Adeel Ahmed Tariq

Ready to let go!

Effects of consumers' task expertise on forming intentions to adopt autonomous products

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Abstract

The concept of self-performing products can be traced back to the world's earliest civilizations and has long been a staple of science fiction. Fiction has now become reality as we experience the rise of autonomous products in every conceivable domain of life. Autonomous products are transforming the way we perform many consumption tasks, including everyday activities such as driving, cooking, and recreational activities such as biking and skiing. However, very little marketing research has examined the consumer preferences for autonomous products. This dissertation seeks to provide deeper insights into whether consumers differ in how they perceive the usefulness and risk associated with autonomous products when adopting such products. The significance of autonomous products is that they can either assist the user by performing a given set of subtasks or replace the user by performing the entire consumption task without user interaction. In this dissertation, I propose that consumers will diverge in their perceptions of usefulness and risk and subsequent intentions to adopt assistive vs. replacement technology, depending on their degree of task expertise. Across three experimental studies using three consumption tasks (i.e., driving, cooking, and skiing), the findings converge.

The results from empirical investigation confirmed that the consumers' task expertise is a crucial driver in the evaluation of usefulness and risks, and subsequent intentions to adopt autonomous products. More importantly, I demonstrated that consumers with higher levels of task expertise perceive assistive technology to be more useful and less risky compared to replacement technology. In contrast, consumers with low task expertise perceive replacement technology to be more useful and less risky compared to assistive technology.

Finally, perceptions of usefulness and performance risk will further affect adoption intentions. The findings have substantial theoretical implications for research on expertise and technology, and managerial implications for targeting autonomous products.

Key words: Autonomous products, consumer task expertise, adoption intentions

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Chapter 1

Introduction

1.1 Background

Throughout human history, we have created tools that increased our individual and collective intelligence and helped us make up for our biological disadvantages (e.g., fatigue, fear, illness). For instance, we started with crude functional tools such as hammers and axes (Steels, 1995). Thousands of years later, vehicles allowed us to move more rapidly than other animals, and to reach remote and inhospitable places. Similarly, various tools such as telescopes, cameras, microphones and other instruments provided us with delicate control and remarkable strength, and extended our visual, auditory, and tactile senses. Along this trajectory, the rise of autonomous systems that embody a significant level of intelligence are our most powerful tool yet, which will change the way we perform many consumption tasks (Wallach, 2015).

Autonomous products are increasingly able to perform tasks that consumers previously had to perform themselves (Rijsdijk & Hultink, 2003). Google and Uber's self-driving cars have already traveled millions of miles on U.S. roads; a new generation of cooking devices can prepare ingredients and implement hundreds of recipes (e.g., Vorvex's Thermomix "does all the work to prepare delicious meals"), and delivery drones are operating in dynamic environments to deliver packages. These innovations are recent examples of a decades-long trend toward increasing autonomy in products such as in the automotive industry (e.g., assistive cruise control) and cooking (e.g., food processors) contexts, and this trend appears bound to increase. Google, IBM, and Intel have acquired start-ups dedicated to artificial intelligence, a fundamental technology in the development of autonomous products and services, reflecting the vast efficiency gains that autonomous systems can provide consumers.

A key characteristic of autonomous products is that they operate intelligently in a dynamic environment with minimal help from the user, if any, and ultimately perform human-like actions (Brooks, 1986). Numerous surveys on self-driving cars, medical robots, and delivery drones have reported a range of consumption benefits that these technological products can offer to the consumers, such as freeing consumers' time and effort, increasing their task efficiency, and enhancing their consumption experiences (Choi & Ji, 2015; Rijsdijk & Hultink, 2003). However, it is unlikely that all consumers will perceive this technology as useful and without the risks that such products might entail.

In this dissertation research, I propose that consumers perceive the usefulness and risk associated with autonomous products differently, depending on the degree of product autonomy. The main aspect of autonomous products is that they can fully or partially replace the entire consumption task; i.e., a new product can be autonomous in performing the entire consumption task without any user interaction, such as self-driving cars. Alternatively, a new product can be autonomous in performing a given set of subtasks while the user largely remains in control of the consumption task, such as alpine skiing shoes performing various functions, including adjusting the sole of the shoes to the slopes, while the skier largely remains in control of the skiing task. However, the perceived usefulness of either replacement technology or assistive technology depends on the individual's attachment to the focal task. Specifically, I propose that individual differences in task expertise will affect how consumers perceive the usefulness and risk associated with autonomous products. We know that consumers engage in everyday tasks with different consumption goals, depending on their degree of task expertise. Prior research has found that task experts concentrate on deeper mechanisms and/or processes to achieve the highest possible level of performance in goal accomplishment (King & Balasubramanian, 1994; Peter & Olsen, 1990). In contrast, consumers with low task expertise focus on the immediate outcome with minimum effort because the processes of engaging in a consumption task are relatively less important to them (King & Balasubramanian, 1994; Anderson, 1990).

Specifically, consumers with higher levels of task expertise will perceive assistive technology to be more useful and less risky (vs. replacement technology) as such product technology would allow the user to coerce the product operations to perform at a higher level and therefore match their consumption goal to maximize their overall task performance. In contrast, consumers with low task expertise will perceive replacement technology to be more useful and less risky (vs. assistive technology) as such technology would replace their poor skills and knowledge in performing the consumption task and therefore match their consumption goal of reaching the desired end state with no/minimum effort. Finally, perceptions of usefulness and performance risk will further affect adoption intentions. These propositions are tested in three experimental studies.

1.2 Research objective

An estimated 50 billion autonomous products are expected to be produced by 2020 (Mani & Chouk, 2017). However, due to the limited volume of consumer research on autonomous products (Hoffman & Novak, 2015, p. 126), it is not clear whether all consumers will perceive them as useful or recognize the risks that such products might entail.

This dissertation has two main research objectives:

1) To provide a deeper insight into whether consumers differ in their perceptions of the usefulness and risk associated with autonomous products. More importantly: do individual differences of task expertise determine consumers' perceptions of the risk and usefulness associated with and intentions to adopt autonomous products?
2) To propose a classification of autonomous products into assistive and replacement technologies highlighting their value proposition in a consumption context.

1.3 The importance of research

1.3.1 Theoretical contributions

This dissertation makes three theoretical contributions. First, it aims to contribute to the literature on autonomous products. Researchers and economists who highlight the phenomena of robots, artificial intelligence and autonomous systems (e.g., Parasuraman & Riley, 1997) have mainly taken a supply-side perspective and examined the consequences of product autonomy for societal welfare and workers. In contrast, this dissertation focuses on the consequences of autonomous products in a consumption context and highlights some previously undocumented effects of product autonomy in the marketplace.

Second, this dissertation aims to contribute to the technology-related marketing literature by complementing the existing research on the dark side of technology (e.g., Wilcox & Stephen, 2013; Mick & Fournier, 1998) and answering recent calls for studies on how technology affects consumers differently, depending on their consumption motives (Reed et al., 2012).

Third, this dissertation aims to add to the consumer expertise theory. Consumer expertise is one of the most important areas of inquiry for consumer researchers (Alba & Hutchinson, 1987). The crux of this literature is that experts and novices differ in how they approach and perform different consumption tasks (Germain & Enrique Ruiz, 2009; Anderson, 1990; Chi, Glaser, & Rees, 1981). Thus, consumers strategically choose products that enable them to achieve their desired consumption goal (King & Balasubramanian, 1994). In this dissertation, I focused on the consequences of consumer expertise in the adoption of autonomous systems, thereby answering recent calls for studies on how expertise affects goal-directed consumer behavior. This is an important issue to investigate because, despite the advantages of autonomous systems and the common belief that experts are more receptive to such innovations, they often resist autonomous products that replace their skills.

1.3.2 Managerial contributions

This dissertation has two significant managerial implications. First, autonomous products have been a crucial trend in consumer markets for decades, but academic marketing research provides little practical guidance on how to manage variations in consumer responses to such products. The findings of this dissertation offer actionable insights into the planning research and development stages of the product development process. Product-centric firms should recognize that autonomous products can increase efficiency in product usage but also realize that this may constrain the success of expertise-related tasks. Consumer-centric firms should consider their target segments' expertise when deciding which tasks, currently performed by consumers, are good candidates for assistive vs. replacement technology.

Second, this dissertation demonstrates that at the product launch stage, managers should consider the people's expertise, and then communicate the benefits of replacement and assistive technologies in a way that matches their target audience's consumption goals to increase the likelihood of product adoption among target consumers.

1.4 Outline of the thesis

This dissertation is structured as follows. Chapter 2 discusses the central concepts that constitute this dissertation and the technology adoption theories underlying the assumptions of this dissertation. Section 2.1 provides a conceptualization of the degree of product autonomy in a consumption context. Next, section 2.2 employs the adoption theory to predict and explain the consumers' adoption of autonomous products. Finally, the conceptual framework and the hypotheses underlying the dissertation are presented at the end of the chapter. Chapter 3 discusses the man-machine phenomenon from an engineering perspective and then from a human (customer) perspective. A classification of autonomous products into assistive and replacement technologies from an engineering perspective is presented (section 3.1), reflecting their key characteristics and differences in value proposition from a consumers' point of view (section 3.2). Chapter 4 presents an empirical investigation of the proposed conceptual framework. This chapter contains a summary of the findings of each study, general discussions, research contributions, and directions for future research.

Chapter 2

Theoretical background and conceptual framework

The consumers' adoption of new product technologies has been widely studied in the marketing and consumer research literature. Although autonomous technologies are a new phenomenon for consumers, I will analyze their adoption through the theoretical lenses developed for other types of technologies and products. In this chapter, I will discuss the central concepts that constitute this dissertation and the technology adoption theories underlying the assumptions of this thesis. Section 2.1 provides a conceptualization of the degree of product autonomy in a consumption context. Next, section 2.2 employs the adoption theory to predict and explain the consumers' adoption of autonomous products. Finally, the conceptual framework and the hypotheses underlying the dissertation are presented at the end of the chapter.

2.1 Conceptualizing the degree of product autonomy

The concept of autonomy has been of scholarly interest for over 300 years and has recently received considerable attention with the advancements in the field of artificial intelligence (AI) and robotics (Wallach, 2015). The word “autonomous” is typically used to qualify the type of agents, robots or systems being investigated. Terms such as “autonomous robots,” “autonomous systems,” and “autonomous agents” are used in articles, media and popular science magazines. Despite this widespread usage, the term “autonomy” does not mean the same thing to everyone who uses it (Smithers, 1997). To better grasp and analyze the concept of autonomous systems/products, we must have a common understanding of what autonomy means.

The central idea in the meaning of autonomy is rooted in the etymology of the term: auto (self) and nomos (rule of law). The ancient Greek word “autonomos” is the quality or state of an individual or system being self-governing. The idea of being self-governing was first applied to the ancient Greek city whose citizens freely exercised the rule of law without being influenced by an external governing power (Steels, 1995). Thus, the citizens had the right to “self-govern” their own affairs, beliefs or desires within the limits of a larger framework set by law.

According to the dictionary definition (from the American Heritage Dictionary of 1969), autonomy is the condition or quality of a system of being self-governing and independent of others. Thus, autonomy is a system’s capacity for self-determination or self-governance. This characterization implies that an autonomous system is freely able to select between options, make choices without external control and respond adaptively to the surrounding environment (from the American Heritage Dictionary of 1969). Beyond that, the concept of autonomy is a much-contested concept that comes up in a number of arenas.

In general, autonomy as a construct represents free will and independence from external control. As discussed above, the word “govern” (self-govern) is the ability of a system to decide and implement decisions (Gunderson & Gunderson, 2004). Thus, self-governing is the ability of an entity/system to decide and implement decisions by itself, act according to its internal states, and knowledge, without outside intervention.

The understanding of conceptualizing autonomy as a self-governing system/entity has been adapted by systems theory and cybernetics, through which the concept of autonomy in terms of the goal-directed behavior of regulatory systems has been studied, including biological and technical systems (Steels, 1995). The broad field of cybernetics in particular encompasses the functions and processes of systems that have goals in their given environment. To accomplish these goals, such systems process and react to information, develop strategies and perform suitable actions to achieve their goals. Thus, an important element of autonomy related to products is the idea of self-determination, meaning that products can operate on their own. In addition, a definition of artificial intelligence is that machines and products can be designed to make decisions and solve problems to meet specific goals (Russell & Norvig, 2002). Based on the ideas of self-determination and self-governing systems, prior research has mostly conceptualized product autonomy in terms of products with goal-directed, pro-active, self-regulating and self-starting behavior (Rijsdijk & Hultink, 2009; Nicoll, 1999; Baber, 1996).

However, conceptualizing autonomy as a self-determination technology is missing independence as a key component of autonomy. For example, an analog clock is not independent from external control as it cannot alter its own state to respond to processes that go across its boundaries, such as adjusting for time changes during daylight saving time (DST). Thus, the clock is unable to adapt to the conditions around it, and certainly cannot anticipate them. Russell and Norvig (2016) addressed this by suggesting that a system with artificial intelligence is autonomous, given the application of certain rules without external help. Thus, an independent product will make decisions on its own and has the ability to learn from its decisions and update its memory to improve future decision-making. Thus, a conceptualization of the degree of product autonomy needs to reflect independence and self-determination. This is guided by artificial intelligence and the capability of the autonomous product to apply a given set of rules to a predetermined set of tasks. An example of an autonomous product would be a self-driving car that is able to operate in complex and open-ended environments with high levels of independence and self-determination. The car perceives, learns, reasons and acts with self-awareness and responds intelligently to unforeseen changes in the environment. Another example of an autonomous product would be a delivery drone that can deliver a package to an address given real-world conditions such as traffic, urban landscapes, emergencies and weather conditions. For instance, a delivery drone or a self-driving car gathers data from its sensors, which indicate a road hazard ahead. The system must then analyze this data and formulate a solution—in this case, it must figure out how to avoid the hazard to achieve the operational goals. The system may determine that it can go around the hazard, so a sequence of actions is planned that will make this possible;

then, that sequence is executed: the car or drone slows down, veers left, straightens out briefly, then veers right, straightens out, and picks up speed again.

Despite the widespread use of the term “autonomous systems”, many researchers have used the terms “autonomous” and “automated” interchangeably (e.g., Vagia, Transeth, & Fjerdingen, 2016; Albus & Antsaklis, 1998). It is therefore important to draw a clear line between the two. The term “automatic” or “automated” originally means self-moving and comes from the Greek word “automatos”, which means self-movement. An automatic system is thus a self-moving system that produces some sort of movement on its own to a specific input (Smithers, 1997). The system has fixed choice points, programmed with a number of fixed alternative actions that are selected by the system in response to inputs. For example, traffic lights are an automatic system that produces some sort of movement because the input (e.g., time to change the lights) is provided. However, an automatic system is unable to perceive its environment and adapt to changing circumstances, handle unforeseen situations and learn from its experiences to make intelligent decisions to achieve its operational goals (Smithers, 1997). Regarding traffic lights, they are unable to predict that a car is approaching the crossing too fast and/or has lost its breaking functions, and thus turn the signal green to avoid an unexpected collision. An autonomous system, on the other hand, is goal-driven and demonstrates a self-governing behavior, senses and controls its environment and takes appropriate actions in performing high-level problem-solving without human intervention, e.g., self-driving cars.

I define product autonomy as the degree to which a product is able to sense and control its environment, make decisions on its own, learn from its decisions and apply a set of rules to a predetermined task independently of the user’s interventions. Consequently, we have products with a high degree of autonomy that replace the need for the consumer to do the task (i.e., replacement in nature), or products with a low degree of autonomy that assist the consumer in performing the task (i.e., assistive in nature). A product with a high degree of autonomy, for instance, has complete control over the task elements (processes) and the outcome of the assigned task, such as a self-driving car (Steels, 1995). The product is self-performing in nature (Hoffman & Novak, 2015) as it applies and executes the commands (rules) itself in performing a task, rather than requiring any user intervention (Gunderson & Gunderson, 2004). Thus, the outcome of the task is the focus of a product with a high degree of autonomy and the technology has complete control over the process of reaching the desired outcome without any user interaction.

In contrast, a product with a lower degree of autonomy has the freedom to control some of the processes (subtasks) of the assigned task (Gunderson & Gunderson, 2004), while the user remains in control of the overall task process. The number of rules given to the product is more limited in scope and thus, the product is mostly assistive in nature. The user can apply such assistive technologies to improve parts of the process involved in a task and therefore this type of technology creates opportunities for the user to improve his/her task performance. Accordingly, an assistive autonomous product is process-focused, allowing the user to be in control and modify the course of the product's actions. This also makes the product more flexible and cooperative in nature. Equipped with limited intelligence and capability (Wallach, 2015), an assistive autonomous product may attempt to merely supplement or enhance the users' existing task capabilities (Russell & Norvig, 2002). For example, a car could be designed and equipped with an assistive mode to alert the driver of a road hazard ahead and will even do some braking or assistive parking whenever necessary. The car can also take partial control of the driving task in steady driving conditions such as driving on highways/motorways using the assistive-navigation system; however, the driver can take control of the car whenever necessary.

