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Journal of Management Information Systems

ISSN: (Print) (Online) Journal homepage: https://www.tandfonline.com/loi/mmis20

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Eun Hee Park, Karl Werder, Lan Cao & Balasubramaniam Ramesh

To cite this article: Eun Hee Park, Karl Werder, Lan Cao & Balasubramaniam Ramesh (2022) Why do Family Members Reject AI in Health Care? Competing Effects of Emotions, Journal of Management Information Systems, 39:3, 765-792, DOI: 10.1080/07421222.2022.2096550

To link to this article: https://doi.org/10.1080/07421222.2022.2096550

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JOURNAL OF MANAGEMENT INFORMATION SYSTEMS
2022, VOL. 39, NO. 3, 765–792
https://doi.org/10.1080/07421222.2022.2096550

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Why do Family Members Reject AI in Health Care? Competing Effects of Emotions

Eun Hee Park[a], Karl Werder[b], Lan Cao[a], and Balasubramaniam Ramesh[c]

[a]Information Technology & Decision Sciences, Strome College of Business, Old Dominion University, Norfolk, VA 23529, USA; [b]Cologne Institute for Information Systems, Faculty of Management, Economics and Social Sciences, University of Cologne, Pohligstr. 1, 50969 Cologne, Germany; [c]Computer Information Systems, J. Mack Robinson College of Business, Georgia State University, Atlanta, GA 30303, USA

ABSTRACT

Artificial intelligence (AI) enables continuous monitoring of patients' health, thus improving the quality of their health care. However, prior studies suggest that individuals resist such innovative technology. In contrast to prior studies that investigate individuals' decisions for themselves, we focus on family members' rejection of AI monitoring, as family members play a significant role in health care decisions. Our research investigates competing effects of emotions toward the rejection of AI monitoring for health care. Based on two scenario-based experiments, our study reveals that emotions play a decisive role in family members' decision making on behalf of their parents. We find that anxiety about health care monitoring and anxiety about health outcomes reduce the rejection of AI monitoring, whereas surveillance anxiety and delegation anxiety increase rejection. We also find that for individual-level risks, perceived controllability moderates the relationship between surveillance anxiety and the rejection of AI monitoring. We contribute to the theory of Information System rejection by identifying the competing roles of emotions in AI monitoring decision making. We extend the literature on decision making for others by suggesting the influential role of anxiety. We also contribute to health-care research in Information System by identifying the important role of controllability, a design factor, in AI monitoring rejection.

KEYWORDS
Artificial Intelligence; AI Monitoring; Emotion; Innovation Resistance; Innovation Rejection; Decision for Others; Healthcare IS; Controllability; Covid-19

Introduction

Interest in the application of artificial intelligence (AI) in health care continues to increase rapidly, as AI provides innovative solutions to improve the quality of health care [48, 65]. AI monitoring, for example, allows for contactless supervision through a variety of technologies, including adhesive patches, sensor devices, and video monitoring systems [54] that are designed to continuously monitor patients [90]; it uses machine learning techniques to learn from the generated data, and it identifies elevated risks for serious illnesses [74]. However, prior studies have suggested that individuals show resistance to such innovative technologies because of technology-specific factors, such as usage difficulty, the risk of unproven innovation, and conflicts with individuals' prior beliefs [44, 72].

CONTACT Balasubramaniam Ramesh bramesh@gsu.edu; Eun Hee Park epark@odu.edu; Karl Werder werder@wiso.uni-koeln.de; Lan Cao lcao@odu.edu
Supplemental data for this article can be accessed online at https://doi.org/10.1080/07421222.2022.2096550.

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Research on Information Systems (IS) resistance has received much attention, particularly in the healthcare[1] context, which involves complex interactions between people, practices, and technology [43]. Prior studies investigating the antecedents of resistance have explored the impact of technology anxiety on behavior. For example, technology anxiety decreases the intention to use the technology [43]. However, the impact of emotions triggered by situation-specific factors is underexplored. In the present study, we examine the effect of the perceived risk of adverse outcomes, an important situation-specific factor for health care, on AI monitoring, which has not received attention in the literature.

Health care decisions are often made by family members who serve as surrogate decision makers on behalf of patients [20]. Family members are key sources of patients' health information and play important roles in the latter's diagnosis, treatment, and recovery [20]. For example, studies have estimated that surrogate decision makers, such as family members, make approximately 75% of the decisions for hospitalized patients with life-threatening illnesses and 44%–69% of the decisions for nursing home residents [40]. However, innovation resistance research often investigates individuals' decision making for themselves [44, 63], with only a few studies focusing on surrogate decision makers. For example, a prior study on surrogate decision makers explored how well they predict patients' care preferences [77]. By contrast, we focus on the factors that impact family members' resistance to healthcare IS when they make decisions for others.

Decisions involving risk are often driven by emotions rather than rational choices [28, 49]. Strong negative emotions are common in health care situations that involve high levels of perceived risks [49]. Specifically, we formulate the following research questions that motivate our work:

> *What is the impact of family members' perceived risks of adverse health outcomes on their rejection of AI monitoring? How is this relationship affected by emotions?*

To address these research questions, we first draw on innovation resistance theory to understand the factors impacting technology resistance [70, 71, 82], particularly AI monitoring rejection, which is a type of innovation resistance behavior. Next, we draw on the literature on emotions in decision making and risk-as-feelings theory [49] to understand how and why individuals appraise a situation, experience emotions [28], and reject innovative technology. We focus on investigating i) the role of the perceived risk of adverse health outcomes in family members' situational emotions, ii) the influence of these situational emotions on family members' AI monitoring rejection, and iii) the impact of AI monitoring emotions on AI monitoring rejection.

While the impact of functional and psychological barriers on innovation resistance has been studied [71], the role of design factors has received less attention. Cenfetelli [15] argues that "we must also consider that system design and function play a role" in technology rejection [15, p. 473] because perceptions about a system's attributes ultimately influence attitudes and behaviors. Their research suggests that studying the attributes of a system that encourage or discourage use is important. Against this backdrop, prior research has revealed that providing users with the ability to control the settings of intelligent systems, such as context-aware systems, increases user's performance [7]. Controllability as a design factor has received much attention in recent studies. For example, a recent review [36] of research on self-monitoring for chronic diseases suggests that many self-monitoring technologies are designed to provide some degree of controllability (e.g., allowing users to set or adjust their own goals and create their own action plans). Recent guidelines for human–AI interaction recommend designing AI systems for controllability to allow users to take actions, such as customizing what the AI system monitors and how it behaves [1]. However, the impact of the controllability of AI systems on users' decisions for others has not yet been explored. Our study examines the role of controllability in AI monitoring rejection by answering the following research question:

What is the impact of the controllability of the system on family members' rejection of AI monitoring?

To answer these questions, we conducted two scenario-based experiments that investigate two different sources of risk [78]. The first experiment investigated family members' decisions on AI monitoring with an environmental factor (COVID-19) as the source of risk, whereas the second experiment investigated an individual factor (dementia) as the source of risk. Our research contributes to the literature in three ways. First, we extend research on IS rejection by revealing the competing effects of family members' emotions triggered by both technology- and situation-specific factors on their rejection of AI monitoring. Second, our study extends research on decision making for others in the context of healthcare IS resistance by suggesting the influential role of anxiety. Third, we identify an important design factor—the controllability of AI monitoring systems—that interacts with a type of AI monitoring emotion in shaping rejection. Therefore, the study also provides important contributions to practice by highlighting the role of emotions and controllability when designing AI monitoring systems.

Theoretical Background

In this section, we first discuss our research context on AI monitoring for health care and decision making for others with relevant literature. Next, we describe the two major theoretical bases for the development of our research model—innovation resistance and emotions in decision making.

AI Monitoring for Health Care

AI is a fundamental technology that has been transforming health care. For example, AI helps in making health care smart, preventing epidemics, reducing maintenance and medication costs, and offering life-saving treatments [32]. AI monitoring for the in-home care of older adults, for example, can significantly increase the quality of care and reduce costs [54, 90]. These systems often use novel detection algorithms to identify abnormal activities and risk factors for adverse events [88]. As such, we highlight two important capabilities of AI monitoring systems: surveillance and delegation.

