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The Consumer Behavior Impact of Data Capture Through Artificial Intelligence

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Doctoral Dissertation Research

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Gardner-Webb University

In Partial Fulfillment

of the Requirements for the Degree of

Doctor of Business Administration

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Abstract

Artificial intelligence is changing the way consumers search for information and purchase items and, thus, how people behave across generations. Due to the nature of this cutting-edge technology, organizations are investigating how much to wisely invest, but the artificial intelligence offerings are outpacing the research. Academic scholars and marketing professionals have issued timely prompts for additional studies to supplement the existing literature, which is limited. This research provides insights into privacy concerns surrounding the data collection of artificial intelligence and whether people feel exploited or served by it. Across two articles, surveys were deployed and collected to provide quantitative data that explains consumer behavior, first by considering the generation an individual belongs to and whether that alone is a determinant of feelings associated with artificial intelligence data capture interactions. Second, in a deeper dive, a Technology Readiness Index score was assessed and then compared to various scales, which once again examined privacy concerns with artificial intelligence data collection, perceived threats with online data housing, and the perceived severity of these actions. Patterns of behavior were detected through Structural Equation Modeling analysis. Findings showed that older generations do in fact feel heightened senses of exploitation with artificial intelligence data capture compared to younger generations. The data also revealed that an individual's Technology Readiness Index score directly relates to whether they feel more exploited or served by artificial intelligence data capture.

Keywords: artificial intelligence, exploitation, consumer behavior, generations, Technology Readiness Index

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Chapter One: Introduction

Research Background

Artificial intelligence (AI) is an emerging technology. Since computers first arrived on the scene in the 1950s, consumers have been experiencing a second renaissance in the field of AI (Tan & Lim, 2018). Therefore, a new research arena has emerged toward the identification of how academics and practitioners will use and interact with it. Marketing managers and consumers are adopting AI, prompting incredible growth (Mariani et al., 2021); in turn, an increase in AI use produces a need, particularly from the marketing discipline, to pursue research regarding consumers, organizations, and strategy-related research (Mustak et al., 2021). Davenport et al. (2020) has asserted that because the marketing discipline has the most to gain from the use of AI, it should be taking a lead role in addressing questions of how it should and will be used. Huang and Rust (2018) identified four distinct intelligence levels, including mechanical, analytical, intuitive, and emotional. Mechanical intelligence is defined as the ability to automatically repeat tasks or perform routine. Analytical intelligence is the ability to process information to solve problems and learn from them (Sternberg, 2005). Intuitive intelligence can be considered wisdom because it is the ability to think creatively and make effective adjustments using insights and creative problem-solving (Huang & Rust, 2018; Sternberg, 2005), and Goleman (1996) defined empathetic intelligence as the ability to recognize and understand peoples' emotions and then respond accordingly. Research regarding intelligence levels inherent to AI speaks to how the machines can be developed to mimic human intelligence (HI), which Russell and Norvig (2010) defined as a machine's ability to imitate the human ability to problem-solve, acquire knowledge and then apply it, communicate, and perceive. Huang and Rust (2018) further deemed the four intelligence levels as ordinal, meaning lower tasks are easier for AI, and higher skills such as intuition and empathy require more time to develop. Customers have readily adopted many of the mechanical and analytical automated activities, but organizations are unsure how consumers will adapt as AI continues to evolve and enter more into the intuitive and emotional realms (Huang & Rust, 2021).

AI has recently become popular because it is a cheap way to make predictions regarding complex problems (Overgooer et al., 2019). One mainstream example of this would be Amazon’s Alexa, which is an artificial intelligence assistant device that can now make product recommendations to a consumer based on previous items purchased (Longoni & Cian, 2022). AI uses previously collected data to inform new decisions. AI has the potential to achieve context awareness, which means it would then be able to deliver holistic, context-specific responses, and this would be a game changer (Huang & Rust, 2018). AI can take either digital or robotic forms, but all forms provide tremendous opportunities to give customers better, more seamless experiences (Grewal et al., 2020). There are two research streams focused on the progress of AI: one is the use of AI, and the other is the effect of AI on jobs (Huang & Rust, 2018). The purpose of this research was to take a deeper look into how consumers may adopt and react to an increased use of AI and to determine if belonging to one generation versus another makes a difference in the adoption and usage behaviors.

Research Questions

Consumers must have confidence in how their personal data is used to fuel AI recommendations that lead to broader acceptance of AI into more aspects of their lives (Kaplan & Haenlein, 2019). This notion led to the present study's main research question about how generational belonging may affect the likelihood of feeling exploited by AI data capture. For example, if Gen X is found to be more upset than Gen Z about the amount of information about them that is being collected, this could affect the adoption of AI in the workplace and consumer activities among Gen X versus Gen Z. Additionally, research to determine if a consumer's Technology Readiness Index (TRI) score would have an effect on the feelings of exploitation by AI would fill a current void in AI literature as well. Most consumers may accept that AI gathers information they post on social media, but they may be more hesitant about information captured through their smartphones or home devices. Understanding AI technology and how it is being used may lessen feelings of exploitation across the generations.

Significance of Research

One top priority for research conducted at the Marketing Science Institute between 2020 and 2022 was centered around customer-technology interface (MSI Research Priorities, 2022). Both articles in this dissertation will answer questions about how technology (such as AI) changes the way customers interact with organizations, how customer decision-making changes with evolving technology, and where customers draw the line between preserving privacy and personalization. Studying which customers may feel exploited by AI when they feel their privacy is invaded can affect their interactions with organizations, but more importantly may change how they make purchase decisions.

Limitations

One obvious limitation of the study resides in sampling Gen Z members. A survey using a convenience sample from college students in the southeastern United States was deployed for this study, and featuring college students left out the many members of that generation group who chose to enter the military or start their careers immediately after high school. Moreover, only people over the age of 18 were surveyed, which limited a large portion of that specific generation group that is younger than 18. Another limitation is the number of participants sourced from other generations for comparison. The reliance on personal contacts and snowball sampling made it difficult to focus on certain generations, therefore, results ended with more Gen Z participants than other generations. Finally, since the questions regarding exploitation were the most open to misinterpretation, this is named as a limitation to the research.

Literature Review

Explanation of Artificial Intelligence

Artificial intelligence (AI) is the study of general principles of rational agents and components for constructing them (Russell & Norvig, 2018). This definition is beneficial for use in the marketing discipline because it emphasizes making the best possible decision with the information provided (Overgoor et al., 2019). Another way AI has been defined is “the use of computational machinery to emulate capabilities inherent in humans, such as doing physical or mechanical tasks, thinking, and feeling” (Rust & Huang, 2021, p. 31). AI has the potential to take raw data, run it through a proprietary computing procedure, and then create answers based on the known information to apply to a variety of marketing problems. Davenport and Ronanki (2018) describe AI not just on its underlying technology but rather on its marketing and usage of business applications, such as automating business processes, gaining insights from data, or engaging employees and customers. AI is breaking new ground and continuously helping deliver more value to its users (Kumar et al., 2019). Consequently, AI remains at the forefront of revolutionizing the marketplace (Henkel et al., 2020). AI can help in the selection of products by advertising messages geared toward an individual's preference, prices for products, and website content (Haenlein & Kaplan, 2019). It is gaining momentum because of an explosion of new data that can train algorithms, and new applications are becoming possible due to the rapid advances in technologies and computer power (Bornet et al., 2021). AI now can be found in almost every aspect of marketing, and marketing research seems to be eager to study this new technology, but hesitant about the implications of it (Wirth, 2018).

Generational Differences

In the United States, generations have been defined by age groups that travel through life experiencing similar events around the same age such as social, historical, political, and economic environments (Williams & Page, 2011). There are currently six generations in the United States, recognized by the following nicknames: pre-Depression, Depression, Baby Boomers, Gen X, Millennials, and Gen Z (Dietz, 2003; Hawkins et al., 2010). The characteristics, attitudes, and lifestyles vary across these generations (Williams et al., 2010). This acknowledgment has led to an increased awareness of multigenerational marketing, which is the practice of appealing to individual needs that are unique to more than one specific generation segment (Morris, 1982). This acknowledgment of similar attitudes based on similar experiences among the generations is also pertinent to the discussion of technology usage.

The pre-Depression generation currently represents the lowest number of people, and all of them are over age 85. This generation had a front-row seat to many social and technological changes and had significant influence on the “macho” mentality of men, which was most likely attributed to their involvement in both World War I and World War II (Dietz, 2003; Hawkins et al., 2010). They held major power in the United States and did not easily relinquish it (Williams et al., 2010). This generation embraced private phone lines, televisions in the home, credit cards, computers, and eventually even the internet (Williams & Page, 2011).

The Depression-era generation was born during the Great Depression or during World War II and value saving money, morals, and being united against common enemies (Williams et al., 2010). They are patriotic and witnessed the rise of the middle class; moreover, they appreciate consistency and have become tech-savvy in using the internet (Bailor, 2006).

Baby Boomers, or Boomers, were born post-World War II between 1946 and 1964 (Kotler et al., 2013). Although most have by now left the workforce, this remains the largest and most influential generation in the United States today regarding impact and their disposable income (Casalegno et al., 2022; Williams et al., 2010). Kotler et al. (2013) asserted that they are known as workaholics and readily define themselves by their careers. This generation has always appreciated learning new skills and setting new goals (Williams & Page, 2011); as such, Chang (2007) noted that Boomers have readily accepted the internet in terms of social media sites, health information resources, and online purchases.

Gen X, also known as the Latchkey Generation, tend to be less traditional than previous generations and have taken more responsibility for raising themselves due to higher divorce rates (Williams & Page, 2011). This generation acts more as free agents than team players, and marketers found they like practical options without long-term commitments (Williams et al., 2010). This behavior is explained by their lack of organizational loyalty and a focus on their own personal wellbeing (Casalegno et al., 2022). The Latchkey Generation represents the first generation to be comfortable with technology and information (Sirias et al., 2007). As such, they place a high value on techno-literacy and see technology as world-changing (Williams & Page, 2011).

Millennials, or Gen Y, are known as the first digital generation (Casalegno et al., 2022). They grew up in a fast-paced environment where dual-income households were standard, divorce was the norm, computers were in homes and school, and much attention was put on ethnic and cultural diversity out of a growing respect for differences (Williams et al., 2010). They are efficient multitaskers who have a greater need for peer acceptance and desire independence but are more skeptical due to the examples of major media figures cheating, lying, and exploiting more than before (Eisner, 2005). Williams et al. (2010) noted that Millennials grew up with the internet as their playground and perceive technology as a given need, not a privileged want.

Gen Z, or the iPad Generation, is comprised of true digital natives who have grown up with handheld technology devices from an early age (Puiu, 2016). They know and accept social media as part of their daily lives, which influences their success or failure, but also are concerned with privacy issues (Casalegno et al., 2022). They appreciate being evaluated, and this is shown by their willingness to attach their names to action, then improve behaviors based on reactions received (Robichaud & Yu, 2021). The Gen Z group values authenticity, traditions, and security more than ever (Williams et al., 2010). They view education as a means to gain security (Jayson, 2009). Therefore, this stands as the most educated and diverse generation in the United States (Williams et al., 2010).

As technology progresses, the adoption of it remains a constant conversation topic for consumer behavior research. Because consumer behavior trends show an acceptance of more AI into daily life, current research points to adopting AI into marketing strategies with some evidence that it increases the effectiveness of human managers and denies the fear of replacement (Davenport et al., 2020). Walker (2016) noted that facial recognition software, along with artificial intelligence, is becoming more conventional in facilitating exchanges. Consumers react differently to AI, so a challenge for current marketers and managers alike is assessing how much AI is too much for consumers (Huang & Rust, 2021). This points to “softer” empathic skills carrying more importance than analytical ones for managers in the future, but it still progresses toward more innovative human-machine integration (Huang & Rust, 2018). Gen Z has posed challenges for decision makers in business due to the generation’s focus on innovation and their varying expectations of service (Priporas et al., 2017). Moreau (2021) found that a deciding factor of the success of smartphone apps was whether teenage consumers adopted and accepted them. Organizations are investing large amounts of money to attract teenagers because of their fascination with tech-based products and large purchasing power (Carufel, 2021; Randall, 2016). The digital frontier will be accelerated by the deployment of AI, and Jacobsen and Barnes (2020) suggested that Gen Z will be at the helm with their tech savviness. There exists a gap in the literature surrounding consumer behavior, specifically regarding the attitudes this group harbors toward an increased use of AI. Both academics and managers need this information, as companies seek to make informed strategic decisions (Huang & Rust, 2021). Jacobsen and Barnes (2020), for example, have claimed that Gen Z will boast nearly 74 million consumers, so it is easy to see where this large amount of buying power will originate. The innovation and the personalized touch that scholars assert this group craves may show companies they can only keep up with these consumers using AI (Priporas et al. 2019).

Other studies present one counterargument to this by addressing the connection between the amount of time Gen Z consumers spend in front of a screen, which is an average of 9 hours a day (Jacobsen & Barnes, 2020), and their desire for more human interaction as compared to previous generations (Barna Group, 2020). Remarkably, Barna Group also noted that this generation finds the technology they crave both a blessing and a curse as 64% of Gen Z consumers feel that smart technology helps them stay connected to friends and family. However, 68% of the same population said that technology actually kept them from having real conversations with people, and 32% claimed their devices separate them from people. Over the next several years, Gen Z is expected to make up 20% of the workforce, and at the rate the Baby Boomers are retiring, Goh and Lee (2018) noted how Gen Z is predicted to bring a significant shift to the work culture and environment. This disconnect from people, combined with tech-savvy skills, explains why several companies speculate that increasing AI will improve relationships with this next generation of customers. These findings point to a need for research on the perception of Gen Z on AI interactions to enhance marketing strategies.

Technology Readiness Index

Literature in this section was reviewed regarding versions 1.0 and 2.0 of the Technology Readiness Index (TRI). The background provided offers comparison to explain why the creators of TRI revisited and updated this methodology. The comparison portion concludes with a rationale about why 2.0 proved more appropriate for the present study. Finally, this section considers each of the four dimensions that make up a consumer's Technology Readiness (TR).

An Overview of TRI

Technology is increasing at a swift pace, and equal to the augmented number of products is the amplified usage of them. Significant attention has been given to TR because researchers have determined it gives marketers insights into which consumers are more likely to adopt certain technologies (Blut & Wang, 2020; Rojas-Mendez et al., 2017). Lin and Hsieh (2006) noted that customers are using the new technologies to consume and produce services without direct personal interaction with an organization's employees, and Parasuraman (2000) defines TR as people's attitude toward embracing the use of new technologies to accomplish goals at both home and work. Technology can produce results of anxiety in individuals triggered by both positive and negative feelings. Due to this, researchers have shown an interest in studying consumers' acceptance and adoption of new technologies (Venkatesh et al., 2012). Parasuraman (2000) further noted that the TRI was constructed in response to the rapid growth of technology-based products and the uncertainty of consumers' readiness to interact with or adopt these technologies. Bitner et al. (2000) and Parasuraman (2000), along with other scholars, have observed a rise in customer frustration correlated with a decrease in service satisfaction despite the benefits that technology products were providing. In turn, consumers were circumventing the use of these products if they were not ready to use them or felt uncomfortable with the systems (Han et al., 2013; Lin & Hsieh, 2012). The TRI framework investigates the conflicting feelings consumers possess that result from their interactions with technology and these feelings are labeled as motivators and inhibitors (Lin & Hsieh, 2012; Parasuraman & Colby, 2015). The four dimensions have been found to be independent of each other, meaning an individual can both praise and fear technology (Parasuraman & Colby, 2015), and Parasuraman (2000) outlined the four dimensions as follows: optimism, innovativeness, discomfort, and insecurity. These dimensions were merged using TRI 1.0, which is a developed scale that assesses a person's level of TR (Blut & Wang, 2020; Parasuraman, 2000). This scale was condensed and updated for more modern technology then launched as TRI 2.0 (Parasuraman & Colby, 2015), and numerous studies have established the effectiveness of this scale as an indicator of technology adoption (Blut & Wang, 2020; Mishra et al., 2018; Smit et al., 2018).