The following section discusses the phenomenon of the consumer adoption of autonomous products; in addition, the support for the conceptual model underlying this dissertation is presented.

2.2 Consumer adoption of autonomous products

With rapid advances in technological innovation occurring in every conceivable domain, the issues related to technological adoption have gained increasing importance in recent years. Large investments are being made by organizations and governments to introduce new technologies that have the potential for a paradigm shift in the lifestyle of the users. However, these investments may not yield results if the innovations are not adopted by the intended users. The bottom line of innovation research findings is that if innovations succeed (fail) to meet consumer needs, wants, and preferences, they are likely to encounter consumer adoption (resistance) (Ram, 1989).

Adoption is a decision to make full use of an innovation (Rogers, 1995). Understanding the consumers' decisions to adopt or resist innovations is important for firms developing new products and services. Different theoretical approaches exist to help predict and explain the users' acceptance and adoption of new technologies. Among the foremost theories are Davis' (1989) technology acceptance model (TAM) and Rogers' (1995) diffusion of innovation theory (DOI).

The diffusion of innovation theory describes the process through which new ideas, practices, or technologies spread into a social system (Rogers, 2003). According to this theory, innovation is an idea, process, or a technology that is perceived as new or unfamiliar to individuals within a particular social system. Diffusion is the process by which the information about the innovation flows from one person to another over time within the social system (Rogers, 2003). Rogers (2003) asserted that there are four main elements in the diffusion process: (a) the attributes of the innovation, (b) the communication channels through which the innovation is diffused, (c) the characteristics of the adopters, and (d) the social system. The attributes of an innovation include five user-perceived qualities: relative advantage, compatibility, complexity, trialability and observability (Rogers, 2003). The communication channels refer to the medium through which people obtain the information about the innovation and perceive its usefulness. This involves both mass media and interpersonal communications. Rogers has also divided the individuals of a social system into five groups based on their attitudes toward an innovation: innovators, early adopters, earlier majority, later majority and laggards (Rogers, 2003). In this theory, a social system is “a set of interrelated units engaged in joint problem solving to accomplish a common goal” (Rogers, 2003). This constitutes a boundary within which the diffusion of innovation takes place. Rogers (2003) suggests that the structure of a social system affects the individuals’ attitude toward the innovation and consequently, the rate of adoption of innovations.

Whereas DOI is a complex theory that explains the adoption process of new technologies at a societal level (Oliveira & Martins, 2011), TAM, on the other hand, takes the individual user’s perspective and attempts to explain the relationship between beliefs, attitudes, and intentions toward using a new technology (Davis, 1989). The strength of the model lies in its simplicity because there are only two constructs, namely: “perceived usefulness” (PU) and “perceived ease of use” (PEOU) for predicting an individual’s adoption of new technologies. PU is the degree to which a person believes that using a particular system would enhance task performance, whereas PEOU refers to the user’s expectation that using the technology is free of effort.

The technology acceptance model has been widely accepted and applied as it specifically addresses factors that influence the usage of information systems and new technologies. The

TAM model has been validated through examining various types of technologies relevant to organizational and individual adoption, such as the internet (Horton et al., 2001), electronic commerce (Pavlou, 2003), mobile banking adoption (Wakefield & Whitten, 2006), self-serving technologies and decision support systems (Lin & Chang, 2011). A meta-analysis of 88 studies conducted by King and He (2006) has shown that TAM can be used as a reliable model for predicting new technology acceptance.

Many studies have examined TAM's overall explanatory power and measurement validity in different empirical settings, characterized by technology, user groups, and organizational context. For instance, quite a few empirical studies of TAM have tested the theory in academic settings. Davis et al. (1989) longitudinally investigated the validity of TAM and the theory of reasoned action (TRA) in M.B.A. students' acceptance of a word processor application. Mathieson (1991) compared the utility of TAM and theory of planned behavior (TPB), another theory that extends from TRA but does not specifically target information technology acceptance/adoption behavior, in predicting the intention of undergraduate students to use a personal-computer-based spreadsheet application. In another longitudinal study, Taylor and Todd (1995) examined the validity of TAM together with TPB in explaining and predicting the use of a computer resource center by business school students.

The TAM has also been examined in business settings. For example, Davis (1989) tested TAM using acceptance of an e-mail system and a word editor by employees at a large commercial organization. Using an extended TAM, Chau (1996) investigated the acceptance of a newly released personal-computer-based application suite by administrative and clerical staff at a university. Igbaria et al. (1997) investigated personal computing acceptance factors in small firms using TAM as the theoretical basis.

Overall, researchers tend to suggest that TAM is valid, robust, powerful and capable of explaining user behavior across a broad range of end-user technologies and user populations, while being simultaneously parsimonious and theoretically justified (Venkatesh & Davis, 2000; Taylor & Todd, 1995; Chau, 1996; Mathieson, 1991; Davis, 1989). The TAM model is also widely acknowledged for its unique emphasis on the individuals' extrinsic motivations to use new technologies to achieve their consumption goals or tasks (Lee, Kozar, & Larsen, 2003), which is particularly relevant in the context of product technologies that perform tasks on the users' behalf. Moreover, Spotts (2014, p. 213) argues that the strong and consistent predictive power of TAM may offer the opportunity to capture the consumers' perceptions of new technologies at an early prototype development stage, which is useful for predicting their future adoption behavior. Based on this discussion, it is argued that the TAM model is a useful framework in predicting the consumers' adoption and use of new technologies, and may therefore provide a good reference point to analyze consumers' perceptions and reactions toward a new type of product technology, i.e., autonomous products.

The PU of a new technology has been proposed as the key determinant of the attitude toward adoption (Venkatesh, 2000; Davis et al., 1992). Davis (1989) defined PU as the degree to which a person believes that using a particular system (technology) would enhance job performance. People form usefulness judgments by cognitively comparing what an innovation is capable of providing to what they need to accomplish. Thus, PU is the users' mental assessment of the match between the desired outcomes (goals) and the consequences of performing the task using the new product or technology (Venkatesh & Davis, 2000). If the desired outcome (goal) is achieved more effectively using the new product or technology, then it is perceived to have a higher level of usefulness for the consumer.

Studies investigating the consumers' acceptance of new technologies have found PU to be a highly reliable and consistent predictor of technology adoption (e.g., Venkatesh, 1999; Gefan & Straub, 1997; Davis et al., 1992). Similarly, in a comprehensive review of TAMs, King and He (2006) reported a consistently strong empirical relationship between the perceptions of usefulness, and adoption and usage. A key predictor of new technology acceptance, PU is therefore included as a relevant factor in understanding the consumers' motivation to adopt and use autonomous products.

A question of interest concerns whether autonomous product technologies enhance a user's task performance. Previous research on autonomous products suggests that higher levels of product autonomy save consumers from exerting effort while maximizing their overall operational efficiency, productivity and quality in performing consumption tasks (Rijsdijk & Hultink, 2003; Baber, 1996). Baber (1996) further elaborated that with increasing autonomy, domestic products are able to execute their assigned tasks without any human interaction (i.e., substitute for human effort and labor) and make intelligent decisions to achieve their operational goals efficiently. Similarly, Schoettle and Sivak (2014) posited that the use of autonomous products is likely to make consumers perceive that their consumption outcome is improved as the product performs operations in a safe and reliable manner by taking over some or all of the decision-making and execution processes of the assigned task. In another study, Rijsdijk and Hultink (2009) found that technologies that are able to learn and work with little or no user interaction lead to an increase in productivity due to their high level of precision and accuracy in performing consumption tasks.

Autonomous products are equipped with advanced sensor technologies, substantial processing power, and artificial intelligence software that enable these products to sense and control their environment, and make decisions on behalf of the user. A key aspect of autonomous products is that the consumers' personal effort is reduced (i.e., tasks are delegated) as the product takes over some or all of the decision-making and execution processes of the assigned task. In addition, an intelligent product brings precision and accuracy with its unique computing powers in performing the assigned task. Computer-mediated autonomous products work constantly, reliably and their accuracy is greater than that of a human, as they cannot be distracted either by fatigue or other external circumstances, which results in greater efficiency in task performance (Schmidt, 2017). Furthermore, artificial intelligence enables these machines to perceive and process large amounts of real-world data, and use the patterns found within the data to improve their decision-making.

Thus, as the degree of product autonomy increases, computer mediated technologies can offer better results in terms of reliability, accuracy, efficiency gains and ultimately optimize the overall task performance when they make decision/planning and act out on behalf of the user. A technology is perceived to be useful if it enhances the user's task performance (Venkatesh & Davis, 2000; Davis, 1989; Davis et al., 1989). Therefore, an increase in product autonomy is expected to increase its perceived usefulness. Based on the above, I propose that the following:

H1: An increase in product autonomy leads to an increase in perceived usefulness, which leads to an increasingly positive attitude toward adoption.

In the original work on TAM, the attitude toward adoption was determined by a system's perceived usefulness and ease of use (Davis, 1989; Davis et al., 1989). Later ease of use has been suggested as an antecedent of usefulness and not a direct effect on adoption (Gefan & Straub, 1997). Although usefulness is a very broad construct that captures both benefits and costs, it has been suggested that these should be separated. In particular, researchers have proposed that consumers evaluate not only usefulness in terms of benefits, but also the risks involved in adopting new product technology (Dowling & Staelin, 1994; Ram, 1989).

Perceived risk is a psychological construct inherent in consumer product evaluations and is associated with the uncertain and unpleasant consequences of acquiring and consuming products or services (Cunningham, 1967; Bauer, 1960). Related to adoption, it is the perceived risk that the product will not perform as expected and/or will not provide the desired benefits, which is of interest (Grewal et al., 1994; Jacoby & Kaplan, 1972).

Product autonomy is a major change in new product technology, e.g., from manually driven cars that are operated and controlled by humans to self-driving cars that operate on their own in dynamic and uncertain traffic conditions without the need of human input. Advances in sensor technology, embedded processing power, and modeling and reasoning software have enabled autonomous products to sense and control their environment, and make decisions on the user's behalf (Vastenburg, Keyson, & De Ridder, 2007). Though such novel characteristics of an autonomous product may increase the perceptions of its usefulness, they may also have negative consequences by increasing the consumers' perceived risk (Vastenburg et al., 2007). The initial skepticism inherent to such innovative features is that autonomous products do not have a history of past performance (Olson, 2017). Consequently, there is a greater uncertainty about the potential flaws involved in such an immature technology where consumers may have to relinquish the control of important functions to the product. In addition, consumers have limited experience with autonomous products and are therefore likely to associate a higher level of performance risk with adoption (Aggarwal & Wilemon, 1998).

Furthermore, as the degree of product autonomy increases, a product becomes more technologically sophisticated (Rijsdijk & Hultink, 2003). Autonomous products are equipped with state-of-the-art equipment and computer-mediated technologies whose nature is complex and unfamiliar to the user (Wallach, 2015). Therefore, consumers understand increasingly less about the inner workings of the system that performs broader and more complex tasks, independent of the user's help (Rijsdijk & Hultink, 2009). Prior research has shown that technologically sophisticated products lead consumers to perceive risk (Folkes, 1988). Because autonomous products are more technologically sophisticated, they will be perceived as riskier.

Based on the discussion above, I argue that, as the degree of product autonomy increases, consumers are more uncertain about autonomous product operations due to the novelty of such products and a lack of prior experience with the product technology. Similarly, an increase in the degree of autonomy is also associated with an increase in technological sophistication. As stated earlier, product newness and technological sophistication increases the consumers' perceived risk. Therefore, I argue that an increase in the degree of product autonomy leads to an increase in perceived risk, which will decrease the intentions to adopt this new product technology. Thus, I propose the following:

H2: An increase in product autonomy leads to an increase in perceived risk, which leads to an increasingly negative attitude toward adoption.

2.2.1 The moderating role of a consumers' task expertise

Previous research suggests that consumer characteristics may play a key role in the perceptions of usefulness and risk and the subsequent intentions to adopt new products (e.g., Wood & Lynch, 2002; Moreau et al., 2001). The consumer differences that are relevant for adoption include the consumers' psychographic profiles, personality traits and demographic factors. Dabholkar and Bagozzi (2002) have further stressed that the variation in consumer differences arising from personality traits is of greater interest because such variations are at the center of consumer attitude formation and behavioral intentions. Therefore, in this dissertation, I am motivated to explore the moderating effect of consumer task expertise as an important personality trait that has received considerable attention in adoption literature and may have direct relevance in the context of products taking control over task operations. Moreover, Alba and Hutchinson (1987) suggested that consumers use their expertise to perform product-related tasks in achieving their consumption goals. This further highlights the need to investigate the role of task expertise to help our understanding of the underlying motivation of the consumers' acceptance or rejection of new product technology, i.e., autonomous products that will replace the consumers' need to perform consumption tasks, such as driving or cooking.

A consumer's expertise within a given task domain is a function of skills and knowledge in performing a specific task (Shanteau, 2015; Germain & Enrique Ruiz, 2009; Braunsberger & Munch, 1998). In the research on cognitive science, it is reported that individuals with higher levels of task expertise exhibit higher cognitive functioning, reasoning, and problem-solving capabilities within their domain of expertise (Germain & Enrique Ruiz, 2009; Anderson, 1990; Chi, Glaser, & Rees, 1981). In addition, task experts have also been found to concentrate on deeper mechanisms and/or processes in achieving the highest possible level of performance in goal accomplishment (King & Balasubramanian, 1994; Peter & Olsen, 1990). Consequently, consumers with higher levels of knowledge and skills show greater interest and enthusiasm when engaging in task processes to achieve their desired goal. Similarly, consumers with higher levels of task expertise respond, not just accurately but also rapidly to changing situations and demonstrate higher adaptability and creativity in performing the focal task (Ericsson & Charness, 1994).

Furthermore, scholars agree that task experts possess a large body of well-organized domain-specific knowledge and procedural skills (e.g., Ford & Kraiger, 1995; Green & Gilhooly, 1992; Newell & Simon, 1972). Procedural knowledge refers to "knowing how" to do something (e.g., riding a bicycle, knowing how to use a manual transmission car) and represents one's knowledge of procedures that is gained through experience (Newell & Simon, 1972). Procedural learning describes the formation of the skills needed to perform particular actions to accomplish task goals. This is the most primitive form of learning and the first to develop in infancy (Knowlton, Siegel, & Moody, 2017). Because procedural learning requires extensive practice and knowledge compilation, it is a slow learning system that eventually takes on an automatic or reflexive quality (Anderson, 1996). However, this becomes long-lasting and reliable—e.g., a skier, even after years of absence from skiing, likely retains this skill because of such a learning system. Knowledge compilation acts as a translation device that interprets or compiles bits of information from the environment into a set of specific procedural rules, which have been given a particular goal. As those procedures (rules) are repeatedly applied, they become concatenated into more compact rules. This mechanism shows how cognitive processing changes from relying on the interpretation and retrieval of pieces of information to embedding that information into a set of procedural rules that become more compact with use. The result is a context-specific representation of the skill that can be quickly and efficiently executed.

Studying the nature and development of expertise also requires the analysis of knowledge structures in experts and novices. Experts have more nodes in their knowledge domains and more links among these nodes, and their structures are more easily accessible and hierarchical (Glaser & Chi, 1988). Similarly, French and McPherson (1999) argue that experts have well-developed knowledge structures that include not only traditional propositional networks for conceptual knowledge, but also other specific memory adaptations and structures, such as action plan profiles, detail scripts on how to perform different tasks, and specific strategies that are stored and accessible from long-term memory. Due to well-developed knowledge structures, the cognitive processing of experts is faster, more accurate, automatic and likely to provide appropriate and creative solutions to problems (Sternberg & Horvath, 1995). Whereas novices respond to surface features, experts represent problems more abstractly, use different productions in solving those problems, and are more attentive to deep structural features during the problem-solving process.

Thus, consumers with higher levels of task expertise have higher levels of sophisticated problem representation understanding, and therefore require less cognitive effort for such processes and enjoy engaging in consumption tasks, compared to novices (Janelle & Hillman, 2003). Thus, as the consumers' expertise increases, consumers exhibit greater confidence in problem-solving (Ford & Kraiger, 1995). Similarly, due to their higher cognitive and motivational states of mind, experts are more engaged in problem analysis and task accomplishment. This aligns with Spence and Brucks (1997) who proposed that consumers with higher levels of expertise are more confident than novices in problem-solving and performing consumption tasks to achieve the desired outcome.

