Artificial Intelligence and IT Identity: Towards a Comprehensive Understanding of Human-Machine Integration in the Workplace

by

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Dedication

To my parents, brothers, sister, and friends.

Table of Contents

Dedication		ii
List of Tables		vi
List of Figures		viii
Abstract		ix
CHAPTER 1	Introduction	1
1.1	Motivation	1
1.2	Introduction	2
CHAPTER 2	Theoretical Background	7
2.1	Cognitive Computing Systems	7
2.2	Technology Adaptation	9
2.3	From Technology Adaptation to Co-adaptation	11
2.4	Theory of Co-adaptation	12
2.5	IT identity	14
CHAPTER 3	Hypothesis Development	18
3.1	Co-adaptation and IT identity	18
3.2	Anthropomorphism, Co-adaptation, and IT identity	23
3.3	IT identity and Individual Innovative Performance	24
CHAPTER 4	Methodology	29
4.1	Participants and Procedure	29

4.2 Measurements 29
4.2.1 Independent Variables 30
4.2.2 Dependent Variables 31
4.2.3 Control Variables 31
4.3 Polynomial Regression Analysis 32
4.4 Response Surface Analysis 33
CHAPTER 5 Data Analysis and Results 35
5.1 Construct Reliability and Validity 35
5.2 Confirmatory Polynomial Regression Analysis 37
5.3 Exploratory Polynomial Regression Analysis— Equality Effect Analyses 39
5.4 Moderated Polynomial Regression 41
5.4.1 Moderated Polynomial Regression for Low Anthropomorphism 43
5.4.2 Moderated Polynomial Regression for High Anthropomorphism 45
5.5 IT identity impact on individual innovative performance 47
5.6 Mediated Polynomial Regression 48
5.6.1 Direct effect 50
5.6.2 Indirect effect 52
5.6.3 Total effect 55
5.7 Summary of Results 57
CHAPTER 6 Discussion and Contributions 63
6.1 Discussions 63
6.2 Implications for Theory 64
6.3 Implications for Design 66
6.4 Strength and Limitations 67
6.5 Conclusion 68
6.6 Appendices 69
6.6.1 Descriptive Statistics 69

6.6.2 Co-adaptation Conceptualization and Instrument Development 70
6.6.3 Pilot Studies 72
6.6.4 Survey Items 73
6.6.5 Adaptation in IS Literature 76
6.7 References 85

List of Tables

Table 1. Co-Adaptation Descriptive Statistics and Correlations ... 36

Table 2. Factor Loadings and Cross-Loadings of Constructs ... 37

Table 3. Predicting IT identity Using Human adaptation & Machine adaptation ... 39

Table 4. Results of Tests of First Principal Axis and Shape of Surfaces Along Lines of Equality and Inequality ... 40

Table 5. Results of Moderated Polynomial Regression Analysis ... 43

Table 6. Coefficients for Response Surface Analysis Predicting IT identity at Low Versus High Anthropomorphism ... 43

Table 7. Stationary Points and Principal Axes for Low Anthropomorphism ... 44

Table 8. Slopes Along Lines of Interest for Low Anthropomorphism ... 44

Table 9. Stationary Points and Principal Axes for High Anthropomorphism ... 46

Table 10. Slopes Along Lines of Interest for High Anthropomorphism ... 46

Table 11. Predicting Individual Innovative Performance using IT identity ... 48

Table 12. Tests of Mediated Polynomial Regression for the Effects of co-adaptation on Individual innovative performance. ... 50

Table 13. Stationary Points and Principal Axes for the Direct Effects of Co-adaptation on Individual Innovative Performance ... 52

Table 14. Slopes and Curvatures Along the Lines of Interest for the Direct Effects of Co-adaptation on Individual Innovative Performance 52
Table 15. Stationary Points and Principal Axes for the Indirect Effects of Co-adaptation on Individual Innovative Performance 54
Table 16. Slopes and Curvatures Along the Lines of Interest for the Indirect Effects of Co-adaptation on Individual Innovative Performance 55
Table 17. Stationary Points and Principal Axes for the Total Effects of Co-adaptation on Individual Innovative Performance 57
Table 18. Slopes and Curvatures Along the Lines of Interest for the Total Effects of Co-adaptation on Individual Innovative Performance 57
Table 19. Summary of the Hypotheses Testing Results 62
Table 20. Sample Characteristics 70
Table 21. Co-Adaptation Survey Scale 75
Table 22. Adaptation in IS Literature 85

List of Figures

Figure 1: Co-Adaptation Research Model 18

Figure 2. Response Surface Analysis for Co-Adaptation Predicting IT identity 41

Figure 3. Response Surface for Low Anthropomorphism 45

Figure 4. Response Surface for High Anthropomorphism 47

Figure 5. The Direct and Indirect effects of Co-adaptation on Innovative Performance 49

Figure 6. Response Surface of the Direct Effect of Co-adaptation on Innovative Performance .. 51

Figure 7. Response Surface of the Indirect Effect of Co-adaptation on Innovative Performance 54

Figure 8. Response Surface of the Total Effect of Co-adaptation on Innovative Performance.... 56

Figure 9. Co-adaptation as a Grouping of Two Factors 71

Figure 10. Co-Adaptation First-order Factor Model 72

Abstract

Cognitive computing systems (CCS) are a new generation of automated IT systems that simulate human cognitive capabilities. Cognitive computing reshapes the interaction between humans and machines and challenges the way we study technology use and adaptation in the Information Systems field. The present work introduces co-adaptation theory, which occurs when both the user and the CCS adapt simultaneously to make the system fit the user. Co-adaptation involves two types of adaptation: human adaptation and machine adaptation. Human adaptation refers to the degree to which the user adapts to CCS by either changing system features or changing the way they interact with the system. Machine adaptation refers to the degree to which the user perceives that the CCS adapts itself to fit the user's needs. Using polynomial modeling, moderated polynomial regression, mediated polynomial regression, and response surface analysis, we examine longitudinal survey data of 248 Intelligent Assistant users. The findings show that when individuals and CCS both adapt at the same rate, it has the greatest effect on individual relationships with the CCS (i.e., strong IT identity). Furthermore, IT identity fully mediates the association between co-adaptation and individual innovative performance. Lastly, anthropomorphism moderates the association between co-adaptation and IT identity. The data shows that in low anthropomorphism individuals expect CCS to adapt more to them.

CHAPTER 1 Introduction

1.1 Motivation

Cognitive computing systems (CCS) are rapidly being adopted in organizations across industries, leading to a proliferation of human-machine interactions in the workplace. Despite growing recognition of CCS's critical role, effective human and machine collaboration is still a major challenge. Existing theories don't account for the adaptive capabilities of CCS and the interdependence between systems and individuals. Many technology use theories are built on the premise that IT systems are tools bundled with different functionalities to help users achieve various tasks. Several key theories, including the Adaptive Structuration Theory (DeSanctis & Poole 1994) and Adaptive Structuration Theory for Individuals (Schmitz et al., 2016), focus predominantly on individuals' interactions with technology, whereas less attention is paid to technology's role in shaping and guiding individual interactions with technology. If we had adopted this approach of theorization, we would not understand human-machine collaboration and the genuine impact of CCS use on individual outcomes.

To this end, there are several key challenges to overcome. First, we must account for the theoretically unique aspects of cognitive computing. CCS are highly adaptable, autonomous systems increasingly being designed to be more human in their interactions with users. These unique capabilities are not accounted for in the existing technology use theories. Second, we need robust theoretical frameworks that help explain the impact of collaboration with CCS on individual outcomes such as innovative performance. My Ph.D. thesis addresses all these challenges to provide a more insightful understanding of human-machine interaction.

1.2 Introduction

Cognitive computing has the potential to redefine the nature of relationships between humans and machines in the workplace and beyond. Cognitive computing is a broad term refers to self-learning systems that use data mining techniques, pattern recognition, and natural language processing to mimic the cognitive capabilities of the human mind (Coccoli, Maresca, & Stanganelli, 2016). This type of computing establishes a new relationship between humans and machines to further enhance human capabilities by using cognitive technology capable of understanding natural language and learning as it continues to interact with humans (Spohrer & Banavar, 2015). Cognitive computing holds the ability to transform the way humans accomplish tasks; therefore, it is vital to understand how humans and cognitive computing systems (CCS) work collaboratively.

Despite their importance, IS scholars are still struggling to theoretically comprehend both human interactions with CCS and their implications (Schuetz & Venkatesh, 2020). Theories of adaptation have been used to help understand technology use; yet it is not clear whether adaptation theories can be applied to help understand the use of CCS. Adaptation theories suggest that the interactions between users and technology change as users attempt to alter their behavior or technology to better accommodate technology(Schmitz, Teng, & Webb, 2016). Self-adaptability is one of the key characteristics of CCS. Unlike previous technologies, CCS can self-adapt to the user as the user adapts to it. This co-adaptation is both new and vital to understanding individual interactions with CCS. The newly emerging relationship between users and CCS requires a re-theorization to understand how such systems impact individual performance. The work introduces co-adaptation theory which occurs when both the user and the system adapt simultaneously to make the system fit the user. Co-adaptation involves two types of adaptation: human adaptation and machine adaptation. Human adaptation refers to the user changing their behavior to adjust to the technology or changing the technology to adjust to their use. In contrast, machine adaptation refers to the system adapting itself to fit the needs of the user. We propose co-adaptation as a logical grouping of factors that impact outcomes cooperatively. This work responds to the call for new theories on CCS adaptivity by introducing co-adaptation theory to the technology use literature (Schuetz & Venkatesh, 2020).

Companies increasingly invest in Cognitive Computing and the post-usage behavior as areas that are critical for companies to realize return on IT investments. Technology use and adaptation represent the first stage of technology implementation indicating how individuals appropriate technology to support work tasks. However, the benefits of technology increase when individuals use technology to innovatively change their work outcomes (Rahrovani & Pinsonneault, 2020). The extent IS research has focused primarily on innovative use or how individuals use technology innovatively (Ahuja & Thatcher, 2005; Li, Hsieh, Rai, 2013). This type of theorization can be useful in understanding traditional technology since it has a clearly defined set of features. However, CCS offers a variety of features with the primary aim of revolutionizing the way individuals do their work tasks not just how the technology is preforming. Therefore, this work explores the impact of co-adaptation on innovative performance or how individuals use CCS to do work tasks innovatively.

As individuals adapt to technology and gain experience, they become accustomed to using it routinely which results in fewer innovative IT uses (Schmitz et al. 2016). In order for an organization to benefit from IT investment, it is crucial to eliminate the tension between innovation and individual experience with technology. Recent work has introduced IT identity as a key driver of exploratory IT usage behavior (Carter et al. 2020). IT identity refers to self-identification with technology and is reflected by the degree of reliance, connectedness and emotional attachment to a given technology. IT identity provides a richer understanding of what stimulates individual innovation with existing organizational technologies. As a result, we argue that the impact of co-adaptation on innovative performance is largely determined by the degree of IT identity. Individuals with strong IT identity are more likely to experience a sense of reliance and emotional attachment to the technology which stimulate them to go beyond routine use and innovate with technology (Carter et al. 2015; 2020).

The objective of the present study is to introduce the theory of co-adaptation and examine its impact on individual innovative performance. Furthermore, the study assess the impact of IT identity in mediate the association between co-adaptation and innovative performance. To accomplish this, we conducted a longitudinal study of 249 Intelligent Assistant users. I used polynomial regression, mediated polynomial regression, and response surface analysis to explore the impact of co-adaptation on outcomes. The present study provides several theoretical contributions. First**,** this work contributes to adaptation literature by introducing the concept of co-adaptation as a new and pivotal theoretical view of adaptation. Prior studies have viewed adaptation from the perspective of humans adapting the technology or adapting to the technology (Barki, Titah, & Boffo, 2007; Boudreau & Robey, 2005; Schmitz, Teng, & Webb, 2016). If we had taken that approach, we would not fully understand CCS's use and impact on individual performance. Second, this work offers a strong theoretical argument with supporting evidence that equality between human and machine adaptation plays a critical role in determining the impact of co-adaptation on individuals and their performance. The findings show that equal co-adaptation has the highest impact on IT identity and individual innovative performance. Third, the study contributes to literature by introducing IT identity as a new mediator of technology use and adaptation. Prior studies have focused on either what leads to technology adaptation or the effect of technology adaptation on individual outcomes. However, what facilitates technology adaptation behavior is rarely explored. Our findings show that the impact of co-adaptation on individual innovative performance is fully mediated by IT identity. Individuals with IT identity are more likely to explore system features to perform novel tasks. Lastly, the study builds upon existing literature by identifying IT identity as a key antecedent of individual innovative performance. We find that individuals are more likely to perform tasks innovatively on the CCS when the system becomes a central aspect of their identity. IS studies have mainly focused on the impact of IT identity on technology-related innovation. However, this work finds that IT identity stimulates task-related innovation as well.

CHAPTER 2 Theoretical Background

2.1 Cognitive Computing Systems

Cognitive computing systems (CCS) are the new generation of automated Information Technology systems that mimic human cognitive capabilities (Coccoli, Maresca, & Stanganelli, 2016). Cognitive computing establishes a new relationship between humans and machines to enhance human capabilities by using cognitive technology capable of understanding natural language and learning as it interacts with humans (Spohrer & Banavar, 2015). The consumer market for CCS has been reporting high growth. The global smart speaker market is anticipated to reach $15.6 billion by 2025 from $7.1 billion in 2020 (Marketsandmarkets, 2020), and Amazon Alexa is expected to hold a significant share of the smart speaker. Smart speakers such as Amazon Alexa are CCS that augment human abilities with higher levels of interactivity and adaptability. It is crucial to understand the human-CCS relationship and how they work together, as cognitive computing is capable of changing nearly every task humans can perform.

The advancement of technology allows for more robust and connected systems, but cognitive computing is unique because it aims to make machines act more like humans. CCS replicates the human brain's functionality by using data mining and natural language processing to perform highly sophisticated tasks. Amazon Alexa, for instance, is a cognitive computing system that enables individuals to perform diverse tasks using natural language. Adaptability and interactivity are key characteristics of CCS that distinguish them from other IT systems (Yang et al., 2018). CCS can learn as goals and requirements change and more precise information becomes available.

