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FACTORS INFLUENCING ROBOTIC PROCESS AUTOMATION (RPA) EFFECTIVE USE AMONG EMPLOYEES OF LARGE ORGANIZATIONS

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To: Dean William G. Hardin
College of Business

This dissertation, written by Mauricio Klecky Seselovsky, and entitled Factors Influencing Robotic Process Automation (RPA) Effective Use Among Employees of Large Organizations, having been approved in respect to style and intellectual content, is referred to you for judgment.

We have read this dissertation and recommend that it be approved.

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The dissertation of Mauricio Klecky Seselovsky is approved.

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Florida International University, 2025

DEDICATION

I dedicate this dissertation to my wife, Dafna, and my children, Dalia and Simon. Dafna, your steadfast love and unwavering support have been my anchor throughout this challenging journey. Your encouragement and belief in me, even during the countless late nights of research and writing, have given me the strength to persevere. Dalia and Simon, your joy, curiosity, and boundless energy have been a constant reminder of why I strive to grow and achieve. Amid life's uncertainties, our family has been my safe haven—a source of love, understanding, and constant encouragement. This dissertation represents more than my efforts; it stands as a tribute to our shared journey and the achievements we have built together.

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ABSTRACT OF THE DISSERTATION

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by

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Robotic Process Automation (RPA) is a technology that automates rule-based process tasks by mimicking human behavior. Its purpose is to increase process efficiency, reliability and to reduce costs. RPA implementation constitutes a transformational change within organizations and can be considered as a new enabler of process innovation and e-transformation, noting a shift where tasks are assigned to both human and digital workers (or bots), increasing the allocation of time for high value-added work to human workers.

Despite its promise, the expected impact of RPA implementations has not been as estimated, with 30%-50% of initial RPA projects failing and only about 20% of organizations that implemented RPA in 2019 achieved a business value that exceeded what they had expected. This discrepancy highlights a critical dependency on human factors, as the introduction of this technology causes different reactions among impacted employees, which in turn might impact the outcome of the planned automation. Thus, the objective of this dissertation is to identify the factors that increase employee Effective

Use of RPA to help managers and project leaders to increase the success of RPA projects within large organizations.

Three elements indicate that successful RPA implementations face challenges related to employee attitudes toward the process. First, several elements show that successful RPA implementations need to overcome a barrier represented by the attitudes of employees involved in the process. Secondly, this is a technology whose very objective is to automate manual labor, directly impacting employees and potentially creating strong feelings among impacted workers. RPA is not merely an enhancement of a previously automated process; it is an automation that replaces human workers. It is only logical that it might generate strong feelings among affected employees. Furthermore, it is well documented that a major human concern about technology is its impact on employment. Even when training is made available, employees may still feel replaceable (Armentrout, 1996). Finally, how users accept or use a technology has been proven to be critical in technology implementation.

This study investigates the factors influencing RPA Effective Use employees, integrating the Technology Acceptance Model (TAM), the Unified Theory of Acceptance and Use of Technology (UTAUT), and the Effective Use construct by Burton-Jones and Grange (2013). The study integrates established and emerging theoretical frameworks to offer both academic and practical insights.

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I. INTRODUCTION

Problem Statement

Robotic process automation (RPA) is a technology that automates rule-based process tasks by mimicking human behavior. Its purpose is to increase process efficiency and reliability and to reduce costs. However, the introduction of this technology elicits different reactions among impacted employees, which, in turn, might affect the outcome of the planned automation. The objective of this dissertation is to identify the factors that increase employee effective use of RPA to help managers and project leaders enhance the success of RPA projects within large organizations.

Significance of the Problem

Several elements indicate that successful RPA implementations face challenges related to employee attitudes toward the process. First, the expected impact of RPA implementations has not met initial estimates. A report shows that 30%–50% of initial RPA projects fail (Lamberton et al., 2016), and only about 20% of organizations that implemented RPA in 2019 achieved a business value that exceeded their expectations (Willcocks et al., 2019).

Second, another critical factor in RPA adoption is its primary objective—to automate manual labor. Consequently, it has a direct and significant impact on employees who previously performed those tasks. In other words, RPA is not merely an enhancement of a previously automated process; it is an automation that replaces human workers. It is only logical that it might generate strong feelings among affected employees. This has been a reality for ordinary American workers who have seen their jobs replaced by automation in recent years (Honnen-Weisdorn et al., 2019). Furthermore, it is well documented that a major human concern about technology is its impact on employment. Since the 19th century, an ongoing debate has revolved around the effects of technology on human labor. Marx pointed out the degradation of work and workers caused by technology (Marx, 2018). Conversely, Keynes saw a positive long-term effect for workers, envisioning fewer work hours and longer periods of leisure (Keynes, 1930). More recently, research has shown that when change involves technological advancement, employees fear that their skills may become obsolete. Even when training is made available, employees may still feel replaceable (Armentrout, 1996). For example, a study provided evidence that RPA implementation created fear among employees in the finance and accounting departments of a large oil company (Fernandez & Aman, 2021). In that sense, employees may perceive RPA as a direct competitor, particularly when a significant portion of their work becomes automated.

A third element to consider is that, given the potential for employees to perceive RPA as a threat, user acceptance has been shown to be critical in technology implementation within organizational contexts. In general, user acceptance and confidence are crucial for the continued development of any new technology (Taherdoost, 2014). Effective use is also a variable that reflects how well a technology is implemented. A review of the literature on information technology (IT) implementation demonstrates that employee participation is critical to system design and success (Karsh, 2004; Schraeder et al., 2006; Lai et al., 2013). Conversely, employee resistance can significantly hinder effective organizational change (Cummings & Worley, 1997). Organizational change can generate skepticism and resistance among employees, making implementation difficult or even impossible. This phenomenon is not limited to blue-collar workers. LaNuez and Jermier (1994) argued that managerial sabotage is on the rise and that future saboteurs "may be able to do more damage with a keyboard than with a bomb" (p. 233). In fact, such resistance may result in negative consequences, including reduced job satisfaction, increased stress, and decreased commitment. Additionally, employees may engage in counterproductive behaviors such as sabotaging computer equipment, arriving late or being absent from work, speaking negatively about the system, avoiding the new system in favor of the old one, and tampering with data (Adams et al., 2004; Rivard & Lapointe, 2012). As companies increasingly seek to reduce costs, standardize processes, decrease response times, and ensure error-free execution, successful RPA implementation becomes a relevant challenge. Therefore, increasing employee effective use is crucial.

Research Gap

Despite the growing number of RPA vendors and products on the market, no clear understanding exists regarding how organizations can successfully implement and utilize this technology (Plattfaut et al., 2022). However, there is increasing demand for more specific research and methodologies to ensure its success.

Several researchers have attempted to develop a better framework for improving RPA understanding and implementation. In a study published in 2022, Costa et al. conducted a systematic literature review of RPA adoption, concluding that organizations continue to face challenges due to a lack of frameworks and knowledge. They analyzed 47 papers and found persistent difficulties in RPA implementation. Additionally, Wewerka and Reichert (2022) analyzed 63 publications and found that scientific research on this topic remains limited and primarily qualitative. They highlighted the lack of quantitative research in this area.

Effective use as a construct was proposed by Burton-Jones and Granger (2013) to describe the use of a system in a way that helps achieve a relevant goal. Although this concept has been applied to various contexts, mainly in healthcare systems, it has not yet been tested in RPA implementations to the knowledge of this researcher. Furthermore, effective use has not been integrated with more traditional models such as the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT; Davis et al., 1989; Venkatesh et al., 2000, 2003). In business environments where technology use may be either volitional or mandatory, the concept of effective use becomes highly relevant. The present study seeks to connect effective use to the conceptual framework provided by Venkatesh, Davis, and others.

Finally, as noted, very few quantitative studies analyze RPA implementations. Most existing literature consists of exploratory qualitative research. Among the few exceptions, Wewerka et al. (2020) and Hsiung and Wang (2022) conducted quantitative RPA research studies in highly specific contexts. Wewerka focused on a German automobile company, while Hsiung and Wang examined small accounting firms in Taiwan. Interestingly, both studies utilized UTAUT as their main theoretical framework. The present study aims to conduct more general research that is not limited to a specific company or industry.

Research Question

To address the research gap and contribute to the overall purpose of this study, the following research question is proposed:

What factors impact RPA effective use among back-office employees at large organizations?

This study aims to investigate this question within the context of large companies that have experienced different types of RPA implementations.

Research Contributions

The proposed research will help identify and assess factors influencing RPA effective use among its primary users and stakeholders, thereby improving its success rate. It will provide managers with tools and valuable information to implement more efficient and reliable RPA projects, benefiting employees, supervisors, and institutions in general.

Developing an RPA effective use model facilitates an understanding of the variables influencing RPA utilization and its associated challenges. Consequently, this research will help prevent the underutilization of future RPA bots and increase the adoption of existing ones. In the long term, it also supports further research on this rapidly evolving subject.

Additionally, this study contributes to broader topics such as IT implementation critical success factors, the relationship between technology and the workplace, and the intersection of psychology and technology.

From an academic perspective, this dissertation develops a theoretical model to explain how RPA effective use can be conceptualized and enhanced within large organizations. This research contributes to the limited body of literature on quantitative RPA implementations, which holds significant interest and potential (Costa, 2022). Furthermore, it seeks to identify relevant factors regardless of industry or company.

In addition, this study aims to apply the UTAUT model to RPA implementations, enriching the body of literature on the subject. It also attempts to link UTAUT to the effective use construct proposed by Burton-Jones and Granger.

Given the numerous potential benefits of RPA described in the literature, understanding the factors that improve employee acceptance remains a critical area of investigation.

II. BACKGROUND LITERATURE REVIEW AND THEORY

Context

The impact of disruptive technologies on workers and how they should cope with it is a long-standing and ongoing debate. For instance, Marx highlighted the degradation of work and workers caused by technology. In his view, workers were not liberated by technology; rather, they were enslaved by it (Spencer, 2018). The idea of workers being reduced to mere "appendages" of machines (Marx, 2018), losing their autonomy and cognitive powers, was part of a broader critique of technological advancements.

From a different perspective, Keynes, in his famous 1930 essay *Economic Possibilities for Our Grandchildren*, portrayed a world with fewer work hours and increased leisure time. Although workers might face technological unemployment in the short run, Keynes believed this issue would be resolved in the long run (Spencer, 2018). The replacement of human labor with technology signaled the potential for a better future with a diminished burden of work, and technological progress was to be encouraged as a pathway to a leisure society (Skidelsky & Skidelsky, 2012). These two contrasting perspectives exemplify the conflicting views that have persisted for over a century. Interestingly, both perspectives acknowledge a friction point brought about by the Industrial Revolution: a perceived opposition between disrupting technology and workers. For Keynes, this is merely circumstantial damage that will bring prosperity in the long run. For Marx, technology serves as a tool of oppression wielded by the system. In both cases, workers experience negative outcomes, at least temporarily. This ongoing debate about technological disruption at the organizational level—particularly in the context of RPA—remains highly relevant.

In more recent times, concerns about technology replacing workers and its implications continue to persist. In *The Rise of the Robots* (2015), Ford predicted that automation would affect all modern workers. According to Ford, information technology is a game changer—a uniquely disruptive force with no historical precedent. Unlike previous technological advancements that primarily affected low-skilled labor, Ford argued that highly skilled professionals are also at risk of being displaced by machines (Wajcman, 2017).

Similarly, Susskind and Susskind (2015), in *The Future of the Professions*, asserted that until now, only human professionals possessed the combination of formal knowledge, expertise, experience, and skills they refer to as "practical expertise."

However, they argued that technology will replace doctors, lawyers, accountants, and nearly every other profession as society experienced them in the 20th century. These changes will particularly affect white-collar and back-office employees who, unlike production workers, have not previously faced direct competition from technology. In fact, some authors believe that American workers have seen their jobs replaced by automation and while their wages have stagnated (Honnen-Weisdorn et al., 2019).

Within organizational environments, Markus (1983) noted that numerous explanations have been proposed to account for employees' resistance to change, particularly in the context of IT implementation. Highlighting the importance of understanding resistance, Markus argued that developing stronger theories on resistance to change could pave the way for more effective IT implementation strategies. In some cases, worker retaliation has been significant, and, in their role as voters, some organizations have advocated for a tax on robots. This idea has gained traction among legislators, academia, and policymakers (Oberson & Anton, 2018).

RPA Research

In research on RPA, there is evidence that its implementation has created fear among employees in finance and accounting departments of large oil companies due to concerns that their jobs would be taken over by robots, leading to potential job loss. Employees reported feeling no longer needed by the organization, believing their services had become redundant (Fernandez & Aman, 2021). These fears may be well justified: The same researchers conducted a case study in 2018 at one of the largest global accounting services firms. Their findings indicated that RPA had significant impacts on both individuals and the organization, leading to changes in work processes and a reduction in the number of employees.

Jędrzejka (2019) examined the impact of RPA on the accounting profession. Through a comprehensive literature review, the study concluded that the potential for automating accounting processes with RPA is high, and bots are expected to replace accountants for a considerable portion of their tasks. This is particularly relevant as accounting is a core back-office function in most organizations. However, Jędrzejka also argued that while automation might lead to the disappearance of entry-level accounting positions, it could simultaneously create new accountant roles. The accountants of the future will move beyond bookkeeping and financial reporting toward business advisory and leading RPA transformations. These predictions underscore the importance of understanding how to successfully implement RPA within corporations.

Along the same lines, auditing—another back-office function within organizations—has also been identified as significantly impacted by RPA (Eulerich et al., 2022). The authors provided a conceptual framework for RPA implementation in auditing, which helps explain the mixed findings in prior research regarding the effectiveness and adoption of emerging technologies in audit. They also advocated further research on RPA and emerging technologies in audit (Eulerich et al., 2022).

Given this context, it is reasonable to assume that the automation of back-office tasks would be a source of concern for back-office employees. However, when employee reactions to RPA implementation have been studied, research suggests that employees are not always opposed to it. For instance, employees at the Big Four accounting firms in the United States have reported that RPA has a positive influence on their profession. They perceive that RPA is positively transforming their work and improving their career prospects (Cooper et al., 2022). Similarly, in 2020, Wewerka, Dax, and Reichert studied the acceptance of RPA among employees in the automotive industry. The authors found that RPA can relieve employees from tedious work and enhance their sense of productivity.