Based on the discussion above, as the degree of task expertise increases, consumers tend to rely on their superior knowledge and skills to perform the consumption task and achieve their desired outcome (goal). Similarly, the consumers with a higher level of task expertise expend less cognitive effort since the knowledge is stored in memory, are motivated to search for more information prior to problem-solving and are more confident in achieving their desired outcomes. Therefore, an increase in the degree of product autonomy will be perceived as less useful because experts enjoy doing tasks; thus, there is less value in decreased effort since an autonomous product will replace the consumers' knowledge and skills in performing the consumption task. Furthermore, autonomous products will be perceived as less useful because experts have detailed scripts and bits of information stored in their memory regarding how to perform the task, and autonomous products are unlikely to fit these detailed and varied scripts. Finally, experts may not have the explicit understanding of their (well-developed) procedural skills, making it difficult to evaluate the advantages of an autonomous product. Therefore, I argue that, as the consumers' task expertise increases, an increase in the degree of product autonomy will be perceived as less useful. Thus, I propose:

H3: As the consumers' task expertise increases, an increase in product autonomy will be perceived as less useful, which leads to an increasingly negative attitude toward adoption.

In contrast, as expertise increases, individuals use their superior knowledge and skills to process task-related information rather well and show a greater efficiency in processing new information, which is relevant in decision-making behavior (Alba & Hutchinson, 1987). Alba and Hutchinson (1987) further noted that individuals with a higher level of expertise are unlikely to experience information overload and will have a higher level of motivation in acquiring and evaluating new information. According to Cox and Rich (1964), seeking additional information on probable consequences leads to a reduction in the perceived risk through reducing the uncertainty of the outcome. Therefore, consumers with a higher level of expertise can learn and categorize new information with less effort, which has been found to be an effective strategy in coping with perceived risk in decision-making and purchase situations.

Furthermore, prior research has also found that experts perform product-related tasks more automatically, freeing cognitive resources that can be used to learn new product features (Thompson, Hamilton, & Rust, 2005; Ziefle, 2002). Following this reasoning, Chi et al. (1988) found that experts expend less effort to understand a problem and its basic structure qualitatively, and therefore are able to use complex systems in goal accomplishment more easily than novices. Similarly, Spence and Brucks (1997) proposed that consumers with higher level of expertise may be better able to form judgments about complex products because they focus their attention on a smaller, more diagnostic number of inputs. In another study, Walker and Johnson (2006) noted that the consumers' higher confidence in processing new information could help them mitigate the risk perception in using new technologies.

Based on the discussion above, it is expected that as the consumers' task expertise increases, individuals are better able to direct their information search behavior, learn new information easily and efficiently, and cope rather well with the complexity of new products. Therefore, an increase in the degree of product autonomy is perceived to be less risky as consumers with a higher level of task expertise are able to free up cognitive resources to learn new product-related information and form associations between autonomous product features and consumption goals. Therefore, I argue that, as the consumers' task expertise increases, an rise in the degree of product autonomy will be perceived as less risky. Thus, I propose the following:

H4: As the consumers' task expertise increases, an increase in product autonomy will be perceived as less risky, which leads to an increasingly positive attitude toward adoption.

2.3 Proposed research model

The conceptual model underlying this dissertation is presented in Figure 1. In this dissertation, I mainly study how the degree of product autonomy impacts consumers' intentions to adopt autonomous products. Consumers' perceptions about usefulness and risks are proposed to channel the effect of product autonomy on adoption intentions. Moreover, such a product autonomy-adoption effect is subject to the level of consumer experience with the task. The proposed research model is tested in three experimental studies.

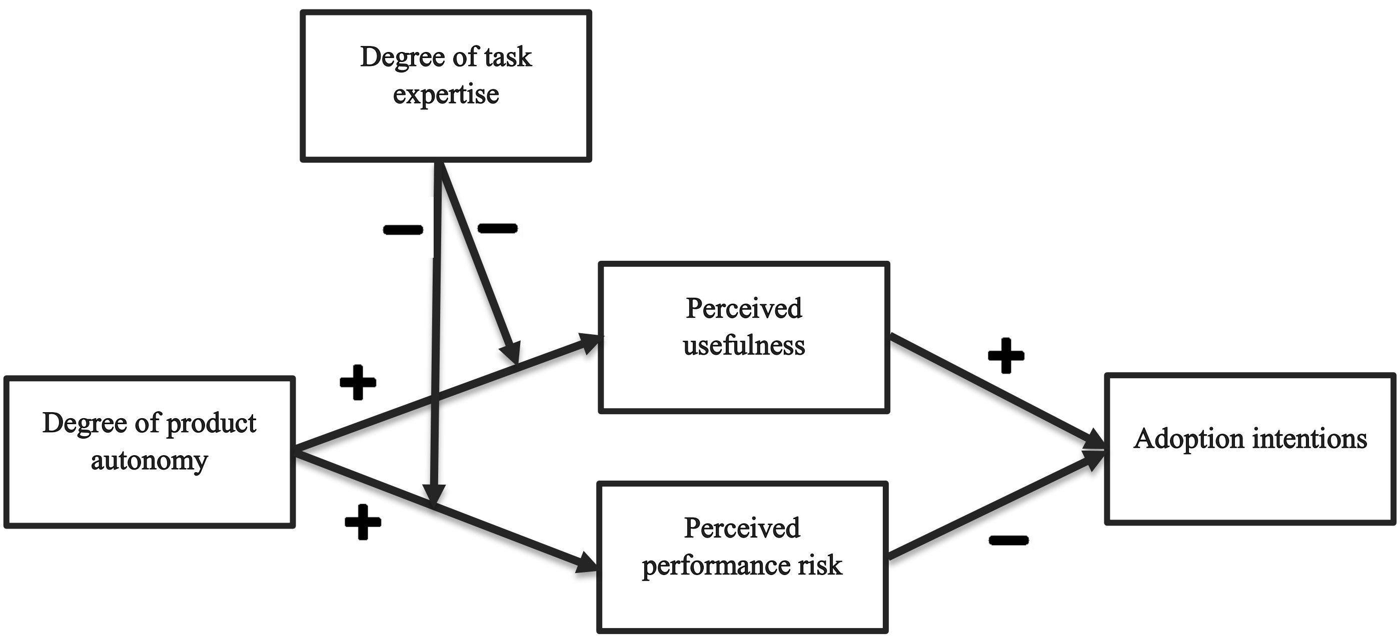

Figure 1: proposed research model

Chapter 3

Conceptualizing autonomous products from a consumer's perspective

Human-machine interaction and cooperation has recently received considerable attention in the academic community, along with labs, technology companies and the media. In this chapter, I will first discuss the man-machine phenomenon from an engineering perspective and then from a human (customer) perspective. A classification of autonomous products into assistive and replacement technologies from an engineering perspective is presented, reflecting their key characteristics and differences in value proposition from a consumers' point of view.

3.1 System autonomy from a designer's perspective

Designing and developing autonomous systems is a challenging and complex task. An important question from a designer's perspective is to determine which functions and tasks to allocate to either a human or a machine to promote effective human-machine interaction and cooperation (Thórisson & Helgasson, 2012). An effective design can allow human and machine understanding, and work together efficiently. However, a poor allocation of functions during the design of such systems can have important impacts, principally in terms of security, safety and performance (Habib, Pacaux-Lemoine, & Millot, 2017). Therefore, it is necessary to consider the technical and functional capabilities of the machine and the level of human engagement during the design of autonomous systems.

An autonomous system has the capacity to achieve a set of goals by its own means and adapting to environmental variations. This signifies that an autonomous system must be able to sense and perceive its environment, make decisions on its own and have the ability to adjust its behavior through learning and reasoning. During environment perception, multisensors (i.e., radar and laser sensors) are deployed to sense the comprehensive information from the environment, which is then fused to perceive the environment. For example, the self-driving car fuses data from radar sensors, laser sensors and visual sensors, and generates the surrounding environment perception, such as obstacle detection, road markings, etc. Then, the system must be able to interpret and analyze the information in a meaningful way to predict or decide the best course of action to achieve its goals (Beer, Fisk, & Rogers, 2014). In the course of its operations, the system must be able to reason and learn from its experiences to improve future decision-making (Beer et al., 2014). Based on these characteristics, various levels of machine autonomy have been proposed in previous literature, addressing action planning, decision-making and implementation in human-machine interaction and cooperation.

Consequently, Sheridan and Verplank (1978) addressed the decision/action challenges in the design of autonomous systems and proposed the earliest and the most cited classification of system autonomy. The authors introduced 10 levels of autonomy; proposed a variety of choices regarding the cooperation of the user and machine in teleoperation; gave an analytical description of who (machine or the human operator) can be in control in every stage of decision-making and action implementation; and explicitly compared various mixes of human and machine decision-making and action implementation (Sheridan & Verplank, 1978). In their proposed taxonomy, level 1 is referred to as fully manual control where the human makes all decisions and actions, and the computer offers no assistance (Sheridan & Verplank, 1978). At level 2, the system processes information, interprets that information and offers a set of choices/action alternatives to the human operator, and at level 3, the system narrows down the choices to a few. At level 4, the system is capable of proposing the best alternative solution to the problem; however, the human operator can overrule the proposal and choose an alternative solution. At levels 5, 6 and 7, the computer becomes increasingly capable of sensing and perceiving its environment and executing the best solution to the problem, only if the human operator approves. In their proposed taxonomy, a fully autonomous system senses and perceives its environment, collects and interprets data and carries out action planning and implementation requiring no further human interaction (Sheridan & Verplank, 1978). A key aspect of Sheridan and Verplank's (1978) proposed taxonomy is that, with increasing autonomy, a system is able to perceive, plan and make decisions, and ultimately work without the need for user interaction to accomplish a set of goals.

Endsley (1987) followed up and improved the previous taxonomy by Sheridan and Verplank (1978). She presented a more compact taxonomy consisting of four levels of autonomy for an advanced cockpit developed in the context of the use of expert systems to supplement human (a pilot, in this approach) decision-making for autonomous system control. Endsley identified four functions during which the human operator or the machine had the possibility of being in control of task operations (1987). These functions included:

1) Decision support (Human acts upon recommendations provided by the system-Human in the loop).
2) Conceptual artificial intelligence (The system can perform and act on some functions or the entire task; however, the consent of the operator is required to carry out actions-Human in the loop).
3) Monitored artificial intelligence (The system performs all aspects of the task but the operator can still regain control and modify the course of actions, if necessary-Human in the loop).
4) Fully autonomous system (The system excluded the human operator from the loop-Human out of the loop).

Endsley classified the functions presented above into two broad categories ranging from assistive assistance, where the system and the user collaborate on a specific problem, to a fully autonomous system, where the user is completely out of the loop (1987). For instance, levels 1 to 3 offer assistive collaboration, where the system perceives its environment and offers a set of alternative choices; however, the human remains in complete authority to select between different options. Thus, the human operator is assisted with machine capabilities to accomplish a set of tasks with greater efficiency. In Endsley's approach, level 4 is a fully autonomous system responsible for each aspect of decision-making and the implementation of the assigned task (1987). The major transformation in Endsley's approach is that in the assistive autonomy condition, the user and the machine can collaborate on achieving the desired goal, combining both human and machine capabilities; however, the user remains in complete control over the task processes and can modify the course of machine's operations to achieve maximum task performance (1987). In the fully autonomous condition, on the other hand, the machine performs all aspects of the task.

Riley (1989) further improved and simplified the earlier taxonomies and proposed a mixed-initiative model of human-machine system along two dimensions: intelligence and capability. At the lowest level of intelligence and capability, the system does not perform real data processing or execute any of the functions in mission accomplishment. However, with increasing capability and intelligence, the system becomes more responsive, can anticipate operator errors and adjust its behavior accordingly. Riley (1989) further classified machines into two broad categories, depending on their level of intelligence (referred to as problem-solving and decision-making), and the ability to implement the choices (capability): associate machine and supervisor machine. An associate machine cooperates with the operator on various problem-solving and decision-making tasks, but the operator has the authority to override or inhibit machine operations. A supervisor machine can override the operator, but the operator may not override its course of action.

Draper (1995) presented a taxonomy by introducing a different layout from those already presented. The author's approach combines human operators with machine control in a teleoperator capable of carrying out functions that can be either semi-autonomous or fully autonomous (Draper, 1995). In his research, Draper identified nine degrees of autonomy functions (1995). In the first five levels, i.e., the assistive autonomous state, the user and the machine share the tasks that need to be controlled. The machine has the ability to become intelligent, giving the user the possibility to teach the machine rudimentary information about the work site, such as defining regions that should not be entered. The machine is able to modify user inputs to provide guidance. The next four levels are referred to as a fully autonomous state in which the computer apparently has more authority than the human.

Parasuraman et al. introduced a novel way to approach the design challenges of autonomous systems by defining autonomous operations at four different stages in human machine cooperation (2000):

1) Sensing and perceiving: the acquisition of multiple sources of information, including sensory processing, preprocessing of data and selective attention.
2) Problem-solving: the manipulation of information in working memory and cognitive operations, such as integration, diagnosis and inference, occurring prior to the point of decision.
3) Decision-making: the decisions based on such cognitive processing.
4) Execution/action implementation: the entailment of an action consistent with the decision choice.

The major difference between the previously proposed approaches and the taxonomy by Parasuraman et al. (2000) is that, instead of classifying the four characteristics above into various levels of autonomy with a gradual increase in assistance system capability and control, these functions are classified into three levels of autonomy:

1) Autonomous sensing (information acquisition and data transformation) to make observations and refine information,
2) Autonomous planning (information interpretation and decision selection) to react to information or decide actions and schedule, and
3) Autonomous acting (action implementation) to execute a planned task or to produce reflexive reactions.

Thus, a system can be autonomous at each of these three levels or perform the overall task in a fully autonomous mode.

In summary, various authors have suggested a variety of frameworks for equipping machines with various capabilities and functionalities in human-machine interaction and cooperation. Accordingly, each taxonomy mentioned above provides an organizational framework in which the purpose or function of an autonomous system can be categorized. These models and frameworks are also important to determine which functions and tasks to allocate to either a human or a machine in human-machine interaction and cooperation to achieve the maximum task performance.

Drawing on the frameworks presented above, there is a consensus that various capabilities and functionalities of autonomous systems can be grouped into two broad categories: assistive and replacement technologies. Assistive technologies further involve various intermediate levels of autonomy and combine various functionalities of machines, such as information acquisition, information analysis and decision selection with the human operator's authority to implement actions. Replacement technologies include higher levels of autonomy where systems can implement actions separately, from information acquisition to decision selection. Table 1summarizes the characteristics of assistive and replacement technologies and the level of human engagement in human-machine interaction.

Table 1: Characteristics of assistive vs. replacement technologies with the level of human engagement

Characteristics/Classification	Assistive technology		Replacement technology	
	Human	Machine	Human	Machine
Sensing and perceiving (System's ability to perceive, monitor, and register data from the environment)		√		√
Information analysis (Ability to process data)		√		√
Decision-making (Ability to analyze the (environment) data and propose solutions to the problem)	√	√		√
Action implementation (Ability to implement the decisions)	√			√

3.2 System autonomy from a consumer's perspective

Based on the previous discussion regarding the engineering perspective, we can conclude that there is a consensus on classifying autonomous systems into assistive and replacement technologies. Such a classification can help designers to not only allocate the appropriate functions to machines in human-machine interaction and cooperation, but more importantly, to design machines that deliver value to the end consumers.

Throughout human history, we have created tools that increased our individual and collective intelligence and helped us compensate for our biological disadvantages (e.g., fatigue, fear, illness). For instance, we started with crude functional tools such as hammers and axes. Thousands of years later, vehicles allowed us to move more rapidly than other animals and reach remote and inhospitable places. Similarly, various tools such as telescopes, cameras, microphones and other instruments provided us with delicate control and prodigious strength, and extended our visual, auditory and tactile senses. Along this trajectory, the rise of autonomous systems that embody a significant level of intelligence are our most powerful yet.

Autonomous technology will fundamentally change the way humans perform tasks. The virtues of autonomous technologies concern extending and expanding human capabilities (Moustris et al., 2011). Compared with other species, humans are average when it comes to agility, speed, stamina, strength, hearing, vision or the ability to withstand the extremes of environmental conditions. Autonomous technologies, however, will improve our ability to interact with the physical world, make better predictions and achieve operational goals safely, efficiently and effectively.

Considering their unique characteristics, next, I will discuss the specific value proposition of replacement and assistive technologies from a consumer's point of view.

Replacement technologies: With replacement technologies, an autonomous product has complete control over the task elements (processes) and the outcome of the assigned task, such as a self-driving car (Steels, 1995). The product is self-performing in nature (Hoffman & Novak, 2015) since it applies and executes the commands (rules) itself in performing a task, rather than requiring any user intervention (Gunderson & Gunderson, 2004). Thus, the outcome of the task is the focus of an autonomous replacement product and the technology has complete control over the process of reaching the desired outcome without any user interaction in the process.

Replacement technologies sense, perceive, decide and act on the users' behalf (Steels, 1995). Taking advantage of their unique characteristics, replacement technologies collect and analyze tremendous amounts of data, detect patterns and determine an appropriate set of actions to achieve their operational goals. These capabilities also allow such systems to accomplish their assigned tasks with greater speed and precision, expanding their productive potential (Wallach, 2015).

