Expanding protection motivation theory: The role of parent and caregiver perceptions in mediating artificial intelligence usage by children

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Abstract

This study aimed to examine parents' and caregivers' perceptions of their behavioral intention to engage in parental mediation of their children's use of AI. Specifically, this study expanded the use of the Protection Motivation Theory and the Risk Behavior Diagnosis (RBD) Scale developed by Witte et al. (1996) to determine the extent that the constructs of perceived severity, perceived vulnerability, self-efficacy, and response efficacy predicted behavioral intention to engage in parental mediation of AI. The participants of this study included parents and caregivers who completed an online survey in the fall of 2024. The results showed that parents and caregivers gave the lowest rating to the statement "It is easy for me to establish limits or restrictions on my child's AI use." (M = 4.24) and the highest training to the statement "I plan to discuss the risks and benefits of AI with my child." (M = 6.16). The evidence showed a positive weak correlation between perceived severity and behavior intention and perceived vulnerability and behavior intention. Perceived severity explained a marginally significant proportion of variance (7.6%) in behavioral intention ratings, as for every 1-point increase on the perceived severity Likert scale, the behavior intention score will increase by .175 points. Recommendations following the study included future research on the most effective and engaging modalities and pathways for supporting parental mediation of AI, including via informal and formal learning structures.

Dedication

I dedicate my dissertation to my family, friends, and colleagues, who provided inspiration, encouragement, and feedback throughout the process. I offer a special thank you to my parents. My mom taught me to love writing from the first writer's notebook we kept together before I could even read. My dad taught me the value of working hard to achieve goals. I also want to give gratitude to my husband, Rich, and my daughter, Adelaide, who have reminded me to have grace with myself while also encouraging me to accomplish this goal. Finally, I dedicate this dissertation to my Aunt Susan, who has always known what to say to keep me moving forward in my academic pursuits.

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Chapter 1

Introduction

In November 2022, OpenAI's release of ChatGPT launched a flurry of interest, excitement, and apprehension regarding generative artificial intelligence (GAI) built on large language models (LLMs) and their impact on education. GAI tools such as ChatGPT, Grammarly, and Google Bard answer questions, complete written tasks, respond to prompts, and produce human-like, multimodal content, leaving many scrambling to unpack the effect on children and their learning (United Kingdom Department of Education, 2023). Yang et al. (2021) noted that the generated text or images using GAI are often indistinguishable from those created by humans, resulting in many possibilities and increasing concerns of misuse for educators and stakeholders throughout K-12 school systems.

The current study explored the perceptions of one of these stakeholder groups, namely parents and caregivers, regarding their role in understanding, discussing, and monitoring AI in education use with children. By applying the Protection Motivation Theory (PMT) to understand better the motivators and behavioral intentions of parents and caregivers when engaging in mediation regarding AI, effective and practical resources can be developed to support this stakeholder group. Further, K-12 school systems, professional organizations, and instructional designers can partner to build resources, tools, and policies for engaging in shared dialogue to maximize the potential and minimize the risks of AI.

Beginning with a brief review of previous technology innovations in K-12 education, this chapter outlines the components of this study and its intention to determine parents' and caregivers' perceptions regarding students' use of AI. This outline includes background information, the problem statement, the purpose and significance, the delimitations and assumptions, the research questions, and the definitions of terms critical to the research.

Background

While the call for AI safeguards, resources, and training in K-12 education systems and the stakeholders within these systems is relatively recent, understanding the impact of technology on children and the need for clarity regarding how best to leverage its impact is certainly not a new phenomenon. Over forty years ago, the Commission on Educational Excellence (1983) published a federal report titled *A Nation at Risk*, which acknowledged the growing ubiquity of computers and the risk of failing to prepare students for the transformation of society via technology. Since then, 21st-century skills, one-to-one device initiatives, social media, gamification, and other innovations have impacted students' classroom experiences. Equally extensive are ways that parents and caregivers, school systems, and professional organizations have attempted to determine best practices, safeguards, and policies to maximize technology's potential rewards and minimize possible harm–a challenge central to today's current AI conversation.

For parents and caregivers, awareness of and adherence to best practices regarding children and technology is often fraught with mixed messages and motivations. For example, Pappas (2020) reported that despite research recommendations frequently being presented as black and white, screen time research has largely been less than definitive due to a lack of robust longitudinal studies. Meanwhile, Elson et al. (2019) analyzed policy statements on the effects of digital media on children and found that the most needed revisions were in substance, scientific basis, and balance. Further, while the variety of tools and guidelines is proliferative, knowing how to translate them to prepare and support students is evolving (Harvard Center for Digital Thriving, 2024). Therefore, understanding how parents and caregivers perceive AI and appropriate meditative action can support better policies, future research, and school system practices.

Parental perceptions must be considered critical next steps in artificial intelligence in education as this stakeholder group influences students' classroom experiences in many ways. Feser (2024) reported that numerous studies provide evidence that parents have a "decisive impact" on students' educational outcomes, performance, and attitudes via their "support, beliefs, and expectations" (p. 4). Similarly, Dumitra and Campean (2022) cited parents as children's primary instructors and identified the unity of school and family as a significant determinant of compelling educational experiences for students. Several researchers pointed to the impact of parent and caregiver support for technological tools on children's positive beliefs (del Carmen Ramirez-Rueda, 2011; Maxwell et al., 2021; Ortiz et al., 2011). Further, researchers pointed to parents' influence on the effectiveness of past and current technology initiatives, including digital textbooks, one-to-one programs, and digital educational games (Maxwell et al., 2021; Parsons & Adhikar, 2016; Xie et al., 2021). This research includes evidence that parent and caregiver perceptions influenced teachers' attitudes regarding technology implementation (Xie et al., 2021).

Statement of the Problem

Despite the calls for active parent and caregiver engagement in guiding children's use of technology and AI, data regarding parents' and caregivers' perceived efficacy in doing so has yet to be gathered (Sykes & Rezach, 2023). Several surveys have targeted broad topics regarding parents and AI, including the Echelon Insights Survey (2023), which found that 62% of parents reported wanting more information about how AI is used in schools. Feser (2024), whose research found that parents generally held positive views regarding AI chatbots in high school science, technology, engineering, and math (STEM) classes but lacked clarity in other subject areas, stated that in-depth inquiry into parents' attitudes, perspectives, and concerns regarding AI is essential to understanding its impact and effectiveness in educational settings. Further, Reyes-Villalba et al. (2024) stated that collaborative efforts are necessary to leverage AI efficaciously, including acknowledging benefits and challenges across settings. Therefore, a better understanding of parents' and caregivers' perceptions regarding children's susceptibility to AI's possible risks, protective behaviors for limiting these risks, and self-efficacy for effective parental mediation is needed.

Purpose of the Study

This study intends to understand better how parents and caregivers perceive their roles and influence in guiding and mediating children's use of AI. PMT serves as a framework for analyzing parent and caregiver perceptions regarding threat appraisal (TA) and coping appraisal (CA) in the context of parental mediation and AI. By applying the theoretical framework to a survey, an analysis of perceptions regarding the perceived severity of the threat of AI to children and children's perceived vulnerability to AI's possible risks can be weighed against the likelihood of potential protective actions. Further, parents' and caregivers' perceived efficacy (both self-efficacy and response efficacy) in impacting and shaping children's use of AI can be weighed against their behavioral intentions. With this information, stakeholders can more effectively collaborate in creating resources, materials, and guidelines to help families navigate and mediate the ever-evolving AI landscape to support effective learning outcomes and experiences.

Significance of the Study

Tuomi et al. (2022) argued that while claims regarding AI are omnipresent, the research is minimal; certainly, this is true regarding developing AI guidance for parents and caregivers. Indeed, the reality of AI brings both opportunity and risk. Without research and attention to the impact on children, AI's evolution could proceed without considering children's needs, rights, and futures (UNICEF, 2024). By examining the role of the parent and caregiver, a greater understanding regarding perceived response efficacy and self-efficacy in addressing AI with children can drive the development of resources, guidelines, and support. As Jin and Schmidt-Crawford (2017) noted, "Compared to teachers and students, parents are rarely the focus of the [educational technology] research despite their influential roles in student learning" (p. 125).

Woo et al. (2023) identified developers and designers as necessary participants in the process of involving and educating stakeholders regarding AI. This reality allows instructional designers to develop digital safety and curriculum content through various pathways. Long et al. (2022) suggested designing informal learning contexts to provide spaces for families to learn about AI together and facilitating opportunities for collaborative dialogue and multi-generational perspectives regarding its use. In one example, researchers designed a science museum exhibit for families to explore AI together. In another example, Register and Ko (2020) explored Coursera course videos as a vehicle for teaching advocacy regarding machine learning. The results of the current study could add to the body of knowledge on best practices for supporting parents and caregivers in addressing technology's positive and negative impacts on children through mediation. Further, it could help inform policy and educational programs for families regarding AI to enhance children's cognitive, emotional, or social development outcomes.

Delimitations

Delimitations are limitations consciously set as boundaries or limits of a study to ensure focus and feasibility (Theofanidis & Fountouki, 2019). The following delimitations were defined for this study:

1. This research analyzed the protective intentions and perceptions of parents and caregivers living in the United States. The results could differ using similar parent and caregiver populations from other countries.
2. This research's non-experimental quantitative design utilized self-reported data. Hersen and Bellack (1976) noted that behavioral observation can yield a different portrait of the variables than self-report.
3. The research study applies a theoretical framework and survey structure traditionally utilized with specified health behaviors. While it has been applied to technology safeguards, neither has been explicitly applied to parental mediation and artificial intelligence.