The CCS are adaptive and interactive systems capable of engaging with humans in bilateral relationships reshaping the interactions between humans and machines (Schuetz & Venkatesh, 2020). Traditionally, IT systems in the IS field are still seen as tools bundled with functionalities to assist users in achieving their objectives (Benbasat & Zmud, 2003; Schuetz & Venkatesh, 2020). For instance, task-technology fit (Goodhue & Thompson 1995), Adaptive Structuration Theory (DeSanctis & Poole 1994), Fit Appropriation Model (Dennis et al. 2001), Coping Model of User Adaptation (Beaudry & Pisonneault, 2005) and Adaptive Structuration Theory for Individuals (Schmitz, Teng, & Webb, 2016) are key theories in IS consider IT systems as tools used by individuals to achieve desirable outcomes. However, CSS's self-adaptive nature is challenging our long-held assumptions about IT systems that have been framed by the IS community.

Our study extends the research on system use and adaptation by responding to the call for new theories on CCS adaptivity (Schuetz & Venkatesh, 2020). CCS fundamentally differs from previous IT systems which question the applicability of existing technology use and adaptation knowledge. Blurring the lines between humans and machines requires a re-theorization to understand how the new phenomenon impacts individual performance. In response to this call, we introduce the co-adaptation theory to the IS community to offer new insights into human-machine interaction and collaboration.

2.2 Technology Adaptation

Technology adaptation is defined as the cognitive and behavioral efforts exerted by individuals to manage perceived consequences associated with the use of technology (Beaudry & Pinsonneault 2005). It is important to understand adaptation because new technology rarely fits into existing routines and tasks, and task efficiency is primarily determined by technology modifications (Dutton & Thomas 1984; Leonard-Barton, 1988). Adaptation is essentially the key to understanding this change and adjustment that follows a new technology deployment (Tyre & Orlikowski, 1994). Adaptation emerges due to discrepancies between the design of new technology and existing tasks and routines (Nevo, Nevo, & Pinsonneault, 2016). Research has shown that only through experimenting with technology individuals discover its ramifications (Tyre & Orlikowski, 1994). Individuals frequently modify and fundamentally change technology features to accomplish their tasks.

Research on technology adaptation has examined how technology is changed to perform work tasks (Schmitz, Teng, & Webb, 2016). Technology adaptation focuses on the technological aspects of the adaptation process to explore how a particular technology is changed during its adoption and implementation (Fadel, 2012). In technology adaptation, individuals either moderately or substantially change technology to adjust to their use. For example, individuals may change the appearance of the interface, try out new features, or even deviate from the standard use by combining technology features.

Adaptation behavior has been shown to have positive impacts on individual performance. Tong, Tan, and Teo (2015) found that the behavior directed to modify the technology and how technology was used were positively related to individual performance. They demonstrated that using technology to carry out tasks and customizing it to achieve outcomes led individuals to attribute positive meanings to their experiences, enhancing their system-related performance. Furthermore, Wu, Choi, Guo, and Chang (2017) found that users who changed the system features and task procedures to fit their personal preferences were more likely to use the system after deployment. Moreover, Bala and Venkatesh (2016) found that adaptation behavior fostered individual performance. The inability to use the system's features prompted emotional dissonance, motivating individuals to exploit system features more to mitigate the negative effect of such feelings (Bala & Venkatesh, 2016). Such finding is consistent with the results of prior work (e.g., Folkman and Moskowitz 2000; Lazarus and Folkman 1984), which found that when technology was perceived as a threat, individuals adapted their behavior to restore their emotional stability and reduce tensions resulting from new technology use. Thus, adaptation is an important concept that helps to understand system use and individual performance.

2.3 From Technology Adaptation to Co-adaptation

Adaptive Structuration theorization has several limitations with it comes to CCS. AST is based on the premise that "technology [does] not spontaneously adapt of [its] own accord" (Schmitz et al., 2016, p. 667). Thus, the role and impact of technology adaptation are largely excluded from the adaptation theoretical perspective. Such a view constrains our understanding of cognitive computing potentials and effects on individual outcomes. Alternatively, our approach emphasizes that how technology adapts itself is a key additional perspective that helps us understand the adaptation behavior. AST is introduced to explain adaptation behavior in technologies that cannot adapt to the user, such as Group Decision Support Systems (DeSanctis and Poole, 1994) and smartphones (Schmitz et al., 2016). Such technologies have limited functionalities, with system features that can be scaled mainly by system designers. Cognitive computing, however, involves self-learning systems with the capacity to adjust their adaptation behavior based on prior interactions with users (Schuetz & Venkatesh, 2020; Watson, 2017). The co-adaptation approach emphasizes that how users adapt to technology and how the technology adapts to users are entangled — changes in technology behavior are associated with changes in user behavior. We propose expanding AST by accounting for the role played by technology and the interdependence between individuals and technology.

2.4 Theory of Co-adaptation

In this paper, we introduce the Theory of Co-adaptation, a process where both the user and the CCS adapt simultaneously to make the system fit the user. Co-adaptation involves two distinct types of adaptation: human adaptation and machine adaptation. Human adaptation refers to the user changing their behavior to adjust to the technology or changing the technology to adjust to their use. In contrast, machine adaptation refers to the system adapting to fit the user's needs. We propose co-adaptation as a logical grouping of factors that impact outcomes cooperatively. Prior studies have only considered what can be called human adaptation (e.g., Barki, Titah, & Boffo, 2007; Boudreau & Robey, 2005; Schmitz, Teng, & Webb, 2016); however, this study goes a step further by considering machine adaptation. It is an additive adaptation perspective that helps understand human-machine interaction in the CCS. Although these two aspects of adaptation are conceptually distinct, they are not entirely independent. Co-adaptation aspects coexist and correlate because the change in human adaptation is associated with the change in machine adaptation.

Co-adaptation and adaptation share several commonalities and differences. Both arise from the differences between recently used technology and existing routines and tasks. Both assist users in maximizing their benefits and improving their performance. On the other hand, the fundamental difference lies in the direction of the adaptation. Adaptation is unidirectional; it mainly relates to how users modify technology. Co-adaptation, however, is bidirectional, with the user and the technology adapting to each other simultaneously.

Research discussing co-adaptation in which both the user and the technology adapt during the interaction is severely lacking (Cecez-Kecmanovic et al., 2014). Several research studies have stressed the importance of adaptation (e.g., Leonard-Barton, 1988; Majchrzak et al., 2000; Tyre & Orlikowski, 1994), but IS researchers have generally neglected co-adaptation in favor of focusing on mutual influences between technology and organizing context. For instance, Grabowski & Roberts (2011) employed adaptive structuration theory to investigate mutual adaptation between technology and organization. Vessey and Ward (2013) suggested that sustainable IS alignment occurs when technology co-evolves with the organization. Although this work sheds significant light on the interaction between technology and organization, the theorization of adaptation in those papers is incomplete.

Emerging technologies such as CCS challenge our assumption of technology adaptation. Unlike previous technologies, CCS can adapt to the user as the user adapts to it. It is unclear how users and CCS adapt to one another. Therefore, co-adaptation will improve our understanding of how CCS impacts individual performance.

2.5 IT identity

Cognitive computing are becoming increasingly integrated into work systems. Due to their exceptional capabilities, such systems are more likely to influence who we are and how we perform work tasks. IT identity has been proposed as a key theory to understand the impact of technology embeddedness on individuals. It manifests itself through an overlap of boundaries between technology and self, experienced as a sense of reliance and connectedness to technology (Carter & Grover, 2015; 2020). IT identity is a critical theoretical lens for understanding the impact of co-adaptation on individuals. Since CCSs are interactive and adaptive, they are more likely to reshape individuals' identities and become part of who they are. IT identity originates from the desire to expand the self in that individuals seek opportunities to maximize their potential efficacy by increasing physical and social resources that facilitate attaining personal objectives (Carter, Petter, Grover, Thatcher, 2020). IT identity represents the extent to which individuals self-identify with IT, and a strong IT identity implies a large degree of embeddedness of IT into individuals' lives and high net benefits generated by IT usage.

In IT identity studies, user interactions, and experience with IT are essential to establishing identities (Cheng et al., 2015). Studies have shown that pleasant experiences with technology trigger IT identity (Esmaeilzadeh, 2021). As users learn to use technology, their dependency on it grows, and emotional attachment escalates, triggering IT identity (Lin, Chiang, Jiang, 2015). People are more likely to integrate IT with themselves if they receive significant material rewards and intrinsic gratification. Rai, Lang, and Welker (2002) find that actualized benefits of technology have a remarkable impact on individual perceptions of dependence on it, because if they perceive that their technology is providing them with information and emotional benefits, they are more likely to be attached to it. This relationship is important since technology dependence is a key aspect of IT identity.

The ability of technology to support social interactions plays a significant role in identity construction (Burke & Reitzes, 1981; Stryker & Burke, 2000). Studies have found that when technology increases individual belongingness capacity and connectedness with others, IT identity increases (Ogbanufe & Gerhart, 2020). Individual experiences with technology create a sense of belonging and connectedness as they engage in activities and tasks. IT identity can be compromised by a variety of factors. Studies have also shown that privacy concerns reduce IT identity. Ogbanufe and Gerhart (2020) find that when individuals are considered that their personal information could be misused or exposed, their identity with technology decreases.

It is important for employees to be ready to perform unexpected job tasks, and employees with a strong IT identity will ensure that they are always prepared for such situations. The identity literature argues that when technology is integral to one identity, s/he tends to deeply use the technology's features (Hassandoust et al., 2021). Individuals who have reaped the benefits of IT usage believe that using new features will enhance their performance (Carter et al., 2020). Individuals with a strong sense of dependence on and enthusiasm for an IT system are likely to take action on problems and enhance the quality of their work by making changes in the way they do their jobs, which may include implementing most IT features to improve their work processes. Studies have demonstrated that individuals are more likely to use technology innovatively if it is a key part of their self-concept (Carter et al., 2020; Ogbanufe & Gerhart, 2020). For instance, in addition to using Amazon Alexa for basic daily tasks, individuals with strong IT identities may use Alexa in new ways, such as learning new languages, teaching Alexa what they know, or getting exclusive Amazon deals. IT identity has been shown to decrease the perceived risk of technology (Mirbabaie et al., 2021). By identifying the self with AI, the self-esteem associated with AI is stabilized, and the perception of AI threats is reduced (Craig, Thatcher, & Grover, 2019). Individuals are more willing to accept AI if they have a positive association with it. This supports the argument that humans and technology complement each other when individuals build their identities around technology as a significant part of themselves (Park & Kaye, 2019). On the other hand, studies have shown that IT identity drives subjective well-being (Chiu et al., 2013). In general, if technology gives one multiple benefits, satisfies their needs, and makes their lives easier and their work more efficient, this will positively affect their well-being.

CHAPTER 3 Hypothesis Development

To answer the research questions, I developed a theoretical research model (Figure 1).

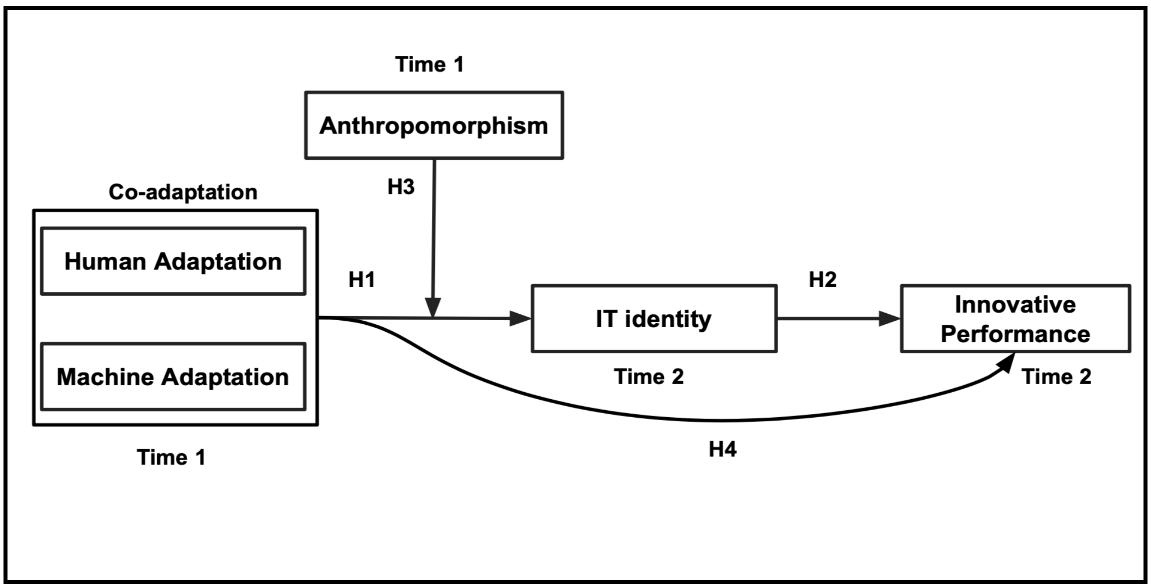

Figure 1: Co-Adaptation Research Model

3.1 Co-adaptation and IT identity

Co-adaptation occurs when both the user and the CCS adapt simultaneously to make the system fit the user. To understand the relationship between co-adaption and IT Identity, we drawn upon social exchange theory and the concept of reciprocity. Social exchange theory is defined as the exchange of tangible or intangible resources between at least two persons (Homans, 1961). Reciprocity is a defining characteristic of social exchange (Cropanzano & Mitchell, 2005).

Reciprocity takes the form of an interdependent exchange, in which one party provides a benefit, and the other responds by providing a benefit in return. In social exchanges, reciprocity is an emotional process (Lawler & Thye, 1999). Individuals process information and interact with each other based on their emotions (Wubben et al., 2009). Individuals with positive emotions perceive and interpret relationships more positively than individuals with negative emotions (Bower, 1981). Similarly, less rewarding experiences in social exchanges can trigger negative emotions (Adams, 1963).

Prior literature has emphasized several aspects of social exchange that support our view of co-adaptation as a form of social exchange. First, reciprocity and commitment form the foundations of social exchange (Cropanzano & Mitchell, 2005). Likewise, co-adaptation is governed by reciprocity norms. Individuals expect the system to adjust to their needs, and so does the system functioning optimally, largely depending on individual responses to the system behavior. Second, social exchange is facilitated by emotions and emotional responses (Lawler & Thye, 1999). Similarly, co-adaptation is an emotional-laden process where individuals spend time and resources on a system they feel will assist them in doing their work better. Therefore, social exchange theory and reciprocity serve as an appropriate theoretical framing to explore co-adaptation and its impact on IT identity.

