping abilities.

○ Not at all true

○ Hardly true

○ Moderately true

○ Exactly true

8. When I am confronted with a problem, I can usually find several solutions.

- Not at all true
- Hardly true
- Moderately true
- Exactly true

9. If I am in trouble, I can usually think of a solution.

- Not at all true
- Hardly true
- Moderately true
- Exactly true

10. I can usually handle whatever comes my way.

- Not at all true
- Hardly true
- Moderately true
- Exactly true

Appendix J

Demographics

PLEASE give careful and honest responses. You will be duly compensated for your time, and it is critically important to have truthful answers for this dissertation project. Thank you!

What is your age?

▼ less than 18 ... greater than 40

What is your ethnicity?

○ White

○ Black or African American

○ American Indian or Alaska Native

○ Asian

○ Native Hawaiian or Pacific Islander

○ Other

What is your gender?

○ Male

○ Female

○ Other: ____

What is your year in school?

○ Freshman

○ Sophomore

○ Junior

○ Senior

○ Graduate

Past Experience Questions

Do you currently, or have you ever, worked in a medical field?

○ Yes, currently

○ Previously but not currently

○ No, never

Do you have any exposure to medical diagnostic knowledge?

○ Nothing formal

○ Minimal (e.g., classroom instruction)

○ Moderate (e.g., some practice/use of knowledge)

○ Extensive (e.g., frequent practice/use of knowledge)

Have you, or anyone close to you, been screened for or diagnosed with skin cancer? (Select all that apply.)

☐ I, myself, have been screened but was not diagnosed

- [ ] I, myself, have been diagnosed with skin cancer
- [ ] Someone close to me has been screened but not diagnosed
- [ ] Someone close to me has been diagnosed with skin cancer
- [ ] Never screened nor diagnosed

Please use the box below to describe any knowledge you have about screening for and/or diagnosing skin cancer. This can be formal training or informal tips you have learned. If you don't have any knowledge, type "N/A."

____

How confident are you in detecting skin cancer?

- ○ Extremely confident
- ○ Very confident
- ○ Moderately confident
- ○ Slightly confident
- ○ Not confident at all

Appendix K

Media and Technology Usage and Attitudes Scale
(MTUAS; Rosen, Whaling, Carrier, Cheever, & Rokkum, 2013)

Please indicate how often you do each of the following activities on any device (mobile phone, laptop, desktop, etc.) using the dropdown box to select your response.

1. Send, receive, and read e-mails (not including spam or junk mail).

▼ Never ... All the time

2. Watch TV shows, movies, video clips, etc. on any device.

▼ Never ... All the time

3. Download or share media files on any device.

▼ Never ... All the time

4. Search the internet for information or news on any device.

▼ Never ... All the time

5. Search the internet for videos, images, or photos on any device.

▼ Never ... All the time

How confident do you feel in performing each of the following tasks?

1. Send, receive, and read e-mails (not including spam or junk mail).

○ Not at all confident

○ Somewhat unconfident

○ Somewhat confident

○ Very confident

2. Watch TV shows, movies, video clips, etc. on any device.

○ Not at all confident

○ Somewhat unconfident

○ Somewhat confident

○ Very confident

3. Download or share media files on any device.

○ Not at all confident

○ Somewhat unconfident

○ Somewhat confident

○ Very confident

4. Search the internet for information or news on any device.

○ Not at all confident

○ Somewhat unconfident

○ Somewhat confident

○ Very confident

5. Search the internet for photos, images, or videos on any device.

- ◯ Not at all confident
- ◯ Somewhat unconfident
- ◯ Somewhat confident
- ◯ Very confident

Please answer how much you agree with each statement below.

I feel it is important to be able to find any information whenever I want online.

- ◯ Strongly agree
- ◯ Agree
- ◯ Neither agree nor disagree
- ◯ Disagree
- ◯ Strongly disagree

I feel it is important to be able to access the Internet any time I want.

- ◯ Strongly agree
- ◯ Agree
- ◯ Neither agree nor disagree
- ◯ Disagree

○ Strongly disagree

I think it is important to keep up with the latest trends in technology.

○ Strongly agree

○ Agree

○ Neither agree nor disagree

○ Disagree

○ Strongly disagree

I get anxious when I don’t have my cell phone.

○ Strongly agree

○ Agree

○ Neither agree nor disagree

○ Disagree

○ Strongly disagree

I get anxious when I don’t have the Internet available to me.