Surveillance is one of the major capabilities of AI monitoring. For example, using video surveillance, sensors, digital devices, and applications within the residential care environment [54], AI systems monitor and support patients' everyday living activities and track the health status and safety of patients in and around the home [61]. Wearable and environmental sensors monitor and collect biometric data and detect adverse events, such as falls. AI monitoring also helps in the management of chronic conditions, provides automatic communication to medical service providers in case of an emergency, and offers the potential to positively disrupt care [73] by utilizing novel techniques, such as instance-based algorithms, clustering, association rule learning, artificial neural networks, and deep learning algorithms [74]. With AI monitoring, certain care activities are delegated to the system, which reduces the workload of the individuals involved in different aspects of care [73]. Delegation can improve coordination among health care agents and contribute to cost savings [54].

AI monitoring is an innovative technology that triggers emotional responses that can have a lasting influence on innovation diffusion [43]. In particular, technology-induced anxiety can prevent the acceptance of a new technology [43]. For older adults, technology-induced anxiety is an important barrier to the use of new and innovative technology [16]. AI monitoring in health care settings can trigger two specific technology-induced anxieties experienced by family members: surveillance anxiety and delegation anxiety. *Surveillance anxiety* is caused by sensor-based systems that provide extensive tracking of users and their behavior [43], whereas *delegation anxiety* is caused by the delegation of some health care tasks to AI, leading to a loss of personal interaction between family members and their parents [4, 73]. However, while technology-induced anxiety may be experienced by the users of AI monitoring, little is known about whether family members experience these emotions and how these emotions impact their decisions to reject AI monitoring.

Innovation Resistance

Innovation resistance theory assumes that individuals manifest resistance either because the technology requires "potential changes from a satisfactory status quo or because it conflicts with their belief structure" [72, p. 6]. Research on innovation resistance has identified various antecedents (see Appendix A for a summary), such as risks, traditions, norms, and usage [41, 44]. Generally, the antecedents to innovation resistance can be categorized as functional and psychological barriers [72]. Functional barriers arise when individuals perceive significant changes caused by adopting an innovation (e.g., usage difficulty, added value, or risk of an innovation) [44]. Psychological barriers arise when the innovation conflicts with individuals' prior beliefs derived from various sources, such as rumors or the media [44, 72].

Healthcare IS resistance has received much attention. For example, a prior study has investigated physicians' resistance to change in the context of IS use intentions [10]. The rejection of healthcare IS post adoption (i.e., IS avoidance) has also been studied, suggesting negative implications for patient care [38]. However, innovation resistance is not the same as the absence of use; rather, it occurs beforehand [70]. IS resistance is a particular behavior toward IS implementations, and it varies among actors [42]. Healthcare IS resistance research focuses on the inhibitors of IS use [42] and is particularly important in the context of innovative technologies [80], as these often cannot be investigated in the use context and are mostly rejected before their possible use. Research on innovation resistance generally agrees on three different types of resistance: opposition, rejection, and postponement [41, 72]. Individuals oppose an innovative technology when they are convinced that it is unsuitable and unfit for their purpose, even before evaluating it. This is the strongest type of resistance, which may include launching an attack on the technology and disseminating negative word-of-mouth [41, 63]. Alternatively, individuals may reject innovative technology after an active evaluation, or they may postpone their decision making to a later point in time [41].

We focus on one type of innovation resistance—rejection—in the context of AI monitoring for health care. *Rejection* refers to "a user's conscious decision to avoid a system" [45, p. 66]. AI monitoring rejection is a form of resistance behavior in which a family member shows a disinclination to use AI monitoring. As health care must often be provided urgently, opposition and postponement are unlikely to be salient in this context.

Prior research suggests that both situation-specific factors (i.e., the circumstances of the decision) and technology-specific factors (i.e., the attributes of the technology) influence decision making [82] (see Appendix B for details). Prior studies on the rejection of technology have focused on identifying technology-specific factors, such as usage, tradition, and image barriers for mobile banking rejection [44], and economic, functional, and social risks, usage patterns, and perceived image for the general rejection of innovative products [41]. Situation-specific factors form an anchor point in innovation resistance decision making, as they can determine individuals' current perceptions [82]. The impact of situation-specific factors on rejection behaviors has been given limited attention. This is problematic, as rejection behavior is likely to form as a response to strong negative emotions toward a technology, such as anxiety, apprehension, fear, and stress [15, 45]. While most previous studies have explored rejection decisions for oneself, the factors influencing the rejection decisions of family members toward AI monitoring have received little attention and thus require further investigation.

Decision Making for Others

Decisions that impact individuals are often made by others [68]. Decision making for others refers to the process in which one person makes a decision for another person who bears the direct results of the decision. While some studies have found that individuals make riskier decisions for others (e.g. [51]), other studies have found that individuals instead tend to make less risky decisions for others [25]. When making decisions for others, individuals perceive risk differently, even when the objective assessment of risk remains the same [68]. For example, individuals may focus more on the positive reasons for making a choice and thus make riskier decisions for others [68]. This implies that individual perceptions of the potential consequences are more positive when they make decisions for others [68]. On the other hand, another study suggests that individuals may take a more cautious approach when making decisions for others [25]. One possible reason is to protect the decision maker's self-image in front of others [68]. Thus, individuals may assess others' prospects differently from their own.

In health care, the medical decisions for patients are frequently made by others [20]. Family members are the ones who have the closest relationships with their parents and have strong emotional ties to them [9]. They, as designated surrogates, often make decisions related to health care on patients' behalf [20]. For example, treatment decisions for older adults who lack the functional capacity to make their own decisions are made by a designated surrogate or next-of-kin [20], such as their adult children. These surrogates make decisions based on their beliefs about decisions that the patient would have made and that are in the patient's best interest. These decisions can relate to everyday care and support and to medical decisions in case of an emergency. Thus far, prior studies of surrogate decision making have been limited to how well surrogates predict their family member's care preferences [77]. Our study adds to the literature by revealing the factors that impact surrogates' decision making toward the rejection of healthcare IS.

In the context of healthcare IS decision making for others, little is known about the factors that impact resistance to IS. Research has found that older adults often have limited knowledge of technology, and the effort required to learn the technology influences their decisions regarding the adoption of that technology [64]. Thus, older adults often turn to their family members for help when making decisions about technology [52]. However, the preferences for and attitudes toward remote monitoring systems among family members and older adults can differ. For example, children prefer remote monitoring technology more than their parents do, and they are confident that they can persuade their parents to adopt such a technology [8]. Thus, identifying the factors that impact a family member's decision is important, as they are often the ones who either make or largely influence older adults' decisions on technology.

Emotions in Decision Making

Research suggests that emotions can influence decision-making choices and behavior [21, 28]. Emotions affect how one acts and decides [28], and they serve as motivational functions in goal achievement [62]. The literature on emotions in decision making suggests that the appraisal of an event or situation triggers particular emotions and action readiness, which, in turn, influence an individual's behavior to engage in interactions with the environment [28]. For instance, individuals can appraise a health care situation as risky. Specific emotions, such as anxiety, are induced by the appraisal of this risk and are associated with action readiness, such as avoidance [28].

Anxiety refers to "a state of chronic apprehension about future harm, characterized by tension, worry, negative affect, and a feeling of insecurity. Anxiety is elicited by unpredictability and by the perception of potential, unseen, or symbolic threat. Behaviorally, anxiety is associated with avoidance" [31, p. 422]. Some scholars suggest that anxiety is "a complex of negative emotions" that incudes fear and other fundamental emotions, such as anger and distress [35, p. 46]. Therefore, anxiety is "not unipolar, unidimensional or unifactorial in nature" [35, p. 46].