We posit that co-adaptation leads to IT identity. Identification with technology is an emotional process characterized by a high level of attachment, connectedness, and reliance on technology

(Carter et al., 2020). Research has consistently shown that emotions are inseparably linked to identity construction and development. In one study, Suh and colleagues (2011) have found that individuals who strongly identify with their avatars have a greater emotional attachment to them. Co-adaptation and emotional investment between the user and the system foster connectedness and attachment to technology. AI and cognitive computing are human-like systems capable of engaging users in bilateral relationships. They are highly responsive and interactive systems that constantly adapt themselves to be better collaborators. Successful resource exchange makes collaborators more interdependent and committed to the relationship (Kelley, 1979). With this dependence, emotional investment is established and boosted, allowing several positive effects, such as trust and intimacy, to emerge (Saavedra & Van Dyne, 1999). Emotional investment improves interaction and helps users understand the system and how it might be used to fulfill different tasks. Relationships and interaction experiences that provide high rewards make individuals more satisfied (Rusbult, Johnson, & Morrow, 1986). Dependence and satisfaction with technology resulting from co-adaptation and emotional investment are key indicators of IT identity.

Co-adaptation and emotional investment lead to the development of a relational, interdependent self (Agnew et al.,1998; Chen, Boucher, & Tapias, 2006; Fitzsimons, Finkel, & Vandellen, 2015). Close relationship dissolves psychological boundaries as individuals become emotionally and cognitively intertwined, leading to the formation of one integrated self (Aron, Mashek, & Aron, 2004; Finkel, Simpson, & Eastwick, 2017). Co-adaptation implies mutual emotional investment and ongoing technology usage behaviors which ultimately may lead individuals to view technology as a key part of who they are.

We also hypothesize that users will have a stronger IT identity with the CCS when they believe it is adapting to them as much as they are adapting to it. There are three possible ways co-adaptation can occur: user adapts more to fit the technology, technology adapts more to fit the user, or the user and technology adapt equally to one another. We propose that equal co-adaptation leads to the highest impact on IT identity. The lack of equality between efforts and rewards could be perceived as one party not fulfilling their obligations and responsibilities (Piccoli & Witte, 2015). We employ equity theory as it relates to reciprocity to understand the role of equal and unequal co-adaptation between the user and CCS on IT identity. Equity theory proposes that individuals believe rewards should be distributed based on their contributions (Adams, 1965). In social exchanges, individuals are primarily concerned about their inputs, outputs, and the fairness of the exchange (Joshi, 1991). Equity theory suggests that to perceive reciprocity, individuals should receive benefits proportionate to the inputs they make. Equity makes individuals more willing to embrace exchange, whereas inequity leads to resentment and resistance (Davlembayeva et al., 2021). Research in IS has employed equity theory to provide a theory-based understanding of individual use of technology. They find that individuals who perceive equity are more willing to accept technology and embrace change (Joshi, 1991). For instance, individuals may increase cognitive effort, learn new skills, or adjust their work habits to accommodate the new system. If the system brings about better work conditions, less tension, more task efficiency, equity will be achieved, and individuals will be more inclined to accept new technology and adapt change.

By the same token, we argue that equity between human adaptation and machine adaptation leads to the highest impact on IT identity. Users who believe they and the CCS are equally co-adapting will feel that they and the CCS are equally emotionally invested in their relationship and will eventually develop a stronger connection with the system. Mutual emotional investment increases reliance on the system to achieve stability and satisfaction. Studies of human interpersonal relationships have demonstrated that emotional investment evolves into involvement and closeness (Saavedra & Van Dyne, 1999), satisfaction (VanYperen & Buunk, 1994), commitment (Tallman, Gray, & Leik, 1991), and dependence (Wageman, 1995). Additionally, studies have shown that individuals are more likely to rely on systems that enhance their capabilities and make them feel powerful in their task performance (Park et al., 2013; Proksch, Orth, & Cornwell, 2015). In the same way, equal co-adaptation strengthens the relationship between users and the CCS, resulting in greater reliance and emotional attachment to the system. Therefore, we hypothesize that:

H1. Equal co-adaptation leads to higher identification with the system.

3.2 Anthropomorphism, Co-adaptation, and IT identity

Anthropomorphism refers to assigning human-like properties to nonhuman agents, so that humans can relate to objects better. We hypothesize that anthropomorphism will moderate the relationship between co-adaptation and IT identity. In low anthropomorphism, high machine adaptations relative to human adaptations leads to a strong IT identity. However, in high anthropomorphism, equality between human and machine adaptation has the most influence on IT identity. Social equality between individuals and technology is essential to identify with technology. Low perceptions of anthropomorphism will result in social inequality. Thus, individuals will see the systems as tools designed to assist them in accomplishing their work tasks, and they will expect the systems to do more to compensate for the lack of social equality. Higher machine adaptation relative to human adaptation causes users to view the system as highly competent and very engaged in the relationship. When the system adapts more, it will be perceived as more responsive and human-like. As the system becomes more emotionally involved in the relationship, it is more likely to become considered an equal human collaborator. The highly engaged system in the relationship produces a greater sense of similarity to humans. This increases positive emotions about the CCS and leads to identification with it.

We also propose that when anthropomorphism is high, equal co-adaptation leads to the highest impact on IT identity. High anthropomorphism will create social equality, as individuals will see the CCS as a human collaborator who actively participates in the relationship, resulting in a strong attachment to the system. Several studies have found that people perceive AI and cognitive systems as social collaborators and expect reciprocity more often when they are anthropomorphized (Kahn et al., 2007). Kahn et al. (2006) found that participants were more engaged and reciprocal when they interacted with AIBO—a robotic dog that showed motioning behavior, verbal directives, and offering— than when they interacted with a toy dog. Attributing human qualities such as intentions and emotions to non-human objects enhances the reciprocity between humans and technology. A recent study by Lee and Liang (2019) shows that if a robot has assisted a human partner in a trivia game, the human is more likely to cooperate with other requests by the robot. Reciprocity is a critical component of human interactions, and studies have found that individuals are also willing to reciprocate with technology that has previously helped them (Fogg & Nass, 1997). Therefore, we hypothesize:

H2. Anthropomorphism moderates the association between co-adaptation and IT identity. In low anthropomorphism, individuals identify with the system when they believe the system adapts more to them. However, in high anthropomorphism, individuals identify with the system when they adapt more to the system.

3.3 IT identity and Individual Innovative Performance

We propose that identifying with CCS impacts innovative performance. Innovative performance is defined as the degree to which technology usage enhances the ability of an individual to generate and promote new ideas in order to perform tasks and activities (Janssen & Van Yperen, 2004). Examples of this behavior include suggesting new ways to complete tasks and developing new methods of using CCS to perform tasks. We focus on innovative performance for two key reasons. First, innovative performance is a key indicator of system use. Innovative performance results from extensive experimenting and tinkering with the system. Exploring a wide range of features to perform tasks maximizes the benefits gained from the system (Ahuja & Thatcher, 2005; Hsieh, Rai, & Xu, 2011). Second, cognitive computing is designed to empower employees and enable them to innovate on their own. The innovation process has shifted from top-down to bottom-up, making individual innovation more important than ever before. It is vital to study how these technologies impact individual innovation.

Emotional attachment and relatedness are two key aspects of IT identity. Emotional attachment refers to the "emotion-laden target-specific bond between a person and specific object" (Thomson, MacInnis, & Whan Park, 2005, p. 77). Relatedness is the blurring of boundaries between technology and self, experienced as a sense of connectedness with technology (Carter & Grover, 2015). Given that innovative performance can be understood as accomplishing new tasks using technology, it may be linked to the emotional bond that individuals believe they have with the technology. According to the broaden-and-build theory, positive emotions such as feelings of attachment and involvement stimulate broader thinking (Fredrickson, 2004). Positive emotions widen the scope of attention, cognition, and action, motivating individuals to pay attention to details to identify and exploit opportunities. They encourage individuals to engage with their environment and participate in different activities, creating various experiences that one can draw on to understand problems and make decisions (Fredrickson, 2001; Isbell, Lair, & Rovenpor, 2013). Emotional attachment results in the development of “enduring personal resources” (e.g., psychological, social, physical) that one can use as reserves to cope with difficult situations (Fredrickson & Branigan, 2005). Positive emotions impact innovation performance by boosting cognitive capabilities and unusual thinking and increasing access to a broad spectrum of material in memory (Isen, 2002; Isen, Johnson, Mertz & Robinson, 1985). The “ thought-action repertoires” accrued from positive emotional experiences induce individuals to pursue a wide range of thoughts and actions than is typical (Fredrickson & Branigan, 2005). Therefore, emotional attachment and relatedness can impact individual innovative performance.

Technology dependence is the third key dimension of IT identity, reflecting the reliance on technology. Studies have shown that reliance on technology increases perceived usefulness and intention to use technology (Balapour et al., 2019; Rai, Lang, Welker, 2002). A high degree of reliance implies that individuals are willing to link their future success and performance to using the systems (Carter et al., 2020; Kankanhalli, Ye, & Teo, 2015). Similarly, users who demonstrate a certain degree of reliance on technology are more likely to associate their future innovative performance with the technology.

Individuals with IT identity are more likely to explore system features to perform existing and novel tasks. Individuals with strong IT identity with a technology tend to use more features in different work-related tasks (Hassandoust et al., 2021). This happens because they attribute a higher level of emotional attachment and enthusiasm to the technology. In particular, being enthusiastic and emotionally connected to technology create positive attitudes and encourage exploration IT usage behavior (Carter et al., 2020). IT identity manifests a high level of use where the system is applied in more sophisticated ways. For instance, when a work situation presents an opportunity for creativity, a user with a CCS identity would use CCS rather than other systems to demonstrate their ability to perform creatively. To this end, they would use CCS features for additional tasks, use new CCS features, or use CCS features in different situations. Engaging with technology features increases knowledge and enhances individuals' capacity to use the system for innovative performance (Schmitz, Teng, & Webb, 2016). Studies have shown that utilizing system features has a remarkable impact on the innovative use of the system (Wang & Hsieh, 2006). Individuals who have experience and knowledge with the system are more likely to explore additional functionalities which can lead to innovative performance. Prior studies have shown that identifying with technology significantly impacts innovative performance. Ogbanufe and Gerhart (2020) find that those with strong smartwatch IT identity are more likely to come up with new ideas for socializing with others.

We also propose that IT identity mediates the association between co-adaptation and individual innovative performance. Mutual technology use and emotional investment increase emotional attachment and connectedness to the systems which may trigger innovative performance. Therefore, we hypothesize that:

H3. IT identity positively relates to individual innovative performance.

H4. IT identity mediates the association between co-adaptation and individual innovative performance.

CHAPTER 4 Methodology

4.1 Participants and Procedure

The setting for this study is Intelligent Assistant (IA) users. We used a market research company to recruit participants and administer the online survey. In the first wave of data collection, the company randomly sampled individuals who used IA. In all, 796 participants accessed the survey. A total of 450 participants completed the first wave of the survey. Two weeks later, the company sent a follow-up survey to the participants who responded to the first survey. The surveys included attention check questions to reduce lower-quality responses due to inattention. Of these individuals, 277 completed the wave two survey. We screened the data set for incomplete or inaccurate responses and rejected twenty-nine responses. Before conducting the analysis, we checked for outliers using Cook's D and standardized residuals. We also inspected kurtosis and skewness to ensure that the distribution was not overly peaked or flat and the data were symmetrical around the mean. Table 20 presents sample characteristics of participants in our study.

4.2 Measurements

We collected data with a two-week time difference between the first and second time points. Predictors (human adaptation and machine adaptation) and moderator (anthropomorphism) variables were drawn from Time 1 and the mediator (IT identity) and dependent variables (innovative performance) from Time 2. The variables were each measured on a seven-point Likert scale with values ranging from "Strongly Disagree" to "Strongly Agree".

4.2.1 Independent Variables

We assessed human adaptation using items from Schmitz et al. (2016) and machine adaptation was measured using revised items develop by the author. Human adaptation items include 1) “I have experimented with new features on my Alexa.”, 2) “I have changed the settings on my Alexa to alter the way I interact with it.” 3) “I have adapted to Alexa in a way that is consistent with how I am supposed to be interacting with it.” 4) “I have found new ways of using Alexa.” 5) “I have experimented with new ways of my Alexa.” 6) “I have adapted to the Alexa way of use.” Machine adaptation sample items include 1) “Alexa has experimented with me by presenting me with new features.” 2) “Alexa has changed its settings to alter the way it interacts with me.” 3) “Alexa has taken advantage of its ability to adapt to me in a way that is consistent with how it was supposed to be used.” 4) “Alexa has suggested new ways I could use it.” 5) “Alexa has experimented with me by suggesting new uses.” 6) “Alexa has adapted to my usage patterns.” The items are listed in the appendix.

4.2.2 Dependent Variables

IT identity was measured using four items from Carter et al. (2020). Sample items include 1)"Thinking about myself in relation to Alexa, I am dependent on Alexa", 2) "Thinking about myself in relation to Alexa, I am enthusiastic", 3) "Thinking about myself in relation to Alexa, I am linked with Alexa", 4) "Thinking about myself in relation to Alexa, I am connected with Alexa". Anthropomorphism was measured using three items developed by Moussawi and Koufaris (2019) and Waytz, Cacioppo & Epley (2010). Example items include 1) "Alexa is able to speak like a human", 2) "Alexa can be friendly", and 3) "Alexa can be funny". The scale of the innovative performance consisted of three items adapted from Kuegler, Smolnik, and Kane (2015). Sample items include: 1) "Using Alexa helps me create new ideas for task improvements more often", 2) "Using Alexa improves my ability to generate innovative solutions to problems", 3) "Using Alexa makes me more often produce innovative ideas for task improvement". The items are listed in the appendix.

4.2.3 Control Variables

We also used several control variables to rule out any potential alternative explanations for the results. We controlled for age, gender, personal innovativeness with IT, performance expectancy, and technology use.

4.3 Polynomial Regression Analysis

The hypotheses in this work emphasize the impact of equality and inequality in values between human adaptation and machine adaptation. Prior studies have relied on difference scores between two constructs to examine equality (i.e., congruence, fit, match, similarity, or agreement) (Edwards & Parry, 1993). Difference scores is the algebraic, squared, or absolute difference between the values of two variables. Single-index measures confound the impact of each variable on the outcome (Shanock et al., 2010). The difference scores approach would not allow us to explore the degree of contribution of each independent variable and whether it was better or worse for the relationship with the system (i.e., IT identity) to have more human adaptation than machine adaptation or vice versa. Thus, polynomial regression is particularly suitable to explore the impacts of co-adaptation on IT identity.

The analysis was conducted using the polynomial regression model and Response Surface Analysis (RSA). Polynomial regression procedure requires two steps: first, entering X, Y values to test linear relationship (first part of equation 1); second, entering higher-order values (X^2, Y^2) and the product value (XY) to assess the curvilinear relationship.

$$Z = b_0 + b_1X + b_2Y + b_3X^2 + b_4XY + b_5Y^2 + e \qquad \text{(Equation 1)}$$

The measurement of the equality and inequality co-adaptation includes comparing two variables: human adaptation and machine adaptation. The three-dimensional relationship provided by the polynomial regression model enables us to explore the hypotheses, such as the degree of identification with the system when human adaptation and machine adaptation are equal and unequal.