Progression of TRI 1.0 to 2.0

Through the use of TRI 1.0, 127 researchers working in 30 different countries accumulated feedback via LinkedIn and through personal communication (Parasuraman & Colby, 2015). These comments and suggestions highlighted outdated items and terms, as well as the length of the assessment and included ideas surrounding rapidly changing technology. Fifteen years after the release of TRI 1.0 and with the accumulated feedback, Parasuraman and Colby (2015) decided to update the scale, stating the need to "(i) reassess scale statements referencing contexts that were no longer innovative, (ii) examine and incorporate relevant implications of a changing technology environment and (iii) make the instrument more parsimonious (p. 61)." The authors reduced the survey from 36 to 16 items to help researchers when deploying surveys that use multiple constructs and to increase its application over extended periods and across different contexts. These refinements were initiated with updates to the wording of various statements, making them more applicable to modern descriptions of technology. Parasuraman and Colby (2015) also introduced nine new statements across the four dimensions that better capture new themes relating to technology, such as the ability to select one's own location for usage. The newly created 45-item TRI was then paired down, based on mixed methods research, into the four dimensions and overall TR, which thus became the 16-item TRI 2.0 (Parasuraman & Colby, 2015). Theoretical foundations remained consistent during this refinement process, justifying the use of TRI 2.0 in this paper.

TRI: Optimism Dimension

In the context of this study, the definition of Optimism (OPT) relates to "a positive view of technology and a belief that it offers people increased control, flexibility, and efficiency in their lives (Parasuraman & Colby 2015, p. 18). This dimension relates to the underlying belief that technology is a good thing and that it contributes in a positive way to people's lives (Han et al., 2013; Parasuraman & Colby, 2015). Both TRI 1.0 and 2.0 are designed to capture the positive aspects of technology that include giving people more control over their lives, extending regular business hours, and increasing efficiency in their careers (Han et al., 2013; Lai, 2008; Parasuraman, 2000). The OPT dimension is captured through four statements in TRI 2.0, which determine the strength of a consumer's technological optimism (Han et al., 2013; Parasuraman & Colby, 2015). These four were pared down from the 10 statements included in TRI 1.0 because some were moved to another dimension (innovativeness) and others were removed and the remaining two statements were rewritten, and then merged with two new statements reflecting the changes being experienced in the technological environment (Parasuraman & Colby; 2015). The four OPT statements in TRI 2.0 include OPT 1: New technologies contribute to a better quality of life; OPT 2: Technology gives me more freedom of mobility; OPT 3: Technology gives people more control over their daily lives; and OPT 4: Technology makes me more productive in my personal life.

TRI: Innovativeness Dimension

In the context of this study, Innovativeness (INN) is defined as a "tendency to be a technology pioneer and thought leader" (Parasuraman & Colby, 2015, p. 18). This is reinforced by the explanation of innovativeness being "a natural desire to experiment with new technologies" (Elliot et al., 2013, p. 131). Parasuraman and Colby relate innovativeness to a person not needing help when operating or understanding new technologies, or when the person is considered an opinion leader on technology-related topics. Therefore, the innovativeness dimension shows a positive relationship with technology adoption behaviors where the individuals considered to be innovative are presented with opportunities to adopt new technology (Han et al., 2013). Again, this dimension was reduced due to refinements between versions TRI 1.0 and 2.0 for a total of four statements, including INN 1: Other people come to me for advice on new technologies; INN 2: In general, I am among the first in my circle of friends to acquire new technology when it appears; INN 3: I can usually figure out new high-tech products and services without help from others; and INN 4: I keep up with the latest technological developments in my area of interest.

TRI: Discomfort Dimension

In the context of this study, Discomfort (DIS) is defined as “a perceived lack of control over technology and a feeling of being overwhelmed by it” (Parasuraman & Colby, 2015, p. 18). This is the first inhibitor of TR, as it relates to a prejudice that consumers may have against technology. Parasuraman and Colby (2015) also noted that consumers may describe DIS as having a general fear or paranoia toward technology where a lack of control is felt or a belief that it is too complicated for normal people exists. The consumers who feel this discomfort are less likely to purchase or adopt new technologies (Han et al., 2013). Again, the statements regarding the discomfort dimension were reduced from 10 to four between versions of TRI and include DIS 1: When I get technical support from a provider of a high-tech product or service, I sometimes feel as if I am being taken advantage of by someone who knows more than I do; DIS 2: Technical support lines are not helpful because they don’t explain things in terms I understand; DIS 3: Sometimes, I think that technology systems are not designed for use by ordinary people; and DIS 4: There is no such thing as a manual for a high-tech product or service that’s written in plain language.

TRI: Insecurity Dimension

Insecurity (INN) is the second inhibitor of TR and in the context of this study is described as “distrust of technology and skepticism about its ability to work properly”

(Parasuraman & Colby, 2015, p. 18). Although the discomfort and insecurity dimensions seem to be related, they differ in that insecurity focuses on the trusting of technological interactions, instead of a consumer's lack of comfort (Lai, 2008). Consumers who experience insecurity do not think that technology should have access to personal information or be able to expose them (Smit, 2018). Individuals who experience high levels of insecurity are more likely to hesitate when adopting new technology (Han et al., 2013). One of the more common areas in which people show a high sense of insecurity is the internet and e-commerce due to the expanse of the platform and its intangible nature (Han et al., 2013; Parasuraman & Colby, 2015). Due to the rapidly changing landscape of mobile device use and the increase of e-commerce over the internet, the dimension of insecurity exhibited the most significant changes from TRI 1.0 to 2.0 (Smit et al., 2018). The new statements for this dimension include INS 1: People are too dependent on technology to do things for them; INS 2: Too much technology distracts people to a point that is harmful; INS 3: Technology lowers the quality of relationships by reducing personal interaction; and INS 4: I do not feel confident doing business with a place that can only be reached online.

TRI: How the Dimensions Relate to one Another

The four different dimensions of TR are independent of one another, meaning a consumer can both praise and fear technology (Blut & Wang, 2020; Parasuraman & Colby, 2015). Mishra et al. (2018) asserted that the first two dimensions are "motivators," which contribute to a person's TR, and the last two dimensions are "inhibitors," which challenge the TR of an individual. The motivator and inhibitor dimensions were found to be strongly independent of one another, but weak associations were identified between the two motivators as well as the two inhibitors (Blut & Wang, 2020; Han et al., 2013; Mishra et al., 2018; Parasuraman & Colby, 2015). Although an individual can harbor both positive and negative beliefs about technology, the dominant set will push them toward or pull them away from the adoption of new technology (Lin & Hsieh, 2012; Parasuraman & Colby, 2015). Blut and Wang (2020) found that the impact on technology usage had a stronger relationship with the motivators than the inhibitors, so they urged scholars to differentiate between the two dimensions, but to always consider both when technology usage was being examined. Findings from several researchers have revealed a positive influence between an overall TR score and the likelihood of a consumer adopting new or existing technologies (Lai, 2008; Parasuraman & Colby, 2015; Rojas-Mendez et al., 2017).

TRI: Justification for Usage

The TRI 2.0 measures individual behaviors and beliefs regarding technology (Mishra et al., 2018). This study intended to determine if an individual's TRI score poses a direct impact on their usage or feelings toward AI. Another popular measure for technology adoption is the Technology Acceptance Model (TAM); however, Lin et al. (2007) asserted that TAM is more system-specific, and although it has been the most widely cited, it was expressly developed to predict technology-adopting behaviors within the workplace (Davis, 1989). This means that when using a measure for marketing applicability where consumers' adoption behaviors are not being forced by an organization, TR will prove more indicative of how an individual may use a technology-based product or service (Parasuraman, 2000).

An Overview of Consumer Exploitation

In economic literature, exploitation is determined to take place between two individuals, and it involves either immoral conduct or unfairness (Berkey, 2019; Mulkeen, 2021). Psychology scholars such as Levinthal and March (1993) defined exploitation by claiming it involves the use and development of things already known, that are considered less risky, but self-destructive in the long run. Exploitation is related to high-level engagement designed to optimize task performance at the individual level (Laureiro-Martinez et al., 2015). These studies lead to a definition of consumer exploitation as a process that utilizes existing knowledge to make a quick decision at the expense of the consumer (Choi et al., 2021). When considering how consumers are interacting with AI technology, it becomes clear that both economic and psychology literature exhibit a more complete mindset involving consumer exploitation.

Puntoni et al. (2021) found that "Consumers lose ownership of their data and feel a loss of control over their lives while technology companies, firms, and governmental agencies gain financial and political power" (p. 85). A sense of control is a basic individual need and a precondition of psychological welfare (Leotti et al., 2010). Therefore, AI's lack of transparency can cause feelings of exploitation that are then fueled by a perceived loss of control, leading to psychological consequences (Botti & Iyengar, 2006). These existing studies have clarified that although consumers are using AI to make decisions using items with which they are familiar, such as smartphones, the data being culled can elicit a sense of unfairness.

Consumer Exploitation with AI Data Capture

The data capture process of AI can make consumers feel exploited through information exchanges. Consistent with Puntoni et al. (2021), in this research data capture is defined as “the experience of endowing individual data to AI (p. 132).” Consumers can intentionally provide data even though they have different levels of understanding regarding the process (Walker, 2016). Data can also be collected by AI from the “shadows” that consumers leave behind as they move through daily activities (Kuniavsky, 2010). Puntoni et al. (2021) also asserted that data capture experiences can feel threatening to consumers as a lack of ownership over personal data in popular culture is associated with a loss of personal control stemming from technology’s potential to monitor human behavior. Data that are transmitted socially foster uncertainty, placing consumers at risk, and increasing their vulnerability to third parties in information exchanges (Walker, 2016).

Consumer Exploitation Versus Consumer Vulnerability

Consumer exploitation was previously defined as utilizing existing knowledge to make quick decisions at the expense of a consumer (Choi et al., 2021). The definition of consumer vulnerability is adopted from Yu Shi et al. (2017), who stated that it is an individual characteristic that refers to a tendency to make damaging decisions to one’s welfare when external factors in the consumption situation are used to stimulate or tempt. In exchanges online, individuals are overloaded when they lack time and attention, which causes them to experience vulnerability, uncertainty, and risk (Walker, 2016). Therefore, in the context of the consumer exploitation felt through the usage of AI, these terms are interchangeable since creating a vulnerable situation is exploiting the consumer. These definitions enable a better understanding of consumer issues, as opposed to other definitions that focus more on disadvantaged groups and demographic variables such as income, race, and education (Andreasen & Manning, 1990; Lee & Soberon-Ferrer, 1997). Disadvantaged groups may be more vulnerable, but this is not applicable to all segments grouped by income, race, or education (Berg, 2015). Three major themes regarding consumer exploitation of AI data capture are present throughout the literature: privacy control, perceived severity, and perceived threat. This article combines them to offer an overarching category identified as feelings of exploitation.

Privacy Concerns Among Consumers

The increased use of AI technology has contributed to many conversations surrounding consumer privacy. As consumer shopping behavior, both online and offline, is increasingly monitored, more data is being collected than ever before (Kopalle et al., 2022). Malhortra et al. (2004) noted that the digital collection of personal information can lead to robust descriptions of individuals because the information is easily copied, transmitted, and integrated. Additionally, as consumers adopt AI technologies into their daily lives, there is a growing concern about the features that may result in disadvantages or harm (Davenport et al., 2020; Kaplan & Haenlein, 2020). Data capture is the result of employing the listening capability of AI to collect data about consumers and their environment, then transferring it in various ways to businesses (Puntoni et al., 2021). The increasing invisibility, due to AI's embeddedness in appliances and automobiles, shows the potential to sway human behavior as AI technology makes more autonomous decisions (Kopalle et al., 2022). Dawar (2018) offers one example of how Amazon's Alexa could monitor patterns in telecommunication and then automatically switch consumers to less expensive providers or plans. Although some consumers may view this as a valuable service, others will be concerned over the lack of consumer privacy, resulting in additional feelings of exploitation. Previous literature has referred to this type of information collection as a double-edged sword because it could prove beneficial and increase public utility or abuse consumers by invading their privacy (Culnan, 2000; Laufer & Wolfe, 1977; Malhortra et al., 2004). Because not all consumers understand AI's operating criteria, they can feel exploited through these data capture experiences (Puntoni et al., 2021). Consumers have become vulnerable regarding the release of personal information as organizations have sought opportunities through these transactions (Laufer & Wolf, 1977; Malhotra et al., 2004; Puntoni et al., 2021), As a result, this unease served as a motivation to develop the Internet Users' Information Privacy Concerns (IUIPC) scale.

Internet Users' Information Privacy Concerns

As e-commerce began rapidly increasing, the topic of information privacy was identified as a topic of concern for consumers (Malhotra et al., 2004). Information privacy is a concept that deals with the rights of people whose information is shared (Okazaki et al., 2009). Malhotra et al. (2004) developed a scale to measure privacy concerns specifically related to internet usage concentrating on three different factors: collection, control, and awareness. In two empirical studies, support was found for the IUIPC scale's reliability and validity (Malhotra et al., 2004; Okazaki et al., 2009), and notably, this scale was theoretically based on the social contract theory (Macneil, 1974).

Social Contract Theory

Social contract theory provides a rationale for the belief that authority must be granted from the consent of those being governed (Macneil, 1974). Culnan and Bies (2003) used this theory to explain consumer behavior beliefs regarding information privacy, and Okazaki et al. (2009) explained that the exchange of information involves an implied social contract of benefits. When this theory is applied to information privacy, it suggests that an organization's collection of personal information is perceived to be fair only when consumers are granted control over the information and informed about how their information will be used (Malhotra et al., 2004).

Collection

Puntoni et al. (2021) noted that information privacy concerns start with data collection as the ways in which AI is acquiring data are becoming more intrusive and difficult to avoid. Furthermore, users fail to understand how much of their collected data will be captured and what security risks or privacy vulnerabilities they may be exposing themselves to through this gathering process (Acquisti et al., 2017). Data brokers lack transparency and accountability and for the most part remain unregulated (Grafanaki, 2017), which results in consumers feeling a loss of control over the ownership of their personal data through the data capture experience (Puntoni et al., 2021). In the IUIPC scale, this collection factor is rooted in the social contract theory's principle of distributive justice (Malhotra et al., 2004), which Culnan and Bies (2003) have defined as "the perceived fairness of outcomes that one receives" (p. 328). In the collection process, consumers are giving up information in return for something of value; however, individuals will be reluctant to share their personal information if their expectations are negative (Cohen, 1987). As such, collection is the first dimension of the IUIPC because it captures the central theme of information exchange and the degree to which a person is concerned about it (Malhotra et al., 2004).