Assumptions

Certain assumptions associated with the measurement tool and data collection were made for this study. It was assumed that survey participants had a general knowledge of artificial intelligence. It was also assumed that participant responses equated to their perceptions of the survey questions and an accurate understanding of them. Additionally, participant demographic information used to determine the study's criteria was self-reported. Finally, it was assumed that PMT can be applied to this research study. Even though this theory has not been explicitly applied to predict protective intentions or perceptions of parents and caregivers regarding AI, it is reasonable to apply because it is a widely used theory applied to health-related decision-making and, more recently, technology safeguards.

Research Questions

The research questions for this study are as follows:

RQ1

To what extent does the perceived threat severity of AI to children affect parents' and caregivers' intentions to engage in parental mediation?

RQ2

To what extent does the perceived vulnerability of children to the possible risks of AI affect parents' and caregivers' intentions to engage in parental mediation?

RQ3

To what extent does perceived self-efficacy affect parents' and caregivers' intentions to engage in parental mediation regarding AI?

RQ4

To what extent does perceived response efficacy affect parents' and caregivers' intentions to engage in parental mediation regarding AI?

Definition of Terms

Active Mediation

Active mediation refers to parents' or caregivers' engagement in active discussion regarding technology and includes positive active mediation (i.e., comments on benefits) and negative active mediation (i.e., comments on risks) (Beyens et al., 2019; Snyder, 2023).

Artificial Intelligence

Celik et al. (2022) defined artificial intelligence as computers performing cognitive tasks associated with the human mind. These cognitive tasks include analytical methods such as learning and problem-solving and can be classified as machine learning, neural networks, and deep learning. Gillani et al. (2023) explained machine learning algorithms as those designed to mine datasets to "learn" rules and patterns to inform forecasting. Machine learning includes supervised learning, using historical datasets and targeted outputs that "supervise" the model (Gillani et al., 2023, p. 100). They also include unsupervised learning for pattern recognition without labels determining the desired output (Gillani et al., 2023, p. 100). Neural networks learn the relationships between variables to output predictions and can manifest via various algorithmic architectures (Gillani et al., 2023, p. 101). Deep learning utilizes backward propagation to identify structures in large data sets, thus leveraging complex, multi-layered neural networks (Webb et al., 2020). In other words, deep learning combines small neural networks into larger ones using outputs to discover complex and granular relationships (Gillani, 2023).

Co-use

Co-use refers to parents and caregivers consuming or co-using technology or media content with their child without additional commentary about its use (Valkenburg et al., 1999).

Parents and caregivers

Caregivers are the adults most responsible for a child's day-to-day care and decision-making in their home environment (Cohen et al., 2011). This study's caregivers include biological, foster, and adoptive parents and non-parent guardians (Hammes, 2023). Betts (2024) wrote, "Parents are their children's first teachers and are often the most well-positioned in terms of proximity (both physical and relational) to provide children with modeling, scaffolding, and expectations" (p. 5). Therefore, parents and caregivers in this study are also regarded as the first instructors of their children with a long-lasting impact on attitudes, perceptions, and academic outcomes (Dumitru & Campean, 2022).

Parental mediation

Parental mediation includes strategies parents or caregivers use to limit, supervise, or interpret media and technology consumption for children (Mendoza, 2009). Research on parental digital mediation has distinguished different types of mediation, including restrictive mediation, active mediation, and co-use (Douglas et al., 2020; Karner, 2023).

Perceived Severity

Miraja et al. (2019) define perceived severity as a person's perception of the magnitude of the penalty or consequence for a particular threat. Similarly, Marrett et al.

(2011) defined it as the perceived degree of "seriousness" of a threat, risk, or harmful behavior.

Perceived Vulnerability

Perceived vulnerability is defined as a person's perception regarding the chance they will experience harm. Along with susceptibility, this construct is the primary determinant of threat appraisal minus the perceived rewards.

Protection Motivation Theory

PMT proposes that people protect themselves based on their perceptions of the threat and ability to cope. A person's perception of a threat is viewed through the constructs of severity, vulnerability, and susceptibility to the threat (Marett et al., 2011; Miraja et al., 2019). Further, the theory posits that high self-efficacy and response efficacy levels will increase a person's motivation to practice protective behavior (Ismail, 2020).

Response Efficacy

Response efficacy is the confidence a person has in a behavioral response intended to mediate a perceived threat (Hodge, 2022; Milne et al., 2000). According to Moriarty (2009), it is an individual’s belief regarding whether a response will work.

Restrictive Mediation

Restrictive mediation refers to parents or caregivers limiting technology consumption or usage through verbal rules or device settings (e.g., screen time limits) (Snyder, 2023).

Self-Efficacy

Self-efficacy, defined within the PMT model, assesses an individual's beliefs about whether they can perform a recommended coping response to a perceived threat (Hodge, 2022; Milne et al., 2000). Westcott et al. (2017) identified self-efficacy as a pivotal predictor of behavioral intentions preceding actions.

Organization of the Study

The first chapter of this study included background about the current reality regarding AI facing stakeholders as they attempt to navigate the ever-evolving challenges of addressing emerging technology with children. The problem statement, purpose of the study, significance, delimitations, and assumptions were identified. The next chapter provides a literature review that includes background on the theoretical framework of PMT, the independent variables, the dependent variable, and the behavioral intention of parental mediation. Chapter 3 consists of the research design, selection of participants, an explanation of the measurement instrument, data collection procedures, and an overview of the analysis process. In Chapter 4, the study's results are provided. Finally, Chapter 5 includes implications for action and recommendations for future research regarding artificial intelligence, parental mediation, and children.

Chapter 2

Review of the Literature

The literature review begins by examining the current context of AI in education via potential and existing applications and the role of parental influence on technology adoption, integration, and impact on classroom instruction. Next, according to Creswell and Creswell (2018), the literature review for a quantitative study should detail the independent variables, the dependent variables, and studies relating to the two types of variables. With this in mind, this literature review continues with an overview of PMT. Then, it explores the independent variables of perceived severity, perceived vulnerability, self-efficacy, and response efficacy and the dependent variable of behavioral intention. Finally, it examines existing research on the behavioral intention of parent mediation, specifically in the context of technology use and digital media consumption by children.

The Roles of Artificial Intelligence in Education

The roles of AI for students vary and evolve. Hwang and Chen (2023) proposed six roles to consider the implications of AI for students: tutor, tutee, learning peer, domain expert, administrator, and learning tool. Examples of AI as a tutor include chatbots, intelligent tutoring, and adaptive feedback (Celik et al., 2022). In contrast, students can train or tutor AI to improve content quality. For example, students can provide feedback to the AI model Midjourney to enhance drawings (Hwang & Chen, 2023). Similarly, with AI as a learning peer, AI can serve as a collaborative partner to complete an assigned task or prompt in which the student is also instructed to explain how AI contributed to the final product. In the role of domain expert, AI can provide advice or guidance, including serving as a counselor in chatbot form (Gillani et al., 2023).

AI might be utilized as an administrator to synthesize and present findings, including data analysis and displays. Finally, AI can balance cognitive load as a learning tool, allowing students to focus on the most critical learning tasks necessary to achieve intended learning outcomes (Hwang & Chen, 2023).

Young (2023) suggested that AI opens the opportunity to reinvent teaching. Indeed, the possibilities for AI to change how teachers plan, deliver, and assess are extensive; identifying these roles can clarify potential pathways. One of these roles is as a collaborator in managing teacher workload. Hinman (2023) described using ChatGPT to generate a rubric and a student handout on women's suffrage that reduced a teacher planning session to less than 20 minutes. This collaboration might extend beyond generation to evaluate the best pedagogical approach to a particular lesson design. In one example, Zhao & Wang (2022) utilized neural networks to evaluate preschool pedagogy for teaching handmade craft activities. Another role of AI in education is that of an assessor. For example, gameplay and intelligent tutoring systems utilize algorithms to facilitate reinforcement learning and differentiation through immediate feedback loops and adaptation (Gillani et al., 2023). Celik et al. (2022) point to AI algorithms trained in authentic question writing and automated essay scoring systems as further examples of AI's implications on assessment. In a third role, AI's potential to predict outcomes and behaviors supports a role as an intervention tool. Examples include using AI to detect automatically bullying behaviors in virtual learning communities, diagnosing learning conditions requiring intervention, and selecting the optimum learning activity based on screening (Nikiforos et al., 2020; Yang et al., 2021; Celik et al., 2022).

Parental Influence on Educational Technology

The influence of parents on children's learning experiences and education has social cognitive theory as its foundation (Yu et al., 2012; Trucks, 2014). Bandura concluded that dynamic socio-structural factors–environmental, behavioral, and personal–operate through beliefs to construct behavior (Yu et al., 2012; Trucks, 2014). Feser (2024) identified numerous studies as evidence that parents impact children's educational outcomes, performance, and attitudes via their perceptions and expectations. Further, several studies verified parents' impact on using digital technology in classrooms (Feser, 2024; Kong et al., 2019; Ortiz et al., 2011; Xie et al., 2021). Ortiz et al. (2011) noted that this impact is powerful when parents hold positive views regarding educational technology. Kong et al. (2019) identified this as based on the three-dimensional construct of understanding, support, and expectation. Xie et al. (2021) examined parental influence on using digital games in classrooms and found that when parents had negative perceptions, the result was a barrier toward classroom adoption.

Meanwhile, Bourgonjon et al. (2011) found that parents' perceptions influenced teachers' perceptions of digital games regarding their educational value for classroom instruction. More specifically, if parents perceived the technology as harmful, the teachers were also likely to hold less favorable perceptions. Hammer et al. (2021) further found that parents' perceptions regarding digital media and technology in education also impacted students' self-efficacy using these tools. Trucks (2014) pointed to reciprocal determinism and the family dynamic's impact on teens' technology use.