4.4 Response Surface Analysis

Due to the difficulty of interpreting the polynomial regression results, we use Response Surface Analysis (RSA). It is a three-dimensional surface that helps assess the intricacies of polynomial regression results and provides a graphical and statistical explanation of the polynomial regression coefficients (Venkatesh & Goyal, 2010). Each side of the surface presents a different combination of human adaptation and machine adaptation. The equality effect is reflected by a line drawn from the front to the back of the surface. The front corner of the equality line indicates that both human adaptation and machine adaptation are low on a given outcome (e.g., users having both low human adaptation and machine adaptation). However, the back corner of the equality line indicates that both human adaptation and machine adaptation are high. Inequality effect is reflected by a line drawn from the left to right, with the left corner presenting that machine adaptation is high and Human adaptation is low. The right corner indicates that machine adaptation is low and Human adaptation is high.

RSA helps to assess three key features of the surface. First, the stationary point is defined as the point at which the slope of the surface is zero in all directions (Edwards & Parry, 1993). Second, the principal axes of the surface run perpendicular to one another and intersect at the stationary point (Edwards & Parry, 1993). Third, the intercepts and slopes of surfaces along congruence and incongruence lines. In this paper, we run the polynomial regression model first and then use the regression coefficients to generate the response surface and assess the equality and inequality between human adaptation and machine adaptation. These steps are thoroughly explained in the following sections.

CHAPTER 5 Data Analysis and Results

During data analysis and preparation, we centered independent variables around the scale mean and checked multicollinearity and the values was appropriately low (VIF < 2). We also screened the data for outliers using Cook's D and standardized residuals. As Edwards (2002) recommended, we used the bootstrapping procedure to assess the significance of the intercept and slope of the surface along the line of equality and inequality. Using the bootstrapping technique, we generated bias-corrected confidence intervals of the components of the response surface based on Equation 1 and Equation 1.

5.1 Construct Reliability and Validity

The reliability of the constructs can be examined through Cronbach's Alpha and the average variance extracted (AVE). As shown in Table 1, Cronbach's Alpha values are acceptable and all are above 0.7. AVEs are greater than 0.5. The results provide evidence of convergent validity. Table 2 depicts that the square root of AVE for each construct is higher than its correlations with all other constructs, demonstrating discriminant validity. We also conducted a confirmatory factor analysis to further assess discriminant and convergent validity. Except for one item, Table 2 shows that all items had loadings above .62 and cross-loadings lower than .32.

Variable	Mean	SD	CA	1	2	3	4	5
Human Adaptation	5.20	1.04	.86	**1**				
Machine adaptation	4.81	1.10	.86	$.48^{**}$	**1**			
Anthropomorphism	5.13	1.33	.68	$.32^{**}$	$.42^{**}$	**1**		
IT identity	4.01	1.38	.89	$.36^{**}$	$.44^{**}$	$.36^{**}$	**1**	
Innovative Performance	4.84	1.38	.95	$.42^{**}$	$.49^{**}$	$.40^{**}$	$.65^{**}$	**1**

Table 1. Co-Adaptation Descriptive Statistics and Correlations

Constructs	Items	Components				
		1	2	3	4	5
Human Adaptation	Human Adaptation 1	**.80**	.12	.06	.09	.16
	Human Adaptation 2	**.66**	.11	.01	.11	-.01
	Human Adaptation 3	**.67**	.22	.12	.04	.15
	Human Adaptation 4	**.81**	.18	.13	.21	.05
	Human Adaptation 5	**.83**	.20	.09	.16	.05
	Human Adaptation 6	**.66**	.15	.17	.06	.16
Machine Adaptation	Machine Adaptation 1	.11	**.75**	.11	.14	.18
	Machine Adaptation 2	.25	**.59**	.22	.22	-.05
	Machine Adaptation 3	.15	**.66**	.20	.11	.16
	Machine Adaptation 4	.18	**.80**	.02	.10	.09

	Machine Adaptation 5	.14	**.84**	.06	.12	.15
	Machine Adaptation 6	.30	**.56**	.18	.10	.19
Anthropomorphism	Anthropomorphism 1	.17	.19	.01	.02	**.77**
	Anthropomorphism 2	.14	.13	.24	.16	**.81**
	Anthropomorphism 3	.07	.20	.08	.21	**.82**
Innovative Performance	Innovative performance 1	.22	.24	.25	**.83**	.14
	Innovative performance 2	.19	.22	.29	**.85**	.15
	Innovative performance 3	.18	.22	.33	**.84**	.14
IT identity	IT identity 1	.11	.19	**.89**	.17	.02
	IT identity 2	.11	.25	**.86**	.16	.09
	IT identity 3	.20	.05	**.74**	.40	.17
	IT identity 4	.16	.15	**.62**	.45	.22

Note. Extraction Method: Principal Component Analysis. Rotation Method: Varimax with Kaiser Normalization. Rotation converged in 9 iterations.

Table 2. Factor Loadings and Cross-Loadings of Constructs

5.2 Confirmatory Polynomial Regression Analysis

We conducted an exploratory analysis using polynomial regression and response surface analysis. We found that the variance explained by the higher-order equation is more significant than the variance explained by the first-order equation (Table 3). Thus, the linear model was rejected in favor of the quadratic model. In addition, the F-test shows that R^2 of the quadratic equation for human adaptation and machine adaptation predicting IT identity were significantly higher than the linear equation.

Dependent Variable	Independent Variables	First-Order Linear Equation		Second-Order Quadratic Equation	
		R^2	β	R^2	β
IT identity	Human Adaptation	.38***	-.03	.40*	-.04
	Machine Adaptation		.26***		.09
	$Human\ Adaptation^2$				-.07
	Human Adaptation x Machine Adaptation				.22***
	$Machine\ Adaptation^2$				-.11*

Note.

1. *p < .05, **p < .01, ***p < .001.
2. Significance levels are based on bias-corrected confidence intervals generated from bootstrap estimates.
3. Control Variables:
   - Age (β=.-.008, p > .05)
   - Gender (β=-.076, p > .05)
   - Technology use (β=.192, p < .05)
   - Personal innovativeness with IT (β=.145, p < .05)
   - Performance expectancy (β=.430, p < .05)

Table 3. Predicting IT identity Using Human adaptation & Machine adaptation

5.3 Exploratory Polynomial Regression Analysis— Equality Effect Analyses

For the equality effect hypothesis, a key feature of the response surface plot is the line of equality (i.e., line of congruence; Edwards & Parry, 1993). The equality effect is reflected by all combinations of the predictors for which Y = X (Figure 2). Thus, co-adaptation can be similar on low, mid-level, and high values. The line of equality is described by a formula: Y = $a_1X + a_2X^2$, where a_1 is the slope of the line above the point (0,0) and a_2 the shape of the surface—both are derived from esteemed coefficients of Equation 1.

There are four main conditions to test for the equality effect (Humberg et al., 2018). First, the first principal axis Y= P_{10} + $P_{11}X$ must not be significantly different from the line of equality. Our data showed that P_{10} was not significantly different from 0, and P_{11} was not significantly different from 1 (i.e., the confidence interval of P_{11} includes 1) (Table 4). Second, the line of inequality must have an inverted U-shape and the values must be maximized at the equality predictor combinations (0,0). The line of inequality comprises all combinations of the predictors for which Y = - X. The slope of line of inequality at the point (0,0) (i.e., a_3) must not be significantly different from 0 and the surface along the line of inequality has to be inverted U-shape, thus a_4 must be significantly negative. Clearly, the surface was negatively sloped with no significant value a_3= -0.12 and the surface was inverted U-shape a_4 = -0.40 (Table 4). Therefore, the results indicate an equality effect exists. Overall, the surface reveals that IT identity is higher when human adaptation and machine adaptation values are similar to one another than when they differ, as shown by the downward slope of the surface on either side of the Y = X (Figure 2).

Surface	**Stationary Points**		**First Principal Axis**		**Shape of Surface Along Lines**			
					Line of Equality		**Line of Inequality**	
	X_0	Y_0	p_{10}	p_{11}	a_1	a_2	a_3	a_4
IT Identity	-0.67	0.29	0.29	0.86	0.05*	0.04	-0.12	-0.40***

Table 4. Results of Tests of First Principal Axis and Shape of Surfaces Along Lines of Equality and Inequality

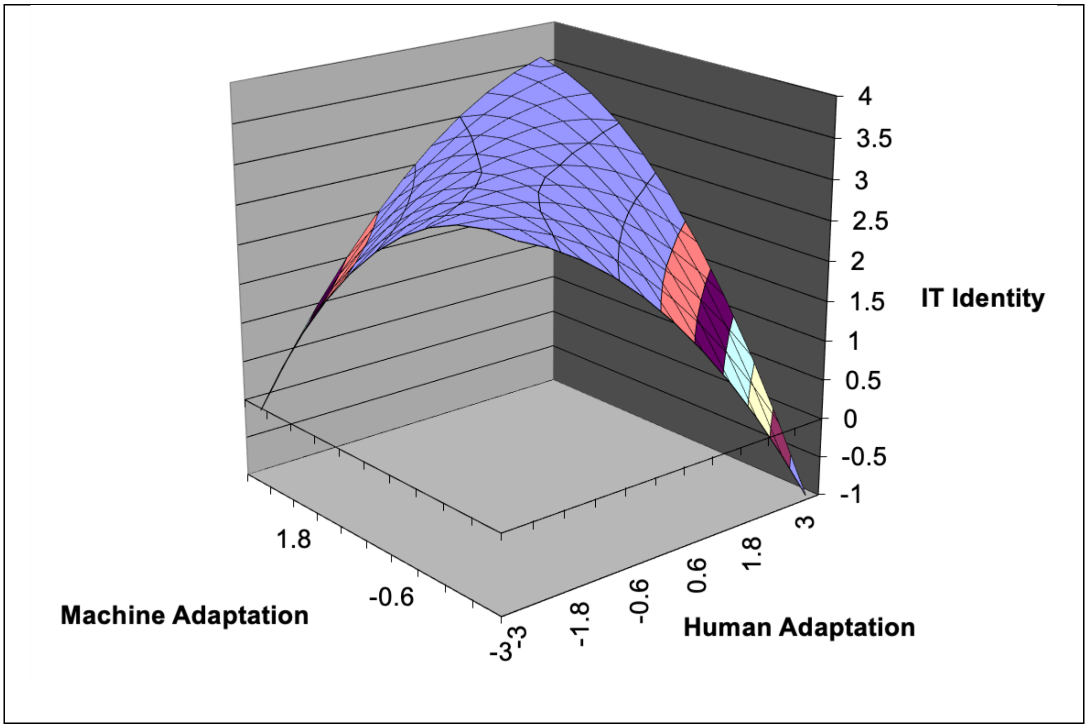

Figure 2. Response Surface Analysis for Co-Adaptation Predicting IT identity

5.4 Moderated Polynomial Regression

We ran moderated polynomial regression (Edwards, 2002; Edwards & Parry, 1993) to assess whether anthropomorphism moderated the association between co-adaptation and IT identity. We incorporated the moderator V into the quadratic regression Equation 1, yielding the following equation (Equation 2):

$$Z = b_0 + b_1X + b_2Y + b_3X^2 + b_4XY + b_5Y^2 + b_6V + b_7XV + b_8YV + b_9X^2V + b_{10}XYV + b_{11}Y^2V + e \quad \text{(Equation 2)}$$

The moderation effect is examined by assessing the increment in R^2 yielded by the terms XV, X^2V, XYV, and Y^2V. The R^2 increment was significant, F change = 2.26, p < .05, R^2 = .44 (Table 5). Thus, the moderated polynomial regression is supported. The values of anthropomorphism at one standard deviation above versus below the mean are computed and depicted in Table 6.

Variables	**Coefficients**	**IT identity**		
		1	**2**	**3**
Human Adaptation	b_1	-.04	-06	-.15
Machine Adaptation	b_2	.09	.04	.00
$Human\ Adaptation^2$	b_3	-.07	-.07	.04
Human Adaptation x Machine Adaptation	b_4	.22***	.23***	.11
$Machine\ Adaptation^2$	b_5	-.11*	-.12*	-.17*
Anthropomorphism	b_6		.13*	.08
Human Adaptation x Anthropomorphism	b_7			.15
Machine Adaptation x Anthropomorphism	b_8			.03
$Human\ Adaptation^2$ x Anthropomorphism	b_9			-.10*
Human Adaptation x Machine Adaptation x Anthropomorphism	b_{10}			.07
$Machine\ Adaptation^2$ x Anthropomorphism	b_{11}			.02
R^2		.40*	.41*	.44*

ΔR^2		.02*	.01*	.03*

Table 5. Results of Moderated Polynomial Regression Analysis

Variables	Coefficients	Low Anthropomorphism	High Anthropomorphism
(Intercept)	b_0	3.44***	3.59***
Human Adaptation	b_1	.46	.76
Machine Adaptation	b_2	.14	.20
$Human\ Adaptation^2$	b_3	-.36	-.56
Human Adaptation x Machine Adaptation	b_4	.39	.52
$Machine\ Adaptation^2$	b_5	-.10	-.07

Note.

- **p* < .05, ***p* < .01, ****p* < .001.
- Significance levels are based on bias-corrected confidence intervals generated from bootstrap estimates.

Table 6. Coefficients for Response Surface Analysis Predicting IT identity at Low Versus High Anthropomorphism

5.4.1 Moderated Polynomial Regression for Low Anthropomorphism

We posited that in the low-anthropomorphism, IT identity is higher when machine adaptation exceeds human adaptation. The surface for human adaptation and machine adaptation predicting IT identity was concave, with its stationary point located at X_0 = -25.52 and Y_0= -48.73, just outside the near corner of the X,Y plane (Figure 3). The first principal axis cross within the range of the component measure (P_{10}= -.78) and the axis is rotated counterclockwise off the Y=X line

(P_{11}= 1.88) (Table 7). The second principal axis is shifted away from the line of inequality, indicating a lateral shift along the line into the region where Y is less than X. The intercept of the second principal axis (P_{20}) was -62.32 and negatively sloped (Table 7). The surface along the second principal axis was concave (a_{x2}= -.60, p < .05) and negatively sloped (a_x= -30.64) (Table 8). Taken together, these results showed that IT identity is maximized when machine adaptation is higher than human adaptation. Furthermore, the downward curvature along the Y=-X line indicated that machine adaptation decreased and human adaptation increased IT identity decreased.