Another key aspect of replacement technologies lies in their reliable and persistent operations (Moustris et al., 2011). Humans are prone to fatigue, distractions and errors. Machines, unlike humans, do not require breaks and refreshments as they are designed to work for long hours and can continuously and consistently perform their assigned goals without becoming bored, distracted or even tired; therefore, this will result in economic and environmental gains, e.g., efficient use of resources, reduced traffic congestion and less emissions in the environment.

In addition, replacement technologies also have the potential to perform dangerous and complex tasks, such as underwater and space exploration, that humans are incapable of performing. Furthermore, replacement technologies promise to enhance the users' consumption experiences by taking over the control of task operations that will give users the opportunity to socialize and engage in other preferred activities.

In the context of replacement technologies, it is also beneficial to understand the nature of the tasks performed by an autonomous replacement product. Autor, Levy, and Murnane (2003) distinguish between manual and cognitive tasks in the field of robotics. They defined manual tasks as those that are mostly repetitive in nature and require no special skill for their execution. The phenomenon of substituting repetitive human labor with machines is not novel. For example, in industrial and manufacturing sectors, machines have long been performing manual tasks such as welding, precision cutting and assembling without human interaction. Accordingly, machines are easily able to execute programmed work sequences with greater efficiency and accuracy. These trends have already been observed in certain consumer products, such as robotic vacuum cleaners and lawn mowers that are able to perform manual tasks that require little to no skill for their execution. Therefore, products that are able to replace humans in performing manual or repetitive tasks exhibit little to no intelligence by following explicit programmed rules, since they mostly operate in constrained environments (Autor et al., 2003). Though such products may have limited ability to reason within their working environment, they lack the ability to learn and generalize from their operations.

Cognitive tasks, on the other hand, require some sort of problem-solving and skill for their execution (Autor et al., 2003). Due to an increase in computing power and the rise of artificial intelligence, machines are now becoming increasingly intelligent and able to perform cognitive tasks that require some degree of skill for their execution (Petropoulos, 2018). Such replacement technologies are able to solve complex problems (e.g., financial robots), learn from their experiences and achieve their assigned goals without any external influence. This is achieved by equipping machines with sufficient computational resources, offering training examples from real world data, and by designing specific algorithms and tools that define a learning process. Consequently, machines can improve their performance through learning by doing, inferring patterns and ultimately replacing human skills to perform their assigned goals (Petropoulos, 2018).

Therefore, replacement technologies will not only reduce the consumers' effort and labor in performing manual and labor-intensive tasks, they will also reduce the consumers' cognitive workload by taking over cognitive tasks that require certain skills and problem-solving. An example of such a scenario is a self-driving car that is able to navigate through city traffic, sense, perceive and react to the environment to perform its operational goals.

Table 2: Value proposition of assistive vs. replacement technologies

Value proposition	Assistive technology	Replacement technology
Precision and accuracy	Human intelligence combined with machine intelligence to find specific and correct solutions to the problems	Machines with on-board computing powers analyze the world and identify the best solutions to the problems
Environmental and economic gains	The use of autonomous systems will enable safer and reliable operations, reduced emissions, efficient use of resources, reduced operation costs	
Cognitive workload	Humans can share their cognitive workload with machines capable of analyzing and interpreting large amounts of data quickly and accurately.	Machines can take charge of the overall task (e.g., self-driving car) freeing consumers from physical and cognitive effort.
Control	Human largely in control	Machine in control
Flexibility	Assistive technology is flexible in nature to allow humans to direct its operations in a meaningful way	Though replacement technology is not flexible in nature, it still learns from its experiences and improves its future decision-making

Creativity	Human intelligence combined with machine-computing power to unlock new problems to the solutions	Replacement technologies perform their assigned tasks on a planned sequence

Assistive technologies: With an assistive technology autonomous product, the user largely remains in control of the task process. The technology only has the freedom to control some parts of the process (subtasks) of the assigned task (Gunderson & Gunderson, 2004). The number of rules given to the product are more limited in scope. The user can apply such assistive technologies to improve parts of the process involved in a task; therefore, this type of technology creates opportunities for the user to maximize his/her task performance. Thus, an assistive technology product is process-focused, allowing the user to be in control and modify the course of action. This also makes the product more flexible and cooperative in nature. Equipped with decision-making and problem-solving abilities (Wallach, 2015), an assistive autonomous product may attempt to merely supplement or enhance the users' existing task capabilities (Russell & Norvig, 2002); e.g., a car with autonomous braking functions that aims to enhance the users' overall driving experience.

Equipped with artificial intelligence and unique computing powers, assistive technologies will boost our analytic and decision-making abilities by providing the right information at the right time. As we develop better and improved autonomous systems, we are discovering that they think in ways that humans cannot. Algorithms that can monitor and process massive amounts of data, and make conclusions based on patterns in the data that leave room for human interpretation, are poised to change every avenue of society (Makridakis, 2017).

Assistive technologies will also empower humans to make more informed decisions and help them harness and channel their creativity (Schmidt, 2017). Combining the assistive technologies' unique capabilities with human strengths and expertise will result in well-informed decision-making, leaving sufficient space for human intuition and inventiveness. Prior research has found that individuals who exhibit the highest cognitive loads are the least creative, whereas individuals with the lowest cognitive loads are the most creative (Baror & Bar, 2016). When our mind is too encumbered by mental taxation, we are unlikely to seek out novelty. Therefore, assistive technologies will allow us the freedom to engage in creative pursuits by taking over some tasks, such as analyzing and finding patterns in large volumes of data more quickly and accurately than can be achieved by humans alone.

Furthermore, due to their unique collaborative and flexible nature, assistive technologies are assumed to form a natural extension of human beings and our physical and mental abilities (Russell & Norvig, 2016). As humans sensing, information retrieval and physical abilities are limited, assistive technologies will supplement our abilities, monitor the world around us and enable us to achieve operational goals in an efficient way. This collaboration in human-machine interaction will enable us to solve some of society's most challenging practical problems, such as in the fields of transport, medicine, agriculture, education and public services.

Chapter 4

Empirical investigation of proposed conceptual framework

The focal interest of this dissertation is to investigate the effect of the degree of product autonomy on the consumers' intention to adopt autonomous products. In a lab experimental setting, one can easily manipulate the key independent variable and establish a causal relationship while keeping all other factors constant.

The empirical studies conducted and reported in this dissertation employed the between-subjects experimental design. The aim of experiments is to identify causal relationships between the degree of product autonomy and adoption intentions. The process involves three main steps. First, the independent variable is manipulated to create systematic variation in terms of different stimuli (Perdue & Summers, 1986). Next, I randomly distributed participants in different groups and then showed them relevant stimuli. In the last step, levels of the dependent variable are measured and results between the experiment groups are compared (Perdue & Summers, 1986). All three studies in my thesis have this three-step procedure at the core of their research design.

Though high in internal validity, experiments suffer from low external validity. Specifically, the need to manipulate the independent variable and control extraneous variables means that experiments are often conducted under conditions that seem artificial (Bauman, McGraw, Bartels, & Warren, 2014). Studies are high in external validity to the extent that the results are generalizable to people and situations beyond those actually studied. Although experiments can seem “artificial” and low in external validity, it is important to consider whether the psychological processes under study are likely to apply to other people and situations (Bauman et al., 2014).

Despite the concerns of low external validity issues, this dissertation employs experimental research design as an appropriate strategy for data collection. Due to the specific nature of the independent variable in this dissertation research, “the degree of product autonomy”, it was not possible to identify useful secondary data sources to obtain enough variability in the independent variable. However, I strongly believe that the development of this topic will benefit greatly from a replication of my research findings with secondary data. Thus, when an appropriate data source for this dissertation topic becomes available, this should be used for replication and an extension of my findings in this work.

The proposed conceptual framework will be tested in three empirical studies. The first two studies are designed to manipulate the level of product autonomy from the assistive technology condition to the replacement technology condition, and to test the proposed research model. Product descriptions were composed of cars in the first study and cooking devices in the second study, with assistive and replacement technology conditions. These product categories (i.e., cars and cooking devices) were chosen because they represent different consumption contexts to enhance the generalizability of the effects. Both driving and cooking are relatively common consumption contexts. Therefore, the possibility of bias due to product unfamiliarity and novelty was avoided in the respondents’ evaluations.

The third study looks at consumption domains where products can only have “assistive autonomy” because they cannot fully replace the user in performing the consumption task.

For instance, for many consumption domains, it is not relevant to have complete replacement technologies because the tasks themselves are done for hedonic reasons (e.g., skiing, dancing, listening to music, etc.), or because the tasks involve elements that will preclude replacement product technologies (taking an exam). In another example, due to the nature of the task (alpine skiing), skiing boots can only be assistive in nature, as the boots cannot do the skiing for the user. Thus, the aim of this study is to test the effect of going from a “no autonomy” condition to an “assistive autonomy” condition and to test the proposed research model.

4.1 Study 1

Study 1 is designed to test the key hypotheses underlying this dissertation (H1-H4). The research design is a one-factor between subject design, where the factor manipulated was the level of product autonomy, represented as assistive vs. replacement technologies.

Pretest

To ascertain whether participants perceived the conditions to be assistive vs. replacement technologies, I conducted a pretest using an online survey, recruiting 45 M-Turk participants. Participants read the product descriptions of a car, "Proxima car", manipulated as an assistive technology condition and replacement technology condition.

The product description for assistive technology was as follows:

> "*Introducing the newly designed "Proxima" car for the ultimate ride of the future. The car is designed and equipped with an assistive mode to alert you and even will do some braking for you whenever necessary. Using the car's assistance system, you are able to efficiently accelerate and decelerate under different driving conditions. With the help of a built-in navigation system, the car can partially take control of the driving in steady traffic conditions such as driving on highways/motorways, and thus you can use assistive-navigation."*

The product description for replacement technology was as follows:

> *"Introducing the newly designed "Proxima" car for the ultimate ride of the future. The car is designed and equipped with the latest technology on board and can apply brakes whenever necessary and drive without user intervention. Using an on-board*

computer system, the car can efficiently accelerate or decelerate under different driving conditions. With the help of a built-in navigation system, the car can sense its environment and drive all by itself wherever you want without you needed to do anything."

The perceptions of assistive technology vs. replacement technology were checked using three 7-point Likert scale items adapted from Rijsdijk and Hultink (2003) (1: strongly disagree, 7: strongly agree): "The Proxima car does things by itself", "The Proxima car works independently", and "The Proxima car takes initiatives." An analysis of the variance confirms that the level of product autonomy perceptions ($M_{\text{Assistive technology}} = 5.44$, $M_{\text{Replacement technology}} = 6.25$) differs significantly between conditions ($F(1, 42) = 14.14$, $p < .00$).

A follow-up question, "Please describe below how you perceived the advertised Proxima car", further revealed that participants under the assistive technology condition perceived the car to be assistive in nature, e.g., "I like the car as it would assist in my driving experience without fully taking over" and "This car will assist me while taking care of some functions". However, consumers under the replacement technology condition perceived the car to be self-performing in nature, e.g., "The car would do things without my input" and "Proxima car drives itself."

4.1.1 Procedure and participants

Data was collected via an online survey (M-Turk participants), through which 170 participants were recruited (36% female, average age 33.96 years) with monetary compensation ($0.5). First, the participants spent 60 seconds reading the product description page to understand the scenarios presented. Then, they were asked about their attitude toward technology adoption, the perceived usefulness, the perceived risk, their task expertise, and a few demographic questions (age and gender). At the end of the instrument, I asked the manipulation check questions.

4.1.2 Measures

The adoption intentions scale items were adapted from Venkatesh et al. (2003) with three 7-point scale items (1: strongly disagree, 7: strongly agree) that were averaged ($\alpha = .94$): "I would enjoy using Proxima car", "In my opinion, it would be very desirable to use Proxima car for driving purposes" and "I would like to own a Proxima car".

Perceived usefulness scale items were adapted from Davis et al. (1989), consisting of four 7-point scale items (1: strongly disagree, 7: strongly agree). These items were combined into one perceived usefulness measure with acceptable reliability ($\alpha = .90$): "The Proxima car would improve the quality of my driving experience" , "I find Proxima car useful for driving purposes", "The Proxima car is convenient for driving purposes" and "The Proxima car would allow me to be more productive".

Performance risk (PR) scale items were obtained from Grewal et al. (1994), consisting of four 7-point scale items (1: strongly disagree, 7: strongly agree) that we reversed and combined ($\alpha = .90$): "The Proxima car will perform well", "The Proxima car will perform the functions above described", "The Proxima car will not create problems" and "The Proxima car will work satisfactorily".

The self-reported measure of task expertise was adapted from Germain & Enrique Ruiz (2009), with two 7-point scale items (1: strongly disagree, 7: strongly agree) combined into one task expertise measure (α = .75): "I consider myself an expert driver" and "I believe in my abilities to drive".

The discriminant validity of the measurement model was assessed using the Fornell-Larcker criterion. As shown in Table 3, the correlations between the factors ranging from 0.240 to -0.791 are smaller than the square root of the average variance extracted estimates, which are in the range of 0.846 to 0.881. This indicates that the constructs are strongly related to their respective indicators compared to other constructs of the model (Fornell & Larcker, 1981), thus suggesting a good discriminant validity. In addition, the correlation between exogenous constructs is less than 0.85 (Awang, 2014). Hence, the discriminant validity of all constructs is fulfilled. In addition, to test the construct reliability, all the composite reliability (CR) values are higher than the recommended value of 0.7 (Gefen, Straub, & Boudreau, 2000) which adequately indicates that the construct reliability has been fulfilled.

Table 3: Study 1: Results of discriminant validity by Fornell-Larcker criterion for the model

		CR	AVE	PU	PR	PA	TE	M	SD
1	**PU**	.933	.776	**.881**				5.43	1.24
2	**PR**	.932	.775	-.791	**.880**			2.68	1.14
3	**PA**	.910	.716	.359	-.294	**.846**		5.55	1.11
4	**TE**	.855	.746	.237	-.314	.240	**.863**	5.44	1.10

Note: Diagonals represent the square root of the average variance extracted while the other entries represent the correlations.

Key: PU: perceived usefulness, CR: composite reliability, AVE: average variance extracted, PR: performance risk, PA: degree of product autonomy, TE: task expertise.

4.1.3 Manipulation test

Manipulation checks reveal that the level of product autonomy perceptions ($M_{\text{Assistive technology}} = 5.3$; $M_{\text{Replacement technology}} = 5.8$) differs significantly between conditions ($F(1, 168) = 5.92$, $p < .016$).

4.1.4 The mediating roles of perceived usefulness and perceived risk on adoption

Testing Hypothesis 1: H1 predicts that an increase in product autonomy, from assistive to replacement autonomy, leads to an increase in perceived usefulness, which then leads to an increasingly positive attitude toward adoption. Following the recommendations of Preacher and Hayes (2004), the statistical significance of the indirect effect (mediation) is tested using the SPSS mediation macro (MOMED; Model 4). This macro facilitates the recommended bootstrapping methods and provides a means for probing the significance of indirect effects (Preacher & Hayes, 2004).

In the analysis, the level of product autonomy (coded as -1=Assistive technology, 1=Replacement technology) was employed as the independent variable (X), perceived usefulness as the mediator (M) and adoption intentions as the dependent variable (Y). I tested the overall significance of the mediation effect by constructing a 95% confidence interval as recommended by Preacher and Hayes (2004). The results show that the mean indirect effect (path $a \times b$) from the bootstrap analysis is insignificant ($a\ x\ b$ = -.28), with the 95% confidence interval including zero (95% CI: -.6697 to .0983). The effect of product autonomy on perceived usefulness (path a) was also found to be insignificant (b= -27, p=.15). Therefore, H1 is rejected because there is insufficient proof of mediation. Figure 2 summarizes the final estimation results for the mediation model.

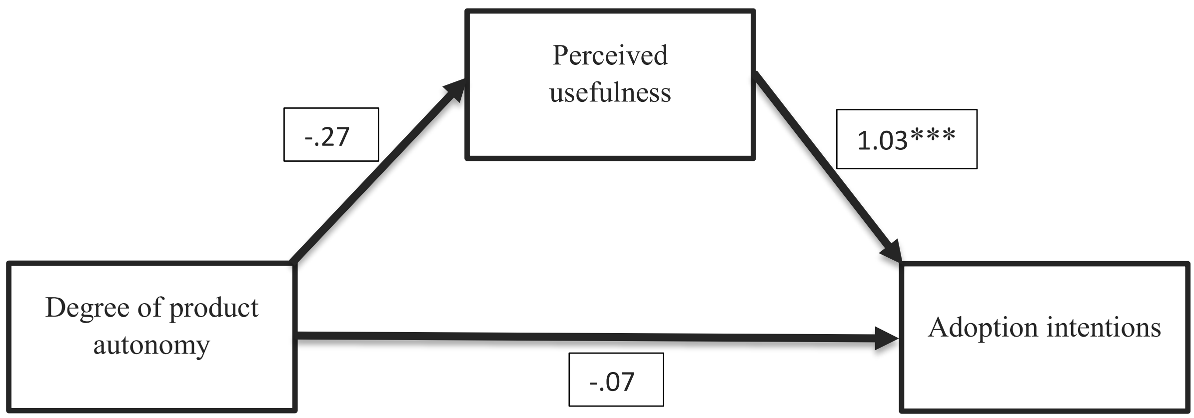

Figure 2: Study 1: Estimates of path coefficients for the relationship between the level of product autonomy and adoption intentions mediated by perceived usefulness.