At the same time, recent research indicates a lack of widely accepted theoretical frameworks specific to RPA. In 2021, Wewerka and Reichert analyzed 63 publications and concluded that insufficient research has been conducted in this area. They predicted that RPA would remain a major area of focus in the coming years. Similarly, Costa (2022) conducted an analysis of 47 papers and found that organizations continue to face various challenges due to a lack of frameworks and knowledge. Costa stated that “the lack of a framework for companies to successfully employ RPA is a common denominator across the literature reviews for future research.” Nevertheless, a few studies will be considered when conceptualizing this research.

A noteworthy research paper that examined the bond between employees and RPA was Katriina Juntunen's thesis on the adoption and acceptance processes of RPA in the finance department of Stora Enso, a Finnish paper manufacturer (Juntunen, 2018). Her work described how the company made the decision to incorporate RPA into its finance operations. This was initially done through a proof of concept and later scaled up to include additional processes. She describes how Stora Enso concluded that, to succeed in future implementations, strong commitment from organizational members is required, as RPA implementations are driven by the business units themselves (Juntunen, 2018). It is worth noting that by delegating the decision of implementation to different business units, the decision-making process begins to incorporate those impacted by the process change.

Another study is *Research on the Introduction of a Robotic Process Automation (RPA) System in Small Accounting Firms in Taiwan* by Hsiung and Wang (2022). This study explores the characteristics that influence the success factors of accounting firms in the introduction of an RPA system based on the measurements of the Technology Acceptance Model (TAM) and the Information System Success Model (DeLone & McLean, 1992, 2003). The conclusion is that independent variables such as gender, daily usage time of the system, and CEO support play a significant role. It is believed that this methodological approach—applying a robust and proven framework combined with more refined success factors related to specific characteristics of RPA implementation—adds more value to the proposed research. Finally, it is worth noting that the study on RPA in small accounting firms in Taiwan analyzes a white-collar population that is not actually back office; accounting is not a support function in accounting firms. Therefore, its conclusions cannot be easily generalized to back-office populations.

Along the same lines, Cooper et al. (2022) also showed that employees have an overall favorable impression of RPA. In a post-implementation study at a large electric utility company in Brazil, Filgueiras et al. (2022) found that although workers expect RPA to lead to job losses, they also believe it will allow them to become more creative and active.

From a different angle, Waizenegger and Techatassanasoontorn, in their 2020 study *"You Have No Idea How Much We Love Casper – Developing Configurations of Employees' RPA Implementation Experiences,"* propose four distinct configurations of employees' RPA implementation experiences. One group of employees sees bots as teammates, describing how these workers anthropomorphize the technology and accept bots as true members of their team. Anthropomorphism is described as the tendency of humans to associate human-like characteristics, properties, or mental states with nonhuman artifacts such as IT systems (Epley et al., 2007). Prior research has also found that technologies with anthropomorphic cues foster trust in the technology and increase the likelihood of adoption (Qiu & Benbasat, 2005). The authors assert that employees who perceive bots as their teammates expect them to reduce their workload and are likely to collaborate closely with the automation team. When discussing interactions with bots or their performance, these employees use terminology commonly ascribed to human colleagues, such as referring to bots as "being sick" when malfunctioning. They anticipate that bots will help them save time, which they can use for other tasks. All the above is meaningful in showing that to some employees, RPA is perceived as a positive element and not a threat. Therefore, it becomes relevant to understand how employees perceive RPA implementations in terms of the impact on their jobs and, consequently, how to leverage that to increase the chances of success.

In sum, there is contradictory evidence regarding employee reactions to RPA. In the present research, a review of theoretical frameworks is presented to better understand employee perceptions and reactions toward RPA.

RPA as a Change

Bu et al. (2022) conceptualize RPA as a new enabler of process innovation and e-transformation. They further describe the transformation as beginning with an old environment in which tasks are assigned to human workers. In this situation, workers have a high manual workload, engaging in what they call simple work (or low-value-added work). In the new RPA-enabled environment, tasks are assigned to both human and digital workers (or bots), increasing the allocation of time for high-value-added work to human workers while leaving simpler tasks to bots. This transformation does not affect only the impacted workers who experience a radical change in their daily tasks; it also alters the entire work environment, requiring managers to adopt a different approach to task assignment, adjust production timelines, and implement new accountability mechanisms.

Similarly, Sideska, in her 2021 study *Robotic Process Automation—A Driver of Digital Transformation?*, asserts that, until now, the concept of digital transformation was primarily associated with production processes, where physical robots supported humans in manufacturing tasks. However, she argues that digital robots represent the most disruptive and novel chapter of robotization. She also emphasizes that the large-scale robotization of business processes must be treated as both an organizational and technological change, leading to the emergence of hybrid work environments.

Along the same lines, Kirchmer and Franz (2019) analyzed how digitalization has transformed organizational operations. They noted that many new digital tools, particularly RPA, enable business process transformations that improve efficiency, agility, compliance, customer experience, and the overall quality of deliverables. These technologies may facilitate a level of process performance not previously envisioned.

The above studies provide a solid framework supporting the view that RPA implementation constitutes a transformational change within organizations. This point becomes relevant when applying other theoretical frameworks and establishing a research focus.

Theoretical Framework: TAM and UTAUT

User acceptance of new technology is described as one of the most mature research areas in contemporary information systems (IS) literature (e.g., Hu et al., 1999). Research in this area has resulted in several theoretical models, rooted in information systems, psychology, and sociology, that routinely explain over 40% of the variance in an individual's intention to use technology (e.g., Davis et al., 1989; Taylor & Todd, 1995; Venkatesh & Davis, 2000).

The Technology Acceptance Model (TAM) is one of the most fundamental models for understanding user acceptance, or, in this case, employee acceptance, of new technology. TAM was developed by Davis et al. (1989) and is based on the prior and more general Theory of Reasoned Action (TRA). It introduces two primary factors influencing an individual’s intention to use new technology: perceived ease of use and perceived usefulness. TAM has been applied to explain and predict user behaviors in adopting technological products. At the same time, it is recognized that external variables can affect perceived usefulness, perceived ease of use, and intention to adopt an information system.

TAM has been fully validated across various domains, including information systems, technical products, internet activities, e-commerce, and e-learning. Several variations of the model, such as TAM2 and TAM3, have since been developed.

In particular, the original TAM (see Figure 1) defines attitude as a mediating variable between perceived usefulness, perceived ease of use, and behavioral intention. However, studies have demonstrated that after removing attitude, the explanatory power of the model remains intact, while the model itself becomes more parsimonious (Davis et al., 1989).

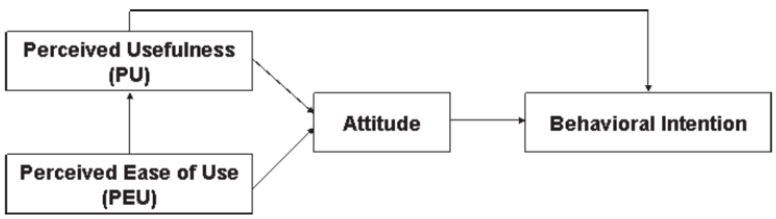


Figure 1: Original Formulation of TAM

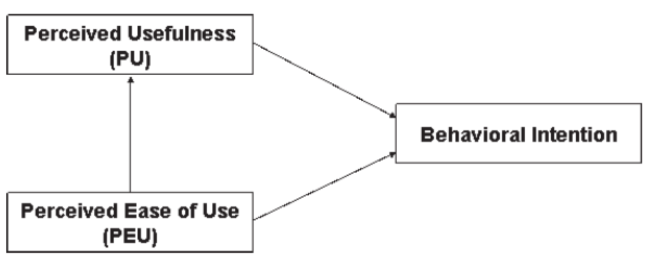


Figure 2: Parsimonious Formulation of TAM

The Unified Theory of Acceptance and Use of Technology (UTAUT) is a model for technology acceptance proposed by Venkatesh and colleagues in their work *"User*

Acceptance of Information Technology: Toward a Unified View." UTAUT aims to elucidate user intentions and subsequent behaviors regarding the use of an information system. The theory posits four key constructs: (1) performance expectancy, (2) effort expectancy, (3) social influence, and (4) facilitating conditions. The first three directly influence usage intention and behavior, while the fourth directly impacts user behavior. Factors such as gender, age, experience, and voluntariness of use are believed to moderate the effects of these constructs on usage intention and behavior. UTAUT was developed by consolidating constructs from earlier models used to explain information system usage behavior. Validation studies, including one conducted by Venkatesh et al. in 2003, found that UTAUT accounted for 70% of the variance in behavioral intention to use (BI) and approximately 50% in actual use. The UTAUT model provides a comprehensive framework for understanding the factors influencing technology adoption and usage. For leaders as enablers of change, the UTAUT model offers valuable insights into enhancing effectiveness and efficiency in the workplace.

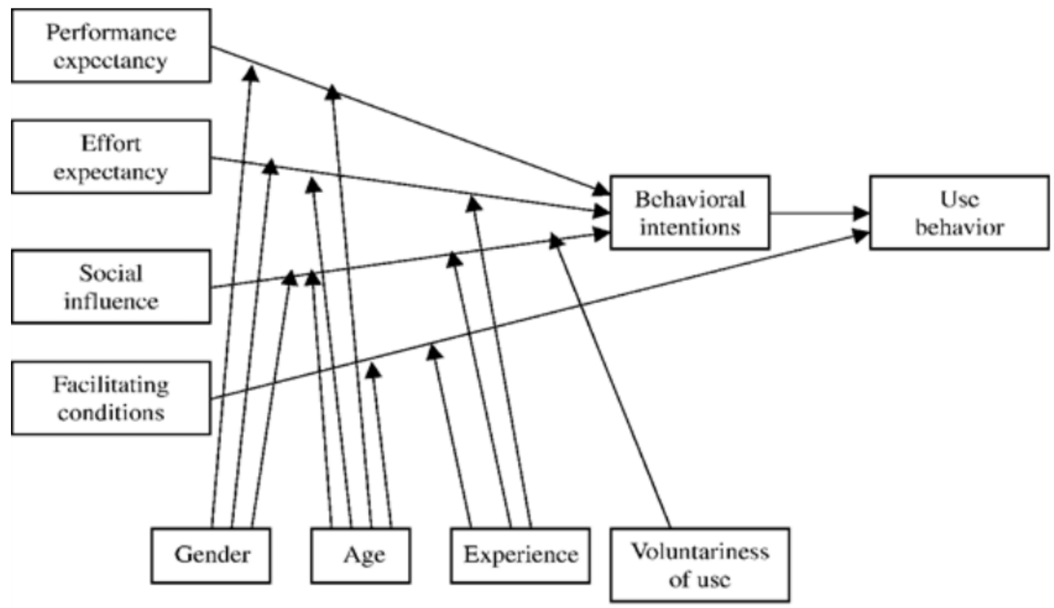


Figure 3: UTAUT Model

Mandatory vs. Volitional Environments and RPA

Initially, the decision to incorporate RPA as a tool is typically mandatory for most organizations: The decision is usually made at the senior management level based on expected increases in productivity, reliability, and cost savings. However, employees engage with different degrees of enthusiasm when implementing specific RPAs, which sometimes could threaten their own jobs. With that in mind, it becomes necessary to define what mandatory and volitional environments are in the context of RPA implementations at the organizational level.

Mandatory: Mandatory adoption of a technology occurs when the end user is forced by the organization, through reward inducements, threats of punishment, or a combination of both, to utilize technology in a way that replaces at least one previous work practice (Rawstorne et al., 1998). On the other hand, if behavioral intention is used as a construct, it is implicit that users have the option to decide their level of technology usage. In corporate environments, this might not always be possible. In simple terms, employees generally do not have the choice to avoid using the system, regardless of their attitude and mental acceptance of it. This scenario defines a mandatory environment.

Volitional: Volitional technology adoption refers to the intentional decision made by an individual or organization to adopt a new technology. In other words, it is a deliberate and purposeful choice to use a particular technology based on perceived benefits or advantages. This decision-making process is influenced by various factors, including the perceived usefulness, ease of use, compatibility, and cost of the technology. Volitional technology adoption can have significant implications for the adoption and diffusion of new technologies, as early adopters often set the stage for broader acceptance and use. The theory of reasoned action (TRA) and related studies support the proposition that perceived ease of use and perceived usefulness significantly impact behavioral intention and usage in voluntary-use environments. TRA focuses on examining the determinants of volitional behavior, or behavior under an individual's control (Karahanna et al., 1999). Previous research suggests that voluntary behavior is likely to result from an individual's favorable attitude, while mandatory behavior is more likely to result from organizational coercion (Hartwick & Barki, 1994).

Is RPA Volitional or Mandatory? Within a specific organization, the decision-making process regarding whether and how to implement RPA can vary significantly. Lievano-

Martínez and Fernández-Ledesma (2022) defined a framework identifying elements that influence the decision to incorporate RPA into an organization. Similarly, Plattfaut et al. (2022) identified critical success factors for RPA developments. It is important to note that, as described by Juntunen (2018), the decision to incorporate RPA as a tool within an organization is typically made by senior management rather than potential users of RPA. This scenario aligns more closely with a mandated environment.

However, there is evidence that once RPA is adopted as a business tool within the organization, employees frequently and voluntarily request specific RPA implementations they perceive as beneficial. That represents volitional behavior. For instance, Kedziora et al. (2021) found that in many cases, implementations were driven by what they call "citizen developers," meaning business workers without technical backgrounds. In one organization, they even stated that "Citizen developers were clearly the promoters of RPA. The impetus of the development work was to increase their personal productivity or that of the team through automating the tasks the citizen developers had first-hand knowledge of." In that case, the decision is not only volitional but also originates from the impacted workers. In conclusion, while the decision to incorporate RPA as a tool is typically mandatory, the reaction to specific bots developed by the company may range from mandatory to volitional.