Dependent Variable	**Stationary Point**		**First Principal Axis**		**Second Principal Axis**	
	X_0	Y_0	p_{10}	p_{11}	p_{20}	p_{21}
IT Identity	-25.52***	-48.73***	-.78	1.88	-62.32***	-.53**

Table 7. Stationary Points and Principal Axes for Low Anthropomorphism

Dependent Variable	**Y = X**		**Y = -X**		**Surface Along First Principal Axis**		**Surface Along Second Principal Axis**	
	a_x	a_{x2}	a_x	a_{x2}	a_x	a_{x2}	a_x	a_{x2}
IT Identity	0.60	-.07	0.32	-0.86*	.71	0.01	-30.64***	-.60***

Table 8. Slopes Along Lines of Interest for Low Anthropomorphism

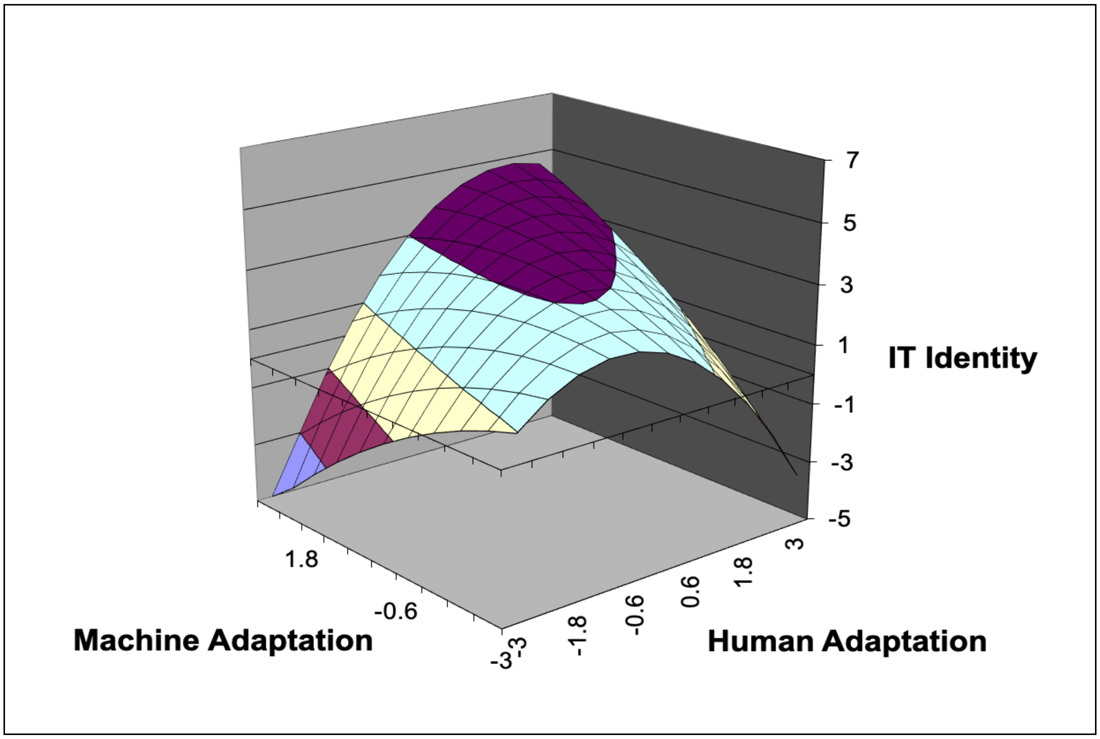

Figure 3. Response Surface for Low Anthropomorphism

5.4.2 Moderated Polynomial Regression for High Anthropomorphism

We posited that in the high-anthropomorphism, IT identity is higher when machine adaptation is equal to human adaptation. The surface for human adaptation and machine adaptation predicting IT identity was concave (Figure 4), with its stationary point at X_0 = -1.66 and Y_0= -4.99, shifted from the origin and became close to the near corner of the X, Y plane (Table 10). The slope of the first principal axis was positive and greater than 1 (P_{11}= 2.30), indicating a marked counterclockwise rotation along the Y = X line (Table 9). The surface was convex along the first principal axis (a_{x2}= .29) and positively sloped where it crossed the y-axis (a_x = .98), but neither

a_x nor a_{x2} were significant (Table 10). The second principal axis is shifted away from the line of inequality. The intercept of the second principal axis (P_{20}) was negative. The surface was concave along the second principal axis (a_{x2}= -.79) and negatively sloped (Table 10). Taken together, in contrast to our proposal, these results showed that IT identity increased when machine adaptation is higher than human adaptation.

Dependent Variable	**Stationary Point**		**First Principal Axis**		**Second Principal Axis**	
	X_0	Y_0	p_{10}	p_{11}	p_{20}	p_{21}
IT identity	-1.66*	-4.99***	-1.15	2.31	-5.71***	-.43**

Table 9. Stationary Points and Principal Axes for High Anthropomorphism

Dependent Variable	**Y = X**		**Y = -X**		**Surface Along First Principal Axis**		**Surface Along Second Principal Axis**	
	a_x	a_{x2}	a_x	a_{x2}	a_x	a_{x2}	a_x	a_{x2}
IT identity	0.96	-.10	.55	-1.14	.98	.29	-2.64	-.79***

Table 10. Slopes Along Lines of Interest for High Anthropomorphism

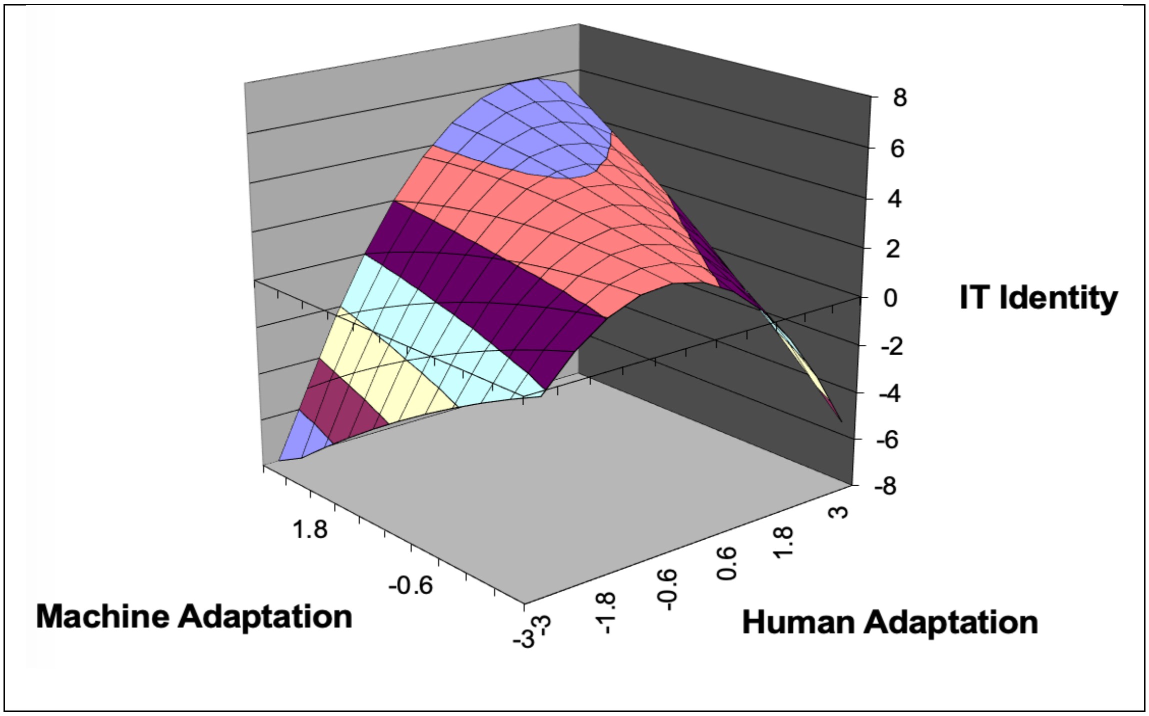

Figure 4. Response Surface for High Anthropomorphism

5.5 IT identity impact on individual innovative performance

Hypothesis 3 posited that IT identity is positively associated with individual innovative performance. The results (Table 11) show that this hypothesis is supported with β = .55 p < .05. We also controlled for demographic data and personal innovativeness with technology (i.e., the intrinsic willingness to experiment with new technologies). The results of an independent T test revealed that individuals who were willing to experiment with new technologies were more likely to use Alexa to perform their tasks innovatively.

Dependent Variable	Independent Variables	R^2	β
Individual Innovative Performance	IT identity	.50***	.55***
***Note*.** *p < .05, **p < .01, ***p < .001.			

Table 11. Predicting Individual Innovative Performance using IT identity

5.6 Mediated Polynomial Regression

I propose that IT identity mediates the association between co-adaptation and individual innovative performance. We run the mediated polynomial regression to assess the direct, indirect, and total effect of co-adaptation on individual innovative performance (Edwards & Lambert, 2007).

We assess the mediation effect using two regression equations (Edwards & Cable 2009). The first equation (Equation 3) regresses the mediator on the five quadratic terms while the second equation (Equation 4) regresses the outcome on the five quadratic terms and the mediator.

$$M = a_0 + a_1X + a_2Y + a_3X^2 + a_4XY + a_5Y^2 + e_m \qquad \text{(Equation 3)}$$

$$Z = b_0 + b_1M + b_2X + b_3Y + b_4X^2 + b_5XY + b_6Y^2 + e_z \qquad \text{(Equation 4)}$$

With reference to Figure 5, equation 3 offers regression coefficients for the first stage while equation 4 provides the coefficients for the second stage and direct effect. The direct effect is the product of the first and second stage, reflecting the impact of co-adaptation on individual innovative performance via IT identity. The sum of direct and indirect effect is the total effect of co-adaptation on individual innovative performance.

We estimated the coefficients of equation 4 and ran another bootstrap to assess the standard errors and confidence intervals. The bootstrapping was carried out using unstandardized coefficients; however, standardized coefficients and their significance are provided in Table 12.

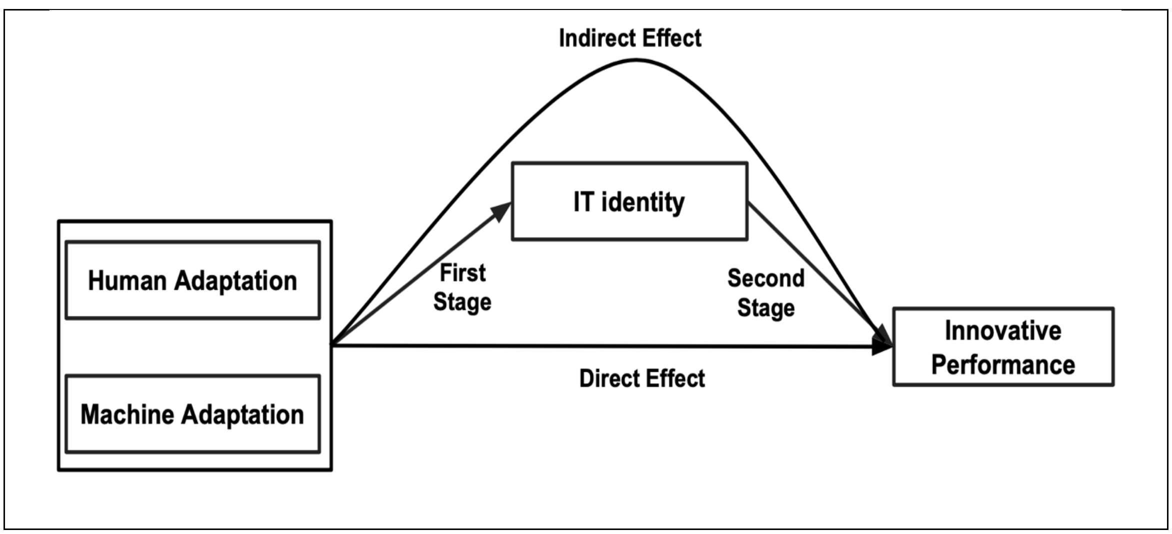

Figure 5. The Direct and Indirect effects of Co-adaptation on Innovative Performance

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	Direct Effect		First Stage		Second Stage		Indirect Effect		Total Effect	
	b	β	b	β	b	β	b	β	b	β
Intercept	3.49	-	4.07***	-	0.38***	.38***	1.54***	-	5.02***	-
Human Adaptation	0.05	.04	-0.04	-.03	0.38***	.38***	-0.01*	-.01*	0.03	.03
Machine Adaptation	0.24*	.18*	0.09	.07	0.38***	.38***	0.03*	.03*	0.26**	.21**
Human Adaptation ^{2}	-0.02	-.04	-0.07	-.13	0.38***	.38***	-0.03**	-.05**	-0.05	-.08
Human Adaptation X Machine Adaptation	0.02	.02	0.22**	.35**	0.38***	.38***	0.08**	.13**	0.10	.16
Machine Adaptation ^{2}	-0.10*	-.15*	-0.11*	-.16*	0.38***	.38***	-0.04**	-.06**	-0.14**	-.21**

Note.
- *p < .05, **p < .01, ***p <.001.
- Significance levels are based on bias-corrected confidence intervals generated from bootstrap estimates.

Table 12. Tests of Mediated Polynomial Regression for the Effects of co-adaptation on Individual innovative performance.

5.6.1 Direct effect

The direct effect refers to the impact of co-adaptation on individual innovative performance after controlling for IT identity. According to Table 13, only machine adaptation has an impact in the direct effect on individual innovation performance, while human adaptation and the interaction between human and machine adaptation are not significant.

The surface for human adaptation and machine adaptation predicting individual innovative performance (Figure 6) is concave, with its stationary point located at X= 1.63, Y= 1.36, shifted upward along the Y=X line (Table 13). The first principal axis does not significantly differ from the line of equality. The analyses also show that the slope of the surface along the Y =X line is positive with a concave shape (a_x= .29, a_{x2}= -.11) (Table 14). Overall, this response surface suggests that the positive relationship between machine adaptation and innovation increases as perceived machine adaptation increases with human adaptation having little overall effect.