***$p< .0001$

Testing Hypothesis 2: H2 predicts that an increase in product autonomy, from assistive to replacement autonomy, leads to an increase in perceived performance risk, which then leads to an increasingly negative attitude toward adoption. Similar to H1, the indirect effect was tested for H2 using bootstrapping procedures. In the analysis, the level of product autonomy was employed (coded as -1=Assistive technology, 1=Replacement technology) as the independent variable (X), perceived performance risk as the mediator (M) and adoption intentions as the dependent variable (Y). I tested the overall significance of the mediation effect by constructing a 95% confidence interval, as recommended by Preacher and Hayes (2004). The results show that the mean indirect effect (path $a \times b$) from the bootstrap analysis is negative and significant ($a \times b$ = -.35), with the 95% confidence interval excluding zero (95% CI: -.7178 to -.0152). The results support H2 and confirm the mediating role of perceived performance risk in the relationship between product autonomy and adoption intentions; thus, the higher the product autonomy, the higher the perceived performance risk leading to lower adoption intentions. Since the direct effect of product autonomy on adoption intentions (path *c'*) was insignificant (b= .001, p=.99) and the effect of product autonomy on perceived performance risk (path *a*) was found to be positive and significant (b= .34, p=.05), we can conclude that the perceived performance risk fully mediates the relationship between product autonomy on adoption intentions. Figure 3 summarizes the final estimation results for the mediation model.

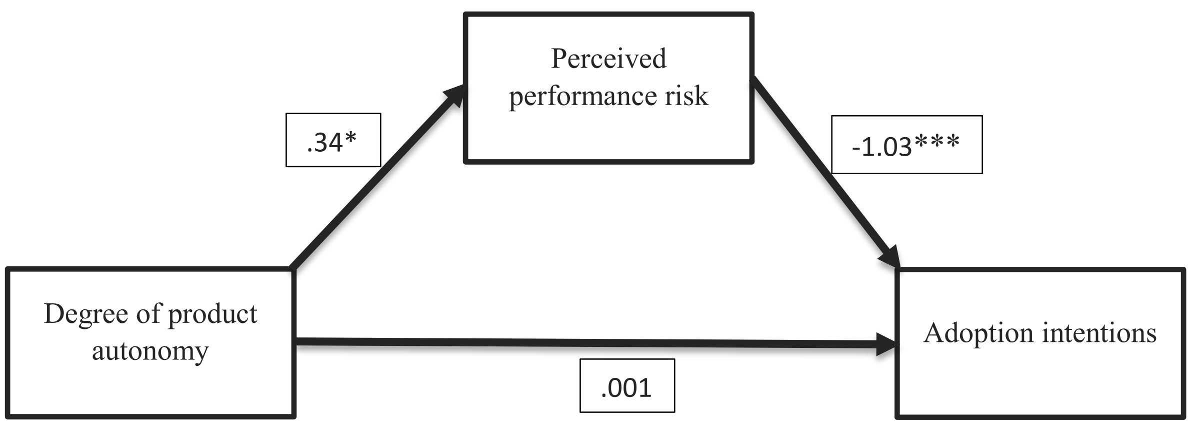

Figure 3: Study 1: Estimates of path coefficients for the relationship between the level of product autonomy and adoption intentions mediated by perceived performance risk.

*$p < .05$

***$p < .0001$

Testing H1 and H2 combined: I also tested the overall mediation model by including both perceived usefulness and performance risk in the analysis. The analysis employed the level of product autonomy (coded as -1=Assistive technology, 1=Replacement technology) as the independent variable (X), perceived usefulness (M1) and perceived performance risk (M2) as mediators and adoption intentions as the dependent variable (Y). I tested the overall significance of the mediation effect by constructing a 95% confidence interval as recommended by Preacher and Hayes (2004). The results show that the mean indirect effect of the level of product autonomy on adoption intentions through perceived usefulness (path $a_1 \times b_1$) from the bootstrap analysis is insignificant ($a_1 x b_1$ = -.21), with the 95% confidence interval including zero (95% CI: -.5291 to .0611). The effect of the level of product autonomy on perceived usefulness (path a_1) was also found to be insignificant (b= -27, p=.15). Thus, perceived usefulness did not mediate the relationship between product autonomy on adoption intentions. However, the mean indirect effect of product autonomy on adoption intentions through perceived performance risk (path $a_2 \times b_2$) from the bootstrap analysis is negative and significant ($a_2 x b_2$ = -.35), with the 95% confidence interval excluding zero (95% CI: -.7178 to -.0152). Thus, we can conclude that perceived performance risk fully mediates the relationship between product autonomy and adoption intentions. Figure 4 summarizes the final estimation results for the mediation model, including both mediators (i.e., perceived usefulness and perceived performance risk).

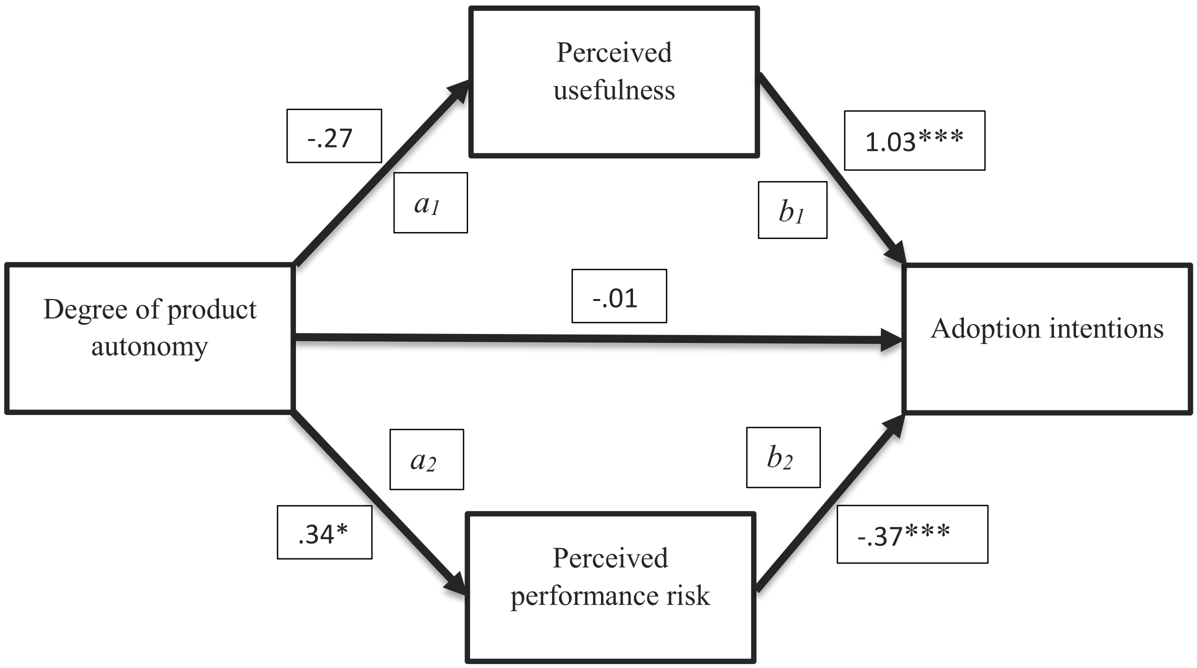

Figure 4: Study 1: Estimates of path coefficients for the relationship between the level of product autonomy and adoption intentions mediated by perceived usefulness and perceived performance risk.

*$p < .05$

***$p < .0001$

4.1.5 The moderating role of the consumers' task expertise

Perceived usefulness. Before testing for the moderated mediation hypotheses (H3 and H4), I first sought evidence regarding whether task expertise is a significant moderator in the relationship between the level of product autonomy and perceived usefulness. To test for moderation, I regressed perceived usefulness on the level of product autonomy (coded as -1=Assistive technology, 1=Replacement technology), the degree of task expertise, and the level of product autonomy × the degree of task expertise interaction. The results show a significant negative effect of the level of product autonomy × the degree of task expertise interaction [b=-.65, $t(151)$=-4.08, p = 0.00] on perceived usefulness. Furthermore, I used the Johnson–Neyman technique to decompose this interaction and identify regions in the range of the moderator variable in which the effect of the independent variable on the dependent variable may be significant (Hayes & Matthes, 2009; Johnson & Neyman, 1936). The Johnson–Neyman point for $p < 0.05$ for the degree of task expertise moderator occurs at values of 4.41 below the mean of 5.40 and 5.50 above the mean of 5.40. This indicates that the perceptions of usefulness for replacement technology are significantly lower than the assistive technology for all values of the degree of task expertise above 5.50. In addition, perceptions of usefulness for replacement technology are significantly higher than the assistive technology for all values of the degree of task expertise below 4.41. Consequently, the results confirm the moderating role of task expertise in the relationship between product autonomy and perceived usefulness. Moreover, the results also show some interesting findings that are worth discussing. In Figure 5, the results show that consumers with a higher level of task expertise perceive replacement technology to be less useful compared to assistive technology. In contrast, as the consumers' task expertise decreases, replacement technology is perceived to be more useful than assistive technology. These findings are further elaborated in detail in the discussion section.

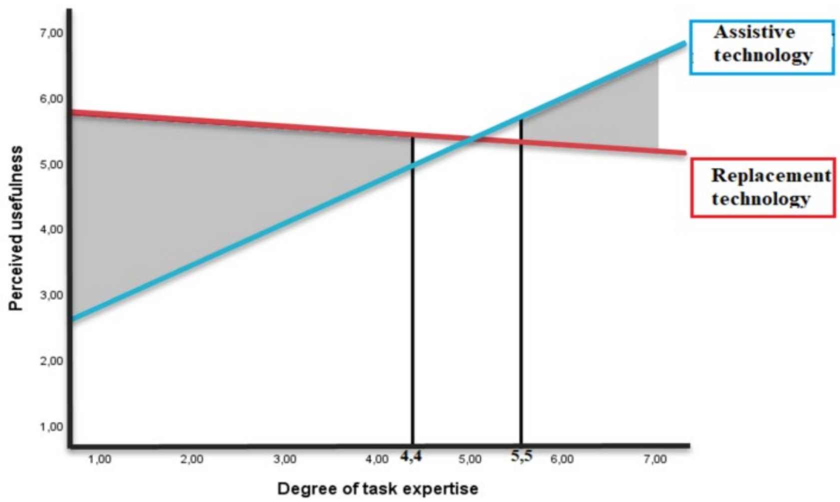

Figure 5: Study 1: Perceived usefulness as a function of the level of product autonomy (Assistive technology vs. Replacement technology) and the degree of consumer task expertise.

Perceived performance risk. Similarly, I also sought evidence regarding whether task expertise is a significant moderator in the relationship between the level of product autonomy and perceived performance risk. To test for moderation, I regressed perceived performance risk on the level of product autonomy (coded as -1=Assistive technology, 1=Replacement technology), the degree of task expertise, and product autonomy × the degree of task expertise interaction. The results show a significant positive effect of product autonomy × the degree of task expertise interaction [b=.70, t(151)=4.84, p = 0.00] on performance risk. Furthermore, I used the Johnson–Neyman technique for identifying regions in the range of the moderator variable in which the effect of the independent variable on the dependent variable may be significant (Hayes & Matthes, 2009; Johnson & Neyman, 1936). The Johnson–Neyman point for p < 0.05 for the degree of task expertise moderator occurs at values of 3.81 below the mean of 5.40 and at the mean value of 5.40. This indicates that the perceptions of performance risk for replacement technology are significantly higher than the assistive technology for all values of the degree of task expertise above 5.40. In addition, perceptions of performance risk for replacement technology are significantly lower than the assistive technology for all values of the degree of task expertise below 3.81. In Figure 6, the results show task expertise to be a significant moderator in the relationship between product autonomy and performance risk. More importantly, the results reveal that as the consumers' task expertise increases, replacement technology is perceived to be riskier compared to assistive technology. In contrast, as consumer task expertise decreases, less performance risk is associated with replacement technology compared to assistive technology.

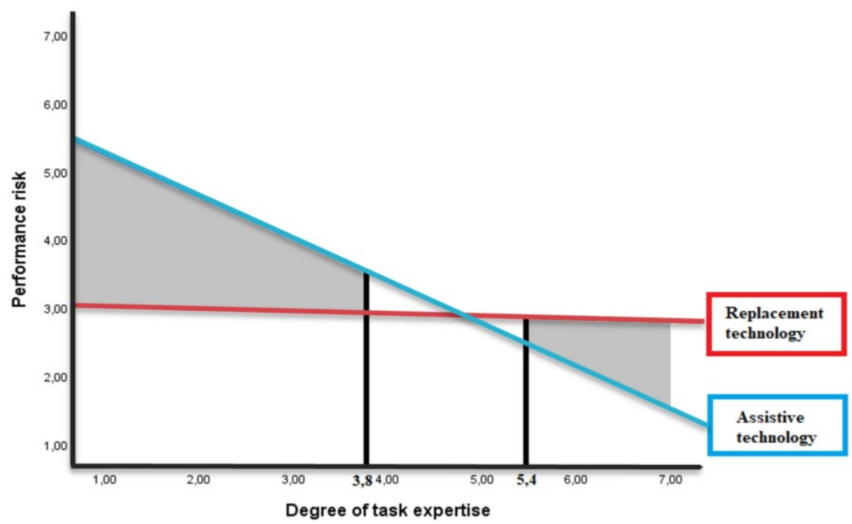

Figure 6: Study 1: Performance risk as a function of the level of product autonomy (Assistive technology vs. Replacement technology) and the degree of consumer task expertise.

Adoption intentions. Finally, I regressed adoption intentions on the level of product autonomy (coded as -1=Assistive technology, 1=Replacement technology), the degree of task expertise and product autonomy × the degree of task expertise interaction. As expected, I observed a significant negative effect of product autonomy × the degree of task expertise [b = -.87, t(151) = -4,95, p =.00] on adoption intentions. Furthermore, I used the Johnson–Neyman technique for identifying regions in the range of the moderator variable in which the effect of the independent variable on the dependent variable may be significant (Hayes & Matthes, 2009; Johnson & Neyman, 1936). The Johnson–Neyman point for $p < 0.05$ for the degree of task expertise moderator occurs at values of 4.00 below the mean of 5.40 and 5.55 above the mean of 5.40. This indicates that the intentions to adopt assistive technology are significantly higher than replacement technology for all values of the degree of task expertise above 5.55. In addition, intentions to adopt replacement technology are significantly higher than assistive technology for all values of the degree of task expertise below 4.00. The results confirm task expertise as a significant moderator in the relationship between product autonomy and adoption intentions.

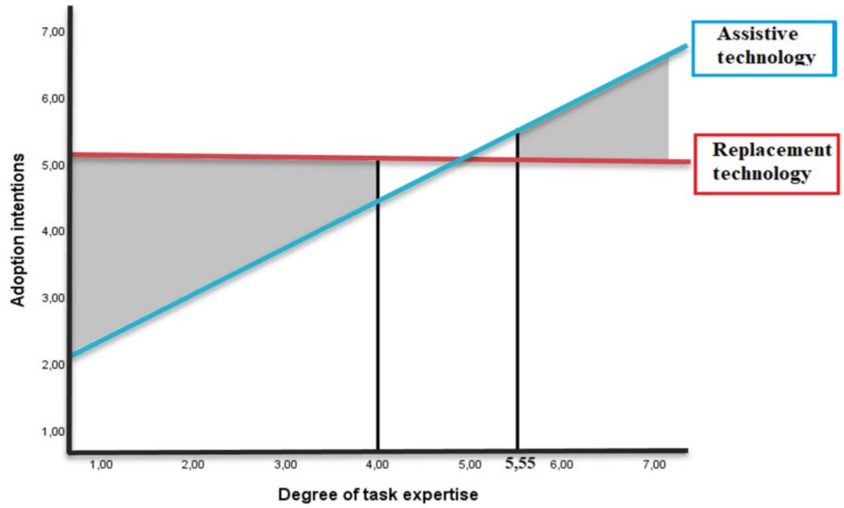

Figure 7: Study 1: Adoption intentions as a function of the level of product autonomy (Assistive technology vs. Replacement technology) and the degree of consumer task expertise.

Moderated mediation analysis: Finally, I examined the conditional indirect effects (calculated using 5,000 bootstrapping samples) of the level of product autonomy on adoption intentions (through perceived usefulness and performance risk) under the moderating effect of task expertise by constructing a 95% confidence interval as recommended by Preacher and Hayes (2004). Thus, I am able to test H3, which predicts that as the consumers' task expertise increases, an increase in product autonomy will be perceived as less useful, which leads to an increasingly negative attitude toward adoption. Additionally, I also test for H4, where, as the consumers' task expertise increases, an increase in product autonomy will be perceived as less risky, which leads to an increasingly positive attitude toward adoption.