In terms of how the degree of voluntariness impacts existing relationships, the literature presents several alternatives, with the two most relevant being:

a) Measuring the extent of voluntariness or mandatoriness in cross-sectional studies and treating it as a moderating variable that impacts the relationships between users' intentions and/or information system (IS) usage behavior and their antecedents. Some studies (Hartwick & Barki, 1994; Venkatesh & Davis, 2000) have shown that significant differences exist in the relationships among model variables due to the moderating effects of users' perceived voluntariness.

b) Studying user adoption behaviors in mandatory adoption and usage contexts through a single-case study, where the adoption and usage of newly implemented information systems are mandated. Nah et al. (2004) used this approach.

Both approaches have faced criticism. Rawstorne, Jayasuriya, and Caputi (1998) indicated that in a purely mandatory adoption setting, the user intentions construct, which is typically used as a gauge of usage behavior, is inappropriate because it would be extremely skewed and unusable in model testing (Nah et al., 2004). Rawstorne et al. (2000) conducted a single-site, single-technology longitudinal study. The outcome was mixed: While TAM successfully predicted some specific behaviors, it failed to predict others.

Finally, Brown et al. (2002) discussed and investigated issues related to user acceptance of mandated technology, including the nature of mandatoriness and the implications of users' attitudes in technology acceptance. They further contended that behavioral intention is not appropriate for assessing users' acceptance of newly implemented information technology in mandatory contexts, such as in the case of RPA.

Due to these considerations, the position taken in this dissertation is skeptical regarding the use and validity of the behavioral intention and usage behavior constructs in mandatory environments. The position of Rawstorne et al. (1998) is adopted, asserting that these two variables may be highly skewed in the mandatory (e.g., RPA) context and thus are inappropriate for model testing, at least in a significant number of cases.

Considering the above, it is relevant to introduce another construct: Effective Use. Burton-Jones and Straub (2006) defined system use in terms of a user, system, and task and defined a task as a "goal-directed activity." To move from use to effective use, Burton-Jones and Grange (2013) shifted the emphasis from "using the system to perform a goal-directed activity" to "using it in a way that helps attain a relevant goal." Four assumptions underpin this definition: First, "use" can occur at any level of analysis, though they focused the initial theory on the individual level. Second, they assumed that systems are never used just for the sake of use; rather, they are employed to achieve other goals. Third, they assumed that goal attainment has objective qualities—it may be difficult to evaluate in some cases, but it is not entirely subjective. Fourth, they recognized that different stakeholders may have different views on the goals for using a system. The authors distinguish effective use from perceived usefulness, stating that the constructs differ in scope because effective use focuses on rewards that arise from the way a system is used, whereas perceived usefulness focuses more broadly on rewards that stem from use, not just the way it is used (e.g., it could include rewards that stem from the context in which an information system is used). The constructs also differ in terms of raters, as perceived usefulness refers to a user's expectation or perception (i.e., it resides in the user's mind), whereas effective use is viewed objectively as an observable behavior (Burton-Jones & Grange, 2013).

Burton-Jones and Grange (2013) derived the Theory of Effective Use (TEU) from the Representation Theory. This theory posits that the fundamental role of an information system (IS) is to furnish users with a representation of a domain. For instance, a sales system might represent a region's sales activities for managers (Trieu et al., 2022). Data in that context only acquires meaning through a deeper structure. Following the provided example, numbers in a database inherit a specific meaning if input as a sales ID.

As Trieu et al. (2022) point out, research on effective use is still in its infancy. Furthermore, they state that TEU has only been partially tested. Even though the main goal of the present dissertation is to identify the factors impacting RPA Effective Use, at the same time, this research also tests and extends TEU.

III: RESEARCH DESIGN

Conceptual Framework

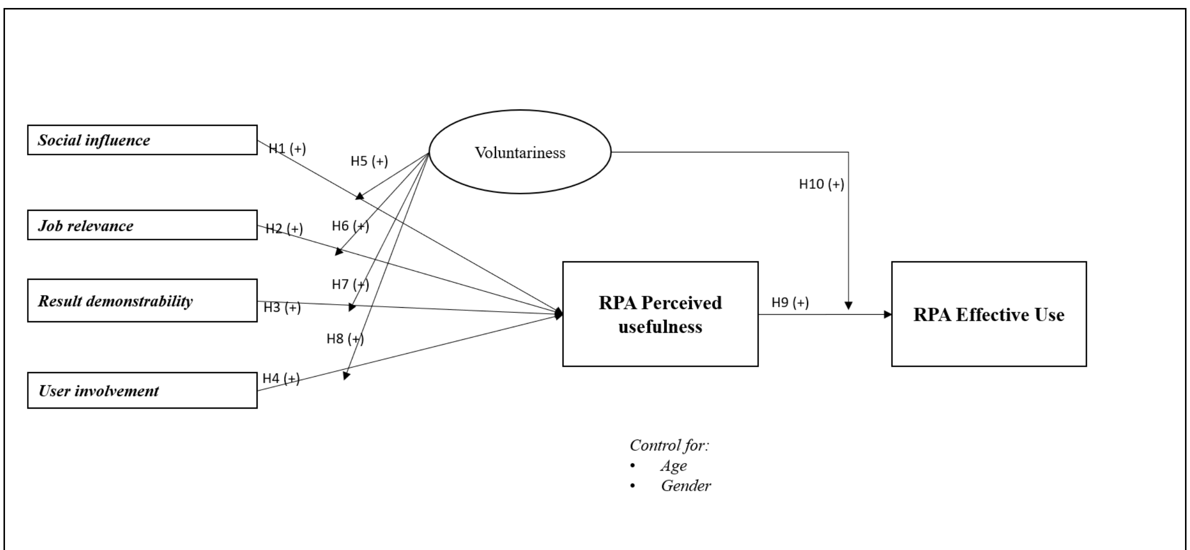


Figure 4: The Conceptual Research Model

Theoretical Development and Hypotheses

The adoption and usage of RPA developments in an organization occur at varying degrees of voluntariness. As discussed in the literature review, behavioral intention is not appropriate for understanding and predicting users' adoption in mandatory adoption and usage contexts, which may be the case for several users. Furthermore, it is not suitable for understanding an implementation that has already taken place. The intention-behavior relationship applies only when the behavior is under a person's volitional control (Ajzen & Fishbein, 1980). To address this issue, the present study used Effective Use. This definition applies well to the varying degrees of voluntariness encountered when examining RPA implementations.

As Venkatesh and Davis (2003) described, Social Influence can significantly impact a user's Perceived Usefulness of a technology. For example, if a user perceives that their colleagues find a technology useful, they may be more likely to adopt it themselves. This is because they believe that their colleagues' positive experiences with the technology indicate that it is valuable and helpful. Therefore, Social Influence can amplify the effect of Perceived Usefulness in the TAM model. If a user perceives a technology as useful and is also influenced by others who endorse it, they are more likely to have a positive attitude toward adopting and using it. Conversely, if a user perceives a technology as useful but lacks social influence, they may be less likely to adopt it. This relationship has been established by researchers studying other technologies, such as delivery systems (Shen et al., 2006) and ERP use (Sternad et al., 2011). Based on the above comments, the following hypothesis is proposed:

H1: As Social Influence increases, PU increases for RPA. If other employees consider it a useful technology (Social Influence increases), employees will identify RPA as useful as well, and RPA Perceived Usefulness (PU) will increase.

Job Relevance and Perceived Usefulness are closely related (Davis, 1989), and research has shown that Job Relevance is a significant factor in users' technology acceptance. If a user perceives that a technology is relevant to their job or work tasks, they are more likely to see it as useful for improving their job performance. For example, a study by Hart and Porter (2004) found that Job Relevance had a significant impact on users' attitudes toward using a specific OLAP vendor. In this way, Job Relevance can enhance the effect of Perceived Usefulness on technology acceptance. Based on the above comments, the following hypothesis is proposed:

H2**:** If RPA Job Relevance increases, the Perceived Usefulness of RPA will increase.

The relationship between Results Demonstrability and Perceived Usefulness was first described in the original TAM model (Davis, 1989). It states that when users can observe the positive outcomes of using a technology, they are more likely to perceive it as useful for improving their job performance. For example, Agbonlahor (2006) found that Results Demonstrability was one of the significant predictors of the number of computer applications used by Nigerian university lecturers. Overall, the relationship between Results Demonstrability and Perceived Usefulness highlights the importance of providing users with tangible evidence of the benefits of using a technology. Technologies that demonstrate positive outcomes of use are more likely to be seen as useful and, therefore, more likely to be adopted. Based on the above comments, the following hypothesis is proposed:

H3: Employees will have a more positive attitude about the system's usefulness if the differences between usage and positive results can be easily observed (Results Demonstrability increases), positively influencing Perceived Usefulness (increased RPA PU).

The relationship between User Involvement and Perceived Usefulness can be traced back to the original TAM model. It describes how, when users are involved in the development and implementation of a technology, they are more likely to perceive it as useful for improving their job performance. User Involvement can provide users with a sense of ownership and control over the technology, which can lead to greater acceptance and use (Bagozzi, 1992). User Involvement can also provide developers with valuable feedback and insights into users' needs and preferences, helping to ensure that the technology is designed to meet those needs (Agarwal & Karahanna, 2000). Using a sample of 118 user-managers in 34 companies, Franz and Robey (1986) showed that User Involvement in design and implementation is positively related to users' perceptions of system usefulness. Based on the above comments, the following hypothesis is proposed:

H4: As employees are more involved during the design and implementation of RPA projects (as User Involvement increases), they will have an increased Perceived RPA Usefulness.

Moore and Benbasat (1991) were among the pioneering scholars to give significance to the concept of voluntariness. Their research aimed to construct an instrument to gauge IT adoption perceptions, and they contend that when examining IT diffusion, it is crucial to consider whether individuals have the liberty to make personal decisions regarding adoption or rejection. Additionally, they argue that there are varying levels of voluntariness concerning behavior in organizations, which is based on their experience and common sense. To assist researchers in specifying assumptions regarding freedom of choice in IT adoption, they created a four-item scale to quantify Voluntariness. Similarly, Venkatesh et al. (2003), in their study on a unified model of IT adoption, explored the moderating effect of environment-based voluntariness. This study employes Moore and Benbasat's (1991) four-item scale of Voluntariness, which they developed and verified as a moderator impacting Social Influence, Job Relevance, Result Demonstrability, and User Involvement.

On the other hand, the UTAUT model established a direct effect of Voluntariness on Social Influence as a moderator (Venkatesh et al., 2003). The model suggests that Voluntariness plays a crucial role in Social Influence. When individuals perceive the decision to adopt a new technology or behavior as voluntary, they are more likely to be influenced by social factors, such as the opinions of others in their social network. However, when individuals feel that they are being forced or coerced, they are less likely to be influenced and may become resistant to change. This kind of relationship has been explored previously by Gomez (2017).

H5: Voluntariness will moderate the effect of Social Influence on Perceived Usefulness, with the effect being stronger with higher Voluntariness.

Job Relevance was defined as a personal perspective on the extent to which the target system is suitable for the job (Venkatesh & Davis, 2000). n mandatory settings, the impact of job relevance is somewhat diminished because employees are required to use the technology regardless of its perceived relevance. In that sense, Voluntariness does not seem to have a logical impact on the relationship between Job Relevance and Perceived Usefulness. Nevertheless, for completion purposes, this hypothesis is tested.

H6: Voluntariness will moderate the effect of Job Relevance on Perceived Usefulness, with the effect being stronger with higher Voluntariness.

As established, Voluntariness is the extent to which the use of the system is perceived as not being required by the organization. When applying this definition to RPA implementations, it has been identified that in certain situations, employees might even request and design their own bots, which should reflect a higher degree of Voluntariness. This has an impact on Result Demonstrability: A by-product of this role for employees is obtaining a final RPA implementation that better meets the desired results in a tangible way or “an increased tangibility of the results of using the innovation.” Shahbaz et al. (2021) detected a significant and positive relationship between Voluntariness and Result Demonstrability.

H7: Voluntariness will moderate the effect of Result Demonstrability on Perceived Usefulness, with the effect being stronger with higher Voluntariness.

User Involvement refers to a subjective psychological state of the individual and is defined as the importance and personal relevance that users attach either to a particular system or to IS in general, depending on the user’s focus (Barki & Hartwick, 1989). In that sense, Voluntariness does not seem to have a logical impact on the relationship between User Involvement and Perceived Usefulness. Nevertheless, for completion purposes, this hypothesis was tested.

H8: Voluntariness will moderate the effect of User Involvement on Perceived Usefulness, with the effect being stronger with higher Voluntariness.

When describing Effective Use, Burton-Jones and Grange (2013) present a theory that explains what people need to do to use systems more effectively and increase their performance. It is related to the achievement of goals and increased performance, as described by Beaudry et al. (2020). The theory builds on factors that flow from Representation Theory but also recognizes that other factors could drive Effective Use (e.g., intention to use and organizational culture). On the other hand, in the traditional TAM model, Perceived Usefulness is a construct impacting Behavioral Intention. As stated in previous sections, Behavioral Intention does not apply to already implemented RPAs, and the chosen dependent variable is, therefore, Effective Use. The present study hypothesizes that Perceived Usefulness (PU) has a direct impact on Effective Use. This has been conceptualized before but under very different conditions.

For example, Or et al. (2010), when studying technology Effective Use in an IT implementation in the healthcare industry, found that Perceived Usefulness significantly and directly influenced Effective Use. Similarly, Tao et al. demonstrated a direct and significant relationship between Perceived Usefulness and Effective Use in a different context of technology implementation.

H9: RPA Perceived Usefulness will impact RPA Effective Use, with the effect being stronger with higher Perceived Usefulness.

Voluntariness is recognized as an important influence on individual and collective technology acceptance (Tsai et al., 2017). Overall, these studies suggest that when individuals have a choice in using technology, they may be more likely to use it effectively. In this case, it is logical to assume that when employees have the choice to use the RPA implementation, their Effective Use will increase.

H10: Voluntariness will moderate the effect of RPA Perceived Usefulness on RPA Effective Use, with the effect being stronger with higher Voluntariness.