Control

Control is an important aspect of information privacy because consumers take on high risks when submitting personal information (Malhotra et al., 2004). Previous studies found that people desire more control over the use of their personal data and were less worried when they gave permission or were given the choice to opt out (Nowak & Phelps, 1995; Phelps et al., 2000). The control issue becomes elevated when there is a high potential for opportunistic behavior that leads to potential breaches in the social contract from exchanges (Malhotra et al., 2004). This second dimension of IUIPC targets many of the top concerns of researchers who have addressed the usage of AI by organizations (Okazaki et al., 2009; Puntoni et al., 2021; Walker, 2016).

Awareness

Control is an active component of information privacy, but awareness is a passive dimension (Malhotra et al., 2004) that refers to a consumer’s understanding of the information privacy practices used by an organization (Culnan, 1995). Because the interactive process of data collection can indefinitely store personal information for later usage, consumers tend to be uncertain of how and when their data will be shared (Okazaki et al., 2009). Awareness is the third dimension of the IUIPC scale and is based on two types of justice: interactional and informational (Malhotra et al., 2004). Violating transparency and ownership ideals of information leads to perceptions of unfairness.

Perceptions of unfairness increase with the specificity of information used to provide a justification (Okazaki et al., 2009).

Perceived Severity

The internet is a global community where security threats and issues are interdependent (Chen & Zahedi, 2016). Perceived severity is defined as the magnitude of possible harm caused by online security threats (Chen & Zahedi, 2016). When users believe they are vulnerable to attacks of a serious level, they perceive threats, and Liang and Xue (2009) found that perceived severity had an interaction with perceived susceptibility. However, that variable of threat is being tracked with various factors to see if an aspect such as age or TR affects consumers' feelings of exploitation when it comes to collection activities with AI. Different individuals perceive different levels of severity because their judgments are heavily influenced by their personal experiences, expectations, and knowledge (Kahneman & Tversky, 1979; Liang & Xue, 2009). Moreover, severity has a direct effect on perceived threat (Chen & Zahedi, 2016; Liang & Xue, 2009), which is why it is important to include survey questions that may help understand a consumer's all-encompassing feelings of exploitation. The survey questions for the present study were based on research from Chen and Zahedi (2016) and on Liang and Xue (2009) and included the following:

- AI may perpetuate cultural stereotypes in available data.
- AI may amplify discrimination in available data.
- AI may be prone to reproducing institutional biases in available data.
- AI may have a propensity for intensifying systemic bias in available data.

- AI may have the wrong objective due to the difficulty of specifying the objective explicitly.
- AI may use inadequate structures, such as problematic models.
- AI may perform poorly due to insufficient training.

Perceived Threat

A huge threat is posed to individuals when information is exploited for malicious purposes. In the world of information technology (IT), these threats come in many forms, including viruses, spyware, adware, and spam that can affect productivity and contribute to financial losses (Bagchi & Udo, 2003). Drawing on threat appraisal, consumers evaluate the potential for negative consequences based on attacks from malicious IT (Liang & Xue, 2009). When it comes to the usage of AI, algorithms can be potentially harmful, and the research of Buolamwini and Gebru (2021) and Ukanwa and Rust (2021) has shown that algorithms can discriminate to produce unfair outcomes. These two misuses of digital data collection threaten the ownership aspect of an individual's information. Feeling threatened or perceiving potential threats changes consumers' behavior as they manage their fear by employing safeguarding actions (Liang & Xue, 2009). Consumers may try to avoid interactions with AI to reduce threats or choose to only use unbiased algorithm-based services that do not collect sociodemographic information (Ukanwa & Rust, 2021). These avoidance or threat-reducing behaviors help complete the picture of how perceived threats play a role in the overall feeling of exploitation. The following questions were added to this study's questionnaire based on the research of Chen and Zahedi (2016) and Liang and Xue (2009):

- My fear of exposure to AI's risks is high.

- The extent of my worry about AI's risks is low.
- The extent of my anxiety about potential loss due to AI’s risks is high.
- The extent of my worry about AI’s risks due to misuse is high.

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Chapter Two: Can age determine an individual's feelings of exploitation from artificial intelligence?

Abstract

As the emerging technology artificial intelligence rapidly increases in both workplaces and home, privacy concerns are mounting. This article aimed to answer a question based on consumer feelings. Existing research points to the need to determine if consumers feel more exploited or served by this advancing technology, which captures personal data from multiple sources to fuel algorithms geared to help personalize offerings back to the consumer. Using an online survey platform, 410 participants were asked their feelings regarding artificial intelligence data capture, and their answers were grouped by age. Using structural equation modeling analysis, it was found that older generations (Baby Boomers, Depression, and pre-Depression) had more heightened feelings regarding exploitation from artificial intelligence than Gen Z, the youngest of the generations surveyed. This study further found that Gen X participants were more aligned with the Gen Z notion of feeling more served than exploited by artificial intelligence data capture. Organizations targeting the Baby Boomer and older audiences can take heed that transparency would be a beneficial tool in winning over consumers.

Recommendation agents based on artificial intelligence (AI) are increasing in the online marketplace (Davenport et al., 2020). These recommendations for new products, television shows, travel locations, and more are supposed to make the customer feel more valued or served by organizations. However, it takes a great deal of personal data to fuel algorithms that produce these recommendations. Privacy concerns regarding how much data is collected, stored, and used have become a focus for many consumers (Lobschat et al., 2021; Puntoni et al., 2021; Walker, 2016). Demarcating the line between which consumers feel served versus exploited through the use of AI and the data used for its algorithms would answer the call of many researchers (Mariani et al., 2021; Marketing Science Institute, 2020–2022; Puntoni et al., 2021).

Lin and Hsieh (2006) have suggested that consumer demographics may be an indicator of adoption behaviors surrounding technology. Grewal (2019) found that early adopters change the rules of the game with the introduction of each new technology, and Mishra et al. (2018) indicated that young people are embracing technology faster than older age groups. Another study by Yu Shi et al. (2017) found that age was the only demographic factor determining whether a consumer was more or less vulnerable when making purchase decisions. Given that the demographic of age is a prevalent focus of previous literature regarding feelings of exploitation and adoption of new technology, this research sought to fill the literature gap concerning feelings of AI data capture through the lens of generational belonging and aimed to determine whether it affects one's feelings of exploitation by AI data capture.

Literature Review

History of AI

Artificial intelligence has been around for many years but is surging in popularity due to advanced techniques and accessibility of big data (Overgoor et al., 2019). AI has been defined as "a system's ability to interpret external data correctly, learn from such data, and use those learnings to achieve specific goals and tasks through flexible adaptation" (Kaplan & Haenlein, 2019, p. 17). The concept of AI began in the 1940s when Alan Turing developed a code-breaking machine that led to his creation of the

Turing Test, which identifies intelligence of an artificial system (Turing, 1950). In 1956, Dartmouth College in New Hampshire held an 8-week-long summer research series where the term “artificial intelligence” was first coined (Kaplan & Haenlein, 2019). This workshop united those who would later be considered the founding fathers of AI. Over the next few decades, AI saw incredible growth through the invention of the ELIZA computer program, the General Problem Solver program, and increases in funding toward more research until the mid-1970s, when criticism was mounted regarding the amount of money it was costing. In 1997, when IBM’s Deep Blue program beat a human world champion chess player, AI started to again become a buzzword. Now, with the progress of artificial neural networks called Deep Learning, incredible advancements in AI research and usage have taken center stage as different organizations try to harness the power of it (Urban et al., 2020). AI uses data that companies may already have to provide an inexpensive and efficient way to make predictions (Overgoor et al., 2019). Despite the clear benefits stemming from the organizational side, Luo et al. (2019) noted that there remains much to learn about consumer behavior and the potential pushback from integrating AI into daily interactions.

Customer Adoption of AI

Alexa, Siri, Roomba, and Nest have become household names across the United States and are gaining users. These applications use AI to translate big data into easy ways to aid consumers in completing simple tasks. Despite this growth, McKinsey and Company (2018) published a report that emphasized how many consumers do not understand the value of connected devices and that early adopters are still having to address pain points in the acceptance process. As AI becomes a larger part of daily life, many organizations seek to understand how to use this technology to best connect with consumers (Luo et al., 2019). Technology leads to fundamental changes in the way that organizations will develop and deliver their services (Meuter et al., 2005). A customer must be willing to actively engage with technology-based services for a successful adoption, but research has neglected to fully explain why some consumers resist adoption (Heidenreich & Handrich, 2014). The insights, through more extensive consumer behavior study, will help explain things like how marketers can best use strategies to emphasize potential benefits of new technology (Rojas-Mendez et al., 2017), and although these insights will be helpful, considering resistance will develop a more complete picture of adoption behaviors. Previous studies by Walker (2016) and Puntoni et al. (2021) have identified AI's exploitation of consumers as a possible common theme underlying adoption resistance or avoidance in previous literature.

Exploitation

As consumers adopt AI technologies into their lives, there is a growing concern about the features that may result in disadvantages or harm (Davenport et al., 2020, Kaplan & Haenlein, 2020). Data capture is the resulting experience from where the listening capability of AI collects data about consumers and their environment, then it is transferred in various ways to AI (Puntoni et al., 2021). The invisibility of AI placement, as it is increasingly embedded into appliances and automobiles, has the potential to sway human behavior as AI technology makes more autonomous decisions (Kopalle et al., 2022). Dawar (2018) offered an example of how Amazon's Alexa could monitor patterns in telecommunication and then automatically switch consumers to less expensive providers or plans. Although some consumers may consider this a service, others show concern over the lack of consumer privacy, which may result in feelings of exploitation. Previous literature has referred to this type of information collection as a double-edged sword as the process could be beneficial and increase public utility, or it could abuse consumers by invading their privacy (Culnan, 2000; Laufer & Wolfe, 1977; Malhortra et al., 2004). Puntoni et al. (2021) further noted that not all consumers understand AI's operating criteria, thus, they may feel exploited through these data capture experiences. Additionally, information privacy is a concept that deals with the rights of people whose information is shared (Okazaki et al., 2009); in response, Malhotra et al. developed a scale that measures privacy concerns specifically related to internet usage by concentrating on three different factors: collection, control, and awareness.

Internet Users' Information Privacy Concerns

Malhotra et al. (2004) founded the IUIPC scale based on the social contract theory, which served as a tool for explaining consumer behavior regarding information privacy (Culnan & Bies, 2003). The scale starts with collection, which mirrors how personalized AI begins through data capture. Puntoni et al. (2021) have asserted that AI is collecting data in ways that are more intrusive and that are becoming more difficult to avoid. The next component of IUIPC is control, and control is important to information privacy because when customers submit personal information, Malhotra et al. (2004) have indicated that they are taking a high risk. Awareness is the passive dimension of the scale that refers to customers' understanding of privacy practices, which includes how and when their data will be shared or used (Okazaki et al., 2009). In two distinct empirical studies, Malhotra et al. and Okazaki et al. tested this scale and found it valid and reliable. As organizations have sought more opportunities to fuel AI algorithms with personal information, consumers have become increasingly more vulnerable (Puntoni et al., 2021; Walker, 2016), and there remains a gap in the literature about the benefits of knowing whether age is a demographic factor in feeling more exploited by AI data capture as revealed through application of the IUIPC scale.

Perceived Severity and Threat

Security threats and issues are parts of the growing global community defined by the internet. Chen and Zahedi (2016) defined perceived severity as the magnitude of possible harm caused by online security threats. When information is exploited and then used for malicious purposes, it turns a threat into reality. Research disseminated by Liang and Xue (2009) showed that consumers evaluate potential negative consequences based on attacks from IT used with malicious intent. They also noted that misuse of information that posed threats and then ranked the severity of the threat changed consumer behavior as they manage themselves with the use of safeguarding actions. The way that AI collects data and then uses the information can possibly increase feelings of exploitation when consumers realize their personal information was mishandled despite safeguards. One example of this relates to a U.S. customer who installed Amazon Echo devices throughout her home, believing the company’s claim that the hardware would not invade her privacy. Instead, this customer felt invaded and lost trust when she determined that one of her Alexa systems recorded a private conversation and then randomly sent it to a number in her address book (Horcher, 2018). This example reveals a security threat turned into a reality with high severity. Therefore, these two components, based on a survey developed by Liang and Xue (2009) and then amended by Chen and Zahedi

(2016), have been added to the IUIPC to further define feelings of exploitation by AI data capture.

Generation Overview

Although older consumers control 50% of the discretionary income (Solomon, 2004), it is the younger consumers who affect adoption behaviors, especially with new technology (Mishra et al., 2018). Based upon previous literature that showed age as a determining factor for adoption of technology-based services (Grewal, 2019; Lin & Hseih, 2006), generations still active in the workforce are discussed.

Looking back to the pre-Depression generation, who boast the lowest number of people currently in the workforce, Hawkins et al. (2010) noted the obvious impact they have had both socially and technologically. This generation saw the uprising of televisions in the home, credit cards, private phone lines, computers, and the internet (Williams & Page, 2011). Snipes (2022) further noted that they were known for their work ethic, which is shown by the small number of nonagenarians who prefer not to retire.

The Great Depression-era generation witnessed the rise of the middle class, and this group also values morals along with saving money (Williams et al., 2010). Research by Bailor (2006) also found that they have become tech-savvy in using the internet and that they even frequent social media sites. Following this generation are the Baby Boomers; even though most of them are in or near retirement, they remain the most influential generation in the United States today due to their disposable income (Casalegno et al., 2022; Williams et al., 2010). Moreover, Chang (2007) noted that the Baby Boomers have always appreciated learning new skills, so they have readily accepted the internet and changed their buying behaviors to accommodate purchasing online, searching for items such as insurance online, and trying items found via social media site exploration.

Members of Gen X are less traditional than the previous three groups (Williams & Page, 2011), tending to be more individualistic and to prefer practical options without long-term commitments (Williams et al., 2010). They also lack organizational loyalty (Casalegno et al., 2022), but Williams and Page indicated that they place a high value on techno literacy and technology advancements. Following Gen X are Millennials, which Casalegno et al. (2022) have deemed the first digital generation. They grew up with the internet as their playground, and having computers positioned both at home and school was the norm (Williams et al., 2010).

These generations, all of which boast at least a few members active in the workforce, precede the up-and-coming generation of workers nicknamed Gen Z. Gen Z, or the iPad Generation, are true digital natives because they have grown up with handheld technology devices from an early age (Puiu, 2016). Furthermore, they are concerned with privacy issues, are risk-adverse, and use daily interactions with social media to influence their success or failures (Casalegno et al., 2022). Notably, Williams et al. (2010) have also deemed Gen Z as the most educated and most diverse generation in the United States, and they wear this label proudly.

Methodology

Huang and Rust (2021) pointed out that consumers react differently to the increased usage of AI, and it is important to find out how much AI is too much. Feelings of exploitation can hinder the usage of AI, but establishing if these feelings are related to demographics such as age is useful for organizations that track consumer behavior. Baron and Kenny (1986) described how statistical demographic information is sometimes best viewed as a moderator instead of a mediator. In line with this research, the present study relied on age to identify the strength of the relationship between the observed variables that constitute feelings of exploitation and generational belonging.