Two aspects of anxiety that have been measured in prior studies are state anxiety and trait anxiety [47, 79]. State anxiety reflects the psychological transient reactions that are directly related to the adverse situations faced by an individual at a specific moment [47]. It involves a transitory condition or state that is impacted by threatening situations [79]. By contrast, trait anxiety refers to the trait of an individual and relies on individual differences related to symptoms of anxiety, and is rather stable over time [47]. It captures the general tendency to feel anxious in threating situations [79]. An example of state anxiety is the intensity of individuals' anxiety at a specific moment in an experiment associated with a dental surgery [47]. An example of trait anxiety is the frequency (e.g., scaling from hardly ever to often) of individuals' symptoms of anxiety representing how they feel in general [47]. This study adopts state anxiety since it captures individuals' subjective experience of anxiety as a response to a randomly assigned scenario in an experiment. Also, risk-as-feelings theory suggests that anxiety is often an anticipatory emotion and can be an instant reaction to risk [49]. In this regard, state anxiety, which is raised by a perceived risk, can influence decision making [49].

Under risky situations, risk-as-feelings theory emphasizes the central role of emotions in decision making [49] and is used as a theory base for the development of our research model. The theory bridges the gap in prior theories on judgment and decision making (e.g., expected utility theory), in which decision making is assumed to be based on rational assessment, and the role of emotions is ignored. By contrast, risk-as-feelings theory states that decision making in risky situations is often driven by emotional reactions, such as anxiety [49]. This study focuses on the theory's proposition that individuals' perceived risk (subjective probabilities of anticipated outcomes) during risky situations can trigger their anticipatory emotion (such as anxiety). Such emotions influence their decisions. Individuals' subjective probabilities of risk better represent their behavior compared with objective measures of risk [13].

Risk-as-feelings theory has been frequently used in studies on decision making for others, with a focus on making risky financial decisions (such as in gambling) [68]. While limited, the theory has also been evaluated in different contexts, such as naturalistic risky situations [67] and medical decisions in health care [33–35]. We seek to extend this theory for health care by investigating AI monitoring rejection behavior.

One emotion that is commonly evoked in risky situations is anxiety [33, 49]. Particularly, in the health care context, anxiety is an important predictor of decision making for others [33]. One important source of anxiety is the quality of care, which refers to the "maximization of the benefits over risks of both technical and interpersonal aspects of patient care" [23, p. 277]. Quality of care can be classified into three categories [24, p. 1745]: structure ("attributes of the settings in which care occurs"), process ("what is actually done in giving and receiving care"), and outcome ("the effects of care on the health status of patients"). While earlier studies (e.g., [23]) have limited their focus to providers of health care, such as professional health care organizations (e.g., hospitals) and staff (e.g., physicians and nurses), later studies (e.g., [12]) have included family members as caregivers.

This study focuses on family members who make AI monitoring decisions for their parents, in which the process and outcome of the quality of care as sources of anxiety are most prevalent. Particularly, we are interested in family members' anxiety about health care received by their parents, that is, anxiety triggered by anticipation of issues in the care process and anxiety about health outcomes. Despite the significant role of anxiety in decision making for others, the role of anxiety for surrogate decision makers, specifically family members, in rejecting AI monitoring for patients has received scant attention.

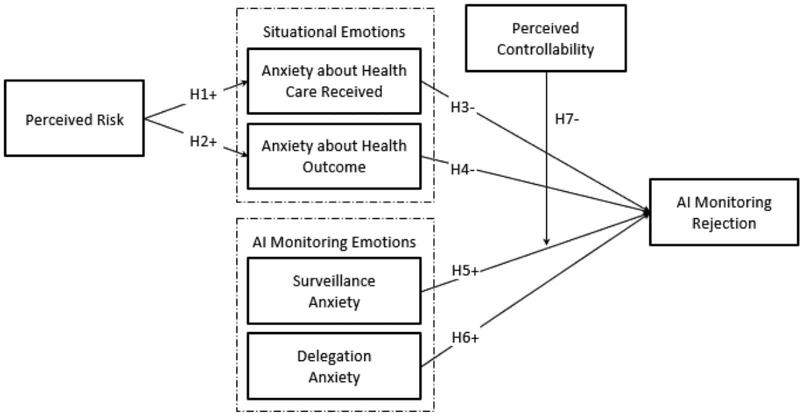

Figure 1. Research Model of Family Members' AI Monitoring Rejection

Hypothesis Development

Drawing on the literature on innovation resistance [70] and risk-as-feelings theory [49], we develop an integrative understanding of the AI monitoring rejection decisions made by family members. Our research model, presented in Figure 1, includes the following associations: the relationship of the family members' perceived risk of adverse health outcomes with two situational emotions, the relationship of situational emotions and AI monitoring emotions, with AI monitoring rejection, and the moderating effect of the perceived controllability of AI monitoring systems in the relationship between surveillance anxiety and AI monitoring rejection. Table 1 defines our constructs.

Table 1. Constructs and Definitions.

Construct	Definition	Source
Perceived risk about adverse health outcome	Family members' perceived subjective probability of the occurrence of negative health consequences (such as hospitalization) of their parents.	[13]
Anxiety about health care received	An anticipatory emotion that is experienced by family members in response to worries about whether their parents receive appropriate monitoring of their health.	[17, 50]
Anxiety about health outcome	An anticipatory emotion experienced by family members in response to worries about the potential negative health consequences to their parents.	[17, 50]
Surveillance anxiety	Anxiety experienced by family members in response to tension, worry, and thoughts resulting from the continuous monitoring of their parents and the continuous collection and analysis of their parents' personal data through an AI monitoring system.	[43, 50]
Delegation anxiety	Anxiety experienced by family members in response to a stressful situation of dehumanization, in which family members and their parents are estranged from each other and experience a loss of personal interactions among them because of the delegation of the care tasks from humans to an AI monitoring system.	[4, 43, 50, 73]
Perceived controllability of AI monitoring systems	The perceived ability to control and configure the settings of an AI monitoring system.	[22]
AI monitoring rejection	A form of resistance behavior in which family members oppose the potential use of an AI monitoring system.	[63]

Perceived risk plays a critical role in behaviors on preventative health care [13]. The *perceived risk of adverse health outcomes* refers to family members' subjective probability of risk associated with negative health consequences for their parents. The risk of adverse health outcomes stems from various sources. For example, COVID-19 is an environmental source of risk for adverse health outcomes, as COVID-19 can lead to complications, particularly in older adults who often have comorbidity conditions. Without proper monitoring of their health status and timely provision of care, the risk of adverse health outcomes, such as hospitalization and even death, increases [81]. In addition to environmental factors, individual factors can be a source of the risk of adverse health outcomes. For example, dementia is a common condition among older adults, requiring continuous monitoring of patients [2].

Anxiety about health care received is an anticipatory emotion experienced by family members in response to worries about whether their parents receive appropriate heath care and monitoring of their health. Monitoring refers to "the process of observing how the care receiver was doing" or "keeping an eye on things" to ensure that changes in the ill person's condition were noticed [76, p. 195]. Here, the decision maker perceives a risk related to the process of care [e.g., 24] as the source of the anxiety. For family members with whom one has an emotional relationship, the process of care involves monitoring the health status [76] and providing physical, psychological, social, and spiritual care support [9]. When family members perceive a high level of risk of adverse health outcomes of their parents, they are likelier to feel anxious about their parents' health care monitoring. For example, during the COVID-19 pandemic, individuals are anxious about the prospect of their elderly parents' health problems being unnoticed because they belong to a high-risk group [83]. Although the recipients of decision making are others (i.e., the patients), the decision maker still experiences a high level of anxiety under risky situations. Therefore, we formulate the following hypothesis:

H1: The perceived risk of adverse health outcomes increases family members' anxiety about health care received by their parents.

We also suggest that the perceived risk of adverse health outcomes leads to *anxiety about health outcomes*, that is, an anticipatory emotion experienced by a family member in response to worries about the potential negative health consequences for their parents. Here, the decision maker perceives a risk related to the outcome of care as the source of anxiety. This outcome of care includes the health outcomes (e.g., functional status) and evaluations of the health status (e.g., dis/satisfaction) [24]. This study focuses on health outcomes because it investigates a family member's emotional factors that influence AI monitoring decisions. The health outcome, for example, includes positive developments (e.g., improvement of symptoms) and negative developments (e.g., deterioration of symptoms, hospitalization) [37, 69]. When family members perceive a high level of risk of adverse health outcomes for their parents, they are likelier to experience anxiety. For example, during the COVID-19 pandemic, the risk of hospitalization of older adults has increased. Family members' appraisal of the anticipated outcomes under risky situations influences their anticipatory emotions [49]. Thus, we hypothesize the following:

H2: The perceived risk of adverse health outcomes increases family members' anxiety about health outcomes.