IV. RESEARCH METHODOLOGY

Participants and Procedure

This study is non-experimental, and data is obtained through a quantitative survey conducted online utilizing the Qualtrics platform to gather data to test the previously presented hypotheses. The goal of this survey is to explore the key factors influencing RPA employees' Effective Use in organizational environments. The approach employed for analyzing the data involves multiple regression. This study employs a quantitative approach rooted in positivism, aimed at obtaining unbiased and objective results. A descriptive approach is also employed to illustrate workers' attitudes toward RPA implementations while measuring the perceived Voluntariness environment in which this takes place.

The use of surveys is chosen as an appropriate tool due to their efficiency in reaching many subjects (Kerlinger & Lee, 2000). Survey questions utilize a series of Likert items using a five-point response scale ranging from "strongly agree" to "strongly disagree." For the collection of demographic information, such as gender identity, race, and years in practice, nominal data is collected. In addition, using this methodology allows for the quantification of responses and statistical analysis of the results.

However, finding participants who have been actively engaged in this type of technological implementation and are representative of all industries, geographies, and demographics proves to be a challenge. Therefore, they were recruited through Cloud Research. The request to participate in the survey clarified that participants had access to the results and conclusions, as well as the consequential benefits.

Research Design

A descriptive approach was employed to illustrate the attitudes of workers toward RPA implementations while measuring the perceived voluntariness environment in which this takes place. The defined timeline was approximately eight months, including the initial information-gathering phase, an informed pilot, and a second pilot following IRB approval before administering the survey.

As previously stated, finding participants who have been actively engaged in this type of technological implementation and are representative of all industries, geographies, and demographics might be a challenge. Therefore, participants in groups of interest on LinkedIn and other platforms were presented with the opportunity to participate in the survey.

The survey was designed with questions covering six factors: four independent variables, one moderator, and one dependent variable. Closed-ended questions were phrased as statements using a five-point Likert scale. Respondents were asked to specify their level of agreement using the following points: (1) Strongly disagree, (2) Disagree, (3) Neither agree nor disagree, (4) Agree, and (5) Strongly agree.

To preserve the integrity of the collected data, three red herring questions were inserted to ensure that respondents are not randomly clicking through the survey. Qualtrics XM was used to build the survey. Qualifiers were inserted at the start of each survey to ensure that the target audience of RPA users is the only group measured. Additionally, measures were implemented to ensure the anonymity of each respondent using options available within the Qualtrics design platform. Clear and concise instructions were provided, and headings were used to make the questionnaire easy to follow.

To reduce nonresponse bias, an incentive was provided to encourage participants to complete the survey within a specific timeframe. Surveys completed within a minute or less were removed from the sample to eliminate responses from speeders, ensuring the integrity of the results. Once a reliable measure has been obtained, the data was imported into statistical software, with the choice between SPSS and SmartPLS determined beforehand.

After collecting and meeting the determined sample size, the subsequent step was to analyze the data. To begin, data cleaning is essential, which involves identifying and eliminating responses that do not meet qualifying criteria, are "speeders," or lack sufficient responses. Outliers were also identified and removed to obtain a clean and reliable dataset. As previously stated, statistical software was employed to perform further data analysis. Specifically, an exploratory factor analysis (EFA) was conducted to establish the proper structure of each factor and the questions that fit within these categories. Items that cross-load into more than one factor and have low scores were eliminated. Finally, a reliability analysis was performed to calculate the measures used, the items within each scale, and the relationships between those items.

Measurements

Independent Variables:

Social influence (SI): The term refers to situations in which people may choose to perform a behavior—even if they are not themselves favorable toward the behavior or its consequences—if they believe one or more important referents think they should, and they are sufficiently motivated to comply with the referents (Venkatesh & Davis, 2000).

To operationalize the construct, the original TAM/UTAUT items developed by Venkatesh and Davis (2000) were used but in an adapted version by Wewerka et al. (2020) for RPA implementations. Responses were elicited from participants using a five-point Likert scale, ranging from "strongly disagree" to "strongly agree."

Job Relevance (JR): Defined as an individual's perception regarding the degree to which the target system is applicable to their job (Venkatesh & Davis, 2000).

To operationalize the construct, the original TAM/UTAUT items developed by Venkatesh and Davis (2000) were used but in an adapted version by Wewerka et al. (2020) for RPA implementations. Responses were elicited from participants using a five-point Likert scale, ranging from "strongly disagree" to "strongly agree."

Result Demonstrability (RD): Defined by Moore and Benbasat (1991) as the "tangibility of the results of using the innovation." Users will have more positive perceptions of the usefulness of a system if positive results are readily discernible.

To operationalize the construct, the original TAM/UTAUT items developed by Venkatesh and Davis (2000) were used but in an adapted version by Wewerka et al. (2020) for RPA implementations. Responses were elicited from participants using a five-point Likert scale, ranging from “strongly disagree” to “strongly agree.”

Voluntariness (VO): Technology adoption ranges between two poles, comprised at one end by voluntary or volitional adoption and at the other by mandatory adoption (Rawstorne et al., 1998).

To operationalize the construct, the original Voluntariness four-item scale developed by Moore and Benbasat (1991) was used. Responses were elicited from participants using a four-point Likert scale, ranging from “strongly disagree” to “strongly agree.”

Perceived Usefulness (PU): Perceived Usefulness, defined by Davis (1986), is the subjective perception of users who believe that using certain technologies can improve their work performance. To operationalize the construct, the items developed by Venkatesh (2003, 2012) were used but in an adapted version by Wewerka et al. (2020) for RPA implementations. Responses were elicited from participants using a five-point Likert scale, ranging from “strongly disagree” to “strongly agree.”

Dependent Variable:

Effective Use: Using a system (RPA in this case) in a way that works well and produces the intended results (adapted from Burton-Jones & Grange, 2013). To operationalize the construct, a five-item Effective Use scale was used based on those developed by Yang et al. (2021) and Haake et al. (2018), which, in turn, are based on

Burton-Jones and Grange's (2013) work. Responses were elicited from participants using a five-point Likert scale, ranging from "strongly disagree" to "strongly agree."

V. FINAL STUDIES

Two studies are presented in this chapter. In the first one, called Study A, all participants who were not removed due to incomplete survey submissions or speeding were considered. In the second one, called Study B, participants who declared not having experience with RPA or that RPA is not being used at their jobs were also excluded. This means that the Study B sample is a subset of the Study A sample. Since the same hypotheses were tested for both studies, the analyses and results were differentiated by adding a letter "A" or "B" to the hypotheses, depending on which study (or sample) is being tested.

STUDY A

The main study was conducted in a manner similar to that of the primary pilot. The Connect Cloud survey platform by Cloud Research was used to administer data collection. The survey questions were developed and administered by Qualtrics, and IBM SPSS as well as Smart PLS were used to conduct analysis and validate the strength of the model constructs. As with the primary pilot, respondents were compensated for their participation in the study, in this case, with $3 per participant. All measures present in the primary pilot were retained and used for the main study. The main study ran from October 25, 2024, through October 26, 2024, and collected 469 respondents. Then, several data-cleansing steps were taken. Out of the 469 total responses (cases in SPSS), 165 cases were removed due to incomplete survey submissions and speeding, resulting in 304 valid responses. The same criteria and qualifications used to select participants for the pilot study were applied in the main study.

This analysis of the reflective model utilizes SmartPLS (4), a structural equation modeling (SEM) software, to test hypotheses and demonstrate causal relationships between the variables discussed in previous chapters. The analysis includes evaluations of construct reliability and validity, content validity, and discriminant and convergent validity (AVE). Further analysis involves a structural equation model with moderator analysis and bootstrapping, as well as an assessment of correlation strengths.

Descriptive Analytics and Frequencies: Study A

Following the data-cleansing steps previously described, 304 valid cases were left for further analysis. Of these, 166 (54.6%) were male, 132 (43.4%) were female, and 6 (2.0%) were non-binary. Most respondents were between the ages of 30 and 39, representing 37.2% (n = 113) of the study sample. Seventy-seven respondents were between the ages of 40 and 49 (25.3%), 76 respondents were between the ages of 20 and 29 (25.0%), 23 respondents were between the ages of 50 and 59 (7.6%), 14 respondents were between the ages of 60 and 69 (4.6%), and only one respondent (0.3%) was 70 years old or more.

Respondents worked for different industries, with information services being the most common (n = 61, 20.1%), followed by other industries (n = 49, 16.1%), health care (n = 34, 11.2%), and finance (n = 33, 10.9%). Respondents tended to work at companies with 251 or more employees (n = 142, 46.7%) and companies with 51 to 250 employees (n = 96, 31.6%). Most survey respondents had a bachelor's degree (148, 48.7%), while 58 had a graduate degree (19.1%). Only 25 respondents had a high school diploma or GED (8.2%).

In terms of RPA utilization, 261 respondents (85.9%) reported that RPA is being used at their companies. Similarly, 228 (75.0%) stated that they have interacted with RPA and that it is being used at their companies, while 39 respondents (12.8%) do not interact with RPA but reported that it is being used at their companies. Only 32 respondents indicated that RPA is not used at their companies, and they have not personally interacted with it, while 5 respondents answered that they do not know.

Table 1A: Study 'A' Descriptive Statistics (Demographic Data)

Characteristics		**Frequency**	**% of Population**
Gender	Male	166	54.6
	Female	132	43.4
	Non-binary	6	2.0
Age	20–29 years old	76	25.0
	30–39 years old	113	37.2
	40–49 years old	77	25.3
	50–59 years old	23	7.6
	60–69 years old	14	4.6
	70 years old or more	1	0.3
Education	Some high school or less	1	0.3
	High school diploma or GED	25	8.2
	Some college but no degree	34	11.2
	Associate's or technical degree	36	11.8
	Bachelor's degree	148	48.7
	Graduate's degree (MA, MS, MBA, PhD, JD, MD, DDS, etc.)	58	19.1
	Prefer not to say	2	0.7
	1–10	29	9.5
	11–50	37	12.2

Number of people working at my organization	51–250	96	31.6
	251 or more	142	46.7
Industry	Agriculture	3	1.0
	Utilities	9	3.0
	Consumer products	25	8.2
	Finance	33	10.9
	Entertainment	7	2.3
	Education	23	7.6
	Health care	34	11.2
	Information services	61	20.1
	Data processing	22	7.2
	Food services	4	1.3
	Heavy machinery	4	1.3
	Hotel services	7	2.3
	Legal services	9	3.0
	Publishing	9	3.0
	Transportation	1	0.3
	Other	49	16.1
	Prefer not to say	4	1.3
Annual income level	$0–$24,999	29	9.5
	$25,000–$49,999	68	22.4
	$50,000–$74,999	84	27.6
	$75,000–$99,999	51	16.8
	$100,000 or more	70	23.0
	Prefer not to answer	2	0.7
RPA used at organization	Yes	261	85.9
	No	43	14.1
RPA use at my organization	Used at my company, and I have personally interacted with it.	228	75.0
	Used at my company. but I have not personally interacted with it.	39	12.8
	Not used at my company. and I have not personally interacted with it.	32	10.5
	I don’t know.	5	1.6

Study A: Exploratory Factor Analysis and Reliability

In the following sections descriptive details and reliability scores for all items used in the final study, along with their construct-level reliability, were shown in Tables 2A, 3A, 4A, and 5A (below). These results indicate that the measurement tool used in the pilot study was reliable and demonstrated satisfactory construct validity.

To analyze the main study's findings, structural equation modeling (SEM) and particularly the partial least squares (PLS) approach was employed. The SmartPLS software was used to model and measure all constructs and indicators included in the survey. All aspects of the model utilized a reflective approach, consistent with the original development and validation of the scales used in this research.

Table 2A below presents a pattern matrix derived from an extraction method using principal axis factoring (PAF) with an oblique rotation method (Oblimin with Kaiser normalization). The rotation converged in seven iterations, indicating that the process successfully found a stable solution for interpreting the relationships between variables and items. This pattern matrix was generated by using SPSS to identify and confirm underlying patterns or latent variables within the final dataset. The rotation helps simplify and visually interpret these patterns.

The pattern matrix shows the loadings of observed variables (labeled as PU3, EU1, JR3, etc.) on the extracted components (1 - 7). Each row's loading represents the correlation between the observed variables and the components. As is usual in these analyses, any loading close to 1 or -1 suggests a strong link between the variable and the component. On the other hand, loadings closer to 0 indicate a weak connection. Variables that exhibit a higher loading on a certain component are more strongly related to that component which indicates they might be contributing more to its definition (discriminant validity). All loadings where the coefficient absolute values were equal or lower than 0.30 were removed. Ultimately, 27 of the initial 42 variables were kept as part of the model.

Table 2A: Final Study Pattern Matrix

Pattern Matrix Study A							
	1	2	3	4	5	6	7
EU1						-0.899	
EU2						-0.771	
EU3						-0.830	
EU4						-0.713	
VO2		0.836					
VO3		0.787					
VO4		0.893					
VO5		0.825					
SI1					0.883		
SI2					0.799		
SI3					0.538		
RD1				0.865			
RD2				0.783			
RD3				0.668			
JR1							0.473
JR2							0.315
JR3							0.571
JR4							0.828
UI3			0.435				
UI4			0.870				
UI5			0.870				
UI6			0.495				

PU1	0.710
PU2	0.734
PU3	0.891
PU4	0.651
PU7	0.678

Extraction Method: Principal Component Analysis.
Rotation Method: Oblimin with Kaiser Normalization.
Rotation converged in 7 iterations.

Note:

- EU: Effective Use
- VO: Voluntariness
- SI: Social Influence
- RD: Result Demonstrability
- JR: Job Relevance
- UI: User Involvement
- PU: Perceived Usefulness

The researcher has interpreted the pattern matrix using the results from the provided loadings:

Effective Use (EU) represents component 6 and is associated with variables EU1 (-0.90), EU2 (-0.77), EU3 (-0.83), and EU4 (-0.71). These variables have negative loadings on all components, suggesting an inverse relationship between these variables and the corresponding elements.

Voluntariness (VO) represents component 2 and is associated with variables VO2 (0.84), VO3 (0.79), VO4 (0.89), and VO5 (0.83). These variables are positively related to each other within this component, indicating high levels of discriminate validity.

Social Influence (SI) represents component 5 and is associated with variables SI1 (0.83), SI2 (0.80), and SI3 (0.54). These variables are positively related to each other within this component, indicating high levels of discriminant validity.