Hypotheses Development

AI will pose an organizational impact both internally and externally. Internal impact relates to how each consumer used AI in the workplace or their homelife. External impact relates to AI's relationships with customers, between other firms, and with society at large (Kaplan & Haenlein, 2019). These organizational impacts are fueled by personal data that customers may or may not be aware that they are providing (Puntoni et al., 2021). Due to the tech-savvy characteristics attributed to Gen Z, all the older generations are compared to this group; therefore, the hypotheses (also seen in Figure 1) are as follows:

H1: Members of Gen X (3) will feel more of a perceived threat by AI data collection compared to Gen Z (1).

H2: Members of older generations (pre-Depression [6], Depression [5], Baby Boomers [4]) will feel a higher perceived threat by AI data capture than Gen Z.

H3: Gen X (3) participants will feel higher perceived severity when interacting with AI than Gen Z (1).

H4: A higher perceived severity will be felt among the Baby Boomer (4), Depression (5), and pre-Depression (6) participants than those in Gen Z (1).

H5: Gen X (3) participants will feel less in control of their data, thus having a higher IUIPC score than Gen Z (1).

H6: Members of the Baby Boomer (4), Depression (5), and pre-Depression (6) generations will also have a higher IUIPC score compared to Gen Z (1) for feelings of heightened awareness and less control.

Millennials (2) could be split based on their age at the time of this survey, therefore, no hypothesis is made regarding if they will feel more served or exploited from AI data capture.

Study Design

Quantitative research can assess differences in relationships through consistent and precise measurements (Bryman & Bell, 2011), making it an appropriate method for assessing the relationship between generational belonging and feelings of exploitation. To evaluate an emotion, the survey asked participants to select a numerical value associated with their degree of intensity. The results were then analyzed to detect potential correlations between the differing variables. One of the most recommended analytical methods in the discipline of marketing is Structural Equation Modeling (SEM) due to its ability to assess latent variables (Hair et al., 2012). The present study used SEM because it can simultaneously estimate multiple regression equations within one framework. Because SEM is a large-sample technique, culling enough data from each generation proved challenging; however, Kenny (2020) stated that in models where there is an upper limit (in the case of this study, age), large numbers may be unrealistic. The relationships were analyzed, and conclusions were inferred to help progress the current understanding of consumer behavior.

Data Collection and Procedures

Surveys (see Appendix B), were deployed electronically with the use of Qualtrics software. Institutional Review Board (IRB) approvals were obtained (see Appendix E) to collect information from adults over the age of 18, then attempts were made through social media, email lists, and university campuses in the Southeast to connect with participants of all generations. This questionnaire was anonymous, but it did collect demographic information about gender, age, race, and education. All participants had to be fluent in English and were asked this qualifying question before they were able to access the survey: “Are you 18 years old or older?” If a participant started the survey and then skipped a question, the option to terminate the survey was offered. If that option was chosen, any answers they had selected were removed from the data. This helped ensure that data collection remained consistent and clean for the optimal responses.

Sample Size

Variance is lowered when the sample size increases, which makes larger sample sizes more desirable. Kenny (2020) marked the sample size standard for SEM research at 200 participants or more, which matches the research of Schumacker and Lomax (2010), whose findings revealed that most studies required between 200 and 500 participants. Bentler and Chou (1987) suggested a minimum of a 5:1 ratio between sample size and estimated parameters, but Schumacker and Lomax (2010) recommended a more conservative ratio of 10:1. This study included 21 parameters, suggesting at least 210 participants were needed for accurate analysis. Survey data was collected from 410 participants, which exceeded guidelines.

Measures

Three existing scales were combined into the self-administered questionnaire administered in this study toward a better understanding of consumer behavior as it may be age-related. Adaptations from the original survey questions were made to incorporate AI data capture and the potential feelings that come from it. Instructions were added at the beginning to appropriately frame the questions for the participants and ensure their mindset was focused on the same instruments as intended for analysis. A 5-point Likert scale was used to measure the 10-item IUIPC scale, as well as the additional 11 items assessing severity and threats felt through AI data capture. These scales have not been previously used in combination; however, their merger adds an extra layer of substance when quantifying a feeling.

Valid and Reliable Scales

IUIPC

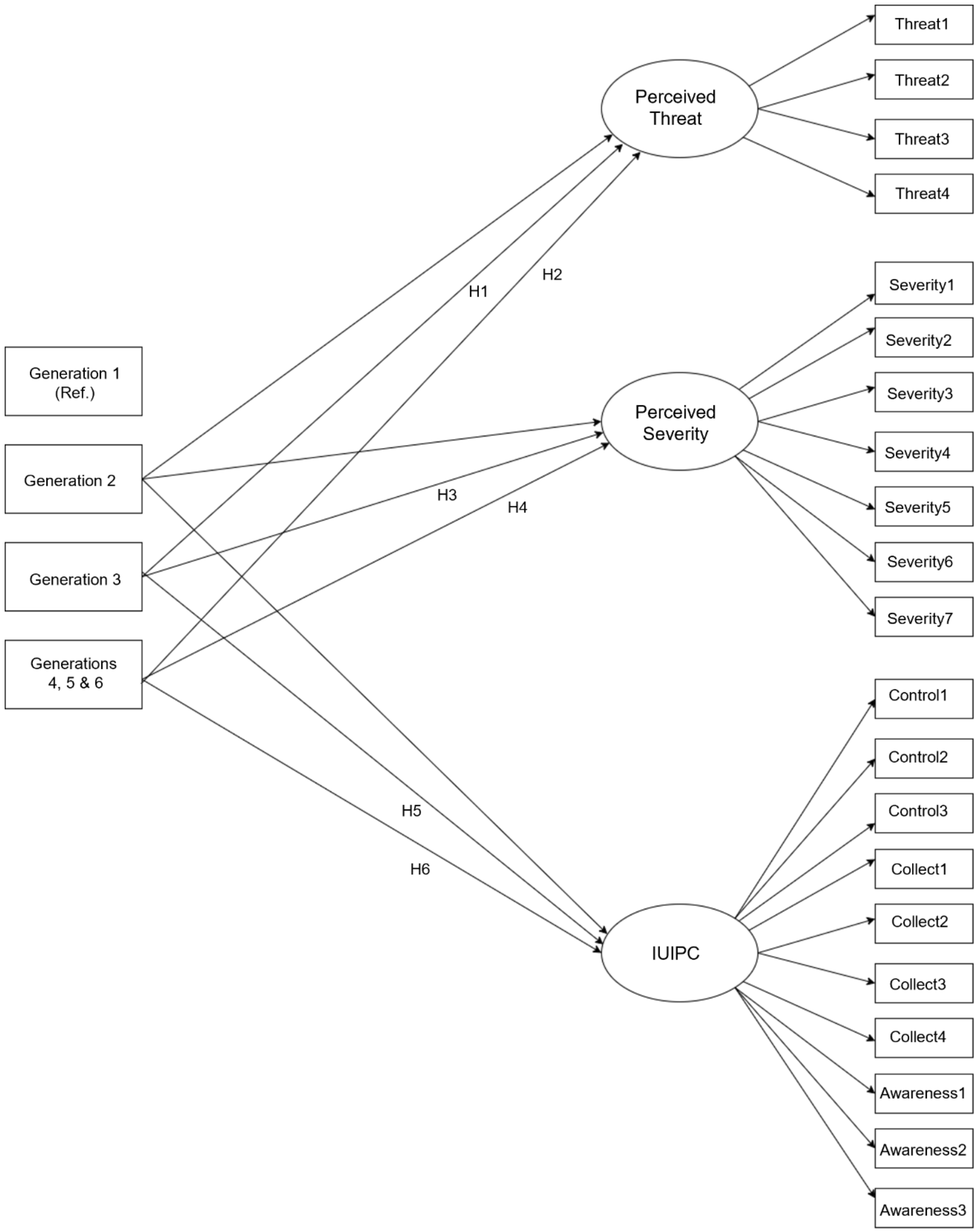
The IUIPC scale was deemed appropriate for empirically testing consumers' feelings of exploitation regarding AI data capture. Malhotra et al. (2004) developed the scale in response to declining customer confidence surrounding information privacy online, and it proved more useful than previously existing scales that examined online privacy because of its expanded theoretical framework, which broadened into emerging technology like AI. Okazaki et al. (2009) successfully used the IUIPC scale to determine consumer behavior with mobile advertising, proving its reliability and validity when tested on different technology. Previously, Hair et al. (2006) found that the IUIPC scale produced consistent and valid results when the composite reliability and average variance extracted were calculated. Malhotra et al. (2004) also tested the scale using the SEM modeling technique and determined that the variance explained 66% of the outcome variables. Overall, the data was found to fit satisfactorily and explained the large variance discovered in behavioral intent.

Perceived Severity and Threat

Liang and Xue (2009) developed a technology threat avoidance theory that included two categories of severity and threat. An individual’s evaluation of their susceptibility to a threat and the severity of that threat is defined as threat appraisal (Chen & Zahedi, 2016). Perceived threats have been found to alter consumer behavior as consumers seek ways to avoid potential harm (Rippetoe & Rogers, 1987).

Figure 2.1

Generations Measurement Model



Liang and Xue (2009) defined perceived severity as the amount of potential harm that could be inflicted by online security threats. The extent to which a consumer feels threatened or that the collection of their information would produce severe harm certainly could make one feel exploited or vulnerable; therefore, the use of these scales (perceived threat and perceived severity), in addition to the IUIPC scale, would result in greater accuracy in measuring a complex emotion. Cronbach's alpha scores exceeded cutoff values of .70 (Nunnally & Bernstein, 1978) in both uses of these scales. Additionally, with the use of exploratory factor analyses, convergent and discriminant validity were checked, and goodness of fit was found to be satisfactory (Chen & Zahedi, 2016).

Measurement Model

Because these are established scales (perceived threat, perceived severity, IUIPC), confirmatory factor analysis (CFA) was used to assess the construct validity of the measurement instruments. Table 2.1 shows the results complete with standardized coefficients, standard errors, *z* scores, *p* values, and 95% confidence intervals for each observed variable and its corresponding latent construct.

The factor loadings were evaluated on each latent construct against the standards of Groenland and Stalper's (2012) research. Their research noted that z-values > 2 confirm significant relationships between the latent construct and the indicator items. According to Kenny et al. (2015), the root mean squared error of approximation (RMSEA) is one of the most popular measures of goodness of fit when using SEM, therefore was used in addition to CFA in assessing the goodness of fit along with the comparative fit index (CFI). All of these tests indicated a good fit for the model. The reliability was determined by using Cronbach's alpha coefficient. Results of the above tests and Table 2.1 were analyzed and reported. Once the measurement model was constructed and tested for goodness of fit, the structural model was validated by investigating the goodness of fit listed in Table 2.1 and found to be reliable.

Table 2.1

Measurement Model for Generational Belonging

	Std β	*SE*	*z*	*p*	95% CI *LL*	95% CI *UL*
Threat						
Threat_1	0.811	0.025	32.400	<.001	0.762	0.860
Threat2_R	0.809	0.025	32.200	<.001	0.760	0.858
Threat_3	0.638	0.035	18.200	<.001	0.569	0.707
Threat_4	0.586	0.038	15.240	<.001	0.511	0.662
Severity						
SEV_1	0.737	0.030	24.420	<.001	0.678	0.796
SEV_2	0.759	0.029	26.450	<.001	0.702	0.815
SEV_3	0.775	0.028	27.390	<.001	0.720	0.831
SEV_4	0.798	0.027	29.940	<.001	0.746	0.850
SEV_5	0.620	0.036	16.990	<.001	0.548	0.691
SEV_6	0.590	0.038	15.530	<.001	0.516	0.665
SEV_7	0.299	0.050	5.960	<.001	0.201	0.398
IUIPC						
Control1	0.052	0.050	1.050	0.293	-0.045	0.150
Control2	0.188	0.050	3.780	<.001	0.091	0.286
Control3	0.364	0.046	7.960	<.001	0.275	0.454
Collect1	0.772	0.024	32.780	<.001	0.726	0.818
Collect2	0.661	0.031	21.200	<.001	0.600	0.722
Collect3	0.846	0.019	45.650	<.001	0.810	0.882
Collect4	0.842	0.019	44.830	<.001	0.805	0.878
Awareness1	0.405	0.044	9.150	<.001	0.318	0.491
Awareness2	0.451	0.042	10.640	<.001	0.368	0.534
Awareness3	0.547	0.038	14.560	<.001	0.474	0.621

Note. CI = confidence interval; *LL* = lower limit; *UL* = upper limit; IUIPC = Internet Users' Information Privacy Concerns.

Results

Data Screening

A total of 433 respondents answered the survey through the anonymous Qualtrics link. Data were screened and eliminated based on completion time if it was excessively low, missing data, and inconsistent answers to reverse questions. During this process, 23 surveys (5.3%) were removed and excluded for analysis. Four hundred and ten surveys met the requirements, deeming them acceptable for analysis. Data were not collected on anyone under the age of 18 or anyone who had never interacted with technology. The data were then categorized by participants' ages into the following six generational groups as discussed: Gen Z, Millennials, Gen X, Baby Boomers, Depression, and pre-Depression. Because the number of participants was lower for the Baby Boomer, Depression, and pre-Depression generations, these groups were combined for analysis.

Sample Demographics

Gen Z constituted 63.20% of the entire study sample. Millennials accounted for 17.3%, and Gen X made up 11.7%. Baby Boomers were 7.1% of the sample, and the Depression and pre-Depression generations accounted for the remaining .7%, demonstrating the need to merge the older three generations to arrive at an adequate sample size. Although age was the only demographic factor considered in the research, other identifying variables were collected, such as education, gender, and ethnicity, and revealed that 46% of participants had a bachelor's degree, the largest of the education categories. Moreover, most of the respondents were female (63%), and Caucasian and African Americans, totaling 83% combined, were the two largest ethnicities represented.

One questionnaire was used for two research questions thus articles, so the demographic information for both is shown here in Table 2.2.

Table 2.2

Demographic Characteristics

Variable	*n*	%
Generation		
1	259	63.20
2	71	17.30
3	48	11.70
4	29	7.10
5	2	0.50
6	1	0.20
Education		
Associate degree or some college	67	16.30
Bachelor's degree	189	46.10
Doctorate or terminal degree	34	8.30
High school or GED	62	15.10
Master's degree	56	13.70
Professional degree	2	0.50
Gender		
Female	258	62.90
Male	148	36.10
Prefer not to answer	4	1.00
Ethnicity		
African American or Black	47	11.50
African American or Black, Caucasian	1	0.20
African American or Black, Caucasian, Native American	1	0.20
African American or Black, Hispanic, Latino, or Spanish	1	0.20
African American or Black, Hispanic, Latino, or Spanish, Caucasian, Asian, Native American, other	1	0.20
African American or Black, Native American, other	1	0.20
Asian	8	2.00
Caucasian	294	71.70

Variable	*n*	%
Caucasian, Asian	5	1.20
Caucasian, Native American	3	0.70
Caucasian, Native American, other	1	0.20
Caucasian, other	1	0.20
Hispanic, Latino, or Spanish	27	6.60
Hispanic, Latino, or Spanish, Asian, Native American	1	0.20
Hispanic, Latino, or Spanish, Caucasian	3	0.70
Native American	4	1.00
Other	11	2.70

Internal Reliability

Cronbach's alpha coefficients were used to determine the reliability of the study constructs. Bryman and Bell (2011) have recommended a value of $\alpha > .7$, which demonstrates adequate reliability. The constructs all returned with strong factor loadings ranging from .810 to .850, as shown in Table 2.3.