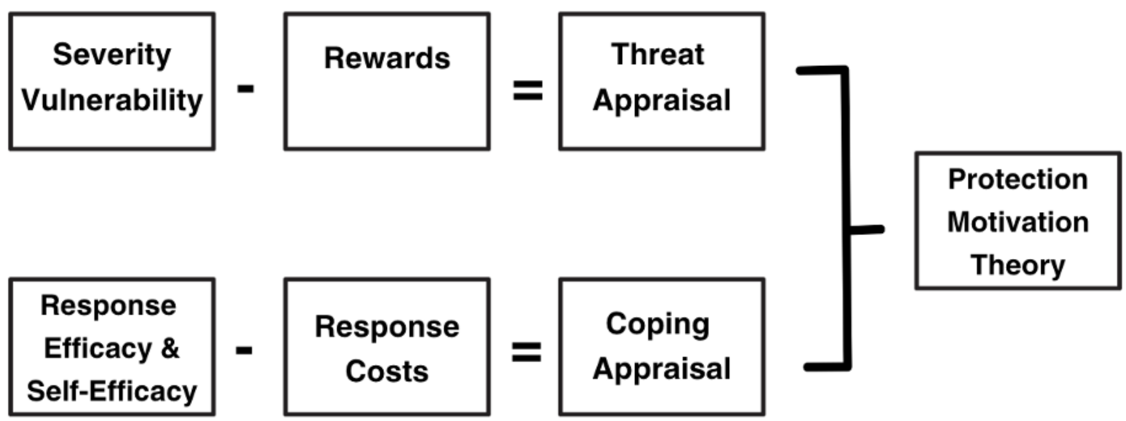
Maxwell et al. (2021) posited that parents can be effective partners in technology adoption, mediation, and effective educational use when their beliefs are valued, and clarity of communication occurs. Similarly, Dumitru and Campean (2022) called for unity of action regarding schools and families to improve effective educational activities and student experiences. Researchers across several past and current educational technology adoption and implementation movements have pointed to the value of understanding parent and caregiver perceptions in designing effective initiatives, policies, and instruction (Bresnihan et al., 2021; Keane & Keane, 2021; Maxwell et al., 2021). For example, Tsuei and Hsu (2019) concluded that family-school partnerships and understanding parents' perceptions regarding devices were consequential to students' successful use of technology when completing homework. Washington (2022) extended the value of understanding parent and caregiver perceptions of technology to encompass digital equity as their knowledge of and engagement in children's use of technology tools is viewed as a "dominant form of capital" (p. 22).

Protection Motivation Theory

Understanding parent and caregiver perceptions and their intentions to mediate AI use can be examined through a theory often applied in a different realm, PMT. PMT was developed initially for the health promotion and disease protection sector to interpret how individuals are motivated to act in self-protective ways towards perceived threats (Westcott et al., 2017; Miraja et al., 2019). PMT accounts for how individuals perceive a threat through the lenses of severity, the extent of the consequences, vulnerability, and the susceptibility of one to the threat. It also accounts for the individual's coping appraisal or ability to reduce or eliminate the risk or threat (Marett et al., 2011; Miraja et al., 2019). The coping appraisal includes self-efficacy as a robust measure of the behavioral intentions that foreshadow actual behaviors and considers potential tangible and intangible rewards for selecting the protective measure (Mutchler, 2012; Westcott et al., 2017). Rogers' (1983) original conception of PMT was as a parallel process model (Figure 1), while Lazarus (1991) later adapted the model, arguing that primary threat appraisal must precede the coping appraisal (Marett et al., 2011). PMT was intended to counter an assessed danger with effective and efficient mitigation efforts (Westcott et al., 2017).

Figure 1

Protection Motivation Theory Developed by R. W. Rogers



Note. Adapted from Floyd et al., 2000

Westcott et al. (2017) lauded PMT for its versatility and reliability beyond the health sector, including its role as a theoretical framework to understand social problems better. Marett et al. (2011) pointed to research indicating that the same factors influencing an individual's response to health threats also correspond to technology-related threats. Sommestad et al. (2015) examined 28 studies to assess the theory's predictive efficacy regarding information security behaviors. Stewart et al. (2021) applied PMT to the parent-child unit, researching factors influencing parents' willingness to adopt parental control software on their children's devices. Meanwhile, Howell (2021) examined PMT and an individual's motivation, decision-making, and follow-through regarding positive cyber hygiene practices to avert cybercrime. Other technology-focused researchers combined or compared PMT with Self-Determination Theory (SDT) to better understand user motivation regarding information security behaviors (Menard et al., 2017; Yang et al., 2019). Similarly, Kessler (2016) applied a case study methodology to examine how PMT could reveal improvement regarding security training in an organization. Overall, PMT's robust adaptability allows it to translate across the technology sector in investigating behavioral safeguards via the parallel, independent cognitive processes of threat appraisal and coping appraisal.

PMT proposes that the perceptions of threats can provoke the individual's cognitive mediating process, resulting in two potential outcomes: adaptive or maladaptive response (Miraja et al., 2019). These cognitive mediating processes follow the two distinct pathways of threat and coping appraisal. Perceived vulnerability and susceptibility are the primary determinants of threat appraisal, minus the perceived rewards. These rewards can be intrinsic, such as physical or psychological pleasure or intangible, or extrinsic, such as status or peer approval (Marett et al., 2011). Response efficacy and self-efficacy are the primary determinants of coping appraisal, minus the perceived response costs. Self-efficacy refers to an individual's belief in their capacity to implement the behaviors necessary to achieve specific performance or goal attainment (Bandura, 1977).

Perceived Severity

According to Miraja et al. (2019), perceived severity is a person's perception of the magnitude of the penalty or consequence for a particular threat. Marrett et al. (2011)

defined it as the perceived degree of "seriousness" of a threat, risk, or harmful behavior. In the original context for PMT, perceived severity was often linked to perceived severity of disease symptoms. In the context of technology, examples have included the perceived seriousness of consequences such as infection by computer viruses, legal penalties, and moral consequences (Miraja et al., 2019).

For this study, perceived severity as an independent variable is the parent or caregiver's perception of the risks of their children misusing AI or being harmed by its use. According to the United Nations International Children's Fund (UNICEF), parents and caregivers should consider these dimensions when evaluating AI's potential severity and impact on their child's privacy and safety: identify protection, harmful content, location detection, and biological safety (UNICEF, 2023). Identity protection includes financial protection, identity theft, and fabricated identities. Adverse content can include the proliferation of harmful stereotypes and biases. Hundt et al. (2022) found that "definitively autonomous racist, sexist, and scientifically- discredited physiognomic behavior is already encoded into Robots with AI" (p. 753). Regarding location detection, a *New York Times* article reported on PimEyes, a search engine that parents can use to find photos of their children online within seconds using facial recognition technology, as an example of the amount of data easily accessible (Hill, 2023). Finally, regarding biological safety, considerations include implications on physiology and psychology. These considerations might include genetic manipulation and prediction, cognitive manipulation, and emotional consequences (UNICEF, 2024).

Perceived Vulnerability

Perceived vulnerability is a person's perception regarding the chance they will experience harm. Again, considering the traditional health application of the theory, examples of perceived vulnerability include the likelihood that one would acquire a contagious disease. Lahiri et al. (2021) examined the role of perceived vulnerability to becoming ill with COVID-19 in adopting protective measures such as mask-wearing and social distancing. Chenoweth et al. (2009) examined perceived vulnerability and adopting anti-spyware software as a protective behavior in the context of technology. According to PMT, perceived vulnerability positively influences behavioral intention. For this study, the perceived vulnerability is the parent and caregiver's perception of their child's likelihood of being harmed by AI. Some might argue that vulnerability is simply a byproduct of AI's ubiquity. Mathiazhagan and La Fors (2023) wrote, "Moreover, the number of AI systems is exponentially increasing in children's everyday education, healthcare, entertainment, and socialization" (p. 142). Others might consider vulnerability through the lens of current AI policies. Goldwasser (2023) investigated how AI policies impact the public's trust. Meanwhile, Ryan (2020) proposed another influence on perceived vulnerability: humanity's tendency to anthropomorphize AI.

Self-Efficacy

In the context of PMT, self-efficacy is the assessment of an individual's beliefs about whether they can perform a recommended coping response to a perceived threat (Hodge, 2022; Milne et al., 2000). Westcott et al. (2017) identified self-efficacy as a key predictor of the behavioral intentions that precede a person's actual behaviors. Several studies have noted a stronger positive significant association with protective behavior outcomes for self-efficacy than PMT's threat constructs (Plotnikoff & Higginbotham, 2002; Mortada et al., 2021; Rad et al., 2021).

This study applies the self-efficacy of parents and caregivers to the protection of children from the risks of AI. Other studies have similarly examined the efficacious beliefs of caregivers as motivation for taking protective or proactive measures. Mayes (2006) investigated the self-identified knowledge of parents regarding household safety hazards as a predictor of home safety behaviors. Olivas (2013) studied parental self-efficacy and homework support. Technology-specific examples include Khil's (2023) study of parents' self-efficacy in identifying technology interference in their interactions with their children and Schatz's (2017) study of parents' self-efficacy in preventing youth internet addiction.

Response Efficacy

Response efficacy is the degree of confidence a person has in a behavioral response to mediate a threat or risk (Hodge, 2022; Milne et al., 2000). In other words, response efficacy is an individual's response to the question, "Does the recommended response work?" (Moriarty, 2009). A commonly cited example is an individual's motivation to use sunscreen based on beliefs regarding its efficacy in preventing sun damage or skin cancer (Hodge, 2022; Maleki et al., 2023). Other topics this construct has been explicitly applied to are abstinence from texting while driving, mammography compliance, and tobacco cessation (Peyton, 2020; Brenes, 1998; Thrasher et al., 2016).