Result Demonstrability (RD) represents component 4 and is associated with variables RD1 (0.87), RD2 (0.78), and RD3 (0.69). These variables are positively related to each other within this component, indicating high levels of discriminant validity.

Job Relevance (JR) represents component 7 and is associated with variables JR1 (0.47), JR2 (0.32), JR3 (0.57), and JR4 (0.837). These variables are positively related to each other within this component, indicating high levels of discriminant validity.

User Involvement (UI) represents component 3 and is associated with survey questions UI3 (0.44), UI4 (0.87), UI5 (0.87), and UI6 (0.50). These variables are positively related to each other within this component, indicating high levels of discriminant validity.

Perceived Usefulness (PU) represents component 1 and is associated with variables PU1 (0.71), PU2 (0.73), PU3 (0.89), PU4 (0.65), and PU7 (0.68). These variables are positively related to each other within this component, indicating high levels of discriminant validity.

Study A revealed a factor structure that effectively gauges the seven primary factors: Effective Use (EU), Job Relevance (JR), Perceived Usefulness (PU), Result Demonstrability (RD), Social Influence (SI), User Involvement (UI), and Voluntariness (VO).

Detailed statistics for the final study data are outlined in Table 3A below, featuring the item identifiers, means, standard deviations, number of responses, and alpha scores for each measurement scale. The analysis of the main study findings includes assessing the loadings to determine which variables have loadings of 0.70 or greater, indicating that the construct explains more than 50% of the indicator's variance, thereby proving adequate reliability. Table 3A below shows that all constructs meet this criterion.

Table 3A: Final Study Construct Reliability

Construct Name and Reference	Item Code	Mean	Std. Deviation	Number of Responses	Alpha
Effective Use	EU1	5.73	.965	304	.906
Burton-Jones & Grange (2013)	EU2	5.65	1.033		
	EU3	5.77	1.041		
	EU4	5.75	1.134		
Job Relevance	JR1	5.42	1.377	304	.846
Venkatesh & Davis (2000)	JR2	5.62	1.352		
	JR3	4.24	1.717		
	JR4	4.92	1.612		
Perceived Usefulness	PU1	5.87	1.105	304	.941
Venkatesh & Davis (2000)	PU2	5.72	1.174		
	PU3	5.82	1.182		
	PU4	5.84	1.207		
	PU7	5.61	1.192		
Result Demonstrability	RD1	5.64	1.263	304	.834
Venkatesh & Davis (2000)	RD2	5.76	1.145		
	RD3	5.66	1.243		
Social Influence	SI4	4.36	1.641	304	.875
Venkatesh & Davis (2000)	SI6	4.07	1.655		
	SI7	3.47	1.765		
User Involvement	UI3	5.02	1.701	304	.856
Venkatesh & Davis (2000)	UI4	4.77	1.758		
	UI5	4.55	1.713		

	UI6	4.60	1.747		
Voluntariness Moore & Benbasat (1991)	VO2	3.71	1.874	304	.914
	VO3	3.45	1.956		
	VO4	3.73	1.934		
	VO5	3.79	1.891		

The evaluation of the reflective model starts with internal consistency reliability, typically assessed using Cronbach's alpha and composite reliability. Cronbach's alpha measures internal consistency/reliability but generally yields lower values than composite reliability. This is because Cronbach's alpha is a less precise measure, as it treats all items equally. On the other hand, composite reliability weights items based on their individual loadings on the construct indicators, resulting in higher values than Cronbach's alpha. While Cronbach's alpha may be overly conservative, composite reliability can be too liberal, with the true reliability of the construct usually considered to lie between these two values (Hair, 2019). Therefore, both measures are included in the analysis and are presented in Table 4A below.

Table 4A: Final Study Construct Reliability

Construct Name and Reference	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
Effective Use	0.906	0.909	0.934	0.780
Job Relevance	0.846	0.879	0.898	0.691
Perceived Usefulness	0.941	0.943	0.955	0.810
Result Demonstrability	0.834	0.840	0.901	0.751
Social Influence	0.875	0.877	0.923	0.799

User Involvement	0.856	0.863	0.903	0.701
Voluntariness	0.914	0.973	0.938	0.792

In terms of construct reliability, all constructs show Cronbach's alpha and composite reliability values greater than 0.70; therefore, each one is considered valid and reliable. This indicates that the constructs are measured with a high degree of internal consistency, providing strong evidence of construct reliability and validity within the model.

In terms of convergent reliability, which is typically demonstrated through the outer loadings of the indicators and the average variance extracted (AVE), Hair et al. (2019) suggest that values in the 0.70–0.90 range are considered satisfactory to good. However, values approaching 1.0 (e.g., 0.95) are concerning as they indicate redundancy and weaken construct reliability. The results show that almost all scores are satisfactory, with Job Relevance being close to the 0.70 threshold, at 0.691.

Regarding model fit, the standardized root mean square residual (SRMR) shows that the model closely represents the observed data, as the value is 0.069— significantly below the 0.08 threshold—and consequently considered indicative of a good fit (Henseler et al., 2014).

Table 5A: Discriminant Validity

	EU	JR	PU	RD	SI	UI	VO	VO X PU	VO X JR	VO X UI	VO X RD	VO X SI
EU												
JR	0.696											
PU	0.740	0.833										
RD	0.610	0.579	0.650									
SI	0.550	0.698	0.590	0.457								

UI	0.601	0.701	0.637	0.539	0.590						
VO	0.268	0.488	0.350	0.248	0.526	0.232					
VO X PU	0.141	0.180	0.250	0.070	0.115	0.087	0.132				
VO X JR	0.092	0.274	0.138	0.076	0.168	0.123	0.088	0.719			
VO X UI	0.020	0.115	0.080	0.103	0.118	0.058	0.039	0.514	0.562		
VO X RD	0.104	0.095	0.016	0.064	0.106	0.120	0.231	0.606	0.509	0.419	
VO X SI	0.079	0.162	0.102	0.095	0.299	0.122	0.045	0.497	0.600	0.501	0.330

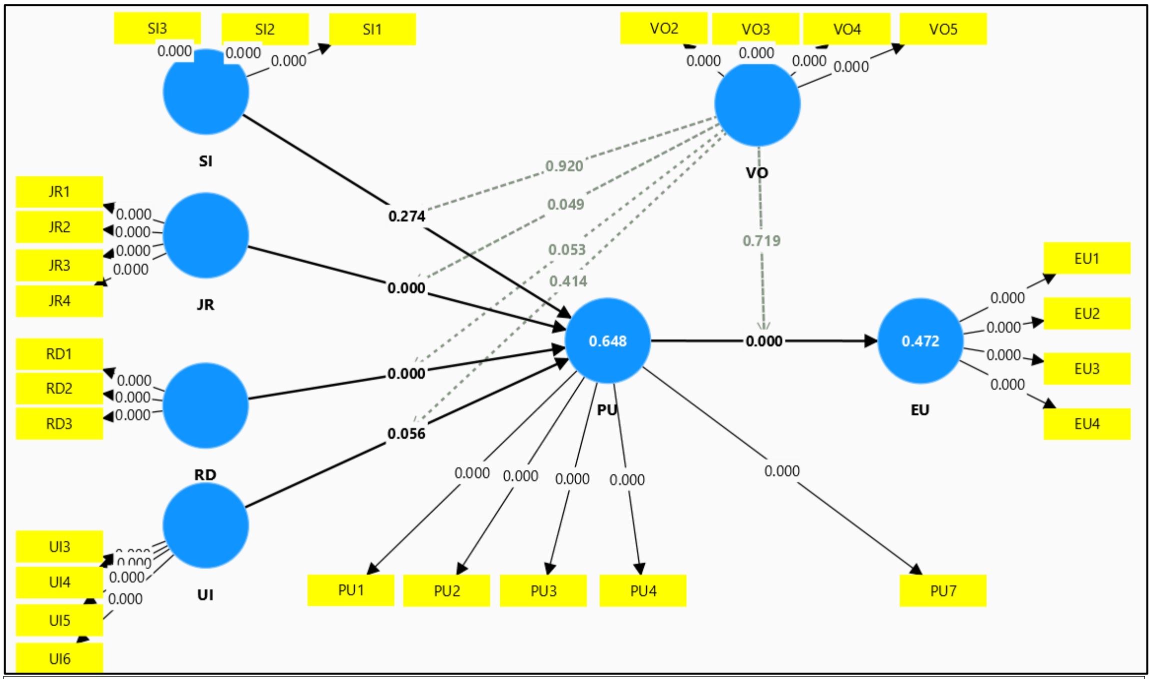
Assessing discriminant validity to empirically demonstrate the distinctiveness between one construct and other constructs within the structural model is also relevant. As observed in Table 5A, all constructs show heterotrait-monotrait (HTMT) values lower than 0.90 and, in fact, lower than 0.85, which tends to be considered an ideal value. This ensures that all constructs that are theoretically distinct are, in fact, empirically distinct in the data.

The HTMT values indicate that each construct shares more variance with its own indicators than with those of other constructs, ensuring that the constructs are not overly related or overlapping. This distinction is essential for accurately interpreting the model, as it confirms that each construct represents a unique concept and is not conflated with others. In summary, all pairs of constructs support discriminant validity, meaning they are empirically distinct.

The highest value in the discriminant validity table above is the relationship between Perceived Usefulness (PU) and Job Relevance (JR). Although this value is below the defined threshold, it indicates a strong relationship between these two variables, yet they still measure different concepts.

In summary, all constructs in the research model demonstrated sufficient reliability (Table 3A), discriminant validity (based on the HTMT criterion, Table 5A), and convergent validity (AVEs, Table 4A), along with sufficiently high loadings for each item on its intended construct (Table 2A). Consequently, the measurement portion of the research model is deemed satisfactory, allowing it to serve as the basis for analyzing the structural relationships of interest.

The initial measurement model in Figure 4 illustrates the relationship between the associated loadings of the exogenous, endogenous, and control variables. The model shows all loadings before the removal of low-loading variables.



Note:

- EU: Effective Use
- VO: Voluntariness
- SI: Social Influence
- RD: Result Demonstrability
- JR: Job Relevance
- UI: User Involvement
- PU: Perceived Usefulness

Figure 5A: Main Study with Initial loadings and Control Variables

Figure 5A presents the results of the structural portion of the research model after the removal of low-loading items. The reported values represent the standardized paths between the different constructs (and control variables) in the research model. The values within parentheses are the p-values for the associated paths, obtained from a bootstrapping calculation using 5,000 replications.

Main Hypotheses: Study A Summary

The conducted study explored the connections among various elements, Perceived Usefulness, and Effective Use. Table 6A presents the condensed structural model, including loadings and path coefficients, excluding control variables. Furthermore, Table 7A offers a summary of the hypotheses derived from the path coefficients in Table 6A, demonstrating that four out of the twelve associations are confirmed.

Table 6A: Path Coefficients

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (│O/STDEV│)	P values
SI→ PU	0.059	0.060	0.054	1.094	0.274
JR → PU	0.569	0.567	0.069	8.268	0.000
RD→ PU	0.208	0.210	0.058	3.592	0.000
UI→ PU	0.140	0.144	0.073	1.914	0.056
VO→ EU	-0.029	-0.031	0.055	0.531	0.595
VO→ PU	0.010	0.008	0.049	0.213	0.831
VO x SI→ PU	0.005	0.005	0.052	0.100	0.920
VO x JR→ PU	-0.117	-0.115	0.060	1.965	0.049
VO x RD→ PU	0.130	0.132	0.067	1.934	0.053
VO x UI→ PU	0.047	0.045	0.057	0.817	0.414
PU→ EU	0.683	0.686	0.041	16.580	0.000
VO x PU→ EU	-0.029	-0.025	0.081	0.359	0.719

Note:

- EU: Effective Use
- VO: Voluntariness
- SI: Social Influence
- RD: Result Demonstrability
- JR: Job Relevance
- UI: User Involvement
- PU: Perceived Usefulness

It can be observed that Job Relevance has a meaningful impact on Perceived Usefulness, Perceived Usefulness has a meaningful influence on Effective Use, and finally, Result Demonstrability has a meaningful impact on Perceived Usefulness. There is also a significant impact of Voluntariness on the relationship between Job Relevance and Perceived Usefulness. All other relationships do not show a meaningful effect based on their reported p-values.

Table 7A: Hypotheses Summary

Hypotheses	Description	p-value
H1A	As Social Influence increases, Perceived Usefulness increases for RPA	Not Supported
H2A	If RPA Job Relevance increases, the Perceived Usefulness of RPA will increase	Supported
H3A	If RPA Result Demonstrability increases, RPA Perceived Usefulness will increase	Supported
H4A	As User Involvement increases, Perceived RPA Usefulness will increase	Not Supported
H5A	Voluntariness will moderate the effect of Social Influence on Perceived Usefulness, with the effect being stronger with higher Voluntariness	Not Supported
H6A	Voluntariness will moderate the effect of Job Relevance on Perceived Usefulness, with the effect being stronger with higher Voluntariness	Supported
H7A	Voluntariness will moderate the effect of Result Demonstrability on Perceived Usefulness, with the effect being stronger with higher Voluntariness	Not Supported
H8A	Voluntariness will moderate the effect of User Involvement on Perceived Usefulness, with the effect being stronger with higher Voluntariness	Not Supported
H9A	As RPA Perceived Usefulness increases, RPA Effective Use will increase	Supported
H10A	Voluntariness will moderate the effect of RPA Perceived Usefulness on RPA Effective Use, with the effect being stronger with higher Voluntariness	Not Supported

Hypothesis H1A states that Social Influence positively affects Perceived Usefulness. As described by Venkatesh and Davis (2001), if a user perceives that their colleagues find a technology useful, they may be more likely to adopt it themselves. The results show no significant relationship between Social Influence and Perceived Usefulness ($b = 0.059$, $p = 0.274$).

Hypothesis H2A posits that Job Relevance positively affects Perceived Usefulness. If a user perceives that a technology is relevant to their job or work tasks, they are more likely to see it as useful for improving their job performance. The findings indicate a strong and meaningful link between Job Relevance and Perceived Usefulness, with a coefficient of 0.569 and a p-value less than 0 ($b = 0.569$, $p < 0.000$). Consequently, as a user's Job Relevance rises, their Perceived Usefulness increases accordingly.