Testing Hypothesis 3: H3 predicts that as the consumers' task expertise increases, an increase in product autonomy will be perceived as less useful, which leads to an increasingly negative attitude toward adoption. To test H3, I sought evidence regarding the role of perceived usefulness as a mediator. A significant index of moderated mediation (95% CI: -.8220 to -

.2218) suggested that the indirect effect of going from assistive technology to replacement technology on adoption intentions via perceived usefulness varied depending on the degree of task expertise. Specifically, the effect of the level of product autonomy on adoption intentions through perceived usefulness is positive and significant (β = .37) at low levels (Mean -1SD) of expertise (95% CI: .0464 to .7613); however, it becomes negative and significant (β = -.85) at high levels (Mean +1SD) of task expertise (95% CI: -1.3457 to -.4501). The results align with our theoretical predictions (H3) that as the consumers' task expertise increases, replacement technology is perceived to be less useful and this decreased usefulness translates into lower adoption intentions. Furthermore, the results highlight that as the consumers' task expertise decreases, replacement technology is perceived to be more useful (vs. assistive technology) and this increased usefulness effect for replacement technology leads to higher adoption intentions for task novices.

Testing Hypothesis 4: Finally, H4 predicts that as the consumers' task expertise increases, an increase in product autonomy will be perceived as less risky, which leads to an increasingly positive attitude toward adoption. A significant index of moderated mediation (95% CI: -.2881 to -.0506) suggested that the indirect effect of going from assistive technology to replacement technology on adoption intentions via performance risk varied depending on the degree of task expertise. Specifically, the effect of product autonomy on adoption intentions through perceived risk is negative and significant (β = -.38) at high levels (Mean +1SD) of expertise (95% CI: -.7049 to -.1745) but becomes positive and significant (β = .09) at low levels (Mean -1SD) of task expertise (95% CI: -.0431 to .3145). The results suggest that, in contrast to the predictions in H4, consumers with a higher level of task expertise perceive replacement technology to be riskier compared to assistive technology, and this increased performance risk decreases their adoption intentions. This is in contrast to consumers with a low level of task expertise perceiving replacement technology (vs. assistive technology) to be less risky. These contradictory findings are further discussed in detail in the next section.

4.1.6 Discussion

Study 1 provides important insights into how consumers respond to replacement vs. assistive technology. Specifically, the results suggest that consumers with higher levels of task expertise perceive replacement technology to be less useful and riskier than assistive technology. Admittedly post hoc, one could argue that this effect is due to consumers with a higher level of task expertise perceiving that it is riskier to totally relinquish control of important functions, which is the case with replacement technologies. Furthermore, in relinquishing task control to replacement technologies, consumers with a higher level of task expertise may be likely to have unresolved goals, in terms of the net benefits achieved from product usage. These unresolved goals will perhaps be perceived as risks because experts are unable to predict whether the replacement technology replacing their skills can perform as expected and deliver the anticipated benefits.

In contrast, consumers with low task expertise have low domain-specific problem solving, lower reasoning capabilities and have been found to concentrate on the immediate outcome with minimum effort because the processes of engaging in a consumption task are relatively less important to them (Anderson, 1990; King & Balasubramanian, 1994). Their consumption goal is to reach the desired end state with minimal effort (King &

Balasubramanian, 1994). Therefore, consumers with low task expertise perceive replacement technology to be more useful and less risky than assistive technology because the product replaces their poor skills in performing the consumption task. It is noteworthy that consumers with low task expertise will perceive a higher performance risk with assistive technology, where the task control largely remains with the user.

The results of Study 1 show that the consumers' task expertise is an important moderator in the relationship between the level of autonomy and adoption intentions mediated through perceived usefulness and performance risk. However, the findings of Study 1 could be an artifact of the product category (i.e., cars), and therefore, Study 2 is designed to replicate the findings in a different consumption domain: cooking.

4.2 Study 2

The purpose of the second study was to replicate the results of the first study with a different product category to demonstrate the generalizability of the effects. The category chosen was cooking devices. Cooking is a relatively common consumption context and therefore, the possibility of bias due to product unfamiliarity and novelty was avoided in the respondents' evaluations. Following the same principles as Study 1, I developed two product descriptions that reflect assistive and replacement technologies. In the assistive technology condition, the cooking device could assist the user during the cooking process, while in the replacement technology condition, the cooking device could perform the cooking task all by itself. The content of the assistive technology condition is based on the semi-autonomous version of the cooking device introduced by Vorvex's Thermomix that can assist the user in making different cooking recipes and learn users' favorite procedures and settings. Product description for the replacement technology condition is based on the cooking device introduced as a prototype by different electronic giants such as Philips and Bosch.

More specifically the assistive technology was described as follows:

> *"KN-P01 is a newly designed cooking device to help you make your daily cooking task a fantastic experience. The cooking device is equipped with an assistive digital system that facilitates your cooking by remembering your favorite procedures and settings whenever necessary. Using the KN-P01 state-of-the-art toolkit, you can use the device to efficiently slice and peel food depending on your choice and desire and make the best cooking recipes suitable for general and special occasions. With the help of an assistive-control system, the device can be set to manage when and how*

much heating energy is directed into food enabling more precise cooking for dramatically improved consistency, taste and nutrition.”

The replacement technology was described as follows:

“KN-P01 is a newly designed cooking device to help you make your daily cooking task a fantastic experience. The cooking device is equipped with an integrated computer system to perform the entire cooking task with minimum user intervention, based on one’s favorite recipes. Using KN-P01 built-in computer system, the cooking device is able to efficiently slice and peel food and make the best cooking recipes suitable for general and special occasions without you needing to do anything. With the help of an independent control system, the cooking device manages and monitors when and how much heating energy is directed into food enabling more precise cooking for dramatically improved consistency, taste and nutrition.”

4.2.1 Procedure and Participants

Data were collected via an online survey (M-Turk participants) through which 156 participants (46% female, average age 37.95 years) were recruited with monetary compensation ($0.5). The procedure was identical as in Study 1.

Similar to the procedures in Study 1, the discriminant validity of the measurement model was assessed using Fornell-Larcker criterion. As shown in Table 4, the correlations between the factors ranging from -0.134 to -0.778 are smaller than the square root of the average variance extracted estimates, which are in the range of 0.860 to 0.921. This indicates that the constructs are strongly related to their respective indicators compared to other constructs of the model

(Fornell & Larcker, 1981), thus suggesting a good discriminant validity. In addition, the correlation between exogenous constructs is less than 0.85 (Awang, 2014). Hence, the discriminant validity of all constructs is fulfilled. In addition, the CR values of the constructs are higher than the recommended value of 0.7 (Gefen, Straub, & Boudreau, 2000) which adequately indicates that the construct reliability has been fulfilled.

Table 4: Study 2: Results of discriminant validity by Fornell-Larcker criterion for the model

		CR	AVE	PU	PR	PA	TE	M	SD
1	**PU**	.958	.850	**.921**				5.41	1.32
2	**PR**	.943	.807	-.778	**.898**			3.01	1.23
3	**PA**	.934	.780	.590	-.479	**.883**		4.99	1.30
4	**TE**	.850	.740	.154	-.134	.146	**.860**	4.56	1.29

Note: Diagonals represent the square root of the average variance extracted while the other entries represent the correlations.

Key: PU: perceived usefulness ,CR: composite reliability, AVE: average variance extracted, , PR: performance risk, PA: degree of product autonomy, TE: task expertise.

4.2.2 Manipulation test

Manipulation checks reveal that the level of product autonomy perceptions ($M_{\text{Assistive technology}}$= 4.74; $M_{\text{Replacement technology}}$= 5.23) differs significantly between conditions (F(1, 154) = 5.74, p < .018).

4.2.3 The mediating roles of perceived usefulness and perceived risk on adoption

Testing Hypothesis 1: Similar to the procedures in Study 1 and following the recommendations of Preacher and Hayes (2004), the statistical significance of the indirect effect is tested using the SPSS mediation macro (MOMED; Model 4).

In the analysis, the level of product autonomy (coded as -1=Assistive technology, 1=Replacement technology) was employed as the independent variable (X), perceived usefulness as the mediator (M) and adoption intentions as the dependent variable (Y). The mean indirect effect (path $a \times b$) from the bootstrap analysis is insignificant ($a \times b$ = .036), with the 95% confidence interval including zero (95% CI: -.3793 to .4641). The effect of product autonomy on perceived usefulness (path *a*) was also found to be insignificant (b= .04, p=.87). Therefore, H1 is rejected, since there is insufficient proof of mediation. Figure 8 summarizes the final estimation results for the mediation model.

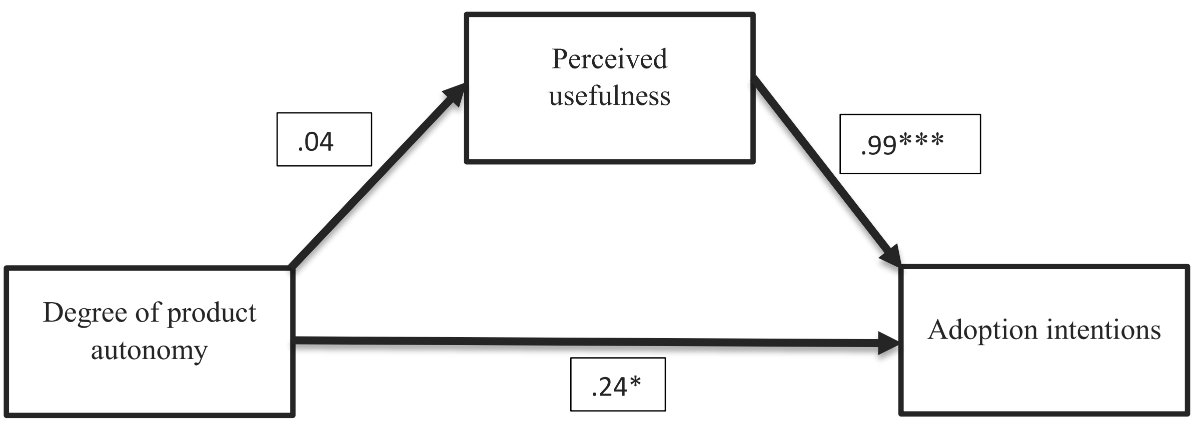

Figure 8: Study 2: Estimates of path coefficients for the relationship between the level of product autonomy and adoption intentions mediated by perceived usefulness.

**p*< .05

****p*< .0001

Testing Hypothesis 2: Similar to H1, the indirect effect using bootstrapping procedures was tested for H2. In the analysis, the level of product autonomy (coded as -1=Assistive technology, 1=Replacement technology) was employed as the independent variable (X), perceived performance risk as the mediator (M) and adoption intentions as the dependent variable (Y). The mean indirect effect (path $a \times b$) from the bootstrap analysis was found to be insignificant ($a \times b$ = -.30), with the 95% confidence interval including zero (95% CI: -.6758 to .0537). Similarly, the effect of product autonomy on perceived performance risk (path *a*) was found to be insignificant (b= .33, p=.09). Therefore, H2 is rejected, as there is insufficient proof of mediation. Figure 9 summarizes the final estimation results for the mediation model.

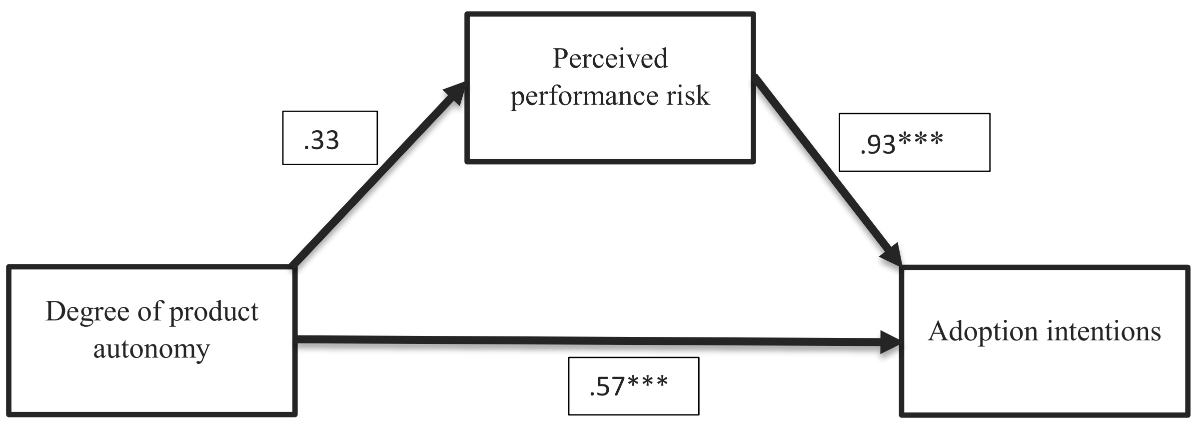

Figure 9: Study 2: Estimates of path coefficients for the relationship between the level of product autonomy and adoption intentions mediated by perceived performance risk.

****p< .0001*

4.2.4 The moderating role of the consumers' task expertise

Perceived usefulness. Similar to the procedures in Study 1, before testing the moderated mediation hypotheses, I first tested whether task expertise is a significant moderator in the relationship between the level of product autonomy and perceived usefulness. Consistent with the findings from Study 1, we observed a significant negative effect of the type of product autonomy × the degree of task expertise interaction [b=-.65, $t(151)$=-4.08, $p < 0.01$] on perceived usefulness. The Johnson–Neyman point for $p < 0.05$ regarding the degree of task expertise moderator occurs at values of 3.92 below the mean of 4.50 and 5.41 above the mean of 4.50. This indicates that the perceptions of usefulness for replacement technology are significantly lower than the assistive technology for all values of the degree of task expertise above 5.41. In addition, perceptions of usefulness for replacement technology are significantly higher than the assistive technology for all values of the degree of task expertise below 3.92. Therefore, these data are consistent with the findings from Study 1, leading to the conclusion that, as shown in Figure 10, when consumer task expertise increases, assistive technology is perceived to be more useful compared to replacement technology. In contrast, as the consumers' task expertise decreases, assistive technology is perceived to be less useful compared to replacement technology.

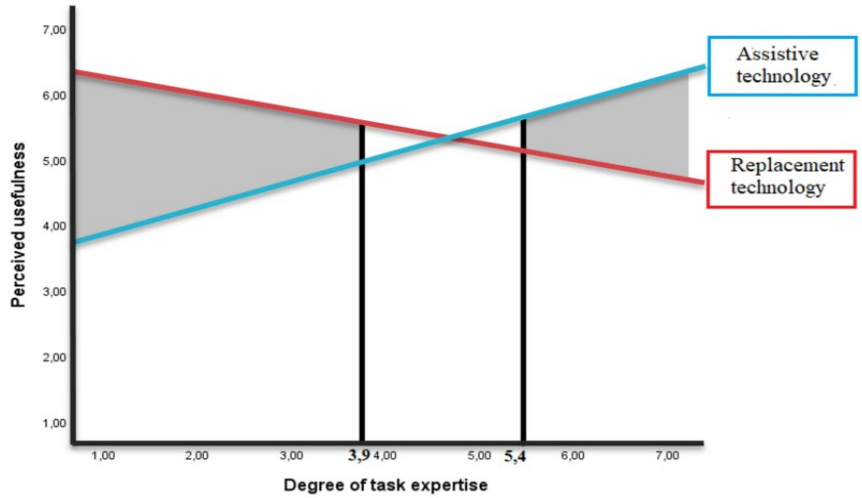

Figure 10: Study 2: Perceived usefulness as a function of the level of product autonomy (Assistive technology vs. Replacement technology) and the degree of consumer task expertise.

Perceived performance risk. I also tested whether task expertise is a significant moderator in the relationship between the level of product autonomy and perceived performance risk. Consistent with the findings from Study 1, we observed a significant positive effect of the type of product autonomy × the degree of task expertise interaction [b=.70, t(151)=4.84, p < 0.01] on performance risk. The Johnson–Neyman point for $p < 0.05$ regarding the degree of task expertise moderator occurs at values of 3.40 below the mean of 4.50 and 4.71 above the mean of 4.50. This indicates that the perceptions of performance risk for replacement technology are significantly higher than the assistive technology for all values of the degree of task expertise above 4.71. In addition, perceptions of performance risk for replacement technology are significantly lower than the assistive technology for all values of the degree of task expertise below 3.40. Therefore, these data are also consistent with findings from Study 1, leading to the conclusion that as consumer task expertise increases, the more performance risk is associated with replacement technology compared to assistive technology, as shown in Figure 11. In contrast, as consumer task expertise decreases, replacement technology is perceived to be less risky compared to assistive technology.