In the context of this study, the response efficacy is the level of confidence that parents and caregivers have in parental mediation efforts. Parental mediation includes restrictive mediation, in which parents set limits; active mediation, in which parents engage in active discussion with their child; and co-using or co-creating, in which parents participate or consume alongside their child (Snyder, 2023). Rudnova et al. (2023) used the term "parental digital mediation" and included such actions as regulating a child's technology use, discussing specifics regarding appropriate use, and the characteristics or purposes of media content. Snyder (2023) explored the impact of parental response efficacy on mediating children's media consumption. Karner (2023) applied parental response efficacy and mediation to social media to examine whether levels differ according to rural, suburban, and urban environments.

Behavioral Intention

Mutchler (2012) wrote, "The individual's perception of the level of threat security [vulnerability], threat susceptibility, response efficacy, and self-efficacy will result in a form of protection motivation, which ideally is the attitude or behavior change" (p. 13-14). In other words, the dependent constructs of PMT predict an individual's protective behavioral intention. Marrett et al. (2011) noted that research indicates that these factors that influence a person's response or intention to respond to health threats also correspond to technology-related threats. Within the expanded application of PMT, behavioral intention can be described as an individual's motivation and plan to react in a self-protective way toward a perceived threat (Westcott et al., 2017).

For this study, the behavioral intent is the parent or caregiver's intent to engage in parental mediation regarding their child's use of AI. Westcott et al. (2017) identified the parent-child unit as one of the many ways the original PMT can be expanded and diversified. Similar studies that examined parental mediation and technology usage include Adorjan et al.'s (2022) study of teenagers' responses to parental digital mediation, Welker's (2006) study of parents' intentions to limit children's internet usage, and Douglas' (2019) study of parents' intentions to mediate and monitor social media.

This study, via the quantitative survey design, investigated three forms of parental mediation: restrictive mediation, active mediation, and co-use. These distinct lenses were first identified and researched in the context of children's television viewing and have been expanded in multiple studies to investigate various forms of digital consumption (Douglas et al., 2020; Karner, 2023). Restrictive mediation refers to exerting control over the interaction with media via rules or restrictions for accessing it (Douglas, 2019). An example is utilizing the American Academy of Pediatrics' Family Media Use Plan to negotiate boundaries and safeguards (Pappas, 2020). Active mediation refers to adult-child conversations about the risks and benefits of the media, including how to think critically about what is consumed or used (Douglas, 2019). For example, Mathiyazhagan and La Fors (2023) proposed a ladder of participation model to build children's agency when using AI. Finally, co-use (or co-viewing) refers to the parent or caregiver interacting with the media with the child. Douglas (2019) reminded us that his co-interaction must be active, and Mathiyazhagan and La Fors (2023) called for a co-creative approach in which the adult and child are co-users, co-testers, and design partners.

Summary

Chapter 2 reviewed the literature to determine the application of the constructs of PMT as dependent and independent variables to the problem statement regarding parental mediation and children's use of AI. Various resources, including research studies, journal articles, websites, and other literature, were consulted that expanded PMT to include technology-related research. The literature review provided an overview of the dependent variables of perceived severity, perceived vulnerability, self-efficacy, and response efficacy, along with examples of the dependent variable of behavioral intention. By establishing the theoretical framework (PMT), this study addresses a gap in prior literature on threat appraisal and coping appraisal's role in motivating parental mediation regarding AI.

Chapter 3

Methods

Chapter 3 presents the methods used in the study to investigate parents' and caregivers' perceptions regarding the severity of AI's possible risks for children, the vulnerability of children to these potential risks, and their response efficacy and self-efficacy in engaging in parental mediation efforts for children's AI usage. This chapter begins with a rationale for and presentation of the research design and variables. Included are details of the development of the measurement instrument as adapted from other quantitative research studies regarding health preventive actions, technology, and perceptions regarding safeguards. The chapter concludes with additional details regarding the survey design, the data collection procedure, the planned analysis and hypotheses testing, and the related assumptions.

Research Design

The purpose of this non-experimental quantitative research design is to examine the perceptions of parents and caregivers regarding their role in addressing and mediating AI use by children for educational purposes. The survey design aligns with this purpose as it expedites data collection turnaround. Davies and West (2014) warned that norms, practices, and policies have yet to keep pace with technological advances. Indeed, several researchers have applied survey designs to perceptions regarding emerging technologies. Examples include a study regarding parental supervision of teenagers' internet use to assess perceived severity and vulnerability (Stewart et al., 2021) and another on compliance with educational software anti-piracy policies to assess response efficacy and self-efficacy (Miraja et al., 2019).

Further, the measurement tool, which will be discussed in more detail later, is based upon a scale initially described by its developer as a "rapid measurement tool to quickly identify where the audience is in terms of salient beliefs" (Witte et al., 2001, p. 68). Hackett (1981) noted that small-scale surveys for exploratory purposes align well with an area of inquiry that is relatively new or limited. AI in educational spaces falls into this category. Using a straightforward survey design, inferences about the broader population can be made, aligning with this research's goal: determining parent and caregiver perceptions and their impact on protective behaviors.

The independent variables of this study included the four constructs of PMT: perceived severity (PS), perceived vulnerability (PV), self-efficacy (SE), and responsive efficacy (RE). Additional independent variables included the demographic variables of age, gender, and personal use of AI. The dependent variable was the protection behavioral intention (BI) of parents and caregivers to engage in parental mediation regarding AI. The variables are summarized in Table 1.

Table 1

Variables of the Study

Variable	Variable Type	Data Type	Abbreviation
Perceived Severity	Independent	Interval	PS
Perceived Vulnerability	Independent	Interval	PV
Self-Efficacy	Independent	Interval	SE
Response Efficacy	Independent	Interval	RE

Gender	Independent	Categorical	G
Age	Independent	Categorical	A
Use of AI	Independent	Categorical	UAI
Behavioral Intention	Dependent	Interval	BI

This research design employed an online multi-item questionnaire to measure the factors comprising the threat and coping appraisals on a sample of adults with one or more children who attend a K-12 school system regarding their role in mediating AI with their children. An online survey employs a standardized measurement promoting consistent data across respondents. Further, a cross-sectional survey design aligns with collecting data at one point instead of a longitudinal approach (Creswell & Creswell, 2018).

Selection of Participants

This research design utilized a voluntary sampling method of parents and caregivers across the U.S. with at least one student enrolled in K-12 school systems and access to the social networking service (SNS) used for the survey distribution. While a larger sample would provide greater accuracy, achieving this would have been time-consuming, costly, and unfeasible within the design's constraints (Creswell & Creswell, 2018). The survey was administered via a Google Form shared via social media in the fall of 2024. Participants completed the survey anonymously on their devices by clicking the URL link. They were presented with informed consent documentation, followed by three screening questions to determine qualification for the survey. These questions included whether the parent or caregiver has at least one child in a K-12 school system and whether the parent or caregiver self-identified as having at least a basic understanding of AI. A notable limitation of this data collection strategy is that not all parents and caregivers in the U.S. have an equal chance of being included in the sampling.

Measurement

The measurement tool used in this study is a modification of the Risk Behavior Diagnosis (RBD) Scale developed by Witte et al. (1996). Like PMT, the RBD Scale was initially designed to predict health-related protective and preventative behaviors, but it has been applied to other contexts (Banas, 2007; England et al., 2021; Johnston & Warkentin, 2010). For example, Banas (2007) used the scale to evaluate lesson design and motivation for students learning to evaluate websites. The survey in this instrument has three parts: the first section for screening purposes, the second section to gather demographic information, and the third section adapting Witte et al.'s (1996) division of questions by the four independent variables: Response Efficacy, Self-Efficacy, Vulnerability, and Severity. The first section included confirmation that the respondent is the parent and caregiver of at least one student in a K-12 school system and has a basic understanding of AI. The second section collected demographic information, including gender, age range, and personal AI use. The third measured the independent variables using a 7-point Likert scale with possible responses ranging from 1 = Strongly Disagree to 7 = Strongly Agree. These items tailor the original RBD Scale, as intended, for the specific health threat (AI). Table 2 shows the original RBD Scale stems aligned with the modifications for this survey.

Table 2

Modified RBD Scale Items for the Independent Variables

Variable	RBD Scale Item	Survey Question
Response Efficacy	[Performing Recommended Response] prevents [Health Threat].	Talking with my child about the benefits and risks of using artificial intelligence prevents misuse.
	[Performing Recommended Response] works in deterring [Health Threat].	Exploring artificial intelligence with my child works in deterring misuse.
	[Performing Recommended Response] is effective in getting rid of [Health Threat].	Establishing agreements regarding artificial intelligence use with my child effectively prevents misuse.
Self-Efficacy	I am able to [Perform Recommended Response] to prevent [Health Threat].	I am able to have meaningful conversations about artificial intelligence with my child.
	It is easy to [Perform Recommended Response] to prevent [Health Threat].	It is easy for me to establish limits or restrictions on my child's AI use.
	I can [Perform Recommended Response] to prevent [Health Threat].	I can use AI with my child to prevent its misuse and limit risks.
Vulnerability	I am at risk for [Getting/Experiencing Health Threat].	My child is at risk for being negatively impacted by AI use.
	It is possible that I will [Get/Experience Health Threat].	It is possible that harm can occur when a child is using artificial intelligence.
	I am susceptible to [Getting/Experiencing Health Threat].	My child is susceptible to the risks (i.e., data privacy) of using artificial intelligence.
Severity	[Health Threat] is a serious threat.	Artificial intelligence is a serious threat to my child's online safety.