Hypothesis H3A examines the relationship between positive Result Demonstrability and RPA Perceived Usefulness. H3A predicted a positive relationship. The findings indicate a strong and meaningful link between Result Demonstrability and Perceived Usefulness ($b = 0.208$, $p < 0.000$). Consequently, as a user's perception of Result Demonstrability increases, their Perceived Usefulness increases accordingly.

Hypothesis H4A examines the relationship between positive User Involvement and RPA Perceived Usefulness. H4A predicted a positive relationship. The findings do not indicate a meaningful relationship between User Involvement and Perceived Usefulness ($b = 0.140$, $p = 0.056$).

Hypothesis H6A explores how Voluntariness moderates the effect of Job Relevance on Perceived Usefulness, with the effect being stronger with higher Voluntariness. The findings indicate a strong and meaningful relationship between Voluntariness and Perceived Usefulness ($b = -0.117$, $p = 0.049$).

Hypotheses H5A, H7A, and H8A predicted a mediating effect of Voluntariness on the relationships between Social Influence, Result Demonstrability, User Involvement, and Perceived Usefulness. The findings do not indicate a meaningful relationship between any of these variables and Voluntariness.

Hypothesis H9A examines the relationship between positive Perceived RPA Usefulness and Effective Use. H9A predicted a positive relationship. The results show a positive and significant relationship between Perceived Usefulness and Effective Use ($b = 0.683$, $p < 0.000$). Consequently, as a user's perception of Perceived Usefulness increases, their Effective Use of RPA increases accordingly.

Lastly, Hypothesis H10A examines whether a moderating effect exists with Voluntariness on the relationship between Perceived Usefulness and Effective Use. The results show no significant moderating effect of Voluntariness on the relationship between Perceived Usefulness and Effective Use ($b = -0.029$, $p = 0.719$).

In summary, Study A provides evidence for the impact of Result Demonstrability and Job Relevance on Perceived Usefulness, the mediating effect of Voluntariness on the Job Relevance–Perceived Usefulness relationship, and the role of Perceived Usefulness in Effective Use in the context of RPA implementations. On the other hand, the study failed to uncover evidence backing the favorable effects of Social Influence and User

Involvement on Perceived Usefulness. Likewise, it did not detect proof suggesting that Voluntariness serves as a mediator for all other associations.

The lack of empirical support for the positive effects of Social Influence and User Involvement on Perceived Usefulness, as well as the mediating effect of Voluntariness, can be attributed to the interplay of various factors, contextual variations, measurement challenges, and potential limitations in the study. These findings underline the need for continued research to unravel the intricate dynamics of RPA implementations and the specific conditions under which these factors may influence Perceived Usefulness and the role that Voluntariness may play in various relationships.

STUDY B

Descriptive Analytics and Frequencies: Study B

Study B was conducted with a sample that is a subset of Study A and was therefore conducted under the same conditions. The only difference is that Study B excludes participants who did not declare having personal experience with RPA implementations and those who reported that RPA is not used at their jobs.

Following this phase, out of the 227 valid responses, 125 (55.1%) identified as male, 97 (42.5%) as female, and 5 (2.2%) as nonbinary. Most respondents were between the ages of 30 and 39, comprising 39.2% (n = 89) of the study sample. Fifty-eight respondents were between the ages of 40 and 49 (25.6%), 56 were between the ages of 20 and 29 (24.7%), 17 were between the ages of 50 and 59 (7.5%), and 7 were between the ages of 60 and 69 (3.1%). No respondents were 70 years old or older.

Respondents worked in various industries, with information services being the most common (n = 49, 21.6%), followed by Other (n = 34, 15.0%), Health Care (n = 22, 9.7%), and Finance (n = 22, 9.7%). Respondents tended to work at companies with 251 or more employees (n = 108, 47.6%) or companies with 51 to 250 employees (n = 77, 33.8%). Most survey respondents had a bachelor's degree (n = 122, 53.7%), and 41 had a graduate degree (18.1%). Only 4 respondents had a high school diploma or GED (5.7%).

As previously stated, all participants in Study B declared that they have used RPA in their companies and have personally interacted with it.

Table 1B: Study 'B' Descriptive Statistics (Demographic Data)

Characteristics		**Frequency**	**% of Population**
Gender	Male	125	55.1
	Female	97	42.7
	Non-binary	5	2.2
Age	2029 years old	56	24.7
	30–39 years old	89	39.2
	40–49 years old	58	25.6
	50–59 years old	17	7.5
	60–69 years old	7	3.1
	70 years old or more	0	0
Education	Some high school or less	1	0.4
	High school diploma or GED	13	5.7
	Some college but no degree	21	9.3
	Associate's or technical degree	27	11.9
	Bachelor's degree	122	53.7
	Graduate's degree (MA, MS, MBA, PhD, JD, MD, DDS, etc.)	41	18.1
	Prefer not to say	2	0.9
Number of people working at my organization	1–10	13	5.7
	11–50	29	12.8
	51–250	77	33.9
	251 or more	108	47.6
Industry	Agriculture	2	0.9
	Utilities	7	3.1

	Consumer products	18	7.9
	Finance	22	9.7
	Entertainment	6	2.6
	Education	17	7.5
	Health care	22	9.7
	Information services	49	21.6
	Data processing	19	8.4
	Food services	3	1.3
	Heavy machinery	2	0.9
	Hotel services	7	3.1
	Legal services	7	3.1
	Publishing	8	3.5
	Transportation	1	0.4
	Other	34	15.0
	Prefer not to say	3	1.3
Annual income level	\$0–\$24,999	14	6.2
	\$25,000–\$49,999	54	23.8
	\$50,000–\$74,999	61	26.9
	\$75,000–\$99,999	42	18.4
	\$100,000 or more	54	23.7
	Prefer not to answer	2	0.9

Study B: Exploratory Factor Analysis and Reliability

Descriptive statistics and reliability metrics for all items used in the concluding study, along with their construct-level reliability, have been provided as shown in Tables 2B, 3B, 4B, and 5B (below). Collectively, these findings indicate that the measurement instrument applied in the preliminary study was dependable and demonstrated acceptable construct validity.

Table 2B, presented below, is a pattern matrix derived from an extraction technique employing principal axis factoring (PAF) and an oblique rotation approach (Oblimin with Kaiser normalization). The convergence of the rotation after eight iterations suggests that the process effectively identified a consistent solution for understanding the connections between variables and components. Using SPSS, the researcher created this pattern matrix to detect and validate underlying patterns or latent variables in the final dataset. All loadings with absolute coefficient values below 0.30 were excluded by the researcher, resulting in 27 of the initial 42 variables being retained in the model.

Table 2B: Final Study Pattern Matrix

Pattern Matrix Study B							
	1	2	3	4	5	6	7
EU1						-0.826	
EU2						-0.674	
EU3						-0.707	
EU4						-0.590	
VO2		0.835					
VO3		0.809					
VO4		0.891					
VO5		0.828					
SI1				0.886			
SI2				0.840			
SI3				0.491			
RD1					-0.842		
RD2					-0.652		
RD3					-0.529		
JR1							0.382
JR3							0.584
JR4							0.805
UI1			0.766				
UI2			0.793				
UI4			0.822				
UI5			0.852				

UI6		0.418
PU1	0.628	
PU2	0.679	
PU3	0.785	
PU4	0.574	
PU7	0.576	

Extraction Method: Principal Component Analysis.
Rotation Method: Oblimin with Kaiser Normalization.

Rotation converged in 8 iterations.

Note:

- EU: Effective Use
- VO: Voluntariness
- SI: Social Influence
- RD: Result Demonstrability
- JR: Job Relevance
- UI: User Involvement
- PU: Perceived Usefulness

The investigator has analyzed the pattern matrix by leveraging the outcomes from the given loadings:

Effective Use (EU) represents component 6 and is associated with variables EU1 (-0.83), EU2 (-0.67), EU3 (-0.71), and EU4 (-0.59).

Voluntariness (VO) represents component 2 and is associated with variables VO2 (0.84), VO3 (0.81), VO4 (0.89), and VO5 (0.83). These variables exhibit a positive correlation with one another within this component, suggesting strong discriminant validity.

Social Influence (SI) denotes component 4 and is linked to variables SI1 (0.89), SI2 (0.84), and SI3 (0.49). These variables are positively related to each other within this component, indicating high levels of discriminant validity.

Result Demonstrability (RD) denotes component 5 and is linked to variables RD1 (-0.84), RD2 (-0.65), and RD3 (-0.53). These variables exhibit a positive correlation with one another within this component, suggesting strong discriminant validity.

Job Relevance (JR) denotes component 7 and is linked to variables JR1 (0.38), JR3 (0.58), and JR4 (0.81). These variables exhibit a positive correlation with one another within this component, suggesting strong discriminant validity.

User Involvement (UI) denotes component 3 and is linked to survey questions UI1 (0.77), UI2 (0.79), UI4 (0.82), UI5 (0.85), and UI6 (0.42). These variables exhibit a positive correlation with one another within this component, suggesting strong discriminant validity.

Perceived Usefulness (PU) denotes component 1 and is linked to variables PU1 (0.63), PU2 (0.68), PU3 (0.79), PU4 (0.57), and PU7 (0.58). These variables exhibit a positive correlation with one another within this component, suggesting strong discriminant validity.

Table 3B below shows that all constructs meet this criterion.

Table 3B: Final Study Construct Reliability

Construct Name and Reference	Item Code	Mean	Std. Deviation	Number of Responses	Alpha
Effective Use	EU1	5.91	0.830	228	0.854
Burton-Jones & Grange	EU2	5.83	0.904		
(2013)	EU3	5.97	0.902		

	EU4	5.97	0.940		
Job Relevance Venkatesh & Davis (2000)	JR1	5.81	1.031	228	.770
	JR2	6.00	0.984		
	JR3	4.46	1.703		
	JR4	5.27	1.390		
Perceived Usefulness Venkatesh & Davis (2000)	PU1	6.12	0.860	228	.910
	PU2	5.96	0.999		
	PU3	6.04	0.968		
	PU4	6.10	0.971		
	PU7	5.82	1.000		
Result Demonstrability Venkatesh & Davis (2000)	RD1	5.88	1.108	228	.768
	RD2	5.99	1.004		
	RD3	5.91	1.103		
Social Influence Venkatesh & Davis (2000)	SI1	5.14	1.505	228	.832
	SI2	5.25	1.355		
	SI3	5.61	1.399		
User Involvement Venkatesh & Davis (2000)	UI3	5.43	1.475	228	.788
	UI4	5.15	1.594		
	UI5	4.91	1.602		
	UI6	4.93	1.646		
Voluntariness Moore & Benbasat (1991)	VO2	3.52	1.918	228	.917
	VO3	3.13	1.896		
	VO4	3.46	1.934		
	VO5	3.64	1.954		

The evaluation of the reflective model starts with internal consistency reliability, which generally encompasses Cronbach's alpha and composite reliability. Cronbach's alpha also gauges internal consistency and reliability but often yields lower values compared to composite reliability. More precisely, Cronbach's alpha is a less accurate reliability measure since the items are not weighted. Conversely, composite reliability weights the items according to the individual loadings of the construct indicators, resulting in higher values than Cronbach’s alpha. While Cronbach’s alpha might be overly cautious, composite reliability could be excessively lenient, and the true reliability of the construct is generally considered to lie between these two extremes (Hair, 2019). With this in mind, both metrics are incorporated into the analysis and presented in Table 4B below.

Table 4B: Final Study Construct Reliability

Construct Name and Reference	**Cronbach's Alpha**	**Composite Reliability (ρ^a)**	**Composite Reliability (ρ^c)**	**Average variance extracted (AVE)**
Effective Use	0.854	0.860	0.901	0.696
Job Relevance	0.770	0.793	0.855	0.601
Perceived Usefulness	0.910	0.916	0.933	0.737
Result Demonstrability	0.768	0.777	0.866	0.685
Social Influence	0.832	0.852	0.899	0.749
User Involvement	0.788	0.818	0.862	0.612
Voluntariness	0.917	0.958	0.940	0.798

In terms of construct reliability, all constructs show Cronbach’s alpha and composite reliability values greater than 0.70; therefore, each one is considered valid and reliable. This indicates that the constructs are measured with a high degree of internal consistency, providing strong evidence of construct reliability and validity within the model.

Concerning convergent reliability, which is commonly demonstrated through the outer loadings of the indicators and the average variance extracted (AVE), Hair et al.

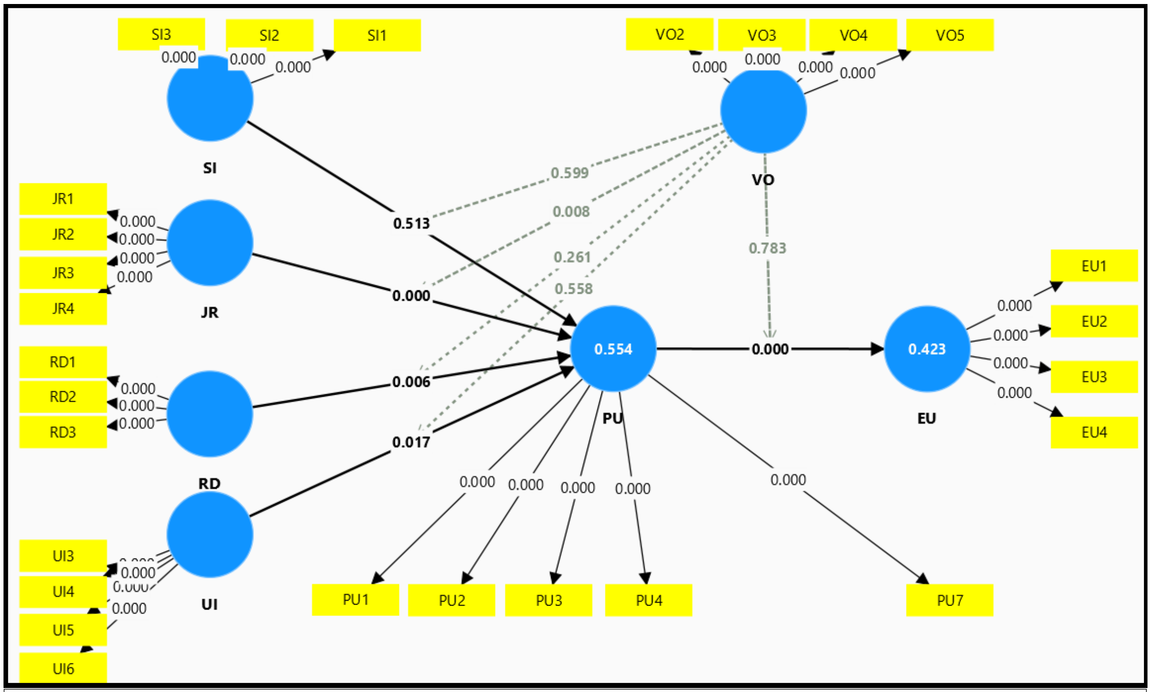
(2019) suggest that values between 0.70 and 0.90 are deemed satisfactory to strong, whereas values approaching 1.0 (e.g., 0.95) raise concerns as they indicate redundancy and undermine construct reliability. The results show that most scores are satisfactory, with Job Relevance and User Involvement below the threshold, meaning the constructs may not be accurately capturing the intended concept based on their items. However, an AVE above 0.50 is generally considered acceptable for convergent validity. Fornell and Larcker (1981) stated that if AVE is less than 0.50 but composite reliability is higher than 0.60, the convergent validity of the construct is still adequate. Finally, Result Demonstrability is close to the 0.70 threshold, with a value of 0.685.