Table 2.3

Internal Reliability

Construct	No. of items	α
Perceived threat	4	.822
Perceived severity	7	.850
IUIPC	10	.810
Control	3	.618
Collect	4	.859
Awareness	3	.718

Note. IUIPC = Internet Users' Information Privacy Concerns

Measurement Model Analysis

Data was analyzed using SEM in STATA-17; SEM is a two-step process that first requires a test of the measurement model's goodness of fit (validity) and subsequently a run of the structural model to find support for the hypotheses. The results for the measurement model, as shown in Table 2.1, revealed that most of the observed variables are statistically significant on their corresponding latent constructs (all p >.001). The Threat latent construct shows that strong positive correlations (.59 to .81) are present for all four observed variables (Threat_1, Threat2_R, Threat_3, and Threat_4). Positive correlations are also present for all seven variables (SEV_1 to SEV_7) of the severity latent construct with a range of .62 to .80. In the IUIPC latent construct, all observed variables were significant. There was one variable in the subset of Control (Control_2) that did not show a significant factor loading; it was retained in the model for its theoretical importance and for stability of the measurement model, as removing a variable based on statistical insignificance could lead to a less stable model. Additionally, the relationship between Control_2 and the latent variable appeared weak, but it still contributes to a more comprehensive understanding of the construct as a whole. Kenny (2020) explained that studies with more than 400 participants almost always produce chi-square tests that are significant, which was found to be true here also (χ^2 [234] = 4054.009, $p < .001$). Because this is not ideal, the present study relied on more accurate tests such as the Comparative Fit Index (CFI), Tucker Lewis Index (TLI), and Root Mean Squared Error of Approximation (RMSEA): CFI = 0.943, TLI = 0.934, and RMSEA = .054, all indicating this model was a good fit. Lastly, the coefficient of determination (CD) was .0995, which means this model explained a large proportion of the variance found in the observed variables.

Structural Model Analysis

The model in Figure 1 shows the six declared hypotheses, and the results are provided in Table 2.4. The following is an evaluation of the six hypotheses individually based on the findings from the statistical analysis.

H1: Members of Gen X, will feel more of a perceived threat by AI data collection compared to Gen Z.

Table 2.4

Structural Model for Generational Belonging

		Std β	*SE*	*z*	*p*	95% CI *LL*	95% CI *UL*
Generation 1		Ref.					
Generation 2	→ Threat	-0.036	0.056	-0.640	0.522	-0.144	0.073
Generation 3	→ Threat (H1)	-0.015	0.055	-0.280	0.782	-0.124	0.093
Generation 4, 5, 6	→ Threat (H2)	0.106	0.055	1.930	0.054	-0.002	0.214
Generation 1		Ref.					
Generation 2	→ Severity	0.198	0.053	3.770	<.001	0.095	0.302
Generation 3	→ Severity (H3)	0.007	0.054	0.120	0.901	-0.099	0.112
Generation 4, 5, 6	→ Severity (H4)	0.117	0.053	2.190	0.028	0.012	0.221
Generation 1		Ref.					
Generation 2	→ IUIPC	0.029	0.053	0.540	0.587	-0.076	0.134
Generation 3	→ IUIPC (H5)	-0.006	0.053	-0.120	0.904	-0.111	0.098
Generation 4, 5, 6	→ IUIPC (H6)	0.125	0.052	2.390	0.017	0.023	0.228

Note. CI = confidence interval; *LL* = lower limit; *UL* = upper limit; IUIPC = Internet Users' Information Privacy Concerns

There were no significant differences (*SE* = 0.054, *z* = 0.120, *p* = 0.901) when comparing Gen X to Gen Z regarding perceived severity. Although it was hypothesized that Gen X would perceive the severity factor more than Gen Z, the study found no support.

H4: A higher perceived severity will be felt among the Baby Boomer, Depression, and pre-Depression participants than those in Gen Z.

There was a significant difference found (*SE* = 0.053, *z* = 2.190, *p* = 0.028) when analyzing the data between Gen Z and the Baby Boomer, Depression, and pre-Depression generations regarding feelings of perceived severity. This is in support of the fourth hypothesis.

> H5: Gen X will feel less in control of their data, thus having a higher IUIPC score than Gen Z.

The data supported that Gen X did not show any significant difference based on their IUIPC scores from Gen Z (*SE* =0.053, *z* = -0.120, *p* = 0.904). This hypothesis was not supported.

> H6: The members of the Baby Boomer, Depression, and pre-Depression generations will also have a higher IUIPC score compared to Gen Z for feelings of heightened awareness and less control.

A significant difference was found between Gen Z and the older generations regarding their IUIPC scores (*SE* = .052, *z* = 2.390, *p* = 0.017), thus supporting the sixth hypothesis.

Of the six hypotheses, only two were supported by the data. No hypotheses were made regarding the Millennial generation, but it is worth mentioning that their data was run, and based on the significant number of participants, which was almost twice as many as the other generations besides Gen Z, the sample size could be a large determining factor. Although four hypotheses went unsupported, collecting more data from those generations could lead to greater statistical power and, in turn, help identify potential statistical differences that were undetected in low numbers.

Discussion

This research studied whether age could be a determining factor for feelings associated with exploitation from AI data collection. Because previous studies found age to be a significant marker of technology adoption and usage (Grewal, 2019; Lin & Hseih, 2006), this analysis was a worthwhile endeavor as organizations are increasing their implementation of AI interactions with consumers (Carufel, 2021; Randall, 2016). Because scholars expect Gen Z to rely on tech savviness to stand at the forefront of an acceleration into a new digital frontier (Jacobsen & Barnes, 2020), this study was designed to determine if feelings of exploitation are associated with current AI interactions and could therefore dictate future AI interactions.

A quantitative study was conducted with 410 participants from six different generations, and each was asked to share thoughts on perceived severity, perceived threat, and privacy concerns while interacting with AI. The research also relied on SEM to test the reliability and relationships of the latent constructs with the observed variables. Three hypotheses investigated differences between Gen X and Gen Z because it was predicted that the Millennial generation would produce heavily skewed data. For the other three hypotheses, the older generations of Baby Boomer, Depression, and pre-Depression, needed to be combined to produce enough data to run the SEM analysis. Two of the six hypotheses were supported (H4 and H6), and one (H2) produced a marginally significant difference, but not enough to support the hypothesis. Interestingly, these supported hypotheses were all tied to the comparisons between the latent constructs associated with Gen Z and the older generations. Gen X did not exhibit statistical differences regarding the latent constructs tested in comparison to Gen Z. This was surprising, but it could be due to the small amount of data culled from Gen X and the older three generations. More data would not only increase the power but could also show correlations that currently went undetected.

Managerial Implications

Organizations focused on using AI to provide a more personalized shopping experience for their consumers would benefit from this research. Depending on their target audience and product offerings, organizations should adjust their inclusion of AI data capture methods appropriately. Recognizing that consumers above a certain age desire more control of their information, organizations can choose to educate consumers on the benefits of AI data collection that they use. This will help build transparency between consumers and organizations. Lastly, since feelings of exploitation differ based on age, managers should be made aware of the potential costs associated with their surveillance techniques and include this in strategic planning.

Limitations

Data collected via an online platform through a self-administered survey produces certain limitations, such as misinterpretations or fatigue, that are difficult to explain. A second limitation is that most of the data collected originated from a single generation as opposed to an even sampling across all six groups. This was a concern before the study began, and although it did not completely hinder the results, larger sample pools, and more evenly distributed pools, would produce more useful results. In addition to the age limitations, the largest group from the sample size also had earned or was pursuing a bachelor’s degree. Because a large portion of the data were collected on university campuses located in the southeastern United States, the views from those in each generation group who chose to follow a different career or life path—one that did not center around a university—were excluded. Additionally, the time collection period posed a limitation. The academic calendar is such that data collection largely occurred in alignment with spring break travel and mid-term burnout. However, due to timing issues with IRB approvals, this limitation could not be avoided.

Future Research

This introductory study opens several paths for future research. For example, now that there exists quantitative evidence of statistical differences, a qualitative study based on interviews to find common themes would be beneficial for identifying the reasons behind participants' responses. Additionally, breaking the survey data down by other demographics, such as ethnicity, may also produce different results explaining feelings of exploitation. Conducting a study to determine if privacy concerns differ between the devices each generation most commonly uses—and from which AI data is captured—is another worthwhile line of research. One final consideration for future research would be a stream delving into those participants who previously used or interacted with AI but now choose to avoid it, as this could further explain buying behaviors associated with devices such as Roomba models that have AI embedded or patronizing restaurants that have incorporated AI into their dining experience.

Conclusion

This study approached the question of whether generational belonging affects feelings of exploitation by AI data capture. Data collection, screening, and SEM analysis revealed that the answer does depend on the generation to which one belongs. Older generations, such as Baby Boomers, Depression, and pre-Depression, were found to have heightened senses of exploitation compared to participants of Gen Z. As organizations seek to implement AI into more interactions with consumers, they need to be aware of this based upon their target market. Currently, the Baby Boomer generation has a large amount of disposable income, which translates into buying power; consequently, if AI makes them feel more exploited due to privacy concerns, perceived severity, and threats of how their data are to be collected and used, then companies with this generation in mind need to approach their target market with transparency about how they and their products collect and use information. This research has shown that age can be a factor in feelings associated with exploitation from AI data capture, but it also revealed that younger generations tend to embrace technological changes and sense they are served by them more than exploited.

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Chapter Three: Using the technology readiness index to predict feelings of exploitation from artificial intelligence data capture

Abstract

The Technology Readiness Index 2.0 is a scale that has proven accurate in assessing a consumer's adoption behavior regarding technology. This research was designed to investigate whether the Technology Readiness Index 2.0 could also indicate a consumer's feelings associated with exploitation from Artificial Intelligence data capture. In this quantitative study, 410 participants were asked a series of questions revolving around feelings of perceived threat, perceived severity, and privacy concerns when dealing with emerging technology like artificial intelligence. The results showed that the Technology Readiness Index scale could in fact indicate whether a person felt exploited or served by Artificial Intelligence and data capture methods. Using structural equation modeling analysis, consumers with higher Technology Readiness Index scores were found to feel less threatened, perceive less severity from the threats, and have fewer privacy concerns than consumers with low Technology Readiness Index scores. This research fills gaps in literature for both academics and practitioners alike regarding consumer adoption behavior.

Technology is increasing at a rapid pace and equal to the augmented number of products is the amplified usage of them. Customers are using the new technologies to consume and produce services without direct personal interaction with an organization's employees (Lin & Hsieh, 2006). Due to this increase, it is essential that marketers understand which consumers are more ready to use technology (Blut & Wang, 2020), thus engage and interact more with it. Technology Readiness (TR) refers to people's attitude toward embracing the use of new technologies to accomplish goals at home and at work (Parasuraman, 2000). Technology can produce anxiety in individuals triggered by both positive and negative feelings (Lin & Hsieh, 2006). These feelings have garnered the interest of researchers studying customers' acceptance and adoption of new technologies (Venkatesh et al., 2012) like artificial intelligence (AI), which Puntoni et al. (2021) determined can elicit dual feelings of being served and being exploited.

Consumers harbor different degrees of understanding about how data will be used (Walker, 2016). Puntoni et al. (2021) also noted that this may produce feelings of exploitation when they do not understand how their information is shared or stored, which results in a loss of personal control. The present study used the Technology Readiness Index (TRI) 2.0 scale to test and determine if consumers with a clearer understanding of technology feel less exploited than consumers with lower TRI scores. This research fills a gap in the literature that was identified in Puntoni et al. (2021), regarding future investigation into "how and when increasing levels of familiarity with AI may reduce consumer sensitivity toward exploitation (p. 135)." Additionally, this article responded to a call disseminated by the Marketing Science Institute that encouraged researchers to examine how "customers face an array of new ways to interact with firms through new devices, which alters the purchasing experience" (Marketing Science Institute, 2018). The following research question was addressed in this study: "Can a consumer's TRI score indicate their feelings of exploitation from AI data capture?"

Literature Review

Theoretical Background

One of the most influential and leading theories in the field of social psychology is the theory of reasoned action (TRA) (Ajzen & Fishbein, 1980; Cooke & French 2008; Trafimow, 2009). This theory states that behavioral intention is driven by attitude and subjective norms; therefore, what a person acts on could be determined by either of these underlying determinants. Beliefs (such as the likelihood of varying consequences) also play a major role in this theory. TRA states that behavioral beliefs determine attitude, and subjective norm is accepted or denied based on beliefs of what others think should happen (Trafimow, 2009; Cooke & French, 2008). By investigating theories that emerge from the idea of weighing the consequences that determine beliefs and attitudes, Parasuraman (2000) found a basis for this in technology paradoxes experienced by consumers. The study by Mick and Fournier (1998) contributed to the development of TRI 1.0 by confirming that people held both positive and negative feelings about technology. Influenced by Mick and Fournier (1998), Parasuraman (2000) identified eight technology paradoxes. Parasuraman (2000) hypothesized that a relationship between a person’s dominant feeling, whether positive or negative, and how they embraced or adopted technology was shown to be accurate. Along similar lines, the diffusion of innovation theory (Rogers, 2005), explains that the diffusion process takes place over time, and potential adopters of technology (innovation) must first learn about the innovation and then confirm (reaffirm or reject) the adoption decision (Surry & Farquhar, 1997). Surry and Farquhar (1997) further discussed a predisposition of innovators that leads to earlier adoption behavior than those that are less predisposed. The present article aimed to discover if this predisposition can be found through the application of TRI 2.0 as an indicator toward harboring lesser feelings of exploitation in adopting a newer technology like AI into one's daily life.

Technology Readiness Index 2.0

The Technology Readiness Index (TRI) was developed in 2000 to measure TR using a 36-item scale (Parasuraman & Colby, 2015). The original model featured TR as more inclusive to assess a user's attitude toward the adoption of technology because it included factors that the Technology Acceptance Model (TAM) did not, such as innovativeness, optimism, and insecurity (Parasuraman, 2000). In 2015, Parasuraman and Colby updated the measurement scale by reducing it to 16 items, stating that updates were needed to assess the shift in the technology environment, identify and correct key issues, and remove questions that were no longer innovative. This pared-down model retained the integrity of the four dimensions: optimism, innovativeness, discomfort, and insecurity and is based on individual behavior and beliefs about technology that focus on the consumer instead of the technology itself (Mishra et al., 2018). Even after updates to the scale, some limitations remain, such as cross-cultural limitations and using the term "media" as an all-encompassing term that represents television, radio, internet, and print. Therefore, certain demographics may have differing results based on the type of media they are identifying in answers. One criticism of the original scale was that the dimensions of discomfort and insecurity were not found to be a significant influence on technology adoption (Chen & Li, 2010; Han et al., 2013). Parasuraman and Colby (2015) overcame these limitations by using more relevant language in the 2.0 version, which improved the applicability across various new-age technologies, such as smartphones and social media platforms. Despite some of the widespread criticism, TRI 2.0 has shown to be a reliable predictor of consumer behavior, especially when a scholar desires to group consumers based on varying understanding of technology in the marketplace (Parasuraman & Colby, 2015; Rojas-Mendez et al., 2017; Smit et al., 2018).