	[Health Threat] is harmful.	Artificial intelligence is harmful to my child's learning.
	[Health Threat] is a severe threat.	Artificial intelligence is a severe threat to my child's data privacy.

For the dependent variable, the protective behavior intentions were the three parental mediation types: active mediation, restrictive mediation, and co-use. These protective behaviors align with those regarding parents' attempted mediation of children's technology and social media use and recommendations from groups such as the American Academy of Pediatrics (Pappas, 2020; Stewart et al., 2022). This adaptation was similar to one that studied COVID-19 protective behaviors among college athletes (Hodge, 2022). These scales have demonstrated reliability and validity from previous studies. Table 3 provides the dependent variables and corresponding survey questions.

Table 3

Modified RBD Survey Items for the Dependent Variable

Variable	Survey Question
Active Mediation	I plan to discuss the risks and benefits of AI with my child.
Restrictive Mediation	I am able to have meaningful conversations about artificial intelligence with my child.
Co-Use	My child is at risk for being negatively impacted by AI use.

The reliability of the scale items was tested using a Chi-square test for independence. The Cronbach’s alpha coefficient was found to be .552. While .7 is frequently cited as the preferred determination of good scale reliability, Hoekstra et al. (2018) argued that these values are not based on empirical research or logic and should be considered “more of a rule of thumb” (p. 352). Further, Hinton et al. (2004) stated that .5 to .7 can be considered moderate reliability. Also, it is essential to consider the larger context (Hoekstra et al., 2018; Peterson, R. A., 1994). Peterson (1994) stated that the desirable degree of reliability is a function of the research purpose and that for preliminary or exploratory research, .5-.6 is acceptable.

Additionally, the item-total statistics were analyzed, and deleting no single item would significantly increase Cronbach’s alpha. Hoekstra et al. (2018) warned against deleting items to improve alpha as this may compromise the instrument and harm validity. Therefore, all items were maintained for analysis.

Data Collection Procedures

Before the data collection began, a proposal for conducting research was submitted to the Baker University Institutional Review Board (IRB) on August 23, 2024 (Appendix B). The IRB granted written permission to proceed with the study on August 23, 2024 (Appendix C).

Burleson et al. (2023) emphasize the importance of data quality procedures, or actions taken before and during data collection, to ensure that collected data is of the highest possible quality. One consideration is reducing the amount of carelessness by increasing respondents' attention. One way to achieve this is by reducing the difficulty and length of the survey (Burleson et al., 2023). The RBD Scale meets this criterion by including only three questions for the four PMT areas. Another way to meet this goal is to conduct pilot testing. According to Creswell and Creswell (2018), pilot testing provides the opportunity to refine questions, formats, and instructions while also giving insight into response latency or the estimated time needed to complete the survey. Two colleagues were invited to review survey items for this study. Upon this review, the survey was revised to account for applicable feedback.

Once the review was complete, the survey was formatted to Google Forms, a survey distribution tool, and information regarding the survey was shared via the social media platform Facebook on August 25, 2024, and it was reshared on August 31, 2024. The social media posts included a brief description of the survey, along with a link to the survey (see Appendix D). A potential participant could review a welcome message, an overview of the study's purpose, and the informed consent notice by clicking the link. The participant was required to provide consent to continue with the survey. If consent was not given, the participant could not proceed with the following survey section. Once the participants had completed the survey, responses were recorded and stored in a Google Spreadsheet. All responses remained confidential throughout the survey completion process, beginning on August 25, 2024, and ending on September 15, 2024.

Data Analysis and Hypothesis Testing

The data analysis for the survey's data set was completed using IBM Statistical Product and Service Solutions for Windows (SPSS) to determine the extent to which the independent variables (perceived severity, severity, self-efficacy, and response efficacy) affect parents' and caregivers' protective behavior using simple linear regression analysis. Descriptive statistics provided means and standard deviations for each variable. A Pearson’s correlation coefficient was computed between each independent variable and the dependent variable to determine if there was a relationship between the variables. Simple linear regression analysis was conducted to determine which IVs (perceived vulnerability, perceived severity, response efficacy, self-efficacy) had influenced the DV (behavioral intention). This analysis was chosen for hypothesis testing since it analyzes the prediction of a numerical dependent variable from different independent variables. The level of significance was set at .05. When appropriate, the effect size or coefficient of determination, R^2, is reported.

The following are the research questions and hypotheses tested in the study:

RQ1

To what extent does the perceived threat severity of AI to children affect parents' and caregivers' intentions to engage in parental mediation?

H1. The perceived threat severity of AI to children affects parents' and caregivers' intentions to engage in parental mediation.

Simple linear regression analysis was conducted to predict parents' and caregivers' intentions to engage in parental mediation (BI) from the perceived threat severity of AI to children (PS). A one-sample t-test was conducted to test for the statistical significance of the slope. The level of significance was set at .05. When appropriate, the effect size or coefficient of determination, R^2, was reported.

RQ2

To what extent does the perceived vulnerability of children to the possible risks of AI affect parents' and caregivers' intentions to engage in parental mediation?

H2. The perceived vulnerability of children to AI affects parents' and caregivers' intentions to engage in parental mediation.

Simple linear regression analysis was conducted to predict parents' and caregivers' intentions to engage in parental mediation (BI) from the perceived vulnerability of children to AI (PV). A one-sample t-test was conducted to test for the statistical significance of the slope. The level of significance was set at .05. When appropriate, the effect size or coefficient of determination, R^2, was reported.

RQ3

To what extent does perceived self-efficacy affect parents' and caregivers' intentions to engage in parental mediation regarding AI?

H3. The perceived self-efficacy affects parents' and caregivers' intentions to engage in parental mediation regarding AI.

Simple linear regression analysis was conducted to predict parents’ and caregivers’ intentions to engage in parental mediation (BI) from the perceived self-efficacy to mediate AI (SE). A one-sample t-test was conducted to test for the statistical significance of the slope. The level of significance was set at .05. When appropriate, the effect size or coefficient of determination, R^2, was reported.

RQ4

To what extent does perceived response efficacy affect parents' and caregivers' intentions to engage in parental mediation regarding AI?

H4. The perceived response efficacy affects parents' and caregivers' intentions to engage in parental mediation regarding AI.

Simple linear regression analysis was conducted to predict parents’ and caregivers’ intentions to engage in parental mediation (BI) from the perceived response efficacy to AI (RE). A one-sample t-test was conducted to test for the statistical significance of the slope. The level of significance was set at .05. When appropriate, the effect size or coefficient of determination, R^2, was reported.

Limitations

One significant limitation of this study is the use of voluntary sampling. As respondents self-selected to participate in this study, the sample does not provide a true random sampling of the parent and caregiver population. Another is that while PMT and the RBD Survey have been applied to various non-health-related topics, neither have been explicitly applied to artificial intelligence in the researcher's review of existing studies. Finally, it is essential to note that survey data is self-reported and subject to respondents' assumptions and biases.

Summary

A non-experimental quantitative design was used to analyze the PMT constructs of severity, susceptibility, self-efficacy, and response efficacy on the perceived behavior intentions of parents and caregivers regarding children's use of artificial intelligence. This chapter contains the research design for the quantitative study, explains the development of the measurement tool as an adaptation of the RBD scale, and details the study’s limitations. The analysis and results from this study are presented in Chapter 4.

Chapter 4

Results

This study aimed to identify how parents and caregivers perceive their roles and influence in guiding and mediating children's use of AI. The measurement tool used in this study was a modification of the Risk Behavior Diagnosis (RBD) Scale. PMT served as a framework for analyzing parent and caregiver perceptions regarding threat appraisal (TA) and coping appraisal (CA) in the context of parental mediation and the use of AI. This chapter discusses the testing hypothesis and results. It includes descriptive statistics for the demographic, independent, and dependent variables. Further, it contains the results of the simple linear regression conducted for each research question and a summary of the data analysis.

Descriptive Statistics

In September 2024, 51 respondents completed the online Parent and Caregiver Perceptions of AI in Education survey. Of the 51 respondents, one respondent failed to meet the study’s stated criteria. The descriptive statistics for the demographic variables are presented in Table 4.

Table 4

Descriptive Statistics for the Demographic Variables

Variable	Category	*n*	*%*
Gender	Female	37	75
	Male	13	25
Age Range	25-34	5	10
	35-44	28	56

	45-54	16	32
	55-64	1	2
Personal AI Use	Daily	4	8
	Sometimes	26	52
	Not at all	20	40

Note. n = 50

For each independent variable (RE, SE, PV, PS) and the dependent variable (BI), data was collected with three survey items using a 7-point Likert scale with possible responses ranging from 1 = Strongly Disagree to 7 = Strongly Agree. The statement with the lowest overall rating was "It is easy for me to establish limits or restrictions on my child's AI use." with a mean of 4.24. The statement with the highest overall rating was "I plan to discuss the risks and benefits of AI with my child." with a mean of 6.16.

Each variable's mean and standard deviation were calculated for the three related survey items. For coping appraisal, response efficacy had a mean of 5.34, and self-efficacy had a mean of 4.81. For threat appraisal, vulnerability had a mean of 5.22, and severity had a mean of 4.61. The dependent variable of behavior had a mean of 5.45. The correlations, means, and standard deviations for the variables are provided in the table below.