○ Strongly agree

○ Agree

○ Neither agree nor disagree

○ Disagree

○ Strongly disagree

I am dependent on my technology.

- ◯ Strongly agree
- ◯ Agree
- ◯ Neither agree nor disagree
- ◯ Disagree
- ◯ Strongly disagree

Technology will provide solutions to many of our problems.

- ◯ Strongly agree
- ◯ Agree
- ◯ Neither agree nor disagree
- ◯ Disagree
- ◯ Strongly disagree

With technology anything is possible.

- ◯ Strongly agree
- ◯ Agree
- ◯ Neither agree nor disagree
- ◯ Disagree
- ◯ Strongly disagree

I feel that I get more accomplished because of technology.

○ Strongly agree

○ Agree

○ Neither agree nor disagree

○ Disagree

○ Strongly disagree

New technology makes people waste too much time.

○ Strongly agree

○ Agree

○ Neither agree nor disagree

○ Disagree

○ Strongly disagree

New technology makes life more complicated.

○ Strongly agree

○ Agree

○ Neither agree nor disagree

○ Disagree

○ Strongly disagree

New technology makes people more isolated.

○ Strongly agree

○ Agree

○ Neither agree nor disagree

○ Disagree

○ Strongly disagree

I prefer to work on several projects in a day, rather than completing one project and then switching to another.

○ Strongly agree

○ Agree

○ Neither agree nor disagree

○ Disagree

○ Strongly disagree

When doing a number of assignments, I like to switch back and forth between them rather than do one at a time.

○ Strongly agree

○ Agree

○ Neither agree nor disagree

○ Disagree

○ Strongly disagree

I like to finish one task completely before focusing on anything else.

○ Strongly agree

- Agree
- Neither agree nor disagree
- Disagree
- Strongly disagree

When I have a task to complete, I like to break it up by switching to other tasks intermittently.

- Strongly agree
- Agree
- Neither agree nor disagree
- Disagree
- Strongly disagree

Appendix L

Multidimensional Health Locus of Control Scale
(MHLC; Wallston, Wallston, & DeVellis, 1978)

Instructions: Each item below is a belief statement about your medical condition with which you may agree or disagree. Beside each statement is a scale which ranges from strongly disagree to strongly agree. For each item we would like you to select the response that represents the extent to which you agree or disagree with that statement.

This is a measure of your personal beliefs; obviously, there are no right or wrong answers.

1) If I become sick, I have the power to make myself well again.

- ○ Strongly disagree
- ○ Moderately disagree
- ○ Slightly disagree
- ○ Slightly agree
- ○ Moderately agree
- ○ Strongly agree

2) Often I feel that no matter what I do, if I am going to get sick, I will get sick.

- ○ Strongly disagree
- ○ Moderately disagree
- ○ Slightly disagree
- ○ Slightly agree
- ○ Moderately agree
- ○ Strongly agree

3) If I see an excellent doctor regularly, I am less likely to have health problems.

- ○ Strongly disagree
- ○ Moderately disagree
- ○ Slightly disagree
- ○ Slightly agree
- ○ Moderately agree
- ○ Strongly agree

4) It seems that my health is greatly influenced by accidental happenings.

- ○ Strongly disagree
- ○ Moderately disagree
- ○ Slightly disagree
- ○ Slightly agree
- ○ Moderately agree
- ○ Strongly agree

5) I can only maintain my health by consulting health professionals.

- ○ Strongly disagree
- ○ Moderately disagree
- ○ Slightly disagree
- ○ Slightly agree

○ Moderately agree

○ Strongly agree

6) I am directly responsible for my health.

○ Strongly disagree

○ Moderately disagree

○ Slightly disagree

○ Slightly agree

○ Moderately agree

○ Strongly agree

7) Other people play a big part in whether I stay healthy or become sick.

○ Strongly disagree

○ Moderately disagree

○ Slightly disagree

○ Slightly agree

○ Moderately agree

○ Strongly agree

8) Whatever goes wrong with my health is my own fault.

○ Strongly disagree

○ Moderately disagree

○ Slightly disagree

○ Slightly agree

○ Moderately agree

○ Strongly agree

9) When I am sick, I just have to let nature run its course.

○ Strongly disagree

○ Moderately disagree

○ Slightly disagree

○ Slightly agree

○ Moderately agree

○ Strongly agree

10) Health professionals keep me healthy.

○ Strongly disagree

○ Moderately disagree

○ Slightly disagree

○ Slightly agree

○ Moderately agree

○ Strongly agree

11) When I stay healthy, I'm just plain lucky.