According to risk-as-feelings theory, emotions that are intertwined with an evaluation of the risk have a significant impact on behavior [49]. An anticipatory emotion, such as anxiety triggered by a perceived threat, leads to a course of action that mitigates the anticipated threat [49], thus regulating the emotion [18]. The emotion regulation aims at modifying the magnitude of the emotional experiences and can involve avoidance of particular situations [60]. Quality of care is a critical source of concern that leads to anxiety of family members [9, 24]. When family members experience high anxiety about the process and outcome of the health care received by their parents, they are less likely to reject AI monitoring.

Against this backdrop, we suggest that family members' anxiety about the process of care [24] reduces their rejection of technology [46]. Specifically, anxiety occurs when family members are concerned about patients' health problems going unnoticed and about missing important signs of changes or deterioration in their health conditions, which are potential issues in the process of care [76]. Family members experiencing high anxiety about health care received by their parents take protective actions such as using AI monitoring. AI monitoring improves the process of care by enabling continuous monitoring of potential symptoms and early detection of serious illnesses [66]. It helps family members avoid often-imagined worst-case scenarios of patients getting sick without anyone noticing it promptly [53]. Family members can provide patients with instrumental support by preparing and installing technology to support such monitoring [9]. Therefore, we suggest that family members with high anxiety about health care received by their parents are less likely to reject AI monitoring. We hypothesize the following:

H3: Family members' anxiety about health care received by their parents decreases their AI monitoring rejection.

In a similar vein, we suggest that anxiety about health outcomes negatively influences AI monitoring rejection. Individuals appraise an event or situation such as negative health outcome of their parents. This appraisal triggers particular emotions such as anxiety [9, 24] when the situation is evaluated as risky. The anxiety about the negative health outcome is associated with action readiness to protect themselves, such as avoiding the threatening situation and pursuing behaviors that can mitigate the anxiety [28]. Individuals may look for support from technology [6, 19] to escape the anxiety-inducing situation. For instance, anxiety associated with contracting severe illnesses positively influences online health information search and posting [6]. Patients with high anxiety related to serious health outcome potentially caused by COVID-19 increasingly use health service websites [19]. Family members' anxiety about their parents' health outcomes occurs when they envision a threat such as the prospect of their parents' hospitalization and even death. AI monitoring has the potential to prevent the illness from getting worse and to avoid hospitalization [53] by supporting chronic condition management and providing automatic communications to health care providers [73]. Family members' willingness to seek support from AI monitoring can be a strategy to regulate their emotions. Thus, we posit the following:

H4: Family members' anxiety about health outcomes decreases their AI monitoring rejection.

We suggest that the surveillance capability of AI monitoring systems induces anxiety, leading to its rejection. Individuals, for example, experience anxiety when they perceive the innovative technology, such as wireless sensor networks, as a threat [43]. *Surveillance anxiety* is a feeling of tension and worry from thoughts resulting from the use of monitoring systems [43]. While surveillance anxiety is a barrier to the acceptance of new technologies [43], it can also lead to resistance behavior [61], despite its various benefits.

When family members making decisions for others, surveillance anxiety may play an important role. They experience surveillance anxiety when they are uncomfortable with the continuous monitoring of their parents and the collection and analysis of their parents' personal data, as these may lead to privacy violations [43]. Family members are emotionally connected with their parents and thus take their parents' feelings of apprehension as their own when making decisions on their behalf [68]. They avoid situations that increase their anxiety in order to minimize the disturbance caused by problematic situations [46, 60]. Family members who experience surveillance anxiety seek mitigating behavior by rejecting AI monitoring. Thus, we hypothesize the following:

H5: Family members' surveillance anxiety increases their AI monitoring rejection.

Family member's *delegation anxiety* is another type of AI monitoring emotion. It can be triggered by a perceived threat and a stressful situation of dehumanization, in which humans are estranged from each other and experience a loss of personal interactions because some aspects of care are delegated to AI [4, 73]. The concept of delegation anxiety has common ground with Kummer et al.'s relational anxiety [43]; both measure individuals' worry about a loss of the personal component and raise ethical concerns because technology use subdues the interaction between health care providers and patients. While relational anxiety encompasses concerns about relational values and ethical values, this study focuses on the delegation effect [4] of a machine replacing personal interactions between the family members and their parents in health care. Therefore, we use the concept of delegation anxiety.

While an AI monitoring system is used to complete health care tasks that would otherwise be performed by humans, family members may experience delegation anxiety. Family members play important roles in providing both physical and psychological support to patients [9]. The use of an AI monitoring system renders a dehumanization of care, in which the parent needs to interact with the AI instead of family members, reducing the personal interactions among them [43, 73]. As this technology supersedes personal components in health care, such dehumanization may be perceived as a threat by family members and induces stress. Therefore, delegation anxiety is a barrier that leads to AI monitoring rejection, in which family members with high delegation anxiety are likelier to reject AI monitoring in order to avoid the anxiety-triggering situation, a loss of the personal interactions. Thus, we posit the following:

H6: Family members' delegation anxiety increases their AI monitoring rejection.

Perceived controllability of AI monitoring systems refers to the perceived ability to control and configure the settings of an AI monitoring system. Controllability can reduce family members' anxiety about AI monitoring and may have antagonistic relationships with their surveillance anxiety in influencing AI monitoring rejection. When individuals appraise a situation as highly controllable, they are less likely to feel negative emotions and are less likely to exhibit moving away behaviors [28]. Individuals may perceive the controllability of a system when they can modify its settings [11]. Individuals' ability to modify a system reduces their system aversion even when the modifications have only a minor impact on the system's performance [22].

Family members feel the need to safeguard their parents with options to control and configure the settings of the system in order to prevent undesirable implications. As a result, they are more in control of the system and can make corresponding adjustments that mitigate the perceived threats resulting from continuous monitoring (e.g., changing settings gives family members the power to limit potential concerns regarding privacy violations and reduce their surveillance anxiety). With low controllability rather than high controllability, family members' surveillance anxiety is more salient. Thus, we hypothesize the following:

H7: The controllability of AI monitoring systems weakens the positive relationship between family members' surveillance anxiety and AI monitoring rejection.

Research Method

We conducted two experiments using a scenario-based approach, which has been widely used for understanding information technology decision making in prior IS research [39]. This approach provides two important benefits [39]. First, the scenarios provide decision settings that are otherwise not easily accessible or are even inaccessible. A controlled experimental setting allowed us to manipulate specific variables and investigate their effects. Thus, we can study individuals' feelings and behaviors that are otherwise not accessible in real-life situations [26] because of possible confounding effects and the novelty of the technology. While industry solutions are beginning to emerge, the use of AI monitoring in healthcare is still limited to promising prototypes [48] that show great potential for the future. Second, scenarios allow us to maximize internal validity by focusing on a relatively small number of variables and examining causal relationships in highly controlled settings.

To examine the impact of different risk sources and test the robustness of our findings in the experimental scenarios, we designed two experiments with two different scenarios. This supports the study's objective to achieve theoretical extension (i.e., "expanding the original theory's nomological network" by reconstructing "the relationships among the existing and new variables") [34, p. 926]. Each scenario was designed with a different risk source in mind, as they may affect individuals' emotional responses [49]. Research has shown that individual and environmental factors impact decision making under risk differently [57]. When facing imminent risks such as COVID-19, people experience more rapid emotional reactions than cognitive evaluations and rely on emotions to make decisions [49]. According to risk-sensitivity theory [84], individual shifts from risk aversion to risk preference in situations of need [58]. Other environmental parameters such as macroeconomic inequality have been shown to impact risk-taking behavior [57]. Furthermore, people's risk assessment process is influenced by whether a risk is seen to be uncontrollable [78].