Table 5

Correlations, Means, and Standard Deviations

	Correlations						
Variable	RE	SE	PV	PS	BI	*M*	*SD*

RE	--	.475	-.129	-.380	-.002	5.34	1.35
SE	.475	--	-.382	-.453	-.043	4.81	1.28
PV	-.129	-.382	--	.597	.240	5.22	1.20
PS	-.380	-.453	.597	--	.276	4.61	1.44
BI	-.002	-.043	.240	.276	--	5.45	.91

Note. $n = 50$

Hypothesis Testing

The research questions focused on the extent to which the independent variables (perceived severity, severity, self-efficacy, and response efficacy) affect parents' and caregivers' protective behavior. A simple linear regression was conducted to address RQ1-4. Simple linear regression was chosen for the hypothesis testing because it examines the prediction or explanation of the dependent numerical variable (BI) from the independent variables (RE, SE, PV, and PS). The level of significance was set at .05. When appropriate, an effect size, R^2, is reported. The following hypotheses were proposed:

RQ1

To what extent does the perceived threat severity of AI to children affect parents' and caregivers' intentions to engage in parental mediation?

H1.The perceived threat severity of AI to children affects parents' and caregivers' intentions to engage in parental mediation.

Pearson's product-moment correlation was conducted to examine the correlation coefficient. For this analysis, correlation coefficient range was set as a value between -1 and 1. The level of significance for the test of the correlation coefficient was set at .05. The result of the analysis was a correlation of .276, which indicated a positive moderate correlation between perceived severity and behavior intention (*r* = .276, *N* = 50, *p* = .026). This determination was based on De Vaus’ (2002) interpretation of correlation coefficients, with the range of 0.10 to 0.29 having a low to moderate strength of association.

A simple linear regression was calculated to predict behavior intention for parental mediation regarding children’s use of AI based on perceived severity. A marginally significant regression equation was identified as $F(1, 48) = 3.964$, p = .052, with $R^2 = .076$. Thus, the results showed that perceived severity significantly predicted behavior intention, $B = .175$, $t(48) = 1.99$, p = .052. Perceived severity explained a marginally significant proportion of variance (7.6%) in behavior intention ratings, as for every 1-point increase on the perceived severity scale, the behavior intention score will increase by .175 points.

RQ2

To what extent does the perceived vulnerability of children to the possible risks of AI affect parents' and caregivers' intentions to engage in parental mediation?

H2. The perceived vulnerability of children to AI affects parents' and caregivers' intentions to engage in parental mediation.

Pearson's product-moment correlation was conducted to examine the correlation coefficient. For this analysis, the range of the correlation coefficient was set as a value between -1 and 1. The level of significance for the test of the correlation coefficient was set at .05. The result of the analysis was a correlation of .240, which indicated a positive moderate correlation between perceived vulnerability and behavior intention (*r* = .240, *N* = 50, *p* = .046). In other words, it was concluded that perceived vulnerability was correlated with behavior intention. This determination was based on De Vaus' (2002) interpretation of correlation coefficients, with the range of 0.10 to 0.29 having a low to moderate strength of association.

A simple linear regression was calculated to predict behavior intention based on perceived vulnerability. A non-significant regression equation was found $F(1, 48) = 2.941$, p = .093, with $R^2 = .058$. The results of the simple linear regression showed that perceived vulnerability did not significantly predict behavior intention, $B = .182$, $B = .182$, $t(48) = 1.72$. Perceived vulnerability explained a non-significant portion of the variance (5.8%) in behavior intention ratings, as for every 1-point increase in vulnerability, the average behavior intention rating will increase by .182 points.

RQ3

To what extent does perceived self-efficacy affect parents' and caregivers' intentions to engage in parental mediation regarding AI?

H3. The perceived self-efficacy affects parents' and caregivers' intentions to engage in parental mediation regarding AI.

Pearson's product-moment correlation was conducted to examine the correlation coefficient. For this analysis, the range of the correlation coefficient was set as a value between -1 and 1. The level of significance for the test of the correlation coefficient was set at .05. The result of the analysis was a correlation of .043, which indicated a positive slight correlation between perceived self-efficacy and behavior intention ($r = .043$, $N = 50$, $p = .384$).

A simple linear regression was calculated to predict behavior intention based on perceived self-efficacy. A non-significant regression equation was found $F(1, 48) = .088$, p = .768, with R^2 = .002. The results of the simple linear regression showed that perceived self-efficacy did not significantly predict behavior intention, *B* = -.030, *t*(48) = -.297. Perceived self-efficacy explained a 2% variance in behavior intention.

RQ4

To what extent does perceived response efficacy affect parents' and caregivers' intentions to engage in parental mediation regarding AI?

H4. The perceived response efficacy affects parents' and caregivers' intentions to engage in parental mediation regarding AI.

Pearson's product-moment correlation was conducted to examine the correlation coefficient. For this analysis, the range of the correlation coefficient was set as a value between -1 and 1. The level of significance for the test of the correlation coefficient was set at .05. The result of the analysis was a correlation of -.002, which indicated no correlation between response efficacy and behavior intention (*r* = -002, *N* = 50, *p* = .493). In other words, it was concluded that perceived response efficacy did not correlate with behavior intention.

A simple linear regression was calculated to predict behavior intention based on perceived response efficacy. A non-significant regression equation was found *F*(1, 48) = .000, p = .986, with R^2 = .000. The results of the simple linear regression showed that perceived response efficacy did not predict behavior intention, *B* = -.002, *t*(48) = -.017.

Summary

This chapter contained descriptive statistics, data analysis, hypothesis testing, and the results for each research question. The results showed the parents and caregivers gave the lowest rating to the statement “It is easy for me to establish limits or restrictions on my child's AI use.” (M = 4.24) and the highest training to the statement “I plan to discuss the risks and benefits of AI with my child.” (M = 6.16). The evidence showed a positive weak correlation between perceived severity and behavior intention and perceived vulnerability and behavior intention. Perceived severity explained a marginally significant proportion of variance (7.6%) in BI ratings, as for every 1-point increase on the PS Likert scale, the behavior intention score will increase by .175 points. The next chapter will include an interpretation of the data analysis, an examination of the findings in the context of literature, potential implications, and recommendations for future research.

Chapter 5

Interpretation and Recommendations

This study was designed to identify how parents and caregivers perceive their roles and influence in guiding and mediating children's use of AI. This chapter summarizes items discussed in the previous four chapters, including a study summary, an overview of the problem, research questions, a review of the methodology, and the major findings. Also discussed are findings related to the literature, implications for actions, future research recommendations, and concluding remarks.

Study Summary

The current study is summarized in this section. This summary includes a review of the problem statement and research questions. The section concludes with a review of the methodology and major findings.

Overview of the Problem

The use of AI in education is an ever-evolving challenge. Calls for policies, guidelines, and AI literacy are pervasive (Harvard Center for Digital Thriving, 2024). Recommendations frequently cite input across educational stakeholder groups, including that of parents and caregivers. Current research on parent involvement in mediating students’ use of AI is limited and emerging (Sykes & Rezach, 2023). Additional recommendations include developing and designing resources to support families regarding AI use. Again, such resources are limited and emerging (Albuquerque et al., 2021; Alfeir, 2024). Therefore, there is a need to examine parent and caregiver perceptions regarding their role, efficacy, and intention to mediate students’ use of AI.

Purpose Statement and Research Questions

The purpose of this study was to examine how parents and caregivers perceived their roles and influence in guiding and mediating children's use of AI. PMT served as a framework for analyzing parent and caregiver perceptions regarding threat appraisal (TA) and coping appraisal (CA) in the context of parental mediation and AI. The threat appraisal, including perceived severity (PS) and vulnerability (PV), and the coping appraisal, including self-efficacy (SE) and response efficacy (RE), were weighed against behavior intentions (BI). The research questions focused on the extent of PS, PV, SE, and RE to predict BI.

RQ1: To what extent does the perceived threat severity of AI to children affect parents' and caregivers' intentions to engage in parental mediation?

RQ2: To what extent does the perceived vulnerability of children to the possible risks of AI affect parents' and caregivers' intentions to engage in parental mediation?

RQ3: To what extent does perceived self-efficacy affect parents' and caregivers' intentions to engage in parental mediation regarding AI?

RQ4: To what extent does perceived response efficacy affect parents' and caregivers' intentions to engage in parental mediation regarding AI?

Review of the Methodology

This study utilizes a quantitative research method based on a non-experimental design. An online survey was adapted from the RBD scale, and data was collected via a Google Form from 50 respondents who self-identified as parents and caregivers. Items on the survey included the four constructs of PMT: perceived severity, perceived vulnerability, self-efficacy, and responsive efficacy; the demographic variables of age, gender, and personal AI use; and the dependent variable of behavior intention. The research design was approved by Baker University Institutional Review Board and was administered in the fall of 2024.

The data analysis for the survey's data set was completed using the IBM Statistical Package for Social Sciences for Windows (SPSS). The reliability of the scale items was tested using a Chi-square test for independence. Pearson product-moment correlation coefficient was calculated to index the strength and direction of the relationship between the independent variables (PS, PV, SE, RE) and the dependent variable (BI). A simple linear regression was calculated to determine the extent to which the independent variables (PS, PV, SE, RE) affect parents' and caregivers' protective behavioral intention (BI) using simple linear regression analyses.

Major Findings

For RQ1, parent and caregiver survey responses demonstrated a positive moderate correlation between the perceived severity of AI’s risks to children and the behavior intention of the parents and caregivers to mediate AI use by their children. Further, the responses showed that as concerns regarding severity increased, a predicted increase in behavior intention occurred. As mentioned earlier, perceived severity explained a marginally significant proportion of variance (7.6%) in behavior intention ratings, as for every 1-point increase on the perceived severity scale, the behavior intention score will increase by .175 points.