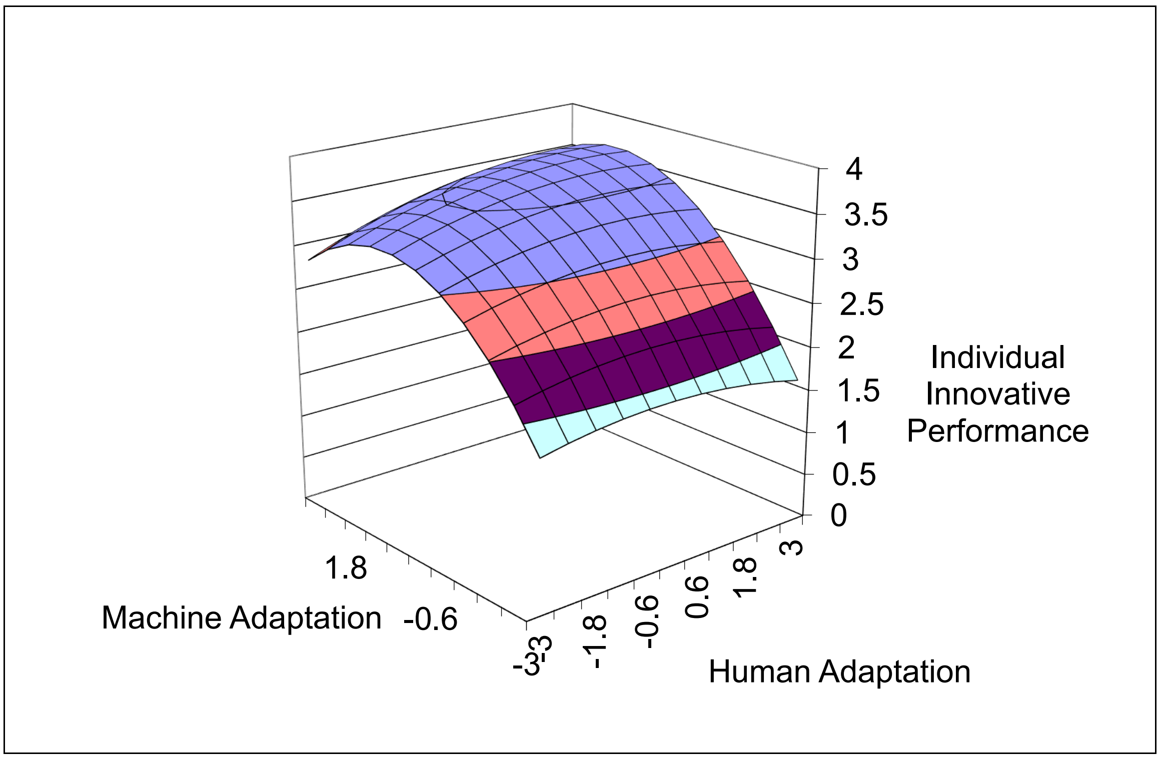

Figure 6. Response Surface of the Direct Effect of Co-adaptation on Innovative Performance

Dependent Variable	**Stationary Point**		**First Principal Axis**		**Second Principal Axis**	
	X_0	Y_0	p_{10}	p_{11}	p_{20}	p_{21}

Individual Innovative Performance	1.63	1.36	1.20	.10	18.43***	-10.50***

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

Significance levels are based on bias-corrected confidence intervals generated from bootstrap estimates.

Table 13. Stationary Points and Principal Axes for the Direct Effects of Co-adaptation on Individual Innovative Performance

Dependent Variable	**Y = X**		**Y = -X**		**Surface Along First Principal Axis**		**Surface Along Second Principal Axis**	
	a_x	a_{x2}	a_x	a_{x2}	a_x	a_{x2}	a_3	a_4
Individual Innovative Performance	.29	-.11***	-.20	-.14*	.07	-.02	36.07***	-11.08***

Note.
- *p < .05, **p < .01, ***p <.001.
- Significance levels are based on bias-corrected confidence intervals generated from bootstrap estimates.

Table 14. Slopes and Curvatures Along the Lines of Interest for the Direct Effects of Co-adaptation on Individual Innovative Performance

5.6.2 Indirect effect

We also look at how co-adaptation impacts individual innovative performance indirectly through IT identity. Table 15 illustrates that the interaction (i.e., co-adaptation) has significant impacts on individual innovative performance (β = .13 , p <.05). Therefore, co-adaptation increases IT identity (β = .35 , p <.05) which in turn impacts individual innovative performance.

The indirect effect surface for human adaptation and machine adaptation predicting individual innovative performance (Figure 7) is concave, with its stationary point located at X= -.67, Y= -.29, shifted downward along the Y= X line. The data shows that P_{10} iand P_{11} are not significantly different from 0 and 1 respectively (Table 15). Furthermore, the slope of the line of equality a_x is almost 0 ($a_x = .02$) meaning the predicted outcome values above the line of equality is almost constant and there is no differences between equality at lower values and equality at higher values of co-adaptation. The shape of the line of equality is almost linear ($a_{x2} = .02$) meaning that it is a straight line (Table 16). Furthermore, the surface along the line of inequality is negatively sloped with no significant value a_3= -0.24 and has an inverted U-shape (a_4 = -0.18) (Table 16). Thus, the values along the line of inequality are maximized at the equality predictor combinations (0, 0).

Overall, the surface reveals that individual innovative performance is higher when human adaptation and machine adaptation values are similar to one another than when they differ, as shown by the downward slope of the surface on either side of the Y = X (Figure 7). The co-adaptation impact increases identification with the system which in turn triggers innovation performance.

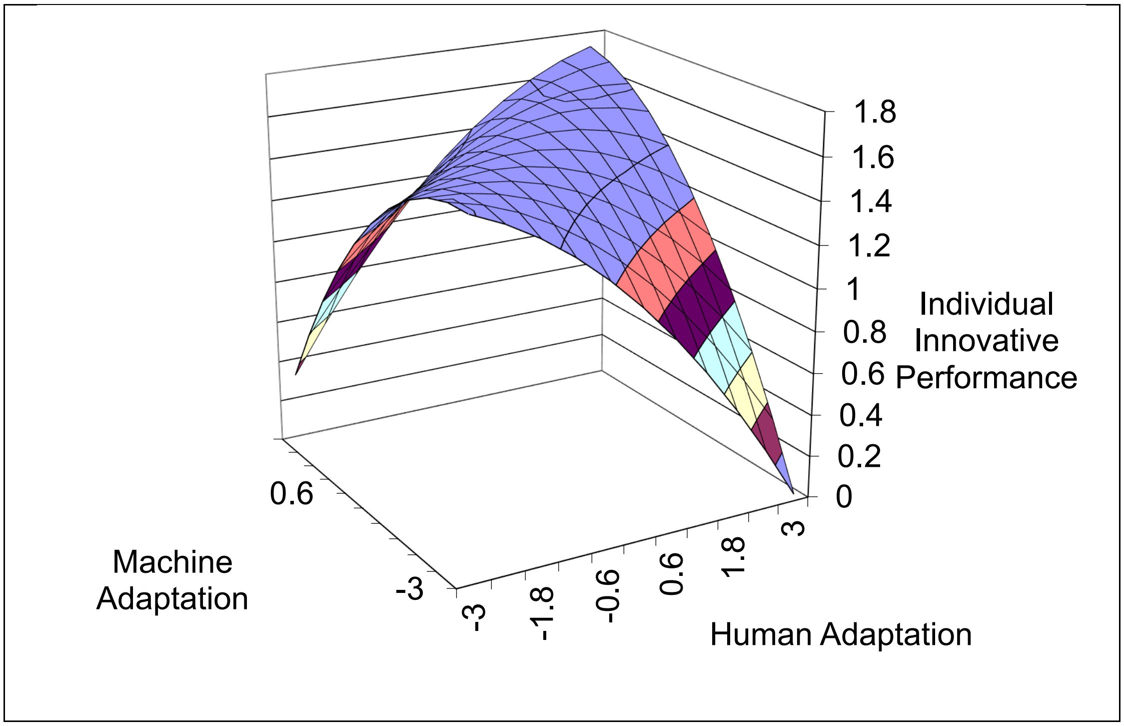

Figure 7. Response Surface of the Indirect Effect of Co-adaptation on Innovative Performance

Dependent Variable	**Stationary Point**		**First Principal Axis**		**Second Principal Axis**	
	X_0	Y_0	p_{10}	p_{11}	p_{20}	p_{21}
Individual Innovative Performance	-.67	-.29	.29	.86	-1.07	-1.16

***Note*.**
- *p < .05, **p < .01, ***p <.001.
- Significance levels are based on bias-corrected confidence intervals generated from bootstrap estimates.

Table 15. Stationary Points and Principal Axes for the Indirect Effects of Co-adaptation on Individual Innovative Performance

Dependent Variable	Y = X		Y = -X		Surface Along First Principal Axis		Surface Along Second Principal Axis	
	a_x	a_{x2}	a_x	a_{x2}	a_1	a_2	a_3	a_4
Individual Innovative Performance	.02	.02	-.05	-.15**	.02	.01	-.24	-.18**

Note.
- *p < .05, **p < .01, ***p <.001.
- Significance levels are based on bias-corrected confidence intervals generated from bootstrap estimates.

Table 16. Slopes and Curvatures Along the Lines of Interest for the Indirect Effects of Co-adaptation on Individual Innovative Performance

5.6.3 Total effect

Total effect refers to the combined impact of direct and indirect effects on the outcome. According to the regression coefficients of the total effect in Table 12, only machine adaptation has an impact on individual innovative performance.

The total effect surface for human adaptation and machine adaptation predicting individual innovative performance (Figure 8) is concave, with its stationary point located at X= 2.09, Y= 1.73, shifted forward along the Y= X line (Table 17). The first and second principal axes do not significantly differ from the line of equality and inequality respectively. The surface along Y = X line is concave and positively sloped (a_x= .31 a_{x2} = -.09) (Table 18). From the surface, it appears that the positive relationship between machine adaptation and individual innovation performance increases as machine adaptation increases, while human adaptation has little overall effect.

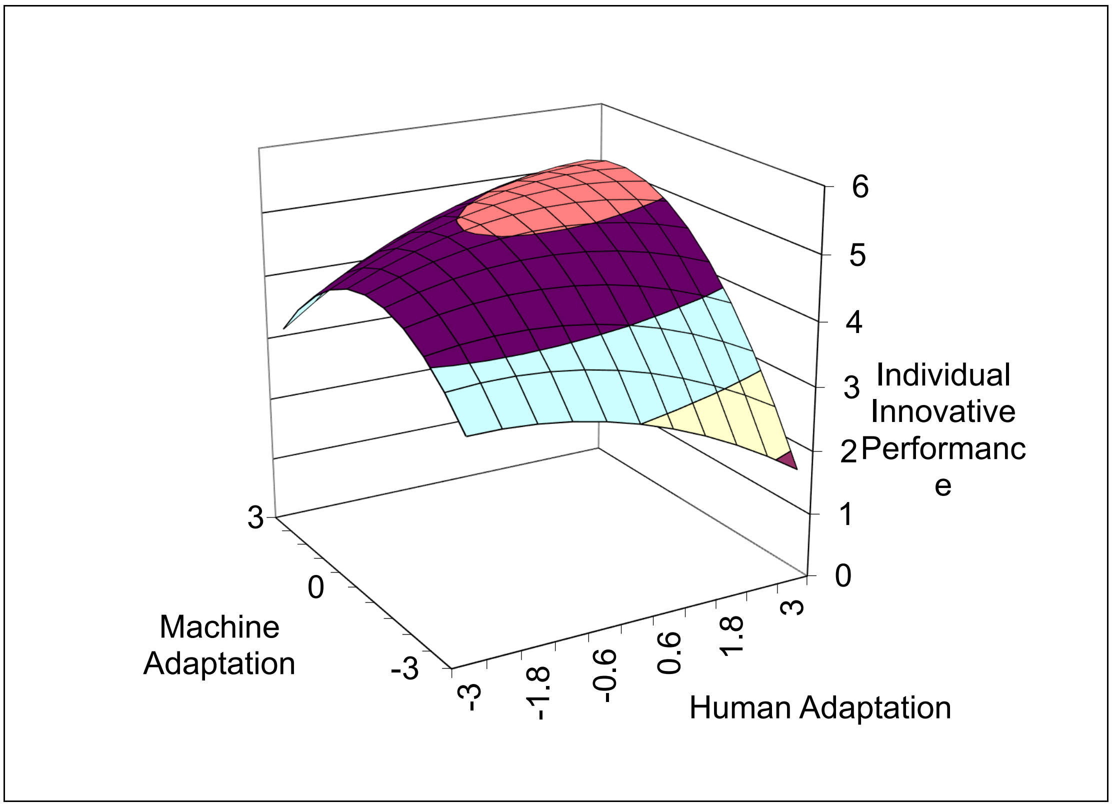

Figure 8. Response Surface of the Total Effect of Co-adaptation on Innovative Performance

Dependent Variable	**Stationary Point**		**First Principal Axis**		**Second Principal Axis**	
	X_0	Y_0	p_{10}	p_{11}	p_{20}	p_{21}
Individual	2.09	1.73	.81	.44	6.50	-2.28

Innovative Performance						

Note.
- **p* < .05, ***p* < .01, ****p* <.001.
- Significance levels are based on bias-corrected confidence intervals generated from bootstrap estimates.

Table 17. Stationary Points and Principal Axes for the Total Effects of Co-adaptation on Individual Innovative Performance

Dependent Variable	**Y = X**		**Y = -X**		**Surface Along First Principal Axis**		**Surface Along Second Principal Axis**	
	a_x	a_{x2}	a_x	a_{x2}	a_x	a_{x2}	a_x	a_{x2}
Individual Innovative Performance	.31	-.09***	-.24	-.28***	.14	-.03*	4.17***	-.10***

Note.
- **p* < .05, ***p* < .01, ****p* <.001.
- Significance levels are based on bias-corrected confidence intervals generated from bootstrap estimates.

Table 18. Slopes and Curvatures Along the Lines of Interest for the Total Effects of Co-adaptation on Individual Innovative Performance

5.7 Summary of Results

The present work provides several important findings. Results of the study show that equal co-adaptation leads to the highest impact on IT identity. Thus, the user's IT identity with the system is maximized when human adaptation and machine adaptation values are equal. The divergence between co-adaptation values leads to lower IT identity values. Additionally, there are no differences between equal co-adaptation at high values and low values. We find that equal co-adaptation impacts on IT identity are similar at low, mid, and high values of co-adaptation. The reasons for is that the slop of the line along the line of equality and the shape of the surface are close to zero (a_1 = .05 , a_2 = .04).

Results of the present study show that anthropomorphism moderates the association between co-adaptation and IT identity. In low anthropomorphism, the first principal axis cross within the range of the component measure (P_{10}= -.78) and the axis is rotated counterclockwise off the Y=X line (P_{11}= 1.88). The intercept of the second principal axis (P_{20}) was -62.32 and negatively sloped. The second principal axis is shifted away from the line of inequality, indicating a lateral shift along the line into the region where Y is less than X. The surface along the second principal axis was concave (a_{x2}= -.60, $p < .05$) and negatively sloped (a_x= -30.64). Taken together, in low anthropomorphism, when machine adaptation is higher than human adaptation, IT identity is maximized.