Each involved a 2 × 2 between-subject factorial design in which the perceived risk of adverse health outcomes and the perceived controllability of AI monitoring systems were independently manipulated, allowing us to examine their effects on AI monitoring rejection. Experiment 1 introduced the probability of hospitalization resulting from an individual factor—dementia—as the main source of risk, whereas Experiment 2 introduced the probability of hospitalization resulting from an environmental factor—COVID-19 pandemic—as the main source of risk. In the remainder of this section, we describe the subjects, decision tasks, and procedures used to conduct the two experiments, highlighting both the similarities and differences between them, as summarized in Table 2.

Sampling and Participants

We hired a professional survey research company to conduct the survey through a crowdsourcing platform. A total of 929 participants (60 for a pilot test + 851 for the major data collection − 18 responses that failed attention checks) were recruited within the US (see Table 2). A total of 397 valid responses for Experiment 1 and 454 for Experiment 2 were obtained. All participants took part in only one experiment. Only those who possessed at least a high school diploma were recruited, as they were likelier to understand the implications of AI. Furthermore, only participants aged 35 or above who were likelier to relate to our senior care scenarios were invited.

Decision Tasks and Procedures

The scenario-based experiment presented a situation in which each participant had to decide about the implementation of a new AI monitoring system in their mother's home. In all four experimental conditions, the mother is at risk of being hospitalized, and the AI

Table 2. Scenarios and Demographics of the Participants.

		Experiment 1	Experiment 2
Context of the Scenario		Mother's risk of hospitalization due to an individual factor - dementia	Mother's risk of hospitalization due to an environment factor - COVID-19 pandemic
Two Manipulations		Risk (probability of the hospitalization risk) & controllability of AI monitoring systems	
Number of Subjects		N = 397	N = 454
Gender	Male	196	191
	Female	190	250
	Not disclosed	11	13
Age	≤40	124	166
	41–50	116	111
	51–60	81	102
	61–70	66	65
	≥ 71	10	10

monitoring system has the same advantages and disadvantages. The treatment conditions manipulated the high and low perceived risks of adverse health outcomes and the high and low perceived controllability of AI monitoring systems (see Appendix C).

In Experiment 1, the source of the risk is an individual factor, specially, the mother suffers from dementia. In Experiment 2, the source of the risk is an environmental factor where the mother is at risk of hospitalization from COVID-19. For both experiments, in the condition of a high risk of adverse health outcomes, the participants were informed that their mother's physician conducted an assessment of various factors that suggested a high possibility of hospitalization. In the condition of a low risk of adverse health outcomes, the participants were informed that their mothers' physicians conducted an assessment that suggested a low possibility of hospitalization. Prior studies suggest that hospitalization is a common type of adverse health outcome [e.g., 55].

For both experiments, in the conditions of the high controllability of AI monitoring systems, the participants were informed that they could make changes to the system's settings, such as the type and frequency of data collected. In the low controllability conditions, the participants were informed that they could not make any changes to the system's settings.

In both experiments, the procedure consisted of three steps. First, the participants were randomly assigned to one of four treatment conditions (high risk/high controllability, low risk/low controllability, high risk/low controllability, and low risk/high controllability). Second, they received a set of manipulation and comprehension check questions [30, 31]. Third, the participants took a survey that included measurements, control variables, and demographic and attention check questions. Scenario-related measurements were asked first, and control variables and demographics were asked toward the end.

Measurements

For all constructs in the model, we adapted previously established measurements (see Appendix D). We provide more details on our measurements in this section. As part of our measurement instrument development efforts, we conducted pre- and pilot tests. We distributed the initial questionnaire to colleagues to receive feedback on the plausibility and comprehensiveness of the questions. Thereafter, we tested the full experimental setup. We conducted pilot tests with a total of 60 participants to examine and improve the quality of the measurements. All participants were drawn from our target sample. Based on the pilot tests, we made some modifications and refinements to our instruments. All participants in the pilot test were excluded from the main experiments.

The perceived risk of adverse health outcomes was measured through individuals' subjective probability of that health outcome, which has been found to predict their behaviors related to preventative health care [13]. Probability was manipulated in the form of the percent chance that an event would occur or that one would select a specific action and can be measured in response scales of the likelihood of the event [13]. The perceived risk of adverse health outcomes was measured using two items indicating the mother's probability of hospitalization.

Perceived controllability was measured through individuals' subjective ability to control the system. Controllability has been shown to influence aversion behavior toward innovative technology [22]. Controllability was manipulated through the ability or lack thereof to control the AI monitoring system's settings, such as the schedule, frequency, and type of data collected. Perceived controllability was measured using three items, which indicated the ability to control the system.

Two situational emotions—anxiety about health care received and anxiety about health outcomes—captured the emotional responses that emerged from the situation. We adapted measures from Lovibond and Lovibond [50] and contextualized them according to Cicirelli [17]. Anxiety about health care received was measured using three items, which indicated the extent to which the participants were anxious about their mother's quality of care process, specifically health care monitoring. Anxiety about health outcomes was measured using three items, which indicated the extent to which the participants were anxious about their mother's health outcomes.

Two AI monitoring emotions—family members' surveillance anxiety and delegation anxiety—captured the emotional responses triggered by the technology. Family members' surveillance anxiety was measured using four items adapted from Kummer et al. [43], which indicated the extent to which the participants were anxious about the system monitoring their mothers. Family members' delegation anxiety was conceptualized based on Baird and Maruping [4] and Rubeis [73]. Its measurements consisted of three items that were adapted from the items for *relational anxiety* from Kummer et al. [43], which measure worry about a system that contradicts relational values because of the depersonification and loss of the personal component of the treatment between the medical staff and patients. While the dehumanization resulting from delegation has other dimensions such as datafication of patients and responsibility and trust issues related to AI's clinical decision making [73], our study focuses on the delegation effect of an AI system that causes the loss of personal interaction between patients and their family members. Therefore, the measurements of family members' delegation anxiety focused on the extent to which the participants were anxious about the loss of personal interaction because of the delegation of their health care tasks to an AI monitoring system.

AI monitoring rejection was measured using three items, which indicated the extent to which individuals did not intend to use the system and rather reject it. We adapted these measures from Park and Koh [63] and Wiedmann et al. [86]. An overview of the constructs and descriptive statistics is presented in Appendix E.

Controls

Additionally, we controlled for three variables that may have an impact on AI monitoring rejection. i) *Anxiety about AI technology* was measured using two items (adapted from Meuter et al. [56]), which indicated the extent to which the participants had difficulty understanding AI technological matters and felt apprehensive about AI technology. Prior research has shown that individuals develop an aversion to algorithms, which are central to any AI-based system [14]. ii) *Propensity to share information* was measured using four items (adopted from Wu et al. [87]), which indicated the extent to which the participants were willing or reluctant to share their information with others. Considering the sensitivity of the information involved, the participants might be concerned about sharing their mothers' information. Prior research has shown that sharing information has a negative relationship with an individual's rejection tendency [3]. iii) *Risk-taking propensity* was measured using two items (adopted from Morrison [59]), which indicated the extent to which the participants were willing to take risks. Individuals who are more willing to take risks might make bolder decisions when facing negative outcomes. A prior study has found a positive relationship between the perception of environmental uncertainty and individuals' risk-taking propensity [29]. We also controlled for *age* and *gender*, which have been found to be significant predictors of rejection decisions [44].

Experiment 1: Individual factor

An individual factor is the source of risk in this experiment. Given the unique context of our study, in which the decision making of family members who are making healthcare decisions on the patient's behalf is investigated, we collected previous care experience (i.e., how much experience the participants had in providing care to a family member) and tested for differences in AI monitoring rejection between the high-experience group and the low-experience group. We did not find a statistically significant difference ($t(394) = 0.71$, $p = 0.48$), suggesting that previous care experience is not an issue. We then checked the experiment for i) the successful manipulation of the risk of adverse health outcomes and the controllability of the system and ii) the lack of a common method bias (see Appendix F for details).