Exploitation

Consumer exploitation is defined as the utilization of existing knowledge to make a quick decision at the consumer's expense (Choi et al., 2021). When consumers experience AI technology, they feel a loss of control, especially over the ownership of their data, while technology companies, governmental agencies, and firms gain both political and financial power from obtaining it (Puntoni et al., 2021). Additionally, the lack of transparency surrounding AI fuels the feelings of exploitation through a perceived loss of control that leads to psychological consequences (Botti & Iyengar, 2006). A consumer's sense of control is a basic need and serves as a precondition to psychological welfare (Leotti et al., 2010). While consumers are using technology with which they are comfortable, such as smartphones, the data being captured through information exchanges can feel unfair or invasive, especially when the consumers' understanding of data collection varies (Walker, 2016). Consumer vulnerability has been defined as an individual characteristic that refers to the tendency to make decisions that are damaging to individuals' welfare when external factors are being used to stimulate or tempt them (Yu Shi et al., 2017). Walker (2016) stated that in online exchanges, consumers are overloaded when they lack time, which causes vulnerable encounters, uncertainty, and risk. The context of consumer exploitation explained in literature is interchangeable with the term consumer vulnerability, based on how consumers currently use AI. This provides more of a theoretical background for related articles such as those addressing, consumer behavior and exploitation through decision-making (Yu Shi et al., 2017), instead of exploiting disadvantaged groups based on demographics found in other sources (Andreasen & Manning, 1990; Lee & Soberon-Ferrer, 1997). Therefore, to identify feelings of exploitation through AI data capture, this study concentrated on the privacy concerns topic most often found in existing literature (Malhortra et al., 2004; Puntoni et al., 2021; Walker, 2016;).

Internet Users' Information Privacy Concerns

As e-commerce started rapidly increasing, information privacy was identified as a topic of concern for consumers (Malhotra et al., 2004). Information privacy is a concept that deals with the rights of people whose information is shared (Okazaki et al., 2009). Malhotra et al. (2004) developed a scale to measure privacy concerns that was specifically related to internet usage and focused on three different factors: collection, control, and awareness. In two empirical studies by Okazaki et al. (2009) and Malhorta et al.(2004), support was found for the reliability and validity of the Internet Users' Information Privacy Concerns (IUIPC) scale. This scale was theoretically based on the social contract theory.

Social Contract Theory

Social contract theory provides a rationale for the idea that authority must be granted from the consent of those being governed (Macneil, 1974). Culnan and Bies (2003) used this theory to explain consumer behavior regarding information privacy, and Okazaki et al. (2009) further confirmed that the exchange of information involves an implied social contract of benefits. When social contract theory is applied to information privacy, it suggests that an organization's collection of personal information is perceived to be fair only when consumers are granted control over the information and are told exactly how their information will be used (Malhotra et al., 2004).

Collection

Information privacy concerns start with data collection. Puntoni et al. (2021) noted that the ways in which AI is acquiring data are becoming more intrusive and difficult to avoid. Furthermore, users fail to understand how much of their collected data will be used and what security risks or privacy vulnerabilities they may be exposing themselves to through this gathering process (Acquisti et al., 2017). Data brokers lack transparency and accountability and, for the most part, remain unregulated (Grafanaki, 2017), which results in consumers feeling a loss of control over the ownership of their personal data through the data capture experience (Puntoni et al., 2021). In the IUIPC scale, this collection factor is rooted in the social contract theory's principle of distributive justice (Malhotra et al., 2004), which Culnan and Bies (2003) have defined as "the perceived fairness of outcomes that one receives" (p. 328). In the collection process, consumers are giving up information in return for something of value; however, individuals will be reluctant to share their personal information if their expectations are negative (Cohen, 1987). As such, collection is the first dimension of the IUIPC because it captures the central theme of information exchange and the degree to which a person is concerned about it (Malhotra et al., 2004).

Control

Control is an important aspect of information privacy because consumers take on high risks when submitting personal information (Malhotra et al., 2004). Previous studies found that people desire more control over the use of their personal data and were less worried when they gave permission or were given the choice to opt out (Nowak & Phelps, 1995; Phelps et al., 2000). The control issue becomes elevated when there is a high potential for opportunistic behavior that leads to potential breaches in the social contract from exchanges (Malhotra et al., 2004). This second dimension of IUIPC targets many of the top concerns of researchers who have addressed the usage of AI by organizations (Okazaki et al., 2009; Puntoni et al., 2021; Walker, 2016).

Awareness

Control is an active component of information privacy, but awareness is a passive dimension (Malhotra et al., 2004) that refers to a consumer's understanding of the privacy practices used by an organization regarding information practices (Culnan, 1995). Because the interactive process of data collection can indefinitely store personal information for later usage, consumers tend to be uncertain of how and when their data will be shared (Okazaki et al., 2009). Awareness is the third dimension of the IUIPC scale and is based on two types of justice: interactional and informational (Malhotra et al., 2004). Violating transparency and ownership ideals of information leads to perceptions of unfairness. Perceptions of unfairness increase with the specificity of information used to provide a justification (Okazaki et al., 2009).

Perceived Severity

Perceived severity is defined as the impact that potential harm can cause from online security threats (Chen & Zahedi, 2016). Individuals have different experiences, expectations, and knowledge which leads to different levels of perceived severity (Kahneman & Tversky, 1979; Liang & Xue, 2009). This latent construct is a good indicator when used with perceived threat to encompass how a consumer can feel exploited with technology, especially newer technology like AI that they may not fully understand. Perceived severity has a direct effect on perceived threat, which is why these are included together.

Perceived Threat

Perceived threat draws on threat appraisal, where consumers evaluate the potential of harmful consequences from attacks of malicious information technology (Liang & Xue, 2009). When individuals have heightened feelings of being threatened, it changes their consumer behavior into avoidance out of protection. Perceived threat then plays into the overall feelings associated with exploitation.

Methodology

The hypotheses and methodology directly relate to the concept that privacy concerns with AI data capture led to feelings of exploitation. Based on empirical evidence from Parasuraman (2000) and Parasuraman and Colby (2015), the TRI was added to the study to determine if this variable affects the feelings of exploitation versus the feelings of being served by AI data collection based on a higher comfort level with technology as reflected in a higher TR score.

Hypotheses Development

As market competition increases, companies are turning their attention to how they can influence consumers through AI data capture (Putoni et al., 2021). Data can be obtained through various levels of understanding. Privacy concerns surrounding consumers' loss of control over their data leave them feeling exploited by AI data capture experiences. One trait variable that has provided insight to marketers regarding customers' use of technology like AI is the TRI score (Rojas-Mendez et al., 2017; Van Doorn et al., 2017). The belief is that consumers with higher scores, as measured by the TRI, will feel more served and less exploited by AI data capture, which led to the first hypothesis shown in Figure 2:

> H1: A negative relationship will exist between a person's TRI score and perceived threat, meaning a person with a low TRI score will feel more threatened by AI data capture.

Consumer vulnerability is more about the situation that people are in than it is about the people themselves (Brennan et al., 2017). This means demographics such as income, age, gender, or education do not necessarily have a direct relationship with a person's vulnerability when facing marketing efforts. However, a person's TR score can affect the anxiety or discomfort they experience when interacting with technology (Blut & Wang, 2020; Parasuraman, 2000); therefore, the second hypothesis reflects the pressure or uneasiness felt, which leaves them feeling more vulnerable or exploited:

> H2: A negative relationship will exist between a person's TRI score and their perceived severity, meaning they feel less secure when interacting with AI.

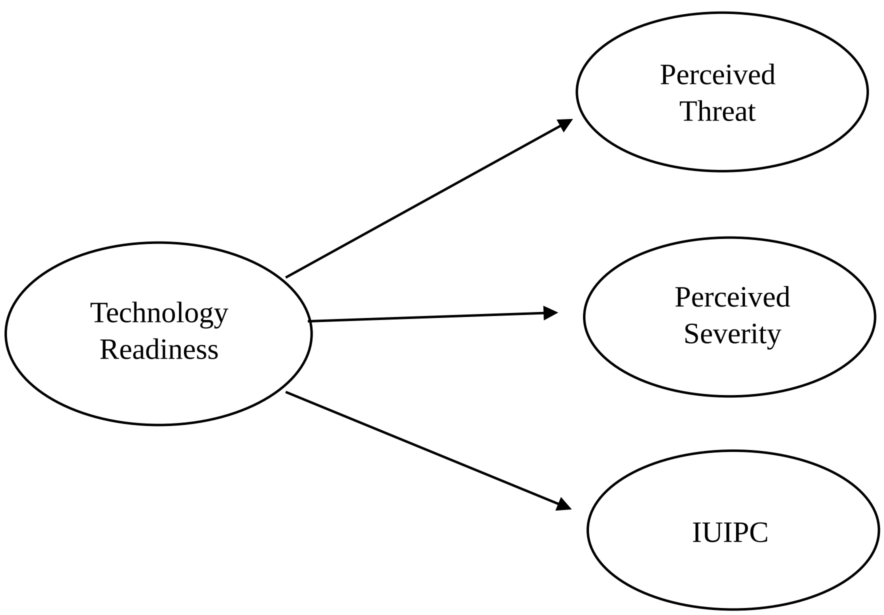
Technology readiness is an individual variable that is trait-like in how it can help assess an individual's attitude toward innovative technology (Parasuraman, 2000). Marketers have applied this understanding to explain consumers' technology usage (Blut & Wang, 2020). A person with a higher TR score finds technology easier to use, which increases their usage of it (Blut et al., 2016). Previous literature has also suggested that a person with a higher TRI score evaluates a particular technology higher in terms of value and satisfaction (Parasuraman & Grewal, 2000). The third hypothesis is based on this relevant research and projects that an increased understanding of AI algorithms used to personalize product selections will be tied to a higher TRI score.

H3: A negative relationship will exist between a consumer's TRI score and their IUIPC, meaning they better understand data capture and are thus less concerned with privacy issues.

These hypotheses are represented through the conceptual model found in Figure 2.

Figure 3.1

Technology Readiness Index Conceptual Model



Study Design

The research design was built on a quantitative approach to observe data collected through surveys regarding an individual's TRI in relation to feelings of exploitation from AI data capture. Quantitative results gained through the survey responses were statistically analyzed to develop insights and detect patterns. Three benefits of quantitative research and the usage of measurements to analyze data were noted by Bryman and Bell (2011): subtle differences can be assessed through measurement between people and the focal variable; measurement makes assessments more consistent; and measurement brings precision when estimating relationships between variables. Structural Equation Modeling (SEM) has become a preferred method for marketing researchers to analyze quantitative data because it offers more benefits and flexibility than first-generation techniques (Martinez-Lopez et al., 2013). Marketing researchers also regularly access the pedagogical work of Baron and Kenny (1986) to understand building models with proper variables being used for mediators and moderators, especially when using SEM, which is a large sample technique, and is better at analyzing complex models that contain many observed variables (Kline, 2015). Marketing researchers appreciate how SEM makes the assessment of latent variables and testing of relationships on a theoretical level possible (Hair et al., 2012), which is why it was chosen for this specific research.

Data Collection and Procedures

Data was obtained through the deployment of surveys once IRB approval had been achieved. Surveys were distributed at two different universities in the southeastern United States and online through social media accounts using the software program Qualtrics. Participants at the two universities were recruited using the nonprobability approach of convenience sampling. The survey link disseminated on social media used the snowball sampling approach, which requests that participants forward the opportunity to friends and family; those who were sent the link were able to complete the survey if over the age of 18 and fluent in English and after acknowledging their consent as seen in

Appendix A, regarding the use of their responses for research purposes. Finally, participants were asked to answer every question; if a participant opted out of any question, the option to terminate the survey was presented.

After the data were collected, it was screened to ensure valid responses and response rate. Surveys were checked for speeders, which are participants who complete the survey quickly and without putting adequate thought into their answers (Schoenherr et al., 2015). The data was cleaned for the most accurate results and tested using a two - step process, which is the standard recommendation when using SEM (Anderson & Gerbing, 1998; Martinez-Lopez et al., 2013). The first step uses the measurement model to test the validity of the constructs. The second step uses the structural model, which tests the hypotheses of the research. As noted by Martinez-Lopez et al. (2013), the most popular way to examine a goodness of fit for the measurement model is CFA, which is discussed below. Kenny (2020) confirmed that in addition to CFA, there exist other useful indexes when seeking model fit, such as the comparative fit index (CFI), the Tucker Lewis index (TLI), and the root mean square error of approximation (RMSEA), which are also discussed below. The structural model was assessed by looking at the factor loadings and critical ratios (*z* value) by using the standards found in a study by Groenland and Stalpers (2012).

Sample Size

Many published studies that rely on SEM are based on inadequate sample sizes (Kline, 2015). To avoid this, Schumacker and Lomax (2010) provided text that served as a basis for identifying a proper estimation. When using SEM analysis, it has been found that the best results appear when collecting the data of between 200 and 500 participants;

Kenny (2020) concurred, stating that SEM analysis should include at least 200 participants. Using the ratio developed by Bentler and Chou (1987), which calls for 5:1 between sample size and estimated parameters, would suggest that 185 participants were needed for the present study because it included 37 parameters. Because this sample fell below the prior recommendations for conducting a SEM analysis, the more conservative ratio of 10:1 suggested by Schumacker and Lomax (2010) was adopted, producing a target of 370 participants. Four hundred and thirty-three results were actually collected before being screened, which was well within range for accurate results.

Measures

A self-administered questionnaire was designed that combined four existing scales to reveal new insights into consumer behavior. The survey instruments were adapted to the context of AI data capture. For example, one item previously read, “New technologies contribute to a better way of life,” and the adaptation reads, “New technologies, such as AI, contribute to a better way of life.” These modifications ensured clarity. Instructions were given to participants before they began the survey that described the common uses of AI and prevalent data capture places that provide data for AI algorithms. The items were measured using the 5-point Likert scale ranging from 1 (*strongly disagree*) to 5 (*strongly agree*).

Each questionnaire included a consent section, a second section that used the 16-item TRI 2.0 scale, a third section that used the 10-item IUIPC scale, and a fourth section that included the scales for perceived severity and perceived threat. These scales have been used independently in many published studies and have been found to accurately test consumer behavior as it pertains to technology usage and privacy concerns. However, these scales have not been used together. Thus, the present study fills this gap in literature. The last section included basic demographic questions such as age, education level, gender, and race.