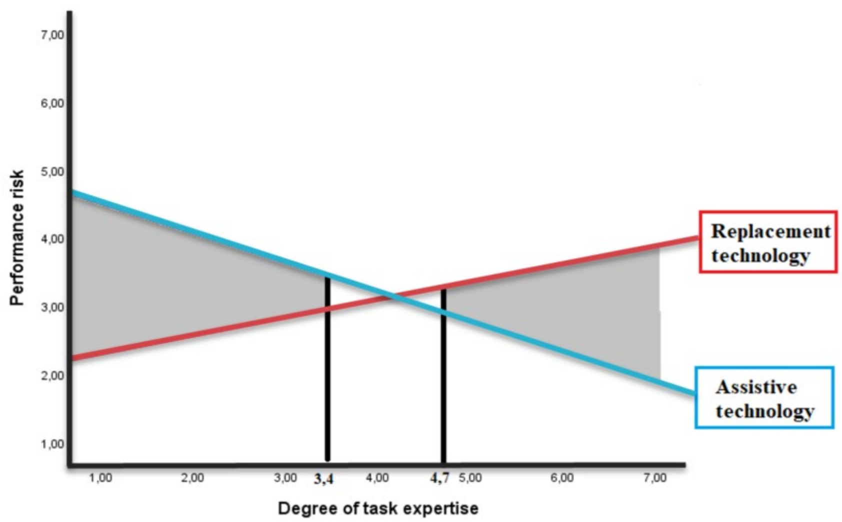

Figure 11: Study 2: Performance risk as a function of the level of product autonomy (Assistive technology vs. Replacement technology) and the degree of consumer task expertise.

Adoption intentions. Finally, I regressed adoption intentions on the level of product autonomy (coded as -1=Assistive technology, 1=Replacement technology), the degree of task expertise and the level of product autonomy× the degree of task expertise interaction. As expected, we observed a significant negative effect of level of product autonomy× the degree of task expertise [b = -.87, t(151) = -4,95, p <.01] on adoption intentions. The Johnson–Neyman point for $p < 0.05$ regarding the degree of task expertise moderator occurs at values of 4.43 below the mean of 4.50 and 5.61 above the mean of 4.50. This indicates that the intentions to adopt assistive technology are significantly higher than intentions to adopt replacement technology for all values of the degree of task expertise above 5.61. In addition, intentions to adopt replacement technology are significantly higher than assistive technology for all values of the degree of task expertise below 4.43. Consistent with the findings from

Study 1, the results confirm task expertise as a significant moderator in the relationship between the level of product autonomy and adoption intentions, as shown in Figure 12.

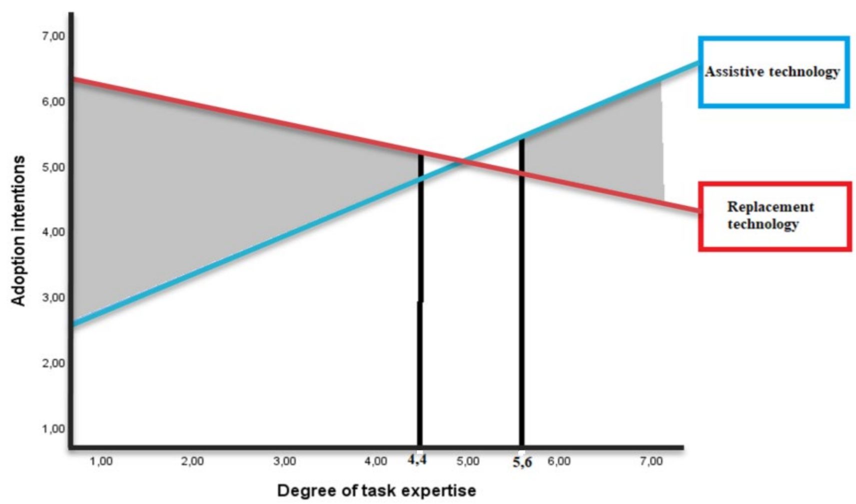

Figure 12: Study 2: Adoption intentions as a function of the level of product autonomy (Assistive technology vs. Replacement technology) and the degree of consumer task expertise.

Moderated mediation analysis: Finally, I examined the conditional indirect effects (calculated using 5,000 bootstrapping samples) of the level of product autonomy on adoption intentions (through perceived usefulness and performance risk) under the moderating effect of task expertise. Consequently, I am able to test H3 and H4.

Testing Hypothesis 3: Consistent with the findings from Study 1, a significant index of moderated mediation (95% CI: -.8220 to -.2218) suggested that the indirect effect of going from assistive technology to replacement technology on adoption intentions via perceived usefulness varied depending on the degree of task expertise. Specifically, the effect of the level of product autonomy on adoption intentions through perceived usefulness is positive and significant ($\beta = .72$) at low levels of expertise (95% CI: .1575 to 1.2870); however, the effect becomes negative and significant ($\beta = -.63$) at high levels of task expertise (95% CI: -

1.1748 to -.1963). The results align with our theoretical predictions (H3) and are similar to the findings in Study 1.

Testing Hypothesis 4: A significant index of moderated mediation (95% CI: -.2881 to -.0506) suggested that the indirect effect of going from assistive technology to replacement technology on adoption intentions via performance risk varied depending on the degree of task expertise. Specifically, the effect of the level of product autonomy on adoption intentions through perceived risk is negative and significant ($\beta = -.26$) at high levels of expertise (95% CI: -.5200 to -.0911) but becomes positive and significant ($\beta = .12$) at low levels of task expertise (95% CI: .0066 to .3179). The results align with the findings from Study 1 and suggest that consumers with higher levels of task expertise perceive replacement technology to be riskier compared to assistive technology, and this increased performance risk decreases their adoption intentions.

The results of Study 2 are consistent and in alignment with the findings of Study 1. More importantly, the results affirm that consumers with higher levels of task expertise perceive replacement technology to be less useful and riskier than assistive technology. In contrast, consumers with low task expertise perceive replacement technology to be more useful and less risky than assistive technology.

4.3 Study 3

In Studies 1 and 2, I tested the effect of higher levels of product autonomy on adoption. It is noteworthy and relevant to test the effect of going from no autonomy to a moderate level of autonomy. For many product categories, it is not relevant to have complete replacement technologies because the tasks themselves are done for hedonic reasons (e.g. skiing, dancing, listening to music, etc.), or because the tasks involve elements that will preclude fully automated product technologies (taking an exam). Thus, the aim of this study is to test the effect of going from a "no autonomy" condition to an "assistive autonomy" condition, and to test the proposed research model.

To ascertain whether participants perceived the conditions as "no autonomy" product vs. "assistive autonomy" product, I conducted a pretest by recruiting 30 undergraduate students at a major Southeastern university in Norway. Participants read product descriptions of alpine ski shoes manipulated as a "no autonomy" condition and an "assistive autonomy" condition.

The "no autonomy" condition was manipulated with the following product descriptions:

> *"Scera alpine ski shoes are well-designed, light and comfortable to wear. These shoes are especially designed and equipped with motion and temperature detectors. The skier can adjust the mode of operation and the desirable temperature inside the shoes before the ride. They also include a ski/walk mechanism, which makes them comfortable and effective in both walking and skiing modes as required by conditions. A flex adjustment switch attached at the back of the shoes allows the user to adjust the boot's stiffness to match a particular type of skiing. Scera alpine ski shoes incorporate long lasting batteries in each shoe which are individually rechargeable."*

The assistive technology condition was manipulated with the following product descriptions:

> *"Scera alpine ski shoes are well-designed, light and comfortable to wear. They have the ability to maintain temperatures and detect motions due to installed sensors inside the shoes. Scera ski shoes adapt themselves to the steepness of the slopes, without user's intervention. The shoes are capable of adjusting to a desirable temperature inside the shoes, and maintaining and balancing skier's weight on the skies during the ride. The function of adjusting skier's balance is accomplished through the ability to adjust the sole of the shoes on the skies depending on the slopes. Scera alpine shoes incorporate long life batteries in each shoe which recharge themselves during the ride."*

The perceptions of "no autonomy" vs. "assistive autonomy" were checked using one 7-point Likert scale item (1: strongly disagree, 7: strongly agree): "Scera alpine shoes definitely help me perform the task." An analysis of variance confirms that the product autonomy perceptions ($M_{\text{No autonomy}} = 3.06$, $M_{\text{Assistive autonomy}} = 4.96$) differ significantly between conditions ($F(1, 28) = 11.18$, $p < .002$). A follow-up question, "Please describe below how you perceived the advertised Scera alpine ski shoes", further revealed that participants under the "no autonomy" condition perceived the ski shoes without any autonomous function, e.g., "I think that Scera ski shoes are very standard shoes for skiing" and "These ski shoes are just regular ski shoes". However, consumers under the "assistive autonomy" condition perceived the ski shoes to be assistive in nature, e.g., "I like the Scera ski shoes as they will help me in my skiing activity" and "I would like to use it because I feel that the shoes will assist me in skiing."

4.3.1 Procedure and participants

For the main study, data were collected via an online survey (M-Turk participants) through which 100 participants (55% female, average age 38 years) were recruited with monetary compensation ($0.5). The measures and procedures were similar to the previous two studies with good reliability. The discriminant validity of the measurement model was assessed using the Fornell-Larcker criterion (Fornell & Larcker, 1981), suggesting a good discriminant validity, as shown in Table 5.

Table 5: Study 3: Results of discriminant validity by Fornell-Larcker criterion for the model

		CR	AVE	PU	PR	PA	TE	M	SD
1	**PU**	.948	.821	**.910**				5.28	1.33
2	**PR**	.954	.838	-.717	**.915**			2.67	1.33
3	**PA**	.939	.793	.341	-.226	**.891**		4.83	1.63
4	**TE**	.856	.748	.274	-.185	.196	**.865**	2.84	1.62

Note: Diagonals represent the square root of the average variance extracted while the other entries represent the correlations.

Key: PU: perceived usefulness, CR: composite reliability, AVE: average variance extracted, PR: performance risk, PA: degree of product autonomy, TE: task expertise.

4.3.2 Manipulation test

Manipulation checks reveal that the level of product autonomy perceptions ($M_{\text{No autonomy}}$= 4.17, $M_{\text{Assistive autonomy}}$= 5.77) differ significantly between conditions ($F(1, 98) = 30.09$, $p < .0001$).

4.3.3 Mediation model

I first tested the overall mediation model by including both perceived usefulness and performance risk in the analysis. In the analysis, the level of product autonomy (coded as -1=No autonomy, 1=Assistive autonomy) was employed as the independent variable (X), perceived usefulness (M1) and perceived performance risk (M2) as mediators and adoption intentions as the dependent variable (Y). The results show that the mean indirect effect of the level of product autonomy on adoption intentions through perceived usefulness (path $a_1 \times b_1$) from the bootstrap analysis is insignificant ($a_1 \times b_1$ = -.09), with the 95% confidence interval including zero (95% CI: -.5192 to .2994). The effect of the level of product autonomy on perceived usefulness (path a_1) was also found to be insignificant (b= .02, p=.84). Thus, perceived usefulness did not mediate the relationship between the level of product autonomy on adoption intentions. Similarly, the mean indirect effect of the level of product autonomy on adoption intentions through perceived performance risk (path $a_2 \times b_2$) from the bootstrap analysis is also insignificant ($a_2 \times b_2$ = -.30), with the 95% confidence interval including zero (95% CI: -.6996 to .0722). The effect of the level of product autonomy on perceived performance risk (path a_2) was also found to be insignificant (b= .40, p=.12). Hence, perceived performance risk also did not mediate the relationship between the level of product autonomy on adoption intentions.

4.3.4 The moderating role of the consumers' task expertise

Perceived usefulness. To test for moderation, I regressed perceived usefulness on the type of product autonomy (coded as -1=No autonomy, 1=Assistive autonomy), the degree of task expertise and the product autonomy × the degree of task expertise interaction. The results show a significant positive effect of the level of product autonomy× the degree of task expertise interaction (*b*=.41, t(96)=2.41, $p < 0.05$) on perceived usefulness. The Johnson–Neyman point for $p < 0.05$ for the degree of task expertise moderator occurs at values of 1.63 below the mean of 3.40 and 6.81 above the mean of 3.40. This indicates that the perceptions of usefulness for the "assistive autonomy" product are significantly lower than the "no autonomy" product for all values of the degree of task expertise below 1.63. In addition, perceptions of usefulness for the "assistive autonomy" product are significantly higher than the "no autonomy" product for all values of the degree of task expertise above 6.81. Therefore, the results shown in Figure 13 indicate that consumers with higher levels of task expertise perceive assistive technology to be more useful compared to "no autonomy" products.

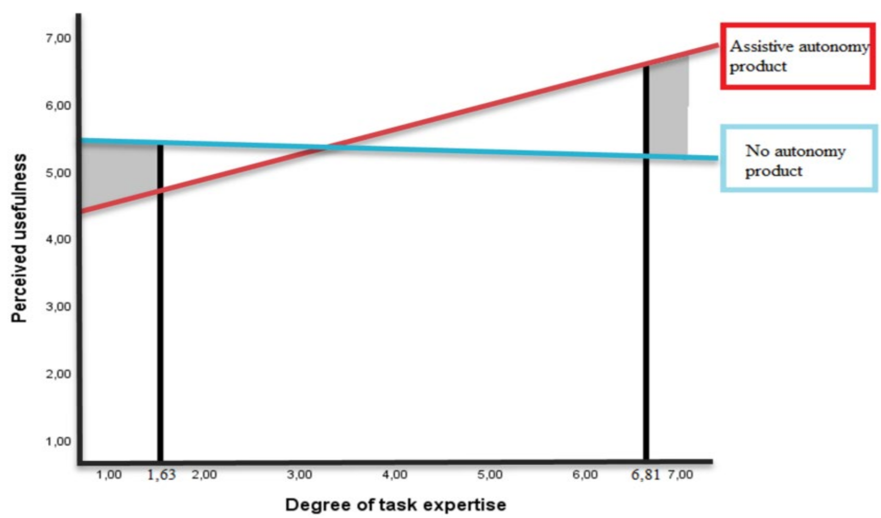

Figure 13: Study 3: Perceived usefulness as a function of the level of product autonomy (Assistive autonomy product vs. No autonomy product) and the degree of consumer task expertise.

Perceived performance risk. Next, I regressed perceived performance risk on the level of product autonomy (coded as -1=No autonomy, 1=Assistive autonomy), the degree of task expertise, and the product autonomy × the degree of task expertise interaction. The results indicate a significant negative effect of the level of product autonomy× the degree of task expertise interaction [b=-.38, $t(96)=-2.08$, $p < 0.05$] on performance risk. The Johnson–Neyman point for $p < 0.05$ ($t = 1.98$) for the degree of task expertise moderator occurs at a value of 2.74 below the mean of 3.40. This indicates that the "assistive autonomy" products result in significantly higher levels of performance risk than "no autonomy" products for all values of the degree of task expertise below 2.74. In addition, there are no significant differences between the "no autonomy" vs. products with "assistive autonomy" conditions above the Johnson–Neyman point. The results indicate that as the consumers' task expertise decreases, assistive technology products are perceived to have a higher level of performance risk, as shown in Figure 14.

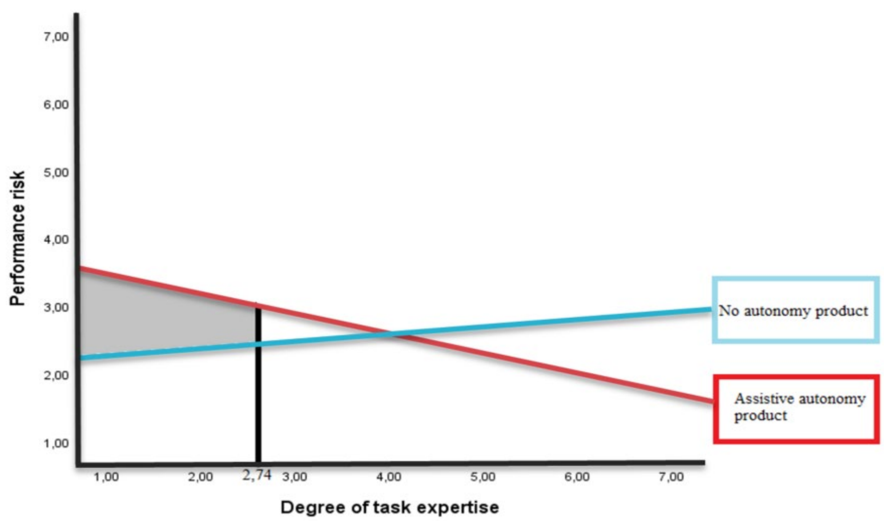

Figure 14: Study 3: Performance risk as a function of the level of product autonomy (Assistive autonomy product vs. No autonomy product) and the degree of consumer task expertise.

Adoption intentions. Next, I conducted a multiple linear regression on adoption intentions as a function of the level of product autonomy (coded as -1=No autonomy, 1=Assistive autonomy) and the degree of task expertise using the PROCESS macro (model 1, in particular) developed by Hayes (2013). As expected, we observe a significant positive effect of the level of product autonomy× the degree of task expertise [b = .39, t(96) = 2,78, $p <$ 0.05] on adoption intentions. Furthermore, I used the Johnson–Neyman technique for identifying regions in the range of the moderator variable in which the effect of the independent variable on the dependent variable may be significant (Hayes & Matthes, 2009; Johnson & Neyman, 1936).