Table 5B: Discriminant Validity

	EU	JR	PU	RD	SI	UI	VO	VO X PU	VO X JR	VO X UI	VO X RD	VO X SI
EU												
JR	0.634											
PU	0.729	0.787										
RD	0.649	0.540	0.598									
SI	0.439	0.502	0.402	0.364								
UI	0.533	0.580	0.581	0.404	0.469							
VO	0.192	0.478	0.278	0.248	0.488	0.205						
VO X PU	0.060	0.070	0.061	0.123	0.042	0.074	0.142					
VO X JR	0.133	0.212	0.036	0.163	0.042	0.088	0.058	0.575				
VO X UI	0.135	0.036	0.032	0.139	0.108	0.105	0.080	0.357	0.407			
VO X RD	0.199	0.177	0.106	0.106	0.161	0.164	0.142	0.562	0.478	0.303		
VO X SI	0.084	0.042	0.034	0.149	0.338	0.137	0.090	0.242	0.344	0.394	0.185	

Discriminant validity is another essential step in the assessment process, ensuring that each construct in the structural model is empirically distinct from others. As shown in Table 5B, all constructs have heterotrait-monotrait (HTMT) values below 0.90, with most falling under the ideal threshold of 0.85. This confirms that theoretically distinct constructs are also empirically distinguishable in the data.

In summary, the research model demonstrates strong measurement properties, including sufficient reliability (Table 3B), discriminant validity (HTMT criterion, Table 5B), and convergent validity (AVEs, Table 4B). Additionally, all items exhibit high loadings on their respective constructs (Table 2B). Consequently, the measurement portion of the model is considered robust, providing a solid foundation for analyzing the structural relationships of interest. Figure 4B illustrates the initial measurement model, displaying the loadings of exogenous, endogenous, and control variables before the removal of low-loading items.



Note:

- EU: Effective Use
- VO: Voluntariness
- SI: Social Influence
- RD: Result Demonstrability
- JR: Job Relevance
- UI: User Involvement
- PU: Perceived Usefulness

Figure 4B: Main Study with Initial loadings and Control Variables

Main Hypotheses: Study B Summary

The research analyzed the relationship between various factors, Perceived Usefulness, and Effective Use. Table 6B presents the summarized structural model, displaying loadings and path coefficients while excluding control variables. Additionally, Table 7B summarizes the hypotheses, based on the path coefficients from Table 6B, revealing that three out of the twelve relationships are supported.

Table 6B: Path Coefficients

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (│O/STDEV│)	P values
SI→ PU	0.041	0.040	0.063	0.655	0.513
JR → PU	0.521	0.516	0.083	6.256	0.000
RD→ PU	0.190	0.203	0.069	2.749	0.006
UI→ PU	0.225	0.228	0.094	2.393	0.017
VO→ EU	-0.011	-0.013	0.066	0.161	0.872
VO→ PU	0.037	0.028	0.058	0.633	0.527
VO x SI→ PU	-0.033	-0.027	0.062	0.526	0.599
VO x JR→ PU	-0.161	-0.153	0.061	2.633	0.008
VO x RD→ PU	0.097	0.109	0.086	1.124	0.261
VO x UI→ PU	0.051	0.044	0.086	0.585	0.558
PU→ EU	0.649	0.655	0.045	14.415	0.000
VO x PU→ EU	-0.023	-0.020	0.084	0.275	0.783

Note:

- EU: Effective Use
- VO: Voluntariness
- SI: Social Influence
- RD: Result Demonstrability
- JR: Job Relevance
- UI: User Involvement
- PU: Perceived Usefulness

It can be observed that Job Relevance has a meaningful impact on Perceived Usefulness, Perceived Usefulness has a meaningful influence on Effective Use, Result Demonstrability has a meaningful impact on Perceived Usefulness, and User Involvement has a meaningful impact on Perceived Usefulness. Finally, Voluntariness mediates the impact of Job Relevance on Perceived Usefulness. All other relationships do not show a meaningful effect based on their reported p-values.

Table 7B: Hypotheses Summary

Hypotheses	Description	p-value
H1B	As Social Influence increases, Perceived Usefulness increases for RPA	Not Supported
H2B	If RPA Job Relevance increases, the Perceived Usefulness of RPA will increase	Supported
H3B	If RPA Result Demonstrability increases, RPA Perceived Usefulness will increase	Supported
H4B	As User Involvement increases, Perceived RPA Usefulness will increase	Supported
H5B	Voluntariness will moderate the effect of Social Influence on Perceived Usefulness, with the effect being stronger with higher Voluntariness	Not Supported
H6B	Voluntariness will moderate the effect of Job Relevance on Perceived Usefulness, with the effect being stronger with higher Voluntariness	Supported
H7B	Voluntariness will moderate the effect of Result Demonstrability on Perceived Usefulness, with the effect being stronger with higher Voluntariness	Not Supported
H8B	Voluntariness will moderate the effect of User Involvement on Perceived Usefulness, with the effect being stronger with higher Voluntariness	Not Supported
H9B	As RPA Perceived Usefulness increases, RPA Effective Use will increase	Supported
H10B	Voluntariness will moderate the effect of RPA Perceived Usefulness on RPA Effective Use, with the effect being stronger with higher Voluntariness.	Not Supported

All hypotheses are the same as in Study A. Therefore, Hypothesis H1B sustains that Social Influence positively affects Perceived Usefulness. The results indicate no meaningful link between Social Influence and Perceived Usefulness ($b = 0.041$, $p = 0.513$).

Hypothesis H2B proposes that Job Relevance has a positive impact on Perceived Usefulness. The outcomes indicate a strong and meaningful link between the two (b =

0.521, $p < 0$), indicating that as Job Relevance increases, Perceived Usefulness also increases.

Hypothesis H3B investigated the relationship between Result Demonstrability and RPA Perceived Usefulness, revealing a significant positive effect ($b = 0.190$, $p = 0.006$).

Hypothesis H4B examined the impact of User Involvement on RPA Perceived Usefulness. The results indicate a strong and meaningful link between Social Influence and Perceived Usefulness ($b = 0.225$, $p = 0.017$).

Hypothesis H6B explored whether Voluntariness moderates the effect of Job Relevance on Perceived Usefulness, with a stronger effect under higher Voluntariness. The outcomes indicate a strong and meaningful link between Social Influence and Perceived Usefulness ($b = -0.161$, $p = 0.008$).

Hypotheses H5A, H7A, and H8A predicted a mediating effect of Voluntariness on the relationships between Social Influence, Result Demonstrability and User Involvement. The findings do not indicate a meaningful relationship between any of these variables and Voluntariness.

Hypothesis H9B analyzed the link between Perceived RPA Usefulness and Effective Use, showing a strong positive and significant relationship ($b = 0.649$, $p < 0.000$).

Finally, Hypothesis H10B assessed whether Voluntariness moderates the relationship between Perceived Usefulness and Effective Usefulness. The results show no significant moderating effect ($b = -0.023$, $p = 0.783$).

In sum, Study B supports the influence of Result Demonstrability, Job Relevance, and User Involvement on Perceived Usefulness, as well as the moderating role of Voluntariness in the Job Relevance–Perceived Usefulness relationship. Additionally, it confirms the role of Perceived Usefulness in driving Effective Use in RPA implementations. However, the study could not show an empirical support for Social Influence positively affecting Perceived Usefulness, nor for Voluntariness mediating any relationships except for the Job Relevance–Perceived Usefulness link.

The absence of empirical support for Social Influence and the mediating role of Voluntariness may stem from contextual variations, measurement challenges, and study limitations. These findings highlight the need for further research to better understand the complexities of RPA implementations and the specific conditions under which these factors shape Perceived Usefulness and the role of Voluntariness in these relationships.

VI. SUMMARY AND OUTCOMES

The present research sought to explore the key factors driving increased Effective Use of RPA implementations. Its contribution to academic knowledge enhances the understanding of RPA by emphasizing the link between Perceived Usefulness and Effective Use, as well as the positive impact of Job Relevance and Result Demonstrability on Perceived Usefulness in this context. It also identifies Voluntariness as a moderator of the Job Relevance–Perceived Usefulness relationship.

These findings empower developers, project managers, and companies in general to approach RPA implementations with a stronger perspective, emphasizing the critical importance of concrete and beneficial outcomes of the projects, as well as highlighting the practical benefits and applicability that a bot can have on the tasks performed in the organization. By taking these steps, organizations can improve Perceived Usefulness and Effective Use, leading to more effective project execution and an RPA implementation that delivers real value to both employees and the company.

This research provides meaningful insights for professionals and academics striving to enhance RPA adoption strategies. Future studies can build upon these findings by investigating other elements that impact the successful utilization of RPA systems.

Practical Implications

A key theoretical implication is clarifying the role of Job Relevance in reinforcing Perceived Usefulness in RPA implementations. As Hypotheses 2A and 2B (H2A and H2B) confirm, this research is consistent with other studies that underscored the importance of Job Relevance in Perceived Usefulness, even in RPA contexts (Wewerka et al., 2017).

The studies conclude that the hypothesized influence of Job Relevance on Perceived Usefulness is empirically supported, which aligns with the Technology Acceptance Model (TAM) literature. This indicates that the Perceived Usefulness of RPA increases when the RPA bot is utilized for frequently recurring or time-consuming tasks. Specifically, the findings suggest that if employees feel their workload is significantly alleviated by RPA bots, they are more likely to perceive these tools as useful in their work context.

The findings also suggest that enhancing the relevance of RPA systems to users' specific job functions can lead to higher Perceived Usefulness, thereby increasing the likelihood of successful adoption and effective utilization. This aligns with findings from small accounting firms in Taiwan by Hsiung and Wuan (2022).

Furthermore, the practical implications extend to Result Demonstrability, as posited in Hypotheses 3A and 3B (H3A and H3B). This means that when users can clearly see and understand the tangible benefits and outcomes of using the RPA bot, they are more likely to perceive it as useful. The ability to demonstrate results effectively reinforces users' beliefs in the system's value, which aligns with the principles of the Technology Acceptance Model (TAM).

Consequently, enhancing the visibility of the results generated by the RPA system can lead to increased Perceived Usefulness, fostering greater acceptance and usage among users in large firms. Conversely, if users cannot trace efficiency improvements back to the use of RPA, they are less likely to recognize its usefulness and, consequently, may not accept it.

The study's findings align with research showing that employees frequently cite tangible time-related advantages as a primary reason for accepting RPA systems (Juntunen, 2018). The concept of Result Demonstrability can be traced back to TAM2, which states that when users can clearly link system outputs to their goals or organizational benefits, they are more likely to perceive the technology as useful (Venkatesh & Davis, 2000).

Organizations can benefit from this practical insight by highlighting the benefits that employees have gained from RPA implementations and ensuring these benefits are meaningful and relevant for their workers.

Additionally, this study advances the implications related to the Perceived Usefulness and Effective Use relationship, as supported by Hypotheses 9A and 9B (H9A and H9B). This relationship has been established for some time but without a direct conceptual impact. In fact, while Perceived Usefulness can influence a user's motivation to engage with a system, Effective Use is about how that engagement translates into actual performance outcomes (Burton-Jones & Granger, 2013).

Thus, understanding both constructs is essential for improving user interaction with information systems and achieving desired results. The study reiterates their theoretical significance and establishes a direct and strong positive relationship between them. This is consistent with concepts detailed in Wewerka’s work (Wewerka et al., 2020), whose study discusses the importance of user-friendly design and communication between RPA bots and users, which are critical for ensuring Effective Use.

Hypothesis 4A (H4A) postulated that User Involvement has a positive impact on Perceived Usefulness but failed to attain empirical support. Although it was hypothesized that users who are involved in clarifying automation needs and testing RPA bots would better understand the technology's usefulness, this effect was not empirically supported in the sample group. The findings suggest that simply being involved in the design and testing processes does not necessarily lead to a higher perception of usefulness regarding RPA. There is at least one precedent in which this relationship was also not meaningful (Wewerka et al., 2020), which might point to an interesting direction for further research, as it could indicate a significant deviation from the traditional TAM2 path. However, when restricting the answers only to those who declared having experience with RPA, the findings validate Hypothesis 4B (H4B). That implies that respondents involved in the RPA design process perceive higher usefulness. This result, compared to its equivalent in Study A, becomes relevant as it highlights the difference between respondents who are familiar with the technology and those who are not.

Hypothesis 1 (H1) centered on the notion that Social Influence positively impacts Perceived Usefulness but did not receive empirical validation. This hypothesis would have indicated that the perceptions of colleagues and management regarding RPA significantly affect an individual's view of its usefulness. Specifically, if employees observe that their peers consider RPA beneficial and useful, they are more likely to adopt a similar view, thereby increasing their own perceived usefulness of the technology.