Results of the study demonstrate that IT identity is positively associated with individual innovative performance (β =.55, $p <.05$).

Results of the present study also demonstrate that IT identity fully mediates that association between co-adaptation and individual innovative performance. The indirect effect of co-adaptation on innovative performance was significant (B = .08, 97% CI 0.01, 0.20). The analyses showed that the first principal axis intercept and slope are not significantly different from 0 and 1 ($a_x = .02,\ a_{x2} = .02$). Furthermore, co-adaptation values are maximized at the center of the line of inequality (0,0) (a_3= -0.24, a_4 = -0.18). This indicates that not only does co-adaptation have a significant effect on individual innovative performance, but also equal co-adaptation (i.e., human adaptation and machine adaptation adapt at an even rate) has the greatest impact. A summary of the results and implications of the hypothesis testing is presented in the following table (Table 19).

Hypotheses	Test Result	Implications
H1. Equal co-adaptation is positively associated with higher values of IT identity. (**Supported**)	The intercept and slope of the first principal axis are not significantly different form 0 and 1 respectively. Furthermore, co-adaptation values are maximized at the center of the line of inequality (0,0). This provides support for the equal co-adaptation impact on IT identity.	The individual's IT identity with a system is maximized when co-adaptation values are similar than when they are different. Divergences between co-adaptation values along the line of equality result in lower IT identity values.

H2a. The impact of co-adaptation on IT identity is moderated through anthropomorphism.	H2a. In low anthropomorphism, high machine adaptation in relation to human adaptation leads to the highest impact on IT identity. (**Supported**)	The first principal axis cross within the range of the component measure (P_{10}= -.78) and the axis is rotated counterclockwise off the Y=X line (P_{11}= 1.88). The intercept of the second principal axis (P_{20}) was -62.32 and negatively sloped. The second principal axis is shifted away from the line of inequality, indicating a lateral shift along the line into the region where Y is less than X. The surface along the second principal axis was concave (a_{x2}= -.60, p < .05) and negatively sloped (a_x= -30.64).	In low anthropomorphism, IT identity is maximized when machine adaptation is higher than human adaptation. In addition, IT identity decreases when human adaptation exceeds machine adaptation, and IT identity drops to zero when human adaptation is maximal.
	H2b. In high anthropomorphism, equal co-adaptation leads to the highest impact on IT identity. (**Not Supported**)	The slope of the first principal axis was positive and greater than 1 (P_{11} = 2.30), indicating a marked counterclockwise rotation along the Y = X line. The	In high anthropomorphism, IT identity is maximized when machine adaptation is higher than human adaptation. This contradicts our hypothesis that in high anthropomorphism equal co-adaptation leads to the highest impact on IT identity.

		surface was convex along the first principal axis (a_{x2}= .29) and positively sloped where it crossed the y-axis (a_x = .98), but neither a_x nor a_{x2} were significant. The second principal axis is shifted away from the line of inequality. The intercept of the second principal axis (P_{20}) was negative. The surface was concave along the second principal axis (a_{x2}= -.79) and negatively sloped. Together, these results showed that, contrary to our proposal, IT identity increased when machine adaptation was greater than human adaptation.	
H3. IT identity is positively associated with individual innovative performance. (**Supported**)		IT identity is positively associated with individual innovative performance (β =.55, p <.05).	The individual's IT identity with a given system is positively related to innovative performance.

H4. The impact of co-adaptation on individual innovative performance is mediated through IT identity. (**Supported**)	The indirect effect of co-adaptation on individual innovative performance was significant (B = .08, 97% CI 0.01, 0.20). The indirect surface analyses show that the first principal axis intercept and slope do not differ significantly from 0 and 1 ($a_x = .02$, $a_{x2} = .02$). Furthermore, co-adaptation values are maximized at the center of the line of inequality (0,0) (a_3= -0.24, a_4 = -0.18). This indicates that not only does co-adaptation have a significant effect on individual innovative performance, but also equal co-adaptation has the greatest impact.	IT identity fully mediates the impact of co-adaptation on individual innovative performance. In addition, equal co-adaptation results in the highest impact on individual innovative performance.

Table 19. Summary of the Hypotheses Testing Results

CHAPTER 6 Discussion and Contributions

6.1 Discussions

The present study introduces co-adaptation as a new theoretical view of adaptation in the AI and cognitive computing systems. Furthermore, it empirically explores the impact of co-adaptation on IT identity and individual innovative performance. By using polynomial regression, moderated polynomial regression, mediated polynomial regression and response surface methods, I find evidence to support equal co-adaptation effects on the outcomes.
The results show that equal co-adaptation is positively associated with higher values of IT identity.

In addition, we find that anthropomorphism moderates the association between co-adaptation and IT identity. In low anthropomorphism high machine adaptation in relation to human adaptation leads to the highest impact on IT identity. Furthermore, the findings reveal that IT identity is a key predictor of individual innovative performance. Lastly, we find that the impact of co-adaptation on individual innovative performance is fully mediated through IT identity. As indicated in Table 12, the bias-corrected confidence intervals demonstrate that there is a significant mediation effect mediated by IT identity (indirect effect .08, CI: .01, .20). The next section discusses the theoretical and design implications of the findings.

6.2 Implications for Theory

The present study provides several theoretical contributions. First**,** this work contributes to adaptation literature by introducing co-adaptation as a new and pivotal theoretical view of adaptation. Prior studies have viewed adaptation from the perspective of humans adapting the technology or adapting to the technology (Barki, Titah, & Boffo, 2007; Boudreau & Robey, 2005; Schmitz, Teng, & Webb, 2016). If we had taken that approach, we would not fully understand CCS use and impact on individual performance. Adaptation in CCS is very complex which had led the IS community to call for new theoretical exploration of CCS adaptivity (Schuetz & Venkatesh, 2020). The findings indicate that machine adaptation is an additional key aspect of adaptation, and co-adaptation is an essential view to understand technology adaptation in the cognitive computing era.

Second, this work offers a strong theoretical argument with supporting evidence that equality between human and machine adaptation plays a critical role in determining the impact of co-adaptation on individuals and their performance. The findings show that equal co-adaptation has the highest impact on IT identity. The IS literature explores adaptivity and mutual interdependency using coevolution and complex adaptive system theories. These theories are employed to theorize coexistence of organization with IT (Benbya et al., 2020; Vessey & Ward, 2013), and alignment of business strategy with competitive environment (Lee et al. 2010). The empirical study of mutual adaptation between individuals and technology is limited due to the difficulty of concretizing abstract ideas of mutual adaptation (Vidgen & Wang, 2009). In spite of the critical role of humans and technology in supporting competitiveness, theorizing and testing human-machine interaction and collaboration present great challenges (Baird & Maruping, 2021). The purpose of this work is to bridge this gap by exploring theoretically and empirically how mutual adaptation between users and technology affects individual performance.

Third, the study contributes to literature by introducing IT identity as a new mediator of co-adaptation. Prior studies have focused on either what leads to technology adaptation or the effect of such behavior on individual outcomes. However, what facilitates technology adaptation is rarely explored. Our findings show that the impact of co-adaptation on individual innovative performance is fully mediated by IT identity. Individuals with IT identity are more likely to explore system features to perform novel tasks. Individuals who have strong IT identity tend to use more features in different work-related tasks because they attribute higher level of emotional attachment and enthusiasm to the technology. (Hassandoust et al., 2021).

Fourth, the present study contributes to technology use literature by introducing anthropomorphism as a new moderator. We posit that anthropomorphism moderates the impact of co-adaptation on IT identity. The results show that in low anthropomorphism, individuals are more likely to have a strong IT identity when machine adaptation is higher than human adaptation. Social equality is fundamental to identifying with CCS; low perceptions of anthropomorphism will cause a social imbalance, and individuals will expect the system to align with their needs rather than the other way around. High machine adaptation helps restore social equality and trigger mutual emotional investment, maximizing human identification with the system.

Lastly, the study builds upon existing literature by identifying IT identity as a key antecedent of individual innovative performance. We find that individuals are more likely to perform tasks innovatively on the CCS when the system becomes a central aspect of their identity. IS studies have mainly focused on the impact of IT identity on technology-related innovation (e.g., Carter et al., 2020, 2015; Chiu et al., 2013). However, this work finds that IT identity stimulates task-related innovation (i.e., individual innovative performance) as well.

6.3 Implications for Design

First, results of this study show that equal co-adaptation has the greatest effect on individual relationship with the system. System designers should develop systems that engage with users and clearly show how and why they do so. For instance, the system could continually indicate their adaptation behavior to the user. Second, emotional attachment and connectedness to technology play a crucial role in enabling individual innovative performance in CCS. System designers should develop systems that evoke positive feelings and happy memories toward the system. By doing this, users will have good experiences with the systems, therefore triggering innovative behavior.

6.4 Strength and Limitations

The study has several strengths worth highlighting, namely the comprehensive nature of our data; we collected data from multiple sources at different points in time, therefore minimizing concerns about common method bias (Podsakoff et al., 2012). This methodological approach is particularly important because many technology use studies have utilized single-source, cross-sectional data. On the other hand, we surveyed Alexa users and their partners, who represent close observers of the main subjects' technology usage behavior.

However, the study is not without its limitations. First, this work assumes that companies do not have an ulterior motive to adapt to their users. Thus, there is no hidden agenda in using user data to manipulate their IT usage behavior. Second, Although polynomial modeling is an excellent way to estimate and predict the impact of equality between two independent variables on a given outcome, it has its own shortcomings (Edwards & Parry 1993). Polynomial modeling relies on numerous tests of significance, which may induce Type I error rates. Polynomial modeling assumes that independent variables are measured without error, so the results should be interpreted with caution because the higher-order coefficients tend to be biased.

6.5 Conclusion

A desire to understand individual use of CCS motivated the introduction of co-adaptation theory. Co-adaptation is defined as the modification of usage behavior simultaneously engaged in by a user and an CCS to make the system fit the user. We used polynomial regression and response surface analysis to gain more insights into the synergistic impact of human and machine adaptation on IT identity and individual innovative performance. Our findings demonstrate that machine adaptation is critical to understand CCS use, and equal co-adaptation is positively associated with IT identity. Furthermore, the mediated polynomial regression results show that IT identity fully mediates the association between co-adaptation and individual innovative performance. We also assess the effect of anthropomorphism on the relationship between co-adaptation and IT identity. Using moderated polynomial regression, we find that individuals expect low-anthropomorphized systems to adapt more. Findings also show that IT identity was higher when human and machine adaptation match at midrange levels than at more extreme levels.

6.6 Appendices

6.6.1 Descriptive Statistics

Variable	Value	Frequency	% Respondents
Gender	Men	117	47
	Women	132	53
Age	21 and under	3	1.2
	22 to 34	110	44.1
	35 to 44	75	30.1
	45 to 54	39	15.6
	55 to 64	17	6.8
	65 and older	5	2
Race	Black	24	9.6
	White	194	77.9
	American Indian or Alaska Native	3	1.2
	Asian	17	6.8
	Native Hawaiian or Pacific Islander	1	0.4
	Other	10	4
Salary	Less than $20,000	17	6.8
	$20,000 to $34,999	35	14.1
	$35,000 to $49,999	59	23.7
	$50,000 to $74,999	63	25.3

	$75,000 to $99,999	45	18.1
	Over $100,000	27	10.8
	I'd rather not to say	3	1.2
Education	Less than a high school diploma	1	0.4
	High school degree or equivalent	19	7.6
	Some college, no degree	48	19.3
	Associate degree	22	8.8
	Bachelor's degree	110	44.2
	Master's degree	36	14.5
	Professional degree	4	1.6
	Doctorate	9	3.6

Table 20. Sample Characteristics

6.6.2 Co-adaptation Conceptualization and Instrument Development

Co-Adaptation Conceptualization.

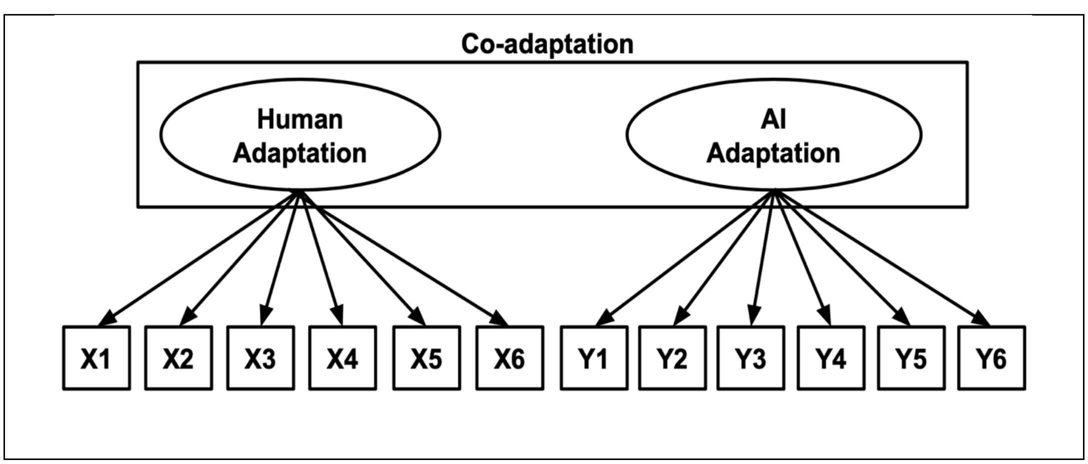

Figure 9. Co-adaptation as a Grouping of Two Factors

We propose co-adaptation as a logical grouping of two factors (i.e., human adaptation and machine adaptation), each with an independent and distinct impact on IT identity (Figure 9). Considering co-adaptation as a first-order model (Figure 10) allows us to capture the variance that is specific to human adaptation and machine adaptation. Prior studies have only considered human adaptation, in which individuals adapt the technology or adapt to the technology (e.g., Barki, Titah, & Boffo, 2007; Boudreau & Robey, 2005; Schmitz, Teng, & Webb, 2016). However, this study goes a step further by considering machine adaptation, an additive adaptation perspective that helps us understand human-machine interaction in the CCS. This model assumes that co-adaptation is a theoretical view allowing us to draw conclusions about individual interactions with cognitive computing. This type of operationalization has been used extensively in IS and management literature; for instance, Mayer, Davis, and Schoorman (1995) conceptualized trustworthiness as a logical grouping of three constructs: ability, benevolence, and integrity. They found the intercorrelations between those constructs were high (.65 - .80) (Mayer & Gavin, 2005). Other studies, such as Stewart and Segars (2002), reported a moderate correlation among constructs.