Scales and Their Validity

Technology Readiness Index

The TRI is based on individual behavior and beliefs surrounding technology (Mishra et al., 2018). Updated by Parasuraman and Colby (2015), TRI 2.0 uses a Likert scale ranging from 1 (*strongly disagree*) to 5 (*strongly agree*) and is more concise than the 1.0 version. However, the revised scale retained the overall structure and content, and is still comprised of four dimensions that include optimism, innovativeness, discomfort, and insecurity. When quantitatively testing for validity and reliability, Parasuraman and Colby (2015) found that the updated TRI 2.0 model had high reliability and explained 61% of the variance spanning the 16-item scale. Two decades of various researchers conducting empirical testing with this scale have confirmed its usefulness for assessing consumer behavior in relation to technology-related items, including social media usage (Lin & Hsieh, 2006; Parasuraman, 2000; Rojas-Mendez et al., 2017). When Parasuraman and Colby (2015) measured the frequency of survey respondents in their use of 11 social media activities, all were found to have significantly higher TR scores when engagement was frequent. This further solidified the validity of the scale to assess consumer behavior surrounding the engagement with AI and to determine if it is related to higher TR scores.

The Internet Users' Information Privacy Concerns Scale

The IUIPC scale was also deemed a good fit for empirically testing consumers' feelings of exploitation regarding AI data capture. The scale was developed in response to declining customer confidence surrounding information privacy (Malhotra et al., 2004). It proved to be more useful than previously existing scales that examined online privacy because it offered a theoretical framework on the specifics concerning information privacy where extensions into emerging technology such as AI could also be tested. Okazaki et al. (2009) successfully used this scale to determine consumer behavior with mobile advertising. It was found that the IUIPC scale produced consistent and valid results using the standards set in the research of Hair et al. (2006) when the composite reliability and average variance extracted were calculated. Malhotra et al. (2004) tested the scale using the SEM modeling technique to find that the variance explained 66% of the outcome variables, and overall, they found that the data fit satisfactorily and explained the large variance discovered in behavioral intent.

Perceived Severity and Threat

Liang and Xue (2009) developed a technology threat avoidance theory because perceived threats and the perceived severity of those threats have been found to alter consumer behavior to avoid potential harm (Rippetoe & Rogers, 1987). Perceived severity is defined as the magnitude of potential harm one could experience from online security threats. How an individual measures personal susceptibility to a threat and the severity of that threat is known as threat appraisal (Chen & Zahedi, 2016). Consumers feel threatened by how their information is collected and then used, and the magnitude to which they perceive those threats to be harmful produces feelings of exploitation and vulnerability. These scales were added to the present study protocols to aid in understanding the complex emotion of exploitation.

Measurement Model

The CFA model is used widely to assess the construct validity of the measurement instruments and represents the first step of the SEM process. Table 3.1 displays the results found from each observed indicator loading on the respective latent constructs.

Table 3.1

Measurement Model for TRI With Exploitation

	Std β	*SE*	*z*	*p*	95% CI *LL*	95% CI *UL*
Threat						
Threat_1	0.813	0.025	32.970	<.001	0.765	0.862
Threat2_R	0.807	0.025	32.370	<.001	0.758	0.856
Threat_3	0.638	0.035	18.260	<.001	0.569	0.706
Threat_4	0.587	0.038	15.320	<.001	0.511	0.662
Severity						
SEV_1	0.737	0.030	24.430	<.001	0.678	0.796
SEV_2	0.760	0.029	26.550	<.001	0.704	0.816
SEV_3	0.773	0.028	27.250	<.001	0.717	0.829
SEV_4	0.797	0.027	29.870	<.001	0.744	0.849
SEV_5	0.620	0.036	17.020	<.001	0.549	0.692
SEV_6	0.591	0.038	15.560	<.001	0.516	0.665
SEV_7	0.301	0.050	5.980	<.001	0.202	0.399
Tech Readiness						
Optimism1	0.443	0.048	9.320	<.001	0.350	0.536
Optimism2	0.329	0.052	6.300	<.001	0.227	0.432
Optimism3	0.287	0.054	5.340	<.001	0.182	0.392
Optimism14	0.384	0.051	7.550	<.001	0.284	0.484
Innovation1	0.292	0.053	5.470	<.001	0.187	0.397
Innovation2	0.246	0.054	4.540	<.001	0.140	0.353
Innovation3	0.303	0.054	5.650	<.001	0.198	0.408
Innovation4	0.226	0.055	4.120	<.001	0.118	0.333
Discomfort1	0.427	0.049	8.730	<.001	0.331	0.523
Discomfort2	0.356	0.052	6.870	<.001	0.255	0.458
Discomfort3	0.434	0.049	8.880	<.001	0.338	0.529
Discomfort4	0.385	0.051	7.560	<.001	0.285	0.485
Insecurity1	0.552	0.044	12.670	<.001	0.467	0.638
Insecurity2	0.490	0.047	10.430	<.001	0.398	0.583
Insecurity3	0.506	0.046	11.020	<.001	0.416	0.596
Insecurity4	0.491	0.046	10.740	<.001	0.401	0.580

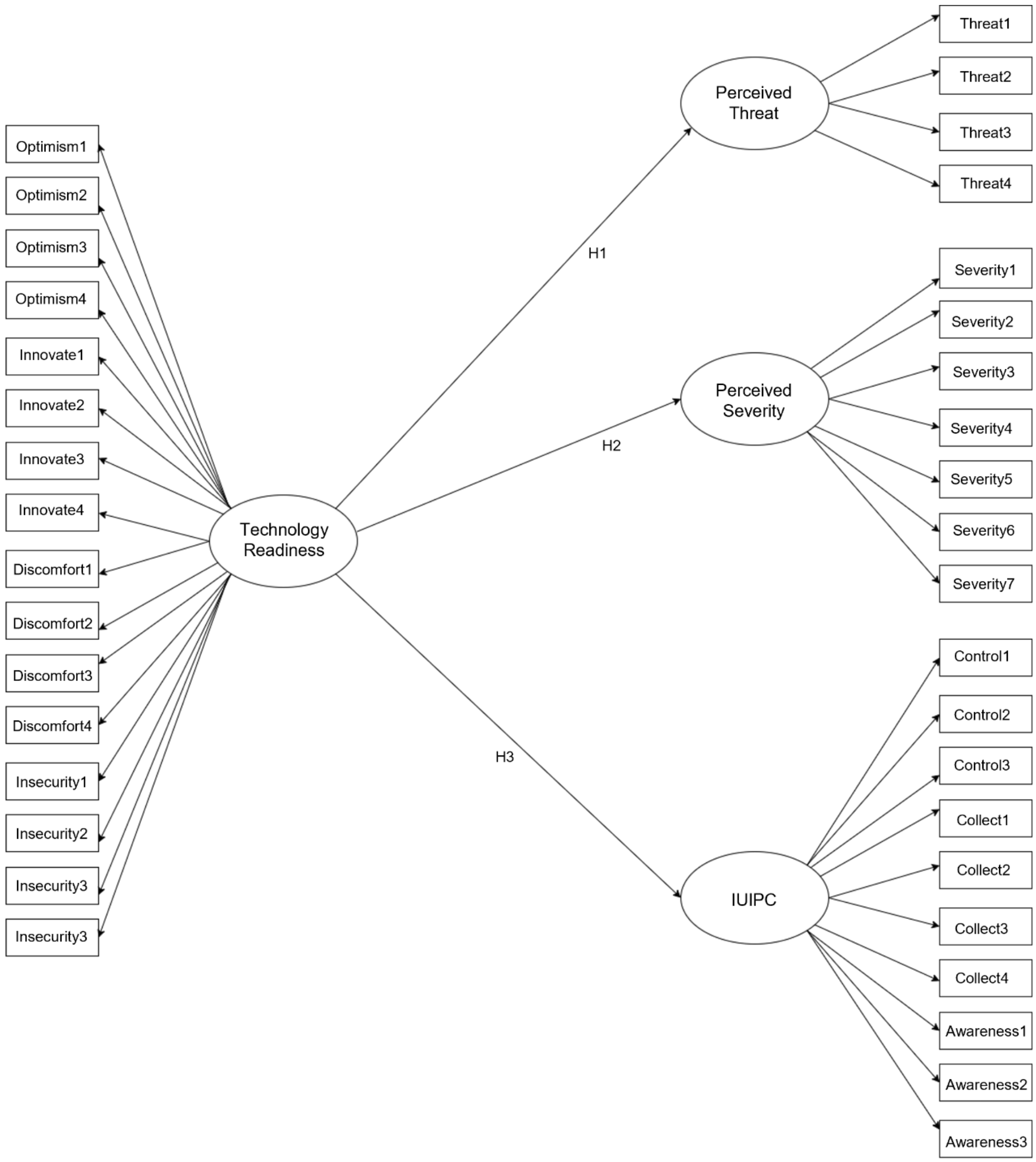
	Std β	*SE*	*z*	*p*	95% CI *LL*	95% CI *UL*
IUIPC						
Control1	0.046	0.050	0.920	0.357	-0.052	0.145
Control2	0.182	0.050	3.630	<.001	0.084	0.280
Control3	0.363	0.046	7.950	<.001	0.274	0.453
Collect1	0.774	0.023	33.270	<.001	0.728	0.820
Collect2	0.663	0.031	21.420	<.001	0.602	0.723
Collect3	0.852	0.018	47.440	<.001	0.817	0.887
Collect4	0.839	0.019	44.660	<.001	0.802	0.876
Awareness1	0.399	0.044	8.990	<.001	0.312	0.486
Awareness2	0.445	0.042	10.480	<.001	0.362	0.529
Awareness3	0.539	0.038	14.200	<.001	0.464	0.613

Note. CI = confidence interval; *LL* = lower limit; *UL* = upper limit; SEV = severity; IUIPC = Internet Users' Information Privacy Concerns.

For most of the latent constructs, the CFA indicates that they have statistically significant loadings. All but one *p* value was < .001, and that one was the Control_1 variable from the IUIPC scale. For the threat, severity, TRI latent constructs, and most of the IUIPC, the observed variables showed strong positive loadings. Control_1 was retained for theoretical purposes. This model shows that it is an acceptable fit for the data, although the RMSEA was 0.055, which is only slightly higher than the 0.05 desired cutoff. The CFI emerged at 0.863, and although it did not meet the ideal cutoff of 0.9, it still showed a reasonable fit. The model does explain a large proportion of the variance in the observed variables (0.998) in the coefficient determination (CD) and because most indicators show strong loadings on their respective latent constructs, this suggests that the model is both valid and reliable for the intended measurements of this study.

Figure 3.2

Technology Readiness Index Score Exploitation Measurement Model



Results

Data Screening

All respondents answered the survey through an anonymous Qualtrics link. Anyone under the age of 18 was not allowed to respond. After the survey had been available for 3 weeks, there were 433 respondents. The data was cleaned, and respondents were removed for not providing complete answers to all questions, taking under 5 minutes to answer, or for abandoning the survey after starting. Data was also studied to ensure that reverse answers were given appropriate ratings in line with other asked questions. This screening process reduced the total amount of usable surveys to 410 (94.6%). Demographic information was collected but not used for screening purposes because it did not account for anything being tested.

Sample Demographics

Even though demographics were not used to analyze relationships, Table 3.2 shows the makeup of the participants. Over 63% of respondents were between the ages of 18 and 26 years old. More than 46% had earned or were pursuing a bachelor's degree in higher education. Females accounted for the majority of respondents, with more than 62% participating, and African American and Caucasians constituted the top ethnicities reporting, making up over 83% combined.

Table 3.2

Demographic Characteristics

Variable	*n*	%
Generation		
1	259	63.20
2	71	17.30
3	48	11.70
4	29	7.10

Variable	*n*	%
5	2	0.50
6	1	0.20
Education		
Associate’s degree or some college	67	16.30
Bachelor’s degree	189	46.10
Doctorate or terminal degree	34	8.30
High school or GED	62	15.10
Master’s degree	56	13.70
Professional degree	2	0.50
Gender		
Female	258	62.90
Male	148	36.10
Prefer not to answer	4	1.00
Ethnicity		
African American or Black	47	11.50
African American or Black, Caucasian	1	0.20
African American or Black, Caucasian, Native American	1	0.20
African American or Black, Hispanic, Latino, or Spanish	1	0.20
African American or Black, Hispanic, Latino, or Spanish, Caucasian, Asian, Native American, Other	1	0.20
African American or Black, Native American, Other	1	0.20
Asian	8	2.00
Caucasian	294	71.70
Caucasian, Asian	5	1.20
Caucasian, Native American	3	0.70
Caucasian, Native American, Other	1	0.20
Caucasian, Other	1	0.20
Hispanic, Latino, or Spanish	27	6.60
Hispanic, Latino, or Spanish, Asian, Native American	1	0.20
Hispanic, Latino, or Spanish, Caucasian	3	0.70
Native American	4	1.00
Other	11	2.70

Cronbach's Alpha

To test for internal reliability, Cronbach's alpha coefficients were used to assess the study measures. The latent constructs that were specifically being tested included perceived threat, perceived severity, IUIPC, and TRI. Some of the subsets were also tested, although these should not be used in isolation. Table 3.3 shows the results.

Table 3.3

Cronbach's Alpha

Construct	No. of Items	α
Perceived threat	4	.822
Perceived severity	7	.850
IUIPC	10	.810
Control	3	.618
Collect	4	.859
Awareness	3	.718
Technology readiness	16	.772
Optimism	4	.758
Innovativeness	4	.747
Discomfort	4	.610
Insecurity	4	.647

Note. IUIPC = Internet Users' Information Privacy Concerns

To demonstrate adequate reliability, Bryman and Bell (2011) have recommended a value of $\alpha > .7$, which all constructs met. The constructs had strong factor loadings ranging from .772 to .850, as seen in Table 3.1.

Measurement Model Analysis

Using the software STATA-17, the data was analyzed using SEM. After running the CFA for goodness of fit, the second step of SEM is to use the structural model to test the hypotheses. Table 3.1 shows the results of the CFA. The model showed an adequate fit for the measurements and was a reliable representation. In addition to the CFA, the CFI was 0.863, and the TLI was 0.850; although slightly lower than the ideal cutoff of

.90, these still met the requirements for an acceptable model. The RMSEA score was 0.055, again in an acceptable fit range. Kenny et al. (2015) discussed that in larger sample surveys, a RMSEA score closer to .08 would be considered a mediocre fit; therefore, this model was well below that cutoff. For the threat latent construct, all four indicators showed strong positive loadings ranging from .587 to .813. The severity construct also showed positive loadings, from .301 to .797, for all seven indicators. Next, the TRI latent construct showed significant loadings for each of the observed variables, ranging from .226 to .552 among all four dimensions tested. Finally, the IUIPC had significant loadings for most of the observed variables (.0182 to .852), except for the observed indicator for Control_1 (.046). This variable was retained for theoretical contribution and because it passed reliability tests in previous literature (Malhotra et al., 2004; Okazaki et al., 2009).

Structural Model Analysis

The three hypotheses shown in Figure 3, were tested after the CFA measurement model found this to be an acceptable fit. The results of the structural model are detailed in Table 3.4. The three hypotheses and their results are detailed as follows:

> H1: A negative relationship will exist between a person's TRI score and perceived threat, meaning a person with a low TRI score will feel more threatened by AI data capture.

Results indicated a strong negative relationship between TRI and threat (*SE* = 0.041, z = -17.210, $p < .001$). This affirms Hypothesis 1, suggesting that the higher a person's TRI score is, the less they feel threatened by AI technology.