While Social Influence is a fundamental component of TAM models (Venkatesh et al., 2000, 2003), this result implies that it may not directly impact Perceived Usefulness in the context of RPA implementations. Therefore, it is possible to sustain that Perceived Usefulness could be influenced by a wider range of factors, including some that were not specifically analyzed in this study.

The unsupported hypotheses offer significant theoretical contributions by underscoring the complexity of Perceived Usefulness in RPA implementation contexts. They reveal that Perceived Usefulness is shaped by a variety of factors, some of which may not have straightforward or linear connections. This perspective broadens the understanding of Perceived Usefulness, suggesting that its influences might extend beyond the traditional constructs of TAM. Future research can expand on these findings by exploring the complex interactions between these factors and their collective impact on the success of RPA implementations.

Hypotheses 7A and 7B (H7A and H7B), 8A and 8B (H8A and H8B), and 10A and 10B (H10A and H10B) showed no empirical support in this study. However, they remain valuable for understanding the role that Voluntariness could have on RPA implementations. Although these hypotheses did not demonstrate a moderating role between the analyzed factors and Perceived Usefulness, their theoretical meaning lies in introducing the potential role of Voluntariness in an environment that ranges from fully volitional to mandatory. This outcome aligns with prior research, which highlights the complexity and challenges that technology adoption might face in mandatory settings (Rawstorne et al., 1998). Acknowledging this factor in RPA implementations opens new paths for understanding Perceived Usefulness and Effective Use in an organizational environment.

On the other hand, Hypotheses 6A and 6B (H6A and H6B) were validated. This means that in both populations, Voluntariness has a mediating effect on the relationship between Job Relevance and Perceived Usefulness. The original hypotheses were shaped by speculating that Voluntariness might moderate some of the existing relationships, as discussed by Hartwick and Barki (1994) and even Venkatesh and Davis (2000). In their studies, they concluded that there are significant differences in the relationships among model variables due to the moderating effects of users' perceived Voluntariness. However, this research could not provide a theoretical argument to support this hypothesis, which was simply tested for completion purposes. This unexpected result shows that more research would be necessary to conceptually support this result

Discussion of Theoretical and Practical Implications

The successful completion of this study has provided several significant contributions, advancing the understanding of Robotic Process Automation (RPA) Effective Use. The findings have confirmed and expanded upon the proposed objectives, yielding insights that are both academically rigorous and practically valuable.

The first contribution is the development of an RPA Effective Use Model. The research has successfully identified and weighted the critical factors influencing RPA Effective Use among its primary users and stakeholders. The development of a theoretical model provides a comprehensive framework for understanding the variables driving RPA utilization and the challenges associated with it. This model not only deepens the academic understanding of RPA but also serves as a foundational tool for practitioners to optimize their RPA implementations. The study demonstrates how the underutilization of future RPA bots can be mitigated and the adoption rates of existing bots significantly enhanced, thus contributing to more successful and impactful RPA initiatives.

A second contribution is the integration of the TAM/UTAUT model and Effective Use constructs. By applying the Unified Theory of Acceptance and Use of Technology (TAM/UTAUT) model to RPA implementations, this research enriches the existing literature on technology adoption. Furthermore, the innovative linkage of TAM/UTAUT to the Effective Use construct proposed by Burton-Jones and Granger offers a new perspective on how theoretical frameworks can intersect to provide a more holistic understanding of technology utilization in large organizations. This integration not only advances the theoretical discourse but also bridges gaps between existing models, contributing to the evolution of technology acceptance theories.

Along the same lines, this study incorporates the Voluntariness variable as a moderator for the traditional Technology Acceptance Model in this specific context. Although most moderating effects could not be proven, at least the relationship between Job Relevance and Perceived Usefulness is significantly moderated by Voluntariness. This opens new avenues of research, understanding that there might be better ways to model this moderating effect, as discussed in the following sections.

Thirdly, this study contributes to answering the dilemma originally posed in this document on whether technology that jeopardizes people's jobs causes a negative or positive reaction. A final answer is clearly beyond the scope of this study, but it has been proven that, at the very least, it can be modeled and that certain factors increase a more favorable reaction from workers.

The study also contributes to interdisciplinary research. It has shed light on interdisciplinary subjects, such as critical success factors in IT implementation, the interplay between technology and the workplace, and the psychological dimensions of technology adoption. These insights are particularly valuable in understanding how RPA impacts employees and organizational dynamics, providing a foundation for further exploration in these areas.

Another salient element the study provides is its contribution to quantitative RPA literature. From an academic perspective, this research contributes to the limited body of quantitative studies on RPA implementations. By focusing on organizations across various industries, the findings are broadly applicable and offer a robust basis for future research. The study confirms the relevance of specific factors regardless of the organizational context, demonstrating the potential for the universal application of the RPA Effective Use model. This generalizability strengthens the study's theoretical impact and broadens its utility for researchers and practitioners alike.

Finally, the study has also established a roadmap for future research by identifying gaps in the current literature and proposing new areas for investigation. The dynamic and rapidly evolving nature of RPA calls for ongoing academic inquiry, and this research serves as a catalyst for subsequent studies. By providing a clear understanding of the factors that enhance employee acceptance and utilization of RPA, this study encourages the development of new methodologies and applications tailored to the needs of modern organizations.

In conclusion, this study has made meaningful contributions to the theoretical and practical understanding of RPA Effective Use. It bridges critical gaps in the literature, integrates established frameworks with innovative constructs, and sets the stage for future research and application. By doing so, it not only enriches academic discourse but also equips managers and organizations with the tools to implement more efficient and reliable RPA projects, ultimately benefiting employees, supervisors, and institutions.

Limitations and Avenues for Future Research

Study A yielded a robust sample size of 304 respondents after filtering out incomplete submissions and outliers based on survey completion time. Increasing the respondent count could strengthen the reliability of the research findings. This becomes more evident when at least one of the conclusions can only be applied to the 227 respondents of Study B. This method is consistent with established empirical research practices, as increasing the sample size and diversity enhances statistical power and improves the generalizability of findings (Bryman, 2016). A larger dataset minimizes errors and increases the likelihood of identifying true effects and relationships among the variables studied (Creswell & Creswell, 2017). Furthermore, expanding the respondent pool allows for a more comprehensive analysis of the complex dynamics affecting project manager situational awareness and its various determinants, leading to a deeper and more nuanced understanding of the phenomena under investigation. A larger sample size strengthens the study's overall reliability and the credibility of its empirical conclusions (Hox & Boeije, 2005).

An obvious and significant limitation of this study is the fact that every RPA implementation is different, being used for a wide range of problems. This means that an RPA implementation or bot might mean something very different to different people. Even if two individuals worked for the same organization and were familiar with the same RPA implementation, their perception of the bot could vary significantly depending on the specific role they play. Keeping this in mind, it is possible that the wide range of RPA understanding and perception among the survey respondents is measuring very different things. On the other hand, this approach allowed the study to outline more general conclusions about RPA implementations and their Effective Use, as opposed to the few available company-specific studies.

The Voluntariness-as-moderator hypotheses were mostly unsupported by the study, except for the case of Job Relevance and Perceived Usefulness. In retrospect, the study considered Voluntariness as a continuous variable, although measured by a 1-through-5 Likert scale. A different way to measure Voluntariness could have been as a binary variable: the respondent considers it voluntary or not. This could have produced different outcomes. Future research should consider this approach when modeling volitional impact as a moderator.

Another limitation is that this study was conducted within the United States of America and therefore provides a uniquely local perspective. Several other studies are conducted abroad, limiting their applicability to the U.S. market. Similarly, the findings from this U.S.-based research may not accurately represent the perspectives of other global markets.

To gain insights into the specific experiences of RPA implementations, participants were asked whether RPA bots had been used at their companies or if they had personally interacted with them. Despite the survey specifically requesting RPA exposure before beginning to answer, 32 out of the 304 respondents in Study A declared that RPA implementations were not used at their organizations and that they had not personally interacted with them. It is reasonable to assume that most of these respondents were perhaps not qualified to complete the survey. Out of curiosity, this research analyzed the same hypotheses for the reduced sample of Study B, obtaining similar results. In retrospect, a stricter method for filtering respondents with no or limited RPA experience should be considered when surveying.

In terms of the long-term usefulness of this study, it is important to acknowledge that while RPA remains a valuable tool, artificial intelligence (AI) is making progress as an alternative. Nicola & Dalessio (2019) established that AI is enhancing efficiency and productivity in areas such as manufacturing, energy management, urban transportation, agricultural production, labor markets, and financial management. It is also impacting organizational structure by changing organizational structures, facilitating cross-functional cooperation, and improving decision-making processes. Although RPA and AI serve different roles, tasks previously performed by RPA bots may be better handled by AI. At the same time, in specific situations, the boundary between RPA and AI becomes blurred, and in many cases, they cooperate to solve specific requests. As RPA and AI increasingly converge, research should address critical questions about organizational readiness, workforce impact, and, most importantly, Effective Use. Through empirical studies and case analyses, research should shed light on successful implementation frameworks and highlight how companies can transition from static automation to adaptive, intelligent systems. Given these rapid advancements, it remains uncertain how useful this study will be for organizations in the mid-term. Future research might build on this study and explore which methodologies and conclusions could be adapted for RPA and AI mixed implementations.

VII. CONCLUSIONS

This study aimed to develop a meaningful conceptual and theoretical approach to determining the factors that could lead to increased RPA Effective Use. Additionally, this study can serve as a baseline conceptual model for developing a framework linking constructs such as Perceived Usefulness and Effective Use to help firms better understand and measure their use of technology in the organization.

Utilizing CFA, EFA, and regression analysis, the researcher concluded that some constructs were proven to have a positive relationship with the Perceived Usefulness of RPA implementations and that this variable has a positive relationship with Effective Use. As today’s firms scramble to adopt RPA bots, having a solid understanding of the drivers for RPA Effective Use could present an opportunity for the monetization of this research for financial gain.

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APPENDICES

Measurements

Filtering and Background Items

DM0	Does your organization have Robotic Process Automation implementations (also called bots) (a) Yes (b) No
DM1	What is your age?* (a) 20–29 (b) 30–39 (c) 40–40 (d) 50–50 (e) 60–69 (f) 70+
DM2	What is your gender?* (a) Male (b) Female (c) Non-binary
DM3	Where do you live, select a country from the list*:
DM4	What is your income level?* (a) $0–$24,999 (b) $25,000–$49,999 (c) $50,000–$74,999 (d) $75,000–$99,999 (e) $100,000+ Prefer not to answer
DM5	At your job, RPA has been*:

	(a) Used in my company, and I have personally interacted with it. (b) Used in my company and, but I have not personally interacted with it. (c) Not used in my company, and I have not personally interacted with it.
DM6	You have interacted with RPA as (please check all that apply)*: (a) A business user, once implemented (b) A business user, during the design phase (c) A technical or IT role (d) A project manager (e) Business leader not directly involved in the implementation or daily use (f) Other
DM7	What is your highest completed level of education?* (a) No formal education (b) High School/GED (c) Associate degree (d) Bachelor's degree (e) Master's degree (f) Doctorate degree
DM8	Below you will find several of the most common RPA areas of application. Please select which of them you participate in or have participated in. Please check as many as necessary. * (a) **Invoice Processing**: Automation of the process of payment (b) **Sales Orders**: Automating tasks such as sales order entry, invoicing, etc. (c) **Payroll**: Automation of payroll-related transactions (d) **Procurement**: Price comparisons, contract compliance, and others (e) **Customer Service**: Answering questions from customers or segregating queries into different categories for a faster resolution. (f) **Other (please specify)**
DM9	Please consider the areas of application that you selected in the previous questions as the ones that you are or have participated in and now rank them in terms of usefulness*: (a) **Invoice Processing** (b) **Sales Orders** (c) **Payroll** (d) **Procurement** (e) **Customer Service** (f) **Other**

DM10	The number of people working at my organization is approximately: (a) **1–10** (b) **11–50** (c) **51–250** (d) **251 or more**

Demographics

DM1	What is your age?*
DM2	What is your gender?*
DM3	Where do you live, select a country from the list*:
DM4	What is your income level?*
DM5	At your job, RPA has been*:
DM6	You have interacted with RPA as (please check all that apply)*:
DM7	What is your highest completed level of education?*
DM8	Below you will find several of the most common RPA areas of application. Please select which of them you participate in or have participated in. Please check as many as necessary.*
DM9	Please consider the areas of application that you selected in the previous questions as the ones that you are or have participated in, and now rank them in terms of usefulness.*

Social Influence

(Five-point Likert scale, ranging from "strongly disagree" to "strongly agree")

SI1	People who influence my behavior think that I should use RPA bots.
SI2	People who are important to me recommend me to use RPA bots.
SI3	The management has advised me to use RPA bots.

<u>Job Relevance</u>

(Five-point Likert scale, ranging from "strongly disagree" to "strongly agree")

JR1	In my job, the usage of RPA is high.
JR2	In my job, the usage of RPA is relevant.
JR3	My workload could hardly be handled without RPA bots.

<u>Result Demonstrability</u>

(Five -point Likert scale, ranging from "strongly disagree" to "strongly agree")

RD1	I have no difficulty telling others about the results of using RPA bots.
RD2	The results of using RPA bots are comprehensible to me.
RD3	I have no difficulty explaining why using RPA bots may or may not be beneficial.

<u>User Involvement</u>

(Five-point Likert scale, ranging from "strongly disagree" to "strongly agree")

UI1	I (or the user group) was involved in the explanation and clarification of the automation needs and objectives.

UI2	I (or the user group) was heavily involved in testing RPA bots.
UI3	Prior to the implementation, I was informed about new possibilities the automation creates for me.

__Perceived Usefulness__

(Five-point Likert scale, ranging from "strongly disagree" to "strongly agree")

PU1	Using RPA in my job would enable me to accomplish tasks more quickly.
PU2	Using RPA would improve my job performance.
PU3	Using RPA in my job would increase my productivity.
PU4	Overall, I find RPA useful to do my job.

__Effective Use__

(Five-point Likert scale, ranging from "strongly disagree" to "strongly agree")

EU1	Our RPA works well for us.
EU2	Our RPA does all that we need