○ Strongly disagree

○ Moderately disagree

- Slightly disagree
- Slightly agree
- Moderately agree
- Strongly agree

12) My physical well-being depends on how well I take care of myself.

- Strongly disagree
- Moderately disagree
- Slightly disagree
- Slightly agree
- Moderately agree
- Strongly agree

13) When I feel ill, I know it is because I have not been taking care of myself properly.

- Strongly disagree
- Moderately disagree
- Slightly disagree
- Slightly agree
- Moderately agree
- Strongly agree

14) The type of care I receive from other people is what is responsible for how well I recover from an illness.

- Strongly disagree
- Moderately disagree
- Slightly disagree
- Slightly agree
- Moderately agree
- Strongly agree

15) Even when I take care of myself, it's easy to get sick.

- Strongly disagree
- Moderately disagree
- Slightly disagree
- Slightly agree
- Moderately agree
- Strongly agree

16) When I become ill, it's a matter of fate.

- Strongly disagree
- Moderately disagree
- Slightly disagree
- Slightly agree
- Moderately agree
- Strongly agree

17) I can pretty much stay healthy by taking good care of myself.

- ◯ Strongly disagree
- ◯ Moderately disagree
- ◯ Slightly disagree
- ◯ Slightly agree
- ◯ Moderately agree
- ◯ Strongly agree

18) Following doctor's orders to the letter is the best way for me to stay healthy.

- ◯ Strongly disagree
- ◯ Moderately disagree
- ◯ Slightly disagree
- ◯ Slightly agree
- ◯ Moderately agree
- ◯ Strongly agree

Appendix M

Pre-Task Questions

Please answer the following, based on your opinion of the automation to which you were just introduced.

I would trust the automation until there is a reason not to.

- ○ Strongly agree
- ○ Somewhat agree
- ○ Neither agree nor disagree
- ○ Somewhat disagree
- ○ Strongly disagree

For the most part, I distrust the automation.

- ○ Strongly agree
- ○ Somewhat agree
- ○ Neither agree nor disagree
- ○ Somewhat disagree
- ○ Strongly disagree

In general, I would rely on this automation to assist me.

- ○ Strongly agree
- ○ Somewhat agree
- ○ Neither agree nor disagree
- ○ Somewhat disagree
- ○ Strongly disagree

My tendency to trust this automation is high.

- ○ Strongly agree

- Somewhat agree
- Neither agree nor disagree
- Somewhat disagree
- Strongly disagree

It is easy for me to trust the automation to do its job.

- Strongly agree
- Somewhat agree
- Neither agree nor disagree
- Somewhat disagree
- Strongly disagree

I am likely to trust this automation even when I have little knowledge about it.

- Strongly agree
- Somewhat agree
- Neither agree nor disagree
- Somewhat disagree
- Strongly disagree

Post-Task Questions

Now that you have completed judging all images, please answer the following questions:

How high was your confidence in the automation’s decision?	▼ Not at all ... Extremely
How much did you trust the automation to make the correct decision?	▼ Not at all ... Extremely
How high was your self confidence in making the correct decision?	▼ Not at all ... Extremely
How confident are you that you could have completed this task most successfully on your own, without the automation’s decisions?	▼ Not at all ... Extremely
How much did you desire to make the correct decision yourself, without using the automation?	▼ Not at all ... Extremely
How much did you desire to make the correct decision no matter whether it was your choice or the automation's decision?	▼ Not at all ... Extremely

Now that you have completed judging all images, please answer the following questions based on the experience you just had with using computer automation (thinking of "automation" as "technology which controls (wholly or in part) a process usually done by humans").

	Strongly disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Strongly agree
I usually trusted the automation until there was a reason not to.	○	○	○	○	○
For the most part, I distrusted the automation.	○	○	○	○	○
In general, I relied on the automation to assist me.	○	○	○	○	○
My tendency to trust the automation was high.	○	○	○	○	○
It was easy for me to trust the automation to do its job.	○	○	○	○	○
I trusted automation even when I had little knowledge about it.	○	○	○	○	○
I believe the automation is a competent performer.	○	○	○	○	○
I trust the automation.	○	○	○	○	○

I have confidence in the advice given by the automation.	○	○	○	○	○
I can depend on the automation.	○	○	○	○	○
I can rely on the automation to behave in consistent ways.	○	○	○	○	○
I can rely on the automation to do its best every time I take its advice.	○	○	○	○	○

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VITA

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