Measurement Model

We performed confirmatory factor analysis of our latent variables to validate the reliability and convergent and discriminant validity of the measurement model. The overall model provided a good comparative fit index (CFI = .98) with acceptable error terms, as indicated by the root mean square error of approximation (RMSEA = .04) and standardized root mean square residual (SRMR = .28). The factor loadings of our model's variables were greater than 0.83 (see Appendix G). All variance inflation factor (VIF) scores of our variables were below 1.92. The correlations of all variables are presented in Appendix H.

Structural Model

We tested the structural model using the lavaan package in R. We applied hierarchical regression analysis and multiple mediator analysis to compare different models and evaluate mediating effects. Mediation testing allows us to understand the mechanisms through which situational emotions affect the relationship between perceived risk and AI monitoring rejection. We estimated four models. First, we estimated a direct-effect model. Second, we estimated a model using mediating variables as dependent variables. Third, we estimated a model with all effects to see whether the mediating variables affected AI monitoring rejection. Fourth, we estimated an interaction model including our moderation (Model 4). We calculated different fit indices comparing these four models (see Table 3).

Table 3. Model Comparison (Experiment 1).

	Chi-squared	df	Chi-squared/df	CFI	RMSEA	SRMR
Model 1: Direct effect	84.42	46	1.84	0.991	0.046	0.028
Model 2: DV: Emotions	243.24	120	2.03	0.984	0.051	0.055
Model 3: Mediation model	461.03	250	1.84	0.980	0.046	0.038
Model 4: Interaction model	668.32	396	1.69	0.980	0.042	0.036

Note: df = Degrees of Freedom, CFI = Comparative Fit Index, RMSEA = Root Mean Square Error of Approximation, SRMR = Standardized Root Mean Square Residuals.

The estimation of our first three models follows established guidelines for mediation analysis [5] and is complemented with significance testing (see post-hoc analysis) to establish mediating effects more rigorously [89]. Table 4 presents the results of the hierarchical regression analysis.

First, we estimated the direct effect model. We tested the direct effect of perceived riskand the association of control variables with AI monitoring rejection. Perceived risk ($\beta = -0.19$, S.E. = 0.05, $p < 0.01$, Cohen's d = −0.19), AI technology anxiety ($\beta = 0.38$, S.E. = 0.06, $p < 0.01$, Cohen's d = 0.32), and propensity to share information ($\beta = -0.14$, S.E. = 0.06, $p < 0.01$, Cohen's d = −0.12) showed statistically significant effects on AI monitoring rejection. These effects reflected prior expectations to include perceived risk in our model and AI technology anxiety and propensity to share information as important controls.

Table 4. Hierarchical Regression Analysis (Experiment 1).

Experient 1: Model	1 – Direct effect	2 - Emotions as DV		3 - Mediation	4 - Interaction
DV	AI monitoring rejection	Anxiety about health care received	Anxiety about health outcome	AI monitoring rejection	AI monitoring rejection
Perceived risk of adverse health outcome	-0.19 (0.05) [0.00]	0.26 (0.05) [0.00]	0.66 (0.06) [0.00]	-0.01 (0.06) [0.94]	0.01 (0.06) [0.83]
Anxiety about health care received				-0.16 (0.06) [0.01]	-0.18 (0.06) [0.01]
Anxiety about health outcome				-0.10 (0.06) [0.10]	-0.12 (0.06) [0.05]
Surveillance anxiety				0.68 (0.09) [0.00]	0.69 (0.09) [0.00]
Delegation anxiety				0.26 (0.08) [0.00]	0.25 (0.09) [0.00]
Perceived controllability					-0.26 (0.06) [0.00]
Surveillance anxiety x Perceived controllability					-0.21 (0.06) [0.00]
AI technology anxiety	0.38 (0.06) [0.00]	-0.04 (0.05) [0.44]	-0.01 (0.05) [0.82]	0.09 (0.06) [0.12]	0.10 (0.06) [0.11]
Propensity to share information	-0.14 (0.06) [0.01]	-0.02 (0.06) [0.77]	-0.01 (0.06) [0.82]	-0.02 (0.06) [0.71]	-0.02 (0.06) [0.73]
Risk-taking propensity	0.03 (0.05) [0.58]	0.01 (0.05) [0.90]	0.03 (0.05) [0.52]	0.10 (0.05) [0.06]	0.13 (0.06) [0.02]
Gender	-0.01 (0.05) [0.90]	0.08 (0.05) [0.14]	0.06 (0.05) [0.22]	0.01 (0.05) [0.86]	0.01 (0.05) [0.83]
Age	-0.03 (0.05) [0.54]	0.04 (0.05) [0.43]	0.02 (0.05) [0.64]	0.05 (0.05) [0.33]	0.03 (0.05) [0.40]
R-squared	0.186	0.069	0.301	0.501	0.550

Note: The table gives standardized coefficients (standardized errors) and [p-values].

Second, we estimated a model using our mediating variables as dependent variables. The perceived risk of adverse health outcomes had significant effects on anxiety about health care received (β = 0.26, S.E. = 0.05, $p < 0.01$, Cohen's d = 0.26) and anxiety about health outcomes (β = 0.66, S.E. = 0.06, $p < 0.01$, Cohen's d = 0.55) in addition to the control variables. Therefore, H1 and H2 are supported.

Third, when estimating the effects of all independent variables on AI monitoring rejection, we found that anxiety about health care received (β = −0.16, S.E. = 0.06, $p < 0.01$, Cohen's d = −0.13), surveillance anxiety (β = 0.68, S.E. = 0.09, $p < 0.01$, Cohen's d = 0.38), and delegation anxiety (β = 0.26, S.E. = 0.08, $p < 0.01$, Cohen's d = 0.16) had statistically significant effects. Therefore, H3, H5, and H6 are supported.

Fourth, we included the interaction term to test our moderation hypotheses. The interaction term (β = −0.21, S.E. = 0.06, $p < 0.01$, Cohen's d = −0.18) and the direct effect of perceived controllability (β = −0.26, S.E. = 0.06, $p < 0.01$, Cohen's d = −0.22) are statistically significant. In addition to previously statistically significant effects of anxiety about health care received, we also find anxiety about health outcomes to be statistically significant (β = −0.12, S.E. = 0.05, $p < 0.01$, Cohen's d = −0.12). Therefore, H4 and H7 are supported. A post-hoc analysis of the mediating effect is presented in Appendix I.

Experiment 2: Environmental factor

Experiment 2 was conducted to examine the impact of an environmental factor and determine the extent to which the results from our first experiment were robust and reliable when changing the source of risk. Overall, Experiment 2 provides additional support for our research model. We confirmed that previous care experience is not an issue ($t(453) = -0.64$, $p = 0.52$). Checks for the successful manipulation of perceived risk and perceived controllability and the lack of a common method bias are presented in Appendix J for details.

Measurement Model

We performed a confirmatory factor analysis of our latent variables to test the reliability and convergent and discriminant validity of our measurement model. The overall model provided good fit indicators (CFI = .98) with acceptable error terms (RMSEA = .04; SRMR = .04). The factor loadings of our model's variables were greater than 0.81 (see Appendix K). All VIF scores of our variables were below 2.44. The correlations of all variables are presented in Appendix L.

Structural Model

As in Experiment 1, we estimated four models: i) a direct effect model (Model 1), ii) a model using our mediating variables as dependent variables (Model 2), iii) a mediation model (Model 3), and iv) an interaction model (Model 4). We calculated different fit indices (see Table 5). Table 6 presents the results of the hierarchical

Table 5. Model Comparison (Experiment 2).

	Chi-squared	df	Chi-squared/df	CFI	RMSEA	SRMR
Model 1: Direct effect	84.35	46	1.83	0.992	0.043	0.032
Model 2: DV: Emotions	278.03	120	2.32	0.984	0.054	0.089
Model 3: Mediation model	516.28	250	2.07	0.980	0.048	0.050
Model 4: Moderated mediation model	682.05	396	1.72	0.982	0.040	0.043

Note: df = Degrees of Freedom, CFI = Comparative Fit Index, RMSEA = Root Mean Square Error of Approximation, SRMR = Standardized Root Mean Square Residuals.

Table 6. Hierarchical Regression Analysis (Experiment 2).