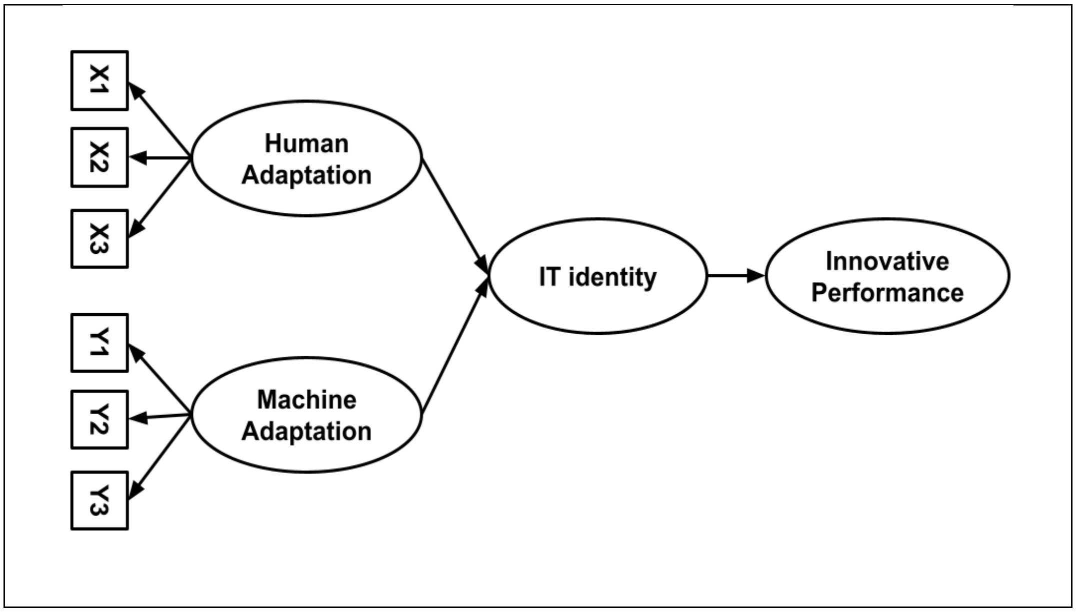

Figure 10. Co-Adaptation First-order Factor Model

6.6.3 Pilot Studies

Before administering the final co-adaptation instrument, we ran several pilot studies to check the discriminant and convergent validity. The co-adaptation survey items were adapted from Schmitz et al. 2016. Thus, our conceptualization of co-adaptation was inclusive, involving technology, task, and individual aspects (Table 21). In addition, the co-adaptation instrument accounted for two modes of adaptation: exploitative, which refers to standard co-adaptation, and exploratory, which refers to the new, unexpected co-adaptation behavior.

The study was administered in a pilot study (N= 46), and the findings showed that the task co-adaptation items were strongly correlated. Thus, human task adaptation items and machine task adaptation items were loaded into one factor. We also found that the non-standard co-adaptation items were strongly correlated, meaning the differences between non-standard human adaptation and non-standard machine adaptation were not evident. We thought this might be due to the sample size, but a second pilot study (N= 300) yielded similar results. After consultation with two senior IS scholars, we dropped task co-adaptation items and focused only on technology co-adaptation aspects. We also reworded the items of non-standard co-adaptation to make the differences between human adaptation and machine adaptation more noticeable. We ran another pilot study (N= 100) to test the new co-adaptation scale involving 10 items for human adaptation and 10 items for machine adaptation. The data showed that non-standard co-adaptation items were strongly correlated, therefore the final co-adaptation instrument consisted of six items of standard adaptation.

6.6.4 Survey Items

Technology Adaptation	
Human Adaptation	Machine Adaptation
Individuals moderately (Standard) or substantially (Non-Standard) change technology.	Technology moderately (Standard) or substantially (Non-Standard) change itself to fit individuals
Standard 1. I have experimented with new features on my Alexa. 2. I have changed the settings on my Alexa to alter the way I interact with it.	*Standard* 1. Alexa has experimented with me by presenting me with new features. 2. Alexa has changed its settings to alter the way it interacts with me.

3. I have adapted to Alexa in a way that is consistent with how I am supposed to be interacting with it. 4. I have found new ways of using Alexa. 5. I have experimented with new ways of my Alexa. 6. I have adapted to the Alexa way of use.	**3.** Alexa has taken advantage of its ability to adapt to me in a way that is consistent with how it was supposed to be used. 4. Alexa has suggested new ways I could use it. 5. Alexa has experimented with me by suggesting new uses. 6. Alexa has adapted to my usage patterns.
$Non - Standard$ 1. I have developed a way of interacting with Alexa which deviates from normal usage. 2. I have employed at least one of my Alexa features in an unusual manner. 3. I have altered Alexa in a way that is nonstandard. 4. I have altered my interaction with Alexa to use it in an unconventional way.	$Non - Standard$ 1. Alexa has developed a way of interacting with me that deviates from normal usage. 2. Alexa has employed at least one of its features in an unusual manner. 3. Alexa has altered itself in a way that is nonstandard. 4. Alexa has altered its way of interaction to interact with me in an unconventional way.
Task Adaptation	
Individuals moderately (Standard) or substantially (Non-Standard) change routines and work activities	Technology moderately (Standard) or substantially (Non-Standard) change routines and work activities
$Standard$ 1. I have tried hard to figure out how to perform tasks that were not possible without my Alexa. 2. I strive to find ways to take on new responsibilities by using my Alexa. 3. I frequently attempt to do new tasks that I could not do in the past without Alexa.	$Standard$ 1. Alexa has tried hard to figure out how to help me perform tasks that were not possible without it. 2. Alexa strives to help me to find ways to take on new responsibilities. 3. Alexa frequently attempts to help me do new tasks that I could not do in the past without it.

4. Overall, my use of Alexa has enabled me to try new and different tasks.	4. Overall, Alexa has enabled me to try new and different tasks.
$Non - Standard$ 1. I try hard to figure out ways to do my existing tasks better with my Alexa. 2. I frequently attempt to do existing tasks differently because of my use of Alexa. 3. I strive to find ways to do my existing tasks faster with Alexa. 4. Overall, I am doing my best in taking advantage of various features of Alexa to perform my existing tasks better.	$Non - Standard$ 1. Alexa tries hard to figure out ways to help me do my existing tasks better. 2. Alexa frequently attempts to help me do existing tasks differently based on my use of it. 3. Alexa strives to find ways to help me do my existing tasks faster. 4. Overall, Alexa is doing its best to help me take advantage of its various features to perform my existing tasks better.

Table 21. Co-Adaptation Survey Scale

IT identity Items

1. Thinking about myself in relation to Alexa, I am dependent on Alexa.
2. Thinking about myself in relation to Alexa, I am enthusiastic.
3. Thinking about myself in relation to Alexa, I am linked with Alexa.
4. Thinking about myself in relation to Alexa, I am connected with Alexa.

Anthropomorphism Items

1. Alexa is able to speak like a human.
2. Alexa can be friendly.
3. Alexa can be funny.

Innovative performance Items

1. Using Alexa helps me create new ideas for task improvements more often.
2. Using Alexa improves my ability to generate innovative solutions to problems.
3. Using Alexa makes me more often produce innovative ideas for task improvement.

6.6.5 Adaptation in IS Literature

We performed a rigorous and structured literature review of prior works to identify relevant studies pertaining to the adaptation behavior. I mainly searched the IS top journals: MIS Quarterly, Information Systems Research, Journal of MIS, Journal of AIS, European Journal of Information Systems, Information Systems Journal, Journal of Information Technology, Journal of Strategic Information Systems. To ensure relevant new studies are included, we read every publication on the IS basket of journals published between 2014 and 2018.

Exploitive Adaptation (E): Standard adaptation

Exploratory Adaptation (R): Non-standard adaptation

Sources	Concepts	Task Adaptation		Technology Adaptation		Individual Adaptation
		R	E	R	E	
Romanow, Rai, and Keil, 2018	Deep structure use: patient care teams' use of features of the CPOE system that support the underlying structure of the task. These features include standardized order sets, decisions support and alerts, clinical			✓		

	results integration, and progress notes.					
Maruping and Magni, 2015	Intention to continue exploring: a user’s motivation to engage in sustained exploration of system to find potential work uses over time. Expectation to continue exploring: a user’s subjective probability of sustaining the exploration of the system and finding potential use based on his or her appraisal of the volitional and non-volitional behavioral determinants. Technology exploration: in which users expand the scope of system features that they use in their work and attempt to find new ways to incorporate the technology in their tasks.	✓				
Venkatesh, Bala, and Sambamurthy, 2016	Technology adaptation: employees’ resistance, avoidance, and workaround behaviors. [resistance: training not attended; speaking negatively about ICT; lack of interest in ICT. avoidance: not using the ICT even when there is no power outage; manual transaction processing. workaround: using ICT in an unintended way; perform			✓		

	transactions manually and then update the ICT when the bank is closed for business].					
Bala and Venkatesh, 2016	Exploration-to-innovate: the degree to which an employee tries to find, extend, and/or change features of an IT to accomplish his or her tasks in novel ways. Exploration-to-revert: occurs when an employee tries to find, extend, and/or change features of an IT to fit with his or her reimplementation work processes and/or habits. Exploitation: the degree to which an employee uses a recommended set of features of an IT to perform his or her portfolio of tasks.			✓		
Robert and Sykes, 2017	Deep structure use: is a post-acceptance behavior that involves the integration of the system with the user's tasks.			✓		
Tong, Tan, and Teo, 2015	Task-technology adaptation behavior: all behavior directed at changing or modifying an IT and how it will be deployed and used in an organization.	✓			✓	

	Exploitation: utilizing past experience/knowledge to refine and extend existing technologies.				✓	
	Exploration: experimenting on innovation				✓	
	Individual adaptation: modifications that individuals make to themselves in order to adapt to IT.					✓
	Standardized system use: refers to the IS utilization of users for accomplishing tasks with limited variations in the set of steps that they need to follow.			✓		
	Non-standardized system use: refers to the IS utilization of users for accomplishing tasks with great variations in the set of steps that they need to follow.				✓	
Gardner, Boyer, and Ward, 2017	Mindful use of technology: the timely utilization of technologies to facilitate ongoing collective alertness and response to customer and operational needs within the specific context and organizational systems.	✓				

	Low/high IT adoption: Providers in low adoption hospitals must necessarily rely less on IT than higher adoption counterparts for processing patient information and delivering quality care			✓		
Hsieh, Rai, and Xu, 2018	Extended use: users extend the scope of the functions that they use through post-adoptive learning.	✓				
Dong, Fang, and Straub, 2017	IOS adaptability: the capacity of IOS [Interorganizational systems] to be readily adjusted and reconfigured to respond to the need for change.	✓				
Barki, Titah, and Boffo, 2007	Technology interaction behavior: all IT interactions undertaken with the purpose of accomplishing an individual or organizational task.	✓				
	Task-technology adaptation behavior: all behaviors directed at changing or modifying an IT and how it will be deployed and used in an organization.	✓		✓		
	Individual adaptation behaviors (i.e., learning): reflects modifications that individuals make to themselves in					✓

	order to adapt to the IT. [it is about individuals]					
Thatcher, Wright, Sun, Zagenczyk, and Klein, 2018	IT mindfulness: a dynamic IT-specific trait, evident when working with IT, whereby the user focuses on the present, pays attention to detail, exhibits a willingness to consider other uses, and expresses genuine interest in investigating IT features and failures. Mindfulness: refers to an individual's continuous scrutiny and refinement of expectations based on new experiences, appreciation of subtleties, and identification of novel aspects of context that can improve foresight and functioning. [it is about individuals]					✓
Sykes and Venkatesh, 2017	Deep structure use: is a post-acceptance behavior that involves the integration of the system with the user's tasks… the extent to which users employ the features of the target system to support their tasks.			✓		

Sun,Fang, and Zou, 2016	Mindfulness of technology adoption: is a psychological state of consciousness in which a person focuses on and is aware of the issues surrounding a technology adoption decision. MTA means that a person investigates technology in detail and in relation to local contexts and alternative technologies.			✓		
Wu, Choi, Guo, and Chang, 2017	Behavioral adaptation: the degree to which users change the functions of an IT system and task procedures to fit personal preferences.	✓				
	Cognitive adaptation: refers to the degree to which users focus on the positive outcome of IT system use, to reflect the importance of cognitive coping. Affective adaptation: the degree to which users direct attention away and detach themselves from an IT system.	✓				
Baird, Davidson, and Mathiassen, 2017	Technology assimilation relates to the process in which organizations become aware of, adopt, deploy, and incorporate organizational technologies into their practices.	✓				
Peng, Dey, & Lahiri, 2014	Absorptive capacity: Actor's receptivity to technological changes, the ability to use external	✓				

	knowledge, and the capacity to learn and solve problems.					
Pan, Lu, Wang, and Chau, 2017	Reinforced use: the use of specific features of a social media site in a repetitive and reinforced way. Inertia: a strong attachment to, and persistence of existing behavioral patterns to use a social media site (i.e., the status quo) [it is about individuals]. It moderates the relationship between identity and IS use…"it is one of the most relevant individual factors for understanding IS use it focuses on users' tendency, orientation, and bias to maintain the status quo and their resistance to change to conserve mental resources and mental energy."	✓				
	Varied use: the use of social media site with diverse features or in a novel way.		✓			
Ma, Kim, and Kim, 2014	Regular use: how consistently a specific IT application is employed over time. Extended use: is a more advanced stage of postadoption than routinization. In this stage, the IT tool is employed in a more	✓				

	comprehensive manner to fulfil a person’s higher-level goals.					
Yen, Hu, Hsu, and Li, 2015	Loyal use: proactive, extended use and willingness to recommend such uses to others. [it is about individuals].					
Roberts, Campbell, and Vijayasarathy, 2016	Routine IS use: is defined as managers’ using IS in a routine and standardized way to support their work	✓				
	Innovative IS use: is defined as managers’ using IS in novel ways to support their work.		✓			
Liang, Peng, Xue, Guo, and Wang, 2015	Extended system usage: using the system to directly compete job tasks.	✓				
	System exploration: the extent to which a user seeks and experiments with new features and explores creative ways of using an information system.				✓	
Bala and Bhagwatwar, 2018	Cognitive absorption use: the extent to which an individual is absorbed and involved in task execution using system.	✓				

	Deep structure use: the extent to which an individual uses the features of a system that relate to his/her tasks.			✓		

Table 22. Adaptation in IS Literature

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