For RQ2, parent and caregiver responses demonstrated a positive, weak to moderate correlation between the perceived vulnerability of children to AI’s risks and the behavior intention of parents and caregivers to engage in mediation regarding its use. The responses did not indicate a significant predicted increase in behavior intention based on perceived vulnerability.

For RQ3, parent and caregiver responses demonstrated a positive slight correlation between perceived self-efficacy in mediating AI use and the behavior intention of parents and caregivers to do so. The responses did not indicate a significant predicted increase in behavior intention based on self-efficacy. In addition, evidence showed that the survey statement with the lowest overall rating was from the self-efficacy domain, “It is easy for me to establish limits or restrictions on my child's AI use.”

For RQ4, it was concluded based on survey responses that perceived response efficacy of parental mediation did not correlate with parent and caregiver behavior intention. Further, the responses did not indicate a significant predicted increase in behavior intention based on self-efficacy.

Regarding the dependent variable of behavior intention, the statement with the highest overall rating was “I plan to discuss the risks and benefits of AI with my child.” Further, when the mean was found for all behavior intention items on the scale, results indicated agreement regarding a desire to engage in mediation actions.

Findings Related to the Literature

The finding that “It is easy for me to establish limits or restrictions on my child's AI use” had the lowest rating of the survey items is supported by other research investigating parental attempts to limit or restrict children’s technology use. Druga et al. (2022) found that while parents enact household technology rules, both parents and children break these rules. Further, they found that children were often frustrated when parents did implement technology limits or restrictions as they believed parents misperceived their actual device use, especially for school responsibilities. Albuquerque et al. (2021) studied parental controls for children using AI via smart toys and found that few specific, concrete solutions currently exist. Meanwhile, Alfeir (2024) found that concerns stem from insufficient knowledge about AI or a lack of transparency in its limitation mechanisms.

Additional findings support this study's finding that parents plan to discuss the risks and benefits of AI with their children (M = 6.16). Han et al. (2024) interviewed parents about AI and found that 100% of participants agreed that AI is unavoidable in their children's lives; therefore, children need to know how to use it safely and responsibly. Garg and Sengupta (2020) found that parents' perceptions included an expectation that they could control and monitor children's use of AI technologies. Su (2024) found via parent interviews that most parents believed AI tools were suitable starting in kindergarten and that this was an appropriate level for their discussions of AI literacy.

The finding that self-efficacy and response efficacy had a non-significant impact on behavior intention corresponds with other exploratory studies at the forefront of the AI evolution. Petsolari et al. (2024) applied a scenario-based intervention to their study and highlighted the "interplay of optimism and apprehension" for parents and AI interactions with children (section 5.1.1, para. 4). They reported that their study showed that designing parental intervention supports is complex and that identifying effective components is challenging. Further, they wrote, "Our findings identified mixed reactions to the potential benefits of AI as well as specific concerns relating to family dynamics and privacy" (section 6, para. 1). Additionally, Schiano and Burg's (2017) survey revealed that parents felt societal pressure to be “good parents” regarding technology and media management. Still, they also felt unclear regarding what that should look like and overwhelmed with the time and energy needed to provide this due diligence.

Conclusions

This section includes conclusions regarding the parents’ and caregivers’ perceptions regarding children’s use of AI. Recommendations for future research follow implications for action.

Implications for Action

The research can serve as evidence that parents and caregivers plan to engage with children regarding AI. It can also serve as evidence that parents are less confident and efficacious about how to limit a child’s use of AI ($M = 4.81$). Therefore, instructional designers can partner with parents to develop design solutions that empower parents to mediate AI use effectively and productively. Further, educational leaders and institutions can seek ways to partner with families to develop AI literacy practices that support all stakeholders in the effective use of AI in education.

Recommendations for Future Research

This research highlights for instructional designers and stakeholders in AI in education the importance of additional research regarding how best to partner with and design for parents and caregivers regarding AI and its use by children. This research study shows that parents plan to discuss AI with their children ($M = 6.16$). Determining the best modalities and pathways for supporting parents in this work is an essential next step. Cranor et al. (2014) noted that parents cannot necessarily draw from their childhood experiences when knowing what works for talking with their children about AI in the ways they can for other topics. Thus, continued studies investigating formal and informal structures, such as Petsolari et al.'s (2024) investigation of socio-technical imaginaries and Druga et al.'s (2022) research on AI-focused experiential museum exhibits, are essential.

Another recommendation for future research is to investigate how parent and caregiver perceptions are impacted by their personal use of AI. In this study, 40% of respondents said they never use AI. This response could indicate that they need to be made aware of how ubiquitous AI is in technology and how it might be used in ways they had not considered as AI. Thus, as adults learn more about AI, it would be helpful to know how this does or does not impact perceptions regarding its use by children.

A final recommendation is to expand this study to a larger population. This recommendation includes implementing a more comprehensive sampling strategy, ensuring representation across socioeconomic demographics, and diversifying recruitment through other social media channels. An example of a demographic not included in this study worth consideration is the grade level bands of students, such as elementary, middle, and high school. Further, partnering with school districts in different settings could expand the scope of the research.

Concluding Remarks

With the release of ChatGPT in November 2022, the urgency of addressing what seemed largely unknown was felt by K-12 school systems everywhere. Committees were formed, policies were drafted, and resources were compiled. When perusing these efforts, an almost universal caveat is included, similar to Lincoln Public Schools in Lincoln, Nebraska: "This topic evolves rapidly. What was true and accurate yesterday may be out of date today" (2023). Indeed, the generative learning that emerges for all stakeholders when considering AI in schools requires flexibility, collaboration, and reflection. The collaboration essential to transformational change regarding this work is still in the early stages: educational leaders, teachers, AI designers and developers, parents and caregivers, students, and instructional designers must partner to leverage the potential of AI to enhance learning for all. This ever-evolving reality also means that the need for high-quality research across the learning sciences is more significant than ever, especially as AI's application expands into higher levels of thinking (Hwang & Chen, 2023).

Regarding the key stakeholder group of parents and caregivers, prior studies have investigated and specified examples of parents and caregivers engaging in mediation efforts regarding children's technology use (Howell, 2021). Other studies have extended the application of PMT to the parent-child unit regarding parents' willingness to engage in restrictive mediation of technology (Stewart et al., 2021). This research study extended the application of PMT via a modified RBD Scale to parents' and caregivers' intentions to engage in mediation regarding their children's use of AI. From this, findings emerged indicating that parents and caregivers plan to engage with their children regarding AI; however, they are less sure how to limit or restrict children's use of AI.

Additional research can shed light on best practices and designs for instructional designers supporting families' joint AI learning and parental mediation efforts. Examples of emerging and innovative research include Druga et al.'s (2022) research on informal learning structures via AI-focused experiential museum exhibits for families and Petsolari et al.'s (2024) investigation of design fiction as a vehicle for envisioning and understanding AI supports for parents. With this sense of possibility, innovative spirit, and sometimes anxiety comes a call for policymakers, designers, and educators to keep families and children at the center. As Yang et al. (2021) write, “AI may be a current trend, but humanistic beauty is eternal” (p. 5).

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Appendices

Appendix A

Survey Script

My name is Sarah Winans, and I am a candidate in the Baker University Instructional Design and Performance Technology Doctoral Program. If you are a parent or caregiver of a student or students in grades K-12, I request your participation in a brief survey to better understand the perceptions of parents regarding their role and efficacy in mediating children's use of artificial intelligence for educational purposes. The brief survey will take about 15-20 minutes to complete. Please click the link below to go to the Google Form for the survey.

Part A: Informed Consent

Purpose: This research study aims to uncover the perceptions of parents and caregivers regarding their role and efficacy in mediating children's use of artificial intelligence for educational purposes.

Participation: Your participation in the survey is entirely voluntary. If you choose to participate, you may withdraw from the study at any time. If you decide not to participate or to withdraw from the survey, you will not be penalized.

Benefits, Risks, & Compensation: This study adds to our understanding of how parents can support children safely using artificial intelligence. No known risks or discomforts are involved with your participation in this study. There are no direct benefits or compensation for your participation.

Confidentiality: All of your responses will be kept confidential. No personally identifiable information will be associated with your responses, nor will any personally identifiable reports of these data exist. The Baker University Institutional Review Board has approved this survey for scholarly purposes only. Once the study concludes, your responses will be permanently deleted.

Should you have any comments or questions, please contact me at sarahlwinans@stu.bakeru.edu. Thank you for your time.