The Johnson–Neyman point for $p < 0.05$ for the degree of task expertise moderator occurs at values of 1.28 below the mean of 3.40 and 5.16 above the mean of 3.40. This indicates that the intentions to adopt the "assistive autonomy" product are significantly higher than the "no autonomy" product for all values of the degree of task expertise above 5.16. In addition, intentions to adopt the "no autonomy" product are significantly higher than the "assistive autonomy" product for all values of the degree of task expertise below 1.28.

Moderated mediation analysis: Finally, I examined the conditional indirect effects (calculated using 5,000 bootstrapping samples) of the level of product autonomy on adoption intentions (through perceived usefulness and performance risk) under the moderating effect of task expertise.

First, I sought evidence regarding the role of perceived usefulness as a mediator in the proposed model. A significant index of moderated mediation (95% CI: .0400 to .3975) suggested that the indirect effect of going from the "no autonomy" product to the "assistive autonomy" product on adoption intentions via perceived usefulness varied depending on the degree of task expertise. Specifically, the effect of product autonomy on adoption intentions through perceived usefulness is negative and insignificant ($\beta = -.27$) at low levels of expertise (95% CI: -.7470 to .0180); however, this effect becomes positive and significant ($\beta = .28$) at high levels of task expertise (95% CI: .0508 to .6940). Within this study model, the results of the moderated mediation analysis confirm that, as the consumers' task expertise increases, "assistive autonomy" products vs. "no autonomy" products are perceived to have a higher level of usefulness, and this increase in perceived usefulness leads to higher adoption intentions.

Similarly, the role of performance risk as a mediator was tested next. A significant index of moderated mediation (95% CI: .0463 to .3850) suggested that the indirect effect of going from the "no autonomy" product to the "assistive autonomy" product on adoption intentions via performance risk also varied depending on the degree of task expertise. Specifically, the effect of product autonomy on adoption intentions through performance risk was negative and significant ($\beta = -.42$) at low levels of expertise (95% CI: -.8483 to -.0741) but became positive and insignificant ($\beta = .20$) at high levels of task expertise (95% CI: -.1045 to .6184). The results indicated that at low levels of consumer task expertise (vs. high task expertise), "assistive autonomy" products were perceived to have a higher performance risk than products with "no autonomy", and this increased performance risk effect decreases adoption intentions.

4.3.5 Discussion

Study 3 extends our insights into the role of the consumers' task expertise in the evaluation of autonomous products. Specifically, the results suggest that consumers with a higher level of task expertise perceive assistive technology to be more useful compared to "no autonomy" products. As previously discussed, task experts concentrate on deeper mechanisms and/or processes in achieving the highest possible level of performance in goal accomplishment (King & Balasubramanian, 1994; Peter & Olsen, 1990). An assistive technology product is mostly process-focused, allowing the user to be in control and modify the course of the technology's actions. This also makes the product more flexible and cooperative in nature. Equipped with limited intelligence and capability (Wallach, 2015), an assistive technology product may attempt to merely supplement or enhance users' existing task capabilities (Russell & Norvig, 2002). Thus, an assistive technology may supplement and enhance the users' existing task performance and therefore be perceived to have a higher level of usefulness compared to "no autonomy" products.

In contrast, the results show that task novices associate higher levels of performance risk with assistive technology's operations and functions; thus, the assistive technology, which is mostly process-oriented and requires the consumer's interaction to reach the desired end-state, will be perceived as riskier by novices. I argue that this effect is due to consumers with low task expertise not only lacking knowledge and/or skills in performing the said consumption task, but also not knowing what to expect from the assistive technology's operations and functions. Since novices cannot transfer sufficient knowledge and skills to recognize the advantage of assistive technology, they may view assistive technology's features as a further complicating issue and thus may perceive it as risky. For example, they may generate concerns about when would they need to step in to assume assistive product control.

4.4 General discussion

Innovation in consumer products is on the cusp of a major technological revolution as the age of autonomous products begins. Autonomous products will profoundly change the way people live. Despite the importance of the increasing prevalence of autonomous products in the marketplace, academic research has offered limited insights into the consequences of this trend for consumers and marketers. The studies in this dissertation research start to address this gap. Autonomous products are technically and functionally superior to traditional products and provide efficiency gains, making consumption more convenient and allowing consumers to more readily enjoy the outcomes of consumption. However, autonomous products are not universally desirable; in particular, autonomous products can be unattractive when the consumers' degree of task expertise drives consumption. In three experimental studies, the author demonstrates that the consumers' task expertise plays an important role when evaluating the usefulness, risks and intentions to adopt autonomous products. To establish the managerial relevance and robustness of the findings, the studies span different activities, levels of autonomy, and products: driving (assistive to replacement autonomy, Study 1), cooking (assistive to replacement autonomy, Study 2), and skiing (no autonomy to assistive autonomy, Study 3).

The following section provides a summary of the empirical investigation of consumers' intentions to adopt autonomous products. The remainder of this chapter is structured as follows: the first section contains a brief summary of the results of the three experimental studies. The theoretical and managerial implications are described in sections 4.6 and 4.7. The purpose of the last section is to reveal potential avenues for future research.

4.5 Summary of key findings

The purpose of this dissertation research was to provide deeper insight into how consumers differ when thinking about usefulness and risk in adopting autonomous products. To determine whether the research question was answered in the course of this dissertation, three empirical studies were conducted. In summary, the results from the empirical investigation showed that the degree of task expertise is a key moderating variable affecting the perceptions of usefulness and risk, and subsequently, the intentions to adopt autonomous products. Specifically, in Study 1 and Study 2, it was found that consumers with higher levels of task expertise perceived replacement technology to be less useful and riskier than assistive technology. In contrast, consumers with low task expertise perceive replacement technology to be more useful and less risky than assistive technology. The third study demonstrated that not all consumption domains can be overtaken by replacement technologies (i.e., skiing, taking exam, dancing) and thus, assistive technologies have their own unique advantages. Specifically, the results showed that task experts, compared to novices, perceived "assistive autonomy" products rather than "no autonomy" products to be more useful and less risky. Overall, the findings highlighted the very important role of the consumer's task expertise in explaining the consumers' intentions to adopt a new type of emerging product technology (i.e., autonomous products) where consumers may have to relinquish task control to the products. The key findings are summarized in Table 6.

Table 6: Summary of key findings

	N	Manipulation	Consumption Context	Moderated Mediation	Contribution
Study 1	170	Assistive to Replacement autonomy	Driving (Cars)	✓	Establishing key moderated-mediation effect. Particularly, effect of degree of product autonomy on adoption intentions is moderated by task expertise.
Study 2	156	Assistive to Replacement autonomy	Cooking (Cooking device)	✓	Replication of Study 1 in a different consumption context. Establishing generalizability of the findings.
Study 3	100	No autonomy to Assistive autonomy	Skiing (Ski shoes)	✓	Establishing key moderated-mediation effect in specific consumption domains where replacement technology is not relevant. However, assistive technology plays an even more significant role for experts.

Taken together, these findings have several theoretical and managerial implications and leave room for future research.

4.6 Theoretical contributions

For decades, researchers and economists have studied how robots, artificial intelligence and autonomous systems affect employment and workers' well-being. In this dissertation research, I take a different perspective: instead of examining the supply side effects of autonomous systems, I examine the demand-side implications, i.e., the opportunity provided to consumers by autonomous systems, in terms of replacing poor skills to accomplish the desired goal or aiding those with superior skills to achieve maximum task performance. My work primarily focuses on consumers, the differential attractiveness of autonomous products for various types of consumers and their different consumption situations. Consequently, I show that not all autonomous technologies are appreciated by consumers. For instance, replacement technology may increase the outcome utility of a product but decrease the sense of accomplishment (Faraji-Rad, Melumad, & Johar, 2017), which is particularly relevant for task experts. Interestingly, this suggestion echoes the Marxist view of automation in production, which sees automation as alienating because it denies workers the self-rewarding features of their work (Braverman 1998).

Though technological progress has its obvious advantages, this also imposes challenges on consumers (Mick & Fournier 1998). The current research, therefore, answers calls to explore how new technologies may affect consumers differently, depending on their consumption motives (Reed et al., 2012).

Beyond a technology context, I contribute a new theory regarding consumer expertise, which is one of the most important areas of inquiry for consumer researchers (Alba & Hutchinson, 1987). The crux of this literature is that experts and novices differ in how they approach and perform dissimilar consumption tasks (Anderson, 1990; Germain & Enrique Ruiz, 2009; Chi, Glaser, & Rees, 1981). Thus, consumers strategically choose products that enable them to achieve their desired consumption goal (King & Balasubramanian, 1994). My work focused on the consequences of expertise in the consumers' adoption of autonomous systems and thereby answers recent calls for studies on how expertise affects goal-directed consumer behavior. Despite the advantages of autonomous systems, experts often resist products that replace their skills.

4.7 Managerial contributions

Across product domains, companies are investing heavily in innovations to make consumers' lives easier. The results of this dissertation research do not question the marketplace value of autonomous products; rather, managers are warned against thinking of autonomous products as universally desirable. Thus, these results have important implications for a range of marketing decisions.

Targeting

In many product categories, experts are highly involved consumers and prime targets for a company's most expensive and innovative products. My findings highlight the risk of targeting expert consumers with product innovations that involve the replacement of expertise-related tasks. Innovations that prevent a sense of accomplishment risk being unappealing to customers, which may help explain the low adoption rates of some innovative products, such as self-driving cars and fully autonomous cooking machines among task experts.

Product innovation

In addition to a potential reason for the disappointing sales to expert consumers, my studies offer suggestions for how to direct a company's innovation efforts. It is crucial to include an assessment of skill relevance when investigating which tasks, currently performed by consumers, could be good candidates for assistive and replacement technology. I am not aware of any company currently performing such analyses systematically.

Communication

The way innovations are marketed also deserves careful attention. Replacement technologies are not always preferable relative to their assistive technology counterparts. For example, some cooking machines explicitly target cooking enthusiasts and stress how cooking could become a matter of "touching a button." However, my results show that many potential customers value the opportunity to express their cooking skills; thus, marketers should not deprive them of the sense that they are responsible for producing the final outcome. In particular, Studies 1 and 2 suggest that convenience is less of a selling point for expert consumers than for novices. Marketers should take people's expertise into account, then communicate the benefits of replacement and assistive technologies in a way that matches their target audience's goals.

Future research

Similar to most phenomena with a broad practical relevance, the effect of the consumers' task expertise on the preferences for autonomous products likely reflects multiple determinants, and it would be interesting to assess the prevalence of other theoretical mechanisms. My theorizing focuses on the role of the perceptions of usefulness and risk; therefore, I concentrate on documenting these factors. Although I identified performance risk as an important predictor of consumers' evaluations, autonomous products are associated with several types of risk. Exploring other risk types (e.g., financial risk, social risk, etc.) would be worthwhile for further research.

Second, additional research should explore whether strategies to counteract the distaste for replacement technologies among task experts might be applicable to cases in which tasks are outsourced to external agents. Furthermore, my results demonstrate that experts resist replacement technologies even when their choices are anonymous. Although this finding suggests that resistance to replacement technologies occurs even when choices are private, this might be amplified when choices are observable. Further research could explore other contextual determinants of how expertise affects the preferences for autonomous products.

Third, future research could test the research hypotheses by having consumers interact with autonomous products, and then measure their interest. Examining other products should also increase the generalizability of these results.

The present research project has helped us to better understand consumer reactions toward a new type of product technology, i.e., autonomous products. However, the methods employed have inherent limitations, which suggest promising avenues for future research. As the current research investigates the consumers' perceptions of autonomous products in an experimental setting, survey data from a larger and more representative sample can further enhance the understanding of consumers' reactions toward autonomous products. Furthermore, only three product categories were studied in this research. Therefore, this is a great opportunity for further research to test whether the findings reported in this study also hold for other product categories.

The ever-increasing range of tasks that machines can perform on the consumers’ behalf is a marker of technological development; we might even argue that autonomous technology defines progress, similar to washing machines in the past, and the likelihood of self-driving cars in the near future. The recent explosion of computing and artificial intelligence promises the appearance of increasingly “skillful” products, capable of autonomous decision-making and action. A fuller appreciation of how product autonomy affects consumers’ relationships with products is therefore crucial for understanding how technology is likely to reshape consumption in the future.

Appendix A

Measures

A.0.1 Adoption intentions (Venkatesh et al., 2003)

All items measured on seven-point scale ("strong disagree", and "strong agree")

I would enjoy using Proxima car

In my opinion, it would be very desirable to use Proxima car for driving purposes

I would like to own a Proxima car

A.0.2 Perceived usefulness (Davis et al., 1989)

All items measured on seven-point scale ("strong disagree", and "strong agree")

The Proxima car would improve the quality of my driving experience

I find Proxima car useful for driving purposes

The Proxima car is convenient for driving purposes

The Proxima car would allow me to be more productive

A.0.3 Performance risk (Grewal et al., 1994)

All items measured on seven-point scale ("strong disagree", and "strong agree")

The Proxima car will perform well

The Proxima car will perform the functions above described

The Proxima car will not create problems

The Proxima car will work satisfactorily

A.0.4 Product autonomy (Rijsdijk & Hultink, 2003)

All items measured on seven-point scale (“strong disagree”, and “strong agree”

The Proxima car does things by itself

The Proxima car works independently

The Proxima car takes initiatives

A.0.5 Task expertise (Germain and Enrique Ruiz, 2009)

All items measured on seven-point scale (“strong disagree”, and “strong agree”)

I consider myself an expert driver

I believe in my abilities to drive

Appendix B

B.0.1 Product description assistive technology condition experiment 1

Introducing the newly designed "Proxima" car for the ultimate ride of the future. The car is designed and equipped with an assistive mode to alert you and even will do some braking for you whenever necessary. Using the car's assistance system, you are able to efficiently accelerate and decelerate under different driving conditions. With the help of a built-in navigation system, the car can partially take control of the driving in steady traffic conditions such as driving on highways/motorways, and thus you can use assistive-navigation.

B.0.2 Product description replacement technology condition experiment 1

Introducing the newly designed "Proxima" car for the ultimate ride of the future. The car is designed and equipped with the latest technology on board and can apply brakes whenever necessary and drive without user intervention. Using an on board computer system, the car can efficiently accelerate or decelerate under different driving conditions. With the help of a built-in navigation system, the car can sense its environment and drive all by itself wherever you want without you needed to do anything.

B.0.3 Product description assistive technology condition experiment 2

KN-P01 is a newly designed cooking device to help you make your daily cooking task a fantastic experience. The cooking device is equipped with an assistive digital system that facilitates your cooking by remembering your favorite procedures and settings whenever necessary. Using the KN-P01 state-of-the-art toolkit, you can use the device to efficiently slice and peel food depending on your choice and desire and make the best cooking recipes suitable for general and special occasions. With the help of an assistive-control system, the device can be set to manage when and how much heating energy is directed into food enabling more precise cooking for dramatically improved consistency, taste and nutrition.

B.0.4 Product description replacement technology condition experiment 2

KN-P01 is a newly designed cooking device to help you make your daily cooking task a fantastic experience. The cooking device is equipped with an integrated computer system to perform the entire cooking task with minimum user intervention, based on one's favorite recipes. Using KN-P01 built-in computer system, the cooking device is able to efficiently slice and peel food and make the best cooking recipes suitable for general and special occasions without you needing to do anything. With the help of an independent control system, the cooking device manages and monitors when and how much heating energy is directed into food enabling more precise cooking for dramatically improved consistency, taste and nutrition.

B.0.5 Product description no autonomy condition experiment 3

Scera alpine ski shoes are well-designed, light and comfortable to wear. These shoes are especially designed and equipped with motion and temperature detectors. The skier can adjust the mode of operation and the desirable temperature inside the shoes before the ride. They also include a ski/walk mechanism, which makes them comfortable and effective in both walking and skiing modes as required by conditions. A flex adjustment switch attached at the back of the shoes allows the user to adjust the boot's stiffness to match a particular type of skiing. Scera alpine ski shoes incorporate long lasting batteries in each shoe which are individually rechargeable.

B.0.6 Product description assistive autonomy condition experiment 3

Scera alpine ski shoes are well-designed, light and comfortable to wear. They have the ability to maintain temperatures and detect motions due to installed sensors inside the shoes. Scera ski shoes adapt themselves to the steepness of the slopes, without user's intervention. The shoes are capable of adjusting to a desirable temperature inside the shoes, and maintaining and balancing skier's weight on the skies during the ride. The function of adjusting skier's balance is accomplished through the ability to adjust the sole of the shoes on the skies depending on the slopes. Scera alpine shoes incorporate long life batteries in each shoe which recharge themselves during the ride.

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