Experient 2: Model	1 – Direct effect	2 - Emotions as DV		3 - Mediation	4 - Interaction
DV	AI monitoring rejection	Anxiety about health care received	Anxiety about health outcome	AI monitoring rejection	AI monitoring rejection
Perceived risk of adverse health outcome	-0.29 (0.05) [0.00]	0.38 (0.05) [0.00]	0.70 (0.06) [0.00]	-0.12 (0.06) [0.06]	-0.12 (0.06) [0.05]
Anxiety about health care received				-0.28 (0.07) [0.00]	-0.28 (0.07) [0.00]
Anxiety about health outcome				-0.17 (0.07) [0.02]	-0.18 (0.07) [0.01]
Surveillance anxiety				0.83 (0.08) [0.00]	0.83 (0.08) [0.00]
Delegation anxiety				0.16 (0.07) [0.02]	0.13 (0.07) [0.07]
Perceived controllability					-0.17 (0.05) [0.00]
Surveillance anxiety x Perceived controllability					-0.06 (0.05) [0.31]
AI technology anxiety	0.25 (0.06) [0.00]	0.03 (0.04) [0.46]	0.02 (0.04) [0.54]	-0.00 (0.05) [0.98]	0.02 (0.05) [0.68]
Propensity to share information	-0.17 (0.06) [0.00]	0.10 (0.05) [0.06]	0.03 (0.05) [0.54]	-0.01 (0.06) [0.84]	-0.02 (0.06) [0.77]
Risk-taking propensity	0.15 (0.05) [0.00]	0.14 (0.05) [0.01]	0.16 (0.05) [0.00]	0.15 (0.06) [0.01]	0.16 (0.06) [0.01]
Gender	-0.03 (0.05) [0.50]	0.05 (0.05) [0.32]	0.02 (0.05) [0.70]	-0.02 (0.05) [0.76]	-0.01 (0.05) [0.90]
Age	0.00 (0.05) [0.97]	0.06 (0.05) [0.19]	0.04 (0.05) [0.39]	0.06 (0.05) [0.22]	0.05 (0.05) [0.30]
R-squared	0.193	0.139	0.333	0.563	0.574

Note: The table gives standardized coefficients (standardized errors) and [p-values].

regression analysis, and they confirm our results from Experiment 1. Thus, for Model 2, the perceived risk of adverse health outcomes had significant effects on anxiety about health care received (β =0.38, S.E. = 0.05, $p < 0.01$, Cohen's d = 0.36) and anxiety about health outcomes (β =0.70, S.E. = 0.06, $p < 0.01$, Cohen's d = 0.55) in addition to our controls.

When estimating Model 3, the effects of all independent variables on AI monitoring rejection, we found that anxiety about health care received (β = −0.28, S.E. = 0.07, $p < 0.01$, Cohen's d = −0.19), anxiety about health outcomes (β = −0.17, S.E. = 0.07, p = 0.02, Cohen's d = −0.11), surveillance anxiety (β = 0.83, S.E. = 0.08, $p < 0.01$, Cohen's d = 0.49), and delegation anxiety (β = 0.16, S.E. = 0.07, p = 0.02, Cohen's d = 0.11) had statistically significant effects.

Table 7. Overview of Results for Hypotheses Testing.

Hypothesis	Experiment 1 (Dementia)	Experiment 2 (COVID-19)
H1: Perceived Risk → Anxiety about Health Care Received	$\beta = 0.26$, $p < 0.01$	$\beta = 0.38$, $p < 0.01$
H2: Perceived Risk → Anxiety about Health Outcome	$\beta = 0.66$, $p < 0.01$	$\beta = 0.70$, $p < 0.01$
H3: Anxiety about Health Care Received → AI Monitoring Rejection	$\beta = -0.18$, $p = 0.01$	$\beta = -0.28$, $p < 0.01$
H4: Anxiety about Health Outcome → AI Monitoring Rejection	$\beta = -0.12$, $p = 0.05$	$\beta = -0.17$, $p = 0.02$
H5: Surveillance Anxiety → AI Monitoring Rejection	$\beta = 0.69$, $p < 0.01$	$\beta = 0.83$, $p < 0.01$
H6: Delegation Anxiety → AI Monitoring Rejection	$\beta = 0.25$, $p < 0.01$	$\beta = 0.16$, $p = 0.02$
H7: Surveillance Anxiety x Perceived Controllability → AI Monitoring Rejection	$\beta = -0.21$, $p < 0.01$	n.s.

In the analysis of Model 4, the interaction term is not statistically significant. The direct effect of perceived controllability ($\beta = -0.17$, S.E. = 0.05, $p < 0.01$, Cohen's $d = -0.16$) is statistically significant. In contrast to Model 3, perceived risk has a statistically significant effect ($\beta = -0.12$, S.E. = 0.06, $p = 0.05$, Cohen's $d = -0.09$). Furthermore, delegation anxiety is no longer statistically significant in this model. Given these results, we tested Models 3 and 4 for the difference. A chi-squared difference test showed no statistically significant difference between both models ($\Delta\chi^2$ (146) = 165.78, $p = 0.13$). Therefore, we suggest that the simpler Model 3 presents the best fit for our data. Table 7 shows the results of the hypothesis testing of the two experiments. A post-hoc analysis of the mediating effect is presented in Appendix M.

Discussion

Contributions to Research

Our study contributes to the literature on healthcare IS resistance and the design of AI monitoring systems by identifying the factors influencing AI monitoring rejection by family members as surrogate decision makers. We developed an integrative model that explains the effects of the perceived risk of adverse health outcomes, situational emotions, AI monitoring emotions, and perceived controllability of the AI monitoring system.

Below, we discuss the three most important contributions of our study to research.

First, our study extends prior research on technology rejection, which is a type of innovation resistance, by exploring the competing roles of emotions triggered by technology- and situation-specific factors. Prior scholars have suggested that technology rejection is best predicted by inhibitors of technology usage [15]. While we are aware of inhibitors at the cognition level [82], such as individuals' perceptions of a system's attributes that discourage usage [15], our study contributes to this discussion by uncovering inhibitors at the emotional level. In particular, we find two types of situational emotions (anxiety about health care received and anxiety about health outcomes) that reduce rejection and two types of technological emotions (surveillance and delegation anxiety) that increase rejection of AI monitoring. We believe that our findings and the extended theory provide a steppingstone toward theoretical generalization in the technology rejection research stream.

Under risky situations, family members experience anxiety about health care received and anxiety about health outcomes. To avoid anxiety-inducing situations, they tend to take protective actions by not rejecting AI monitoring [18, 60]. Many studies have investigated various enablers and inhibitors, that is, an individual's beliefs about functionality that influences either a user's adoption or rejection behavior respectively [15]. Our findings provide additional insights into this research stream by identifying the role of situation-specific factors in discouraging rejection at the emotional level and emphasizing their significant role because they pertain to decision makers' perceptions, emotions, and attitudes toward AI monitoring rejection.

In contrast, technological emotions increase rejection. Surveillance is a major capability of AI monitoring, but it can also create anxiety in individuals who are monitored [43]. We extend prior research on surveillance anxiety by exploring its influence on family members' decisions in healthcare IS. In particular, we find that family members experience anxiety triggered by the appraisal of patients under surveillance. We suggest that individuals in different situations respond differently to AI surveillance. While in a work setting, the decisions of healthcare professionals, such as nurses, are likelier to be based on a cognitive appraisal of the costs and benefits of surveillance [43], our study suggests that family members are more affected by their emotional responses to the AI surveillance of patients in their homes. Thus, compared with healthcare professionals, family members are likelier to reject AI monitoring because of surveillance anxiety.

Delegation is a major result of AI monitoring systems. Most prior studies regarding delegation to AI systems have focused on identifying the factors that influence individuals' delegation behaviors or on comparing human performance with AI performance [75]. Our study extends this stream of research by investigating the delegation anxiety experienced by family members, who are affected by emotions in their decision-making process for others because of their emotional bond. While AI monitoring involves assigning the responsibility for monitoring to an AI-based system with the expectation of optimal outcomes [4], such a delegation creates anxiety in family members because they fear that patients lose the personal interactions and hence dehumanization in care [43, 73]. The decision on AI monitoring is thus influenced by the result of the competition between the two types of emotions. In this regard, it is important for future studies to understand the complex roles of emotions in AI monitoring decision making.