____ By checking this box, you agree to participate voluntarily in the following survey.

Part B: Screening

1. Are you the parent or caregiver of at least one student in grades kindergarten through twelfth grade?

____ Yes, I am a parent or caregiver of at least one student in grades kindergarten through twelfth grade.

____ No, I am not a parent or caregiver of at least one student in grades kindergarten through twelfth grade.

2. Does your student (or students) attend a K-12 public school system in the United States?

____ Yes, my student (or students) attends a K-12 public school system in the United States.

____ No, my student (or students) does not attend a K-12 public school system in the United States.

3. Do you understand what artificial intelligence (AI) is and how a student might use it?

____ Yes, I understand what artificial intelligence (AI) is and know how a student might use it.

____ No, I do not understand what artificial intelligence (AI) is or how a student might use it.

Part C: Demographic Questions

4. I identify as:

- Female
- Male
- Non-Binary
- Prefer Not to Answer

5. My age:

- 18-24
- 25-34
- 35- 44
- 45-54
- 55-64
- 65 or over

6. In my daily life or work, I:

- Use AI daily

- Sometimes use AI
- Do not use AI

Part D: Survey Questions

7. Talking with my child about the benefits and risks of using artificial intelligence prevents misuse.

- Strongly Disagree
- Disagree
- Somewhat Disagree
- Neither Agree nor Disagree
- Somewhat Agree
- Agree
- Strongly Agree

8. Exploring artificial intelligence with my child works in deterring misuse.

- Strongly Disagree
- Disagree
- Somewhat Disagree
- Neither Agree nor Disagree
- Somewhat Agree
- Agree
- Strongly Agree

9. Establishing agreements regarding artificial intelligence use with my child effectively prevents misuse.

- Strongly Disagree
- Disagree
- Somewhat Disagree
- Neither Agree nor Disagree
- Somewhat Agree
- Agree
- Strongly Agree

10. I am able to have meaningful conversations about artificial intelligence with my child.

- Strongly Disagree

- Disagree
- Somewhat Disagree
- Neither Agree nor Disagree
- Somewhat Agree
- Agree
- Strongly Agree

11. It is easy for me to establish limits or restrictions on my child's AI use.

- Strongly Disagree
- Disagree
- Somewhat Disagree
- Neither Agree nor Disagree
- Somewhat Agree
- Agree
- Strongly Agree

12. I can use AI with my child to prevent its misuse and limit risks.

- Strongly Disagree
- Disagree
- Somewhat Disagree
- Neither Agree nor Disagree
- Somewhat Agree
- Agree
- Strongly Agree

13. My child is at risk of being negatively impacted by AI use.

- Strongly Disagree
- Disagree
- Somewhat Disagree
- Neither Agree nor Disagree
- Somewhat Agree
- Agree
- Strongly Agree

14. It is possible that harm can occur when a child is using artificial intelligence.

- Strongly Disagree

- Disagree
- Somewhat Disagree
- Neither Agree nor Disagree
- Somewhat Agree
- Agree
- Strongly Agree

15. My child is susceptible to the risks (i.e., data privacy) of using artificial intelligence.

- Strongly Disagree
- Disagree
- Somewhat Disagree
- Neither Agree nor Disagree
- Somewhat Agree
- Agree
- Strongly Agree

16. Artificial intelligence is a serious threat to my child's online safety.

- Strongly Disagree
- Disagree
- Somewhat Disagree
- Neither Agree nor Disagree
- Somewhat Agree
- Agree
- Strongly Agree

17. Artificial intelligence is harmful to my child's learning.

- Strongly Disagree
- Disagree
- Somewhat Disagree
- Neither Agree nor Disagree
- Somewhat Agree
- Agree
- Strongly Agree

18. Artificial intelligence is a severe threat to my child's data privacy.

- Strongly Disagree

- Disagree
- Somewhat Disagree
- Neither Agree nor Disagree
- Somewhat Agree
- Agree
- Strongly Agree

19. I plan to discuss the risks and benefits of AI with my child.

- Strongly Disagree
- Disagree
- Somewhat Disagree
- Neither Agree nor Disagree
- Somewhat Agree
- Agree
- Strongly Agree

20. I plan to limit, monitor, or restrict my child's use of AI for education.

- Strongly Disagree
- Disagree
- Somewhat Disagree
- Neither Agree nor Disagree
- Somewhat Agree
- Agree
- Strongly Agree

21. I plan to engage in using AI with my child.

- Strongly Disagree
- Disagree
- Somewhat Disagree
- Neither Agree nor Disagree
- Somewhat Agree
- Agree
- Strongly Agree

Appendix B

BAKER UNIVERSITY

IRB Request

Date 8/11/2024 IRB Protocol Number ____________________
(IRB use only)

I. Research Investigator(s) (students must list faculty sponsor)

Department(s) IDPT

	Name	Signature	
1.	Sarah Winans	[signature]	Principal Investigator
2.	Dr. Regena Aye	Regena M. Aye	☑ Check if faculty sponsor
3.	Dr. Kyunghwa Cho	Kyunghwa Cho Digitally signed by Kyunghwa Cho Date: 2024.08.19 17:46:29 -05'00'	☐ Check if faculty sponsor
4.			☐ Check if faculty sponsor

Principal investigator contact information

Note: When submitting your finalized, signed form to the IRB, please ensure that you cc all investigators and faculty sponsors using their official Baker University (or respective organization's) email addresses.

Faculty sponsor contact information

Expected Category of Review: ☐ Exempt ☑ Expedited ☐ Full ☐ Renewal

II. Protocol Title

Expanding protection motivation theory: The role of parent and caregiver perceptions in mediating artificial intelligence usage by children

Appendix C

BAKER UNIVERSITY
Own Confidence

Baker University Institutional Review Board

August 23, 2024

Dear Sarah Winans and Regena Aye,

The Baker University IRB has reviewed your project application and approved this project under Expedited Status Review. As described, the project complies with all the requirements and policies established by the University for protection of human subjects in research. Unless renewed, approval lapses one year after approval date.

Please be aware of the following:

1. Any significant change in the research protocol as described should be reviewed by this Committee prior to altering the project.
2. Notify the IRB about any new investigators not named in original application.
3. When signed consent documents are required, the primary investigator must retain the signed consent documents of the research activity.
4. If this is a funded project, keep a copy of this approval letter with your proposal/grant file.
5. If the results of the research are used to prepare papers for publication or oral presentation at professional conferences, manuscripts or abstracts are requested for IRB as part of the project record.
6. If this project is not completed within a year, you must renew IRB approval.

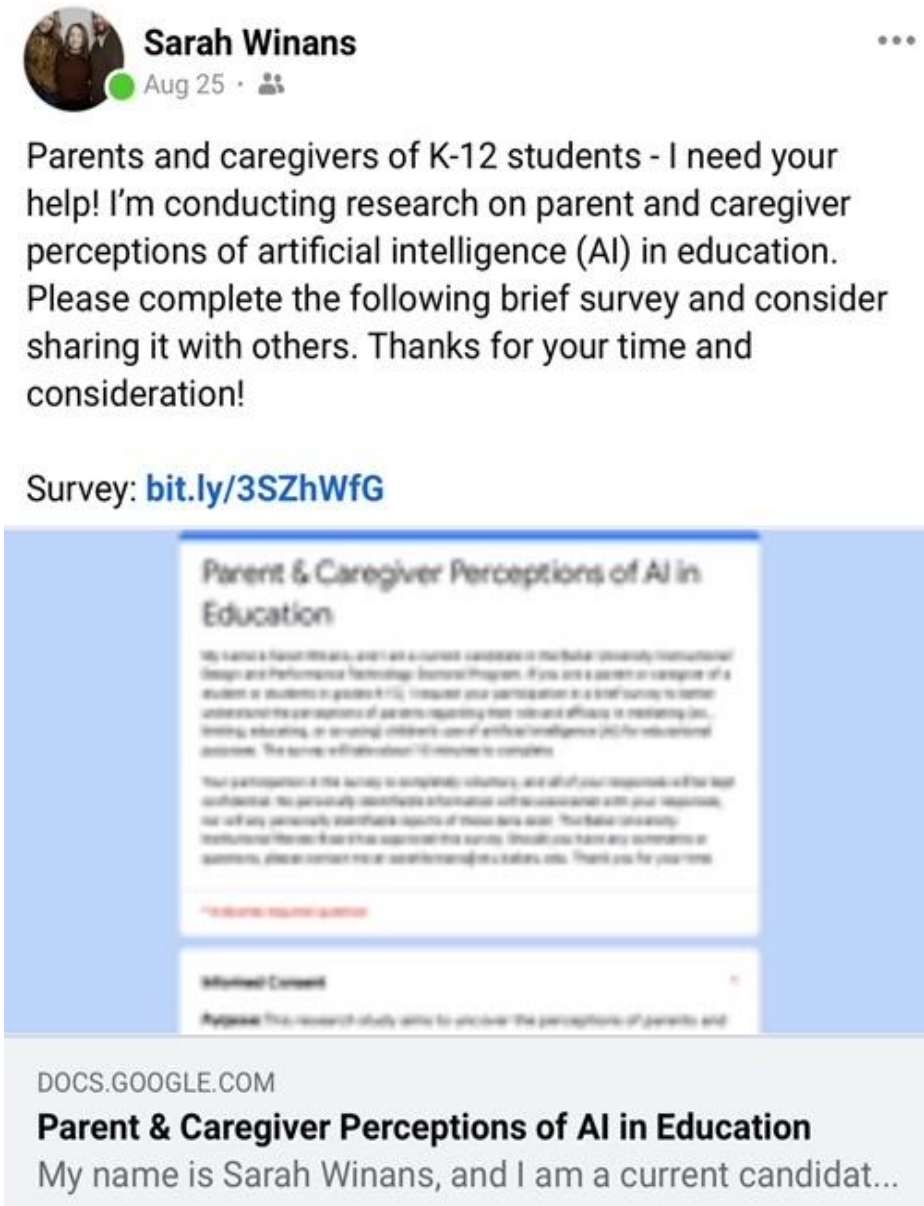
If you have any questions, please contact me at skimball@bakeru.edu or 785.594.4563.

Sincerely,

Scott Kimball, PhD
Chair, Baker University IRB

Baker University IRB Committee
Tim Buzzell, PhD
Steve Massey, EdD
Jiji Osiobe, PhD
Susan Rogers, PhD

Appendix D


Sarah Winans
Aug 25
Parents and caregivers of K-12 students - I need your help! I'm conducting research on parent and caregiver perceptions of artificial intelligence (AI) in education. Please complete the following brief survey and consider sharing it with others. Thanks for your time and consideration!
Survey: bit.ly/3SZhWfG
Parent & Caregiver Perceptions of AI in Education
DOCS.GOOGLE.COM
Parent & Caregiver Perceptions of AI in Education
My name is Sarah Winans, and I am a current candidat...