> H2: A negative relationship will exist between a person's TRI score and their perceived severity, meaning they feel less secure when interacting with AI.

Hypothesis 2 showed a negative relationship between a person's TRI score and severity (*SE* = 0.055, *z* = -6.470, *p* < .001). This supports the hypothesis and explains that as a person's TRI increases, the perception of severity decreases.

> H3: A negative relationship will exist between a consumer's TRI score and their IUIPC, meaning they better understand data capture so are less concerned with privacy issues.

The analysis of Hypothesis 3 revealed a significant negative relationship between TRI score and IUIPC for participants (*SE* = 0.035, *z* = -20.990, *p* < .001). This supports the hypothesis that a person with a higher TRI score exhibits fewer privacy concerns. All three hypotheses were supported with significant negative relationships between the TRI score and the latent constructs of threat, severity, and IUIPC.

Table 3.4

Measurement Model for TR and the latent constructs

		Std β	*SE*	*z*	*p*	95% CI *LL*	95% CI *UL*
TR	→ Threat (H1)	-0.700	0.041	-17.210	<.001	-0.780	-0.620
TR	→ Severity (H2)	-0.353	0.055	-6.470	<.001	-0.460	-0.246
TR	→ IUIPC (H3)	-0.743	0.035	-20.990	<.001	-0.812	-0.674

Note. TR = technology readiness; CI = confidence interval; *LL* = lower limit; *UL* = upper limit.

Discussion

TRI 2.0 is a frequently cited scale that has accurately assessed a person's adoption behavior regarding technology (Parasuraman, 2000; Parasuraman & Colby, 2015). This research evaluated whether a TRI score could indicate whether that person felt more exploited or served by an emerging technology such as AI. Organizations are rapidly looking to increase their usage of AI, but little literature exists on consumer preferences. Researchers have taken note of the increasing interest in consumers' privacy concerns (Davenport et al., 2020; Puntoni et al., 2021) but had not determined the extent to which this may inhibit consumer behavior.

Four hundred and ten participants consented to take an online survey. The results were analyzed quantitatively to see if TRI could accurately determine how a person felt regarding exploitation from AI data capture. Additionally, SEM analysis was used to test the reliability and relationships between the observed indicators and their respective latent constructs. All three hypotheses were supported and showed that TRI was an indicator of complex emotions tied to emerging technology such as AI. Strong negative relationships appeared between the constructs of TRI and threat, severity, and IUIPC. This means that as a person's TRI score increases, their feelings of being threatened, fear of severe impact, and fear of privacy concerns all decrease.

Managerial Implications

This research shows that it would be most beneficial to start discussions of AI data capture within educational institutions since TR was found to be related to consumers feeling more served as opposed to exploited. From early ages, schools across the world educate children on a variety of technology. As the literature suggests, AI has been and will continue to increase, so educating consumers for these constant interactions would augment their overall education experience.

New AI technology, such as Replika, which is self-described as an empathetic AI friend (Replika, 2023), has young consumers gravitating towards it. This research shows that people who have a higher TRI feel more served by AI data capture, and this is a prime example. Organizations can use this knowledge to help encourage the social images of consumers through uplifting messages. On the other side, as trust increases in an inanimate object for consumers, this research helps aid public policy geared towards protection and privacy limitations.

Limitations

This study poses several limitations. Demographic limitations existed due to data being collected largely from young (63% between the ages of 18 and 24), white (Caucasian 72%), educated (68.6% with a bachelor's degree or higher) females (63%). This is not an accurate sample of the current consumer market in the United States. Another limitation is that these data were collected through a self-administered survey where misinterpretations could have occurred. Lastly, this research culled most of its respondents from university campuses in the southeastern United States, which produced geographical limitations from both the cultural and workforce aspects. It should be noted, however, that even with these limitations present, all three theoretically-based hypotheses were supported.

Future Research

One avenue for future research would be to examine these same constructs in a different cultural context. Replicating this study in a country that is distinct from the United States would prove beneficial. Second, this research did not address the variety of data capture methods by each device that AI is currently using. Specifying the brand or type of AI could produce a stream of future research through which individual capture methods may create stronger feelings of exploitation than others. Third, more research regarding privacy concerns surrounding AI friends and where limitations exist would help this emerging product. Lastly, future research could pursue a case study component through which pretests and posttests measure a person's feelings of exploitation around interaction with an AI-embedded robot.

Conclusion

Data were collected, screened, and analyzed using SEM to determine if TRI 2.0 could be an indicator of consumers' feelings of exploitation regarding AI data capture. Four hundred and ten participants were surveyed, and it was found that TRI 2.0 could detect whether a person felt more exploited or served by AI data capture. This finding provides another way that the TRI scale can be used by organizations when determining their target markets and developing products for consumers. Knowing that people who possess a higher TRI score feel less threatened, perceive less severity, and carry fewer privacy concerns regarding AI is beneficial for technology adoption literature. This research filled gaps in the literature for both academics and practitioners about consumer adoption behavior regarding emerging technology. As technology advances, TRI 2.0 can continue to accurately assess changes in consumer behavior.

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APPENDIX A: PARTICIPANT CONSENT FORM

Gardner-Webb University IRB

Informed Consent Form for Online Survey

The Consumer Behavior Impact of data collection through Artificial Intelligence

Hello and thank you for taking time to consider partaking in this survey. My name is Emory Hiott and I am currently pursuing my Doctorate of Business Administration at Gardner-Webb University. Your truthful answers will aid in my research as well as help organizations as they seek to increase their usage of Artificial Intelligence into consumer interactions. I would be honored if you would participate by taking this brief survey.

The purpose of this research is to see if you feel more exploited or served by Artificial Intelligence (AI) data collection. As a participant in the study, you will be asked to answer all of the questions including demographic information. It is anticipated that the study will require about 10 minutes of your time. Participation in this study is voluntary. You have the right to withdraw from the research study at any time without penalty. You also have the right to refuse to answer any question(s) for any reason without penalty. The information that you give in the study will be handled confidentially. Your data will be anonymous which means that your name will not be collected or linked to the data. There are no anticipated risks in this study. You will receive no payment for participating in the study. You have the right to withdraw from the study at any time without penalty by exiting the survey. Data from this study will be used or distributed for future research studies.

<u>If you have questions about the study, contact:</u>
S. Emory Hiott
843-513-7850
Shiott1@gardner-webb.edu

Dr. Ellen Sousa
704-941-5218
esousa@gardner-webb.edu

Dr. Sydney K. Brown
IRB Institutional Administrator
Telephone: 704-406-3019
Email: skbrown@gardner-webb.edu

Clicking the link below to continue on to the survey indicates your consent to participate in the study:
https://gardnerwebb.az1.qualtrics.com/jfe/preview/previewId/8e138bbd-1724-4e35-91d0-5e4d8c8f3a7d/SV_51GoNZ7JX9yadJI?Q_CHL=preview&Q_SurveyVersionID=current

If you are not 18 years of age or older or you do not consent to participate, please close this window.

APPENDIX B: PARTICIPANT SURVEY

Questionnaire:

ARE YOU AT LEAST 18 Years Old?

Social media sites use AI to collect information that you post and that you have previously searched for to personalize advertisements to you. These along with devices such as Alexa or Siri, which are considered Artificial Assistants; and inventions like Roomba collect data from our lives to create AI algorithms. Please use this knowledge when moving forward with the next set of questions.

Have you interacted with AI (Amazon's Alexa, iPhone Siri, Roomba, Social Media, etc.) before?

How often do you use: Alexa, Siri, Roomba, Social Media? Never, Seldom, Occasionally, Every day, Multiple times a day

As you read through the following questions, please rate your feelings on Artificial Intelligence based on the five-point Likert scale. Artificial Intelligence commonly used for data capture include: Amazon's Alexa, Apple's Siri, iRobot's Roomba, social media sites and website cookies to suggest personalized purchases. It is important that you answer these questions with technology such as these examples in mind.

The TRI 2.0 scale (Parasuraman and Colby, 2015)

1. New technologies, like AI, contribute to a better quality of life.
2. Technology, specifically AI, gives me more freedom of mobility
3. Technology, specifically AI, gives people more control over their daily lives.
4. Technology, specifically AI, makes me more productive in my personal life.
5. Other people come to me for advice on new technologies
6. In general, I am among the first in my circle of friends to acquire new technology when it appears.

7. I can usually figure out new high-tech products and services without help from others.
8. I keep up with the latest technological developments in my area of interest.
9. When I get technical support from a provider of a high-tech product or service, I sometimes feel as if I am being taken advantage of by someone who knows more than I do.
10. Technical support lines are not helpful because they don't explain things in terms I understand.
11. Sometimes, I think that technology systems, like AI, are not designed for use by ordinary people.
12. There is no such thing as a manual for a high-tech product or service that's written in plain language.
13. People are too dependent on technology to do things for them.
14. Too much technology distracts people to a point that is harmful.
15. Technology lowers the quality of relationships by reducing personal interaction.
16. I do not feel confident doing business with a place that can only be reached online.

AI collects data from your previous purchases to recommend other items you may enjoy or need. They also collect personal data while setting up the devices and continue gathering information while in use. While answering these next questions, think of items that have been recommended to you on websites, social media, or through a virtual assistant (such as Alexa or Siri). Also, please think of the devices you use and the information you've had to provide for optimal service. Again, use the five-point Likert scale to select the feeling associated with each question.

The Internet Users' Information Privacy Concerns Scale Questions (according to Malhotra et al., 2004):

All are a 5-point Likert scale from strongly disagree to strongly agree

Control:

1. Consumer online privacy is really a matter of consumers' right to exercise control and autonomy over decisions about how their information is collected, used, and shared.
2. Consumer control of personal information lies at the heart of consumer privacy.

3. I believe that online privacy is invaded when control is lost or unwillingly reduced as a result of a marketing transaction.
    a. Collection:
4. It usually bothers me when I think about how AI devices use my personal information.
5. When AI devices ask me for personal information, I sometimes think twice before providing it.
6. It bothers me to give personal information to so many different AI devices.
7. I'm concerned that AI devices are collecting too much personal information about me.
    a. Awareness:
8. Companies seeking information through my AI devices should disclose the way the data are collected, processed, and used.
9. A good consumer online privacy policy should have a clear and conspicuous disclosure.
10. It is very important to me that I am aware and knowledgeable about how my personal information will be used.

Perceived Severity **Chen and Zahedi (2016); Liang and Xue (2009)**

1. PSEV1-AI may perpetuate cultural stereotypes in available data
2. PSEV2-AI may amplify discrimination in available data
3. PSEV3-AI may be prone to reproducing institutional biases in available data
4. PSEV4-AI may have a propensity for intensifying systemic bias in available data
5. PSEV5-AI may have the wrong objective due to the difficulty of specifying the objective explicitly
6. PSEV6-AI may use inadequate structures such as problematic models
7. PSEV7-AI may perform poorly due to insufficient training

Perceived Threat **Chen and Zahedi (2016); Liang and Xue (2009)**

8. PT1-My fear of exposure to AI's risks is high
9. PT2-The extent of my worry about AI's risks is low
10. PT3-The extent of my anxiety about potential loss due to AI's risks is high
11. PT4-The extent of my worry about AI's risks due to misuse is high

Demographic questions

Age: How old are you? (Fill in box)

Education level: High School or equivalent; Some college; Bachelor's degree, Master's degree, Professional Degree, Doctorate or equivalent

Gender: Male, Female, prefer not to answer

Race: Caucasian, African-American, Hispanic, Asian, Native American, Other

APPENDIX C: SURVEY INVITATION

Email Recruitment:

Hello ____,

I am currently collecting data for my DBA dissertation on how people feel either more exploited or served through Artificial Intelligence (AI) data collection. I would be honored if you would take 10 minutes of your time to take my survey. This research will help organizations and academic researchers better understand how consumers feel when their information is gathered.

Thank you in advance for your time,

Emory Hiott

Social Media Post:

I am in the process of researching how people feel about Artificial Intelligence (AI) data collection. This will help me complete the requirements for my DBA degree, so I would appreciate if you were willing to take this 10 min. survey. Thanks!

Verbal Request:

Hello _____,

I am collecting information to better understand how people feel about Artificial Intelligence (AI) data collection. I have a survey that I would like for you to take. It will take 10 minutes of your time and will help me know whether people feel more exploited or served by current AI data collection methods. May I get an email address to send you the survey?

Thanks!

Recruitment Email to Professors:

Hello**,**

I have now made it to the portion of my dissertation where I have begun data collection! To help with this collection process, I would appreciate if you would distribute this survey link to your students. It will not take them more than 10 minutes and it is completely anonymous. If you wish to give extra credit for this then please offer students an alternative assignment if they do not wish to take my survey. The extra assignment could be a short three-page paper on how they think AI will change their lives over the next 10 years. To receive credit and still keep their answers anonymous, students can show or upload the completion page to Blackboard. Thank you for being willing to help my research!

APPENDIX D: PERMISSIONS

Email acknowledgement of Academic license for TRI 2.0.

From: Charles Colby ccolby@rockresearch.com

Monday 12/5/2022

To:shiott1@gardner-webb.edu

Sally Hiott

CAUTION: This email originated from outside of the Gardner-Webb.edu domain. Do not click links or open attachments unless you verify that the links and/or attachments are safe.

Hi Sally, I apologize. The mail must have gotten lost in the chaos of November. You now officially have a license to use the TRI 2.0 for your academic study. As a resource, I am attaching a list of scale items and recommendations on administration. Let me know if you have questions.

CC

IUIPC, PERCEIVED SEVERITY, PERCEIVED THREAT

Marketing Scales Handbook, V6. Copyright © 2012, GCBII Productions. All rights reserved. ISBN-10:0615630685 ISBN-13:978-0-615-63068-7 GCBII Productions 6109 Timberwolfe Fort Worth, Texas 762135 USA Reviews of the measurement scales provided in this book are the intellectual property of GCBII Productions. Unless otherwise noted, ownership and copyright of the scales themselves is not clear. **The overwhelming majority of scales can be used freely but citations of the original source or some previous users is expected when reports or papers are written that refer to the scales.** Published in the United States of America

APPENDIX E: IRB APPROVALS

CHARLESTON SOUTHERN UNIVERSITY

Emory,

Your study is approved, IRB# 2022-74.

Please make sure you submit an IRB completion report when you finish the study.

Just a note, the psychology department would allow you to post on blackboard a recruitment for your study. The only thing they ask is you also encourage your students to participate in our studies. We have a Psychology Research Participation Blackboard page where we advertise research studies.

Amanda Harmon, PhD
Assistant Professor of Psychology
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GARDNER-WEBB UNIVERSITY

Institutional Review Board

THIS IS TO CERTIFY THAT THE RESEARCH PROJECT TITLED

____

being conducted by ______________________________

has received approval by the Gardner-Webb University IRB. Date _02/09/2023_

Exempt Research

Signed Sydney K Brown ______________________________________

IRB Institutional Administrator

Expedited Research

Signed ____

IRB Institutional Administrator

____

IRB Chair

Full Review

Signed ____

IRB Administrator

____

IRB Chair

____

Member

Expiration Date: ___02/08/2024_____ **IRB # 22121302**

IRB Approval: __X_ Exempt _____ Expedited ______ Full Review