Second, our study contributes to research on decision making for others in the context of healthcare IS resistance by suggesting the role of anxiety triggered by concerns about quality of care [24, 55] and innovative technologies. Family members can be designated as decision makers on behalf of (potential) patients in the family [12, 76]. A recent review on decision making for others suggests that emotions may impact the decisions made [68]. We extend prior studies by identifying two specific types of anxieties experienced by family members that play a significant role in their decisions on AI monitoring.

According to risk-as-feelings theory [49], perceived risk triggers emotions that impact behaviors. Our findings provide additional insights into decision making for others by revealing a specific source of the perceived risks and emotions it elicits in family members' healthcare IS decisions. The family is one of the closest networks of relationships in which members are emotionally involved [9]. Our study suggests that emotions play a salient role in family members' decisions because of the close psychological distance between them and the decision recipients. We expose the mediating role of family members' situational emotions in the relationship between perceived risk and AI monitoring rejection.

Third, our research contributes to the literature on the design of AI monitoring systems by illuminating the role of perceived controllability in rejection. The perceived controllability of AI monitoring systems can play a moderating role and weaken the positive relationship between surveillance anxiety and AI monitoring rejection, depending on whether the risk is related to the individual or the environment. When the risk comes from an environmental factor over which the decision maker has no control, the ability to control the system plays a lesser role.

Prior research [8] has advocated the urgent need for studies on how resistance to these systems can be overcome. While individual or situational factors may explain rejection behaviors, the significant role of system design factors requires further investigation [15]. Our research answers this call by examining the role of perceived controllability in AI monitoring rejection. Our findings in the dementia (individual risk factor) scenario-based experiment show that perceived controllability plays a moderating role in the relationship between surveillance anxiety and AI monitoring rejection. This weakens the positive effect of surveillance anxiety on rejection. Therefore, controllability can help mitigate the effects of healthcare agents' surveillance anxiety on AI monitoring rejection.

However, in the COVID-19 (environmental factor) scenario-based experiment, we did not find a significant moderating role. Our post-hoc analysis finds that the perceived risk directly influences AI monitoring rejection. One plausible reason is that, with an environmental factor such as COVID-19, the perceived risk is out of the control of the decision maker. Compared with the individual factor, the impact of surveillance anxiety on AI monitoring rejection is weaker, resulting in a non-significant moderating role of perceived controllability. The differences observed in our study provide important advances for designing innovative technology in critical care infrastructure and for understanding the design decisions needed by system designers.

Practical Implications

Given the tremendous benefits that AI can bring to health care, professional organizations are strongly supporting its use. For example, the FDA encourages the use of remote monitoring devices to effectively fight COVID-19 [27] and has provided emergency authorization for the use of several devices and sensors that can be used for remote monitoring. We identify two important practical implications for the developers of AI monitoring systems.

First, in risky situations, efforts to regulate emotions are likely to minimize the rejection of AI monitoring systems. For example, providing social interaction capabilities (e.g., video interactions with healthcare providers and family members) can minimize delegation anxiety. Design choices, such as blurring images or deidentifying the data before they are shared, are likely to minimize surveillance anxiety.

Second, providing users with control over the elements of the systems that trigger negative emotions decreases rejection. For example, the ability to adjust privacy settings that meet the level of privacy sought by the user is likely to reduce the rejection of AI monitoring systems. As health care decisions are often made by family members, consideration of their preferences in the design of AI monitoring systems is critical.

Limitations and Future Research

We identify three limitations to our study. First, as the applications of AI monitoring in senior care are still limited, we used a scenario-based experimental design (e.g. [39]). Future research could investigate the real-world applications of AI monitoring in healthcare and other contexts, such as education and the workplace. Second, we limited the number of variables included in this study. While other potential variables can influence the effect of the perceived risk of adverse health outcomes on AI monitoring rejection, we accounted for important controls. Future research could investigate security concerns and privacy violations when explaining the effects of emotions on rejection behaviors. The role of policy, the social environment, data provenance [85], social comparison, dehumanization dimensions (e.g., datafication of users, and responsibility and trust issues related to AI's clinical decision making) [73] may also affect AI rejection. Furthermore, investigating the impact of other sources of risk (in addition to environmental and individual factors) on AI rejection can be promising for future research. Third, we investigated the decisions made by family members involved in the implementation of AI technology in the healthcare system. While prior studies support our decision to use and investigate the role of family members who make critical decisions on behalf of their family [12, 76], future studies could investigate the rejection of AI-based systems by healthcare professionals, who have different emotional responses.

Conclusion

This study investigated when and how emotions impact the rejection of AI monitoring by family members. We examined the effects of the perceived risk of adverse health outcomes, the anxiety triggered by concerns about the care situation, and the anxiety resulting from the AI monitoring system's surveillance and delegation on agents' rejection. Based on two scenario-based experiments, we found competing effects of anxiety about the quality of care versus AI monitoring anxiety on rejection in either a subduing or facilitating manner. Furthermore, the controllability of AI monitoring systems moderates the relationship between surveillance anxiety and AI monitoring rejection when the source of the risk is the individual. The results contribute to our understanding of how emotions increase or decrease AI monitoring rejection. More broadly, it extends research on resistance to healthcare IS and innovative technology, such as AI monitoring, by identifying the factors causing AI monitoring rejection.

Note

1. We use both terms, *healthcare*, which refers to the organized provision of medical care, and *health care*, which refers to the process of provisioning necessities for the health of someone. We thank the anonymous reviewer for highlighting the importance of this difference.

Disclosure Statement

No potential conflict of interest was reported by the authors.

Notes on contributors

Eun Hee Park is an Associate Professor of Information Technology & Decision Sciences at the Old Dominion University. She received her Ph.D. in Computer Information Systems from the Georgia State University. Dr. Park's research interests include IT investment decisions, agile project management, IS security, social media, sentiment analysis, and emotion ontology. Her work has appeared in

Journal of Management Information Systems, Information and Management, Information Systems Journal, Journal of the Association for Information Systems, Information Technology and People, Computers & Security, among other journals.

Karl Werder is a Research Fellow at the Cologne Institute for Information Systems of the University of Cologne, Germany. He received his doctorate in Information Systems from the Karlsruhe Institute of Technology, Germany. Dr. Werder's research interests focus on the development of digital products and designing digital innovation. His work has been published or is forthcoming in such journals as *Journal of Management Information Systems, IEEE Transactions on Software Engineering, Journal of the Association for Information Systems, Decision Support Systems, California Management Review, ACM Transactions on Management Information Systems, Information Technology & People*, among others.

Lan Cao is a Professor of Information Technologies and Decision Sciences at Old Dominion University. She received her Ph.D. degree from Georgia State University. Her major research interests are agile software development and software process simulation and modeling. Her work appears in many journals including *Information Systems Research, Journal of Management Information Systems, Journal of the Association for Information Systems, European Journal of Information Systems, ACM Transactions on Management Information Systems, ACM Journal of Data and Information Quality, and IEEE Software*, among others.

Balasubramaniam Ramesh is Distinguished University Professor and holder of the George E. Smith Eminent Scholar's Chair in Information Systems at Georgia State University. His research interests include artificial intelligence, requirements engineering and traceability, agile software development, and knowledge management. His work appears in several leading journals including *Information Systems Research, Journal of Management Information Systems, MIS Quarterly, Journal of the Association for Information Systems, European Journal of Information Systems, l, IEEE Transactions on Software Engineering, ACM Transactions on MIS, Decision Support Systems, Communications of the ACM, IEEE Computer, IEEE Intelligent Systems, IEEE Software, MIT Sloan Management Review*, among others.

ORCID

Karl Werder http://orcid.org/0000-0001-8481-1596
Lan Cao http://orcid.org/0000-0002-3860-7639
Balasubramaniam Ramesh http://orcid.org/0000-0001-9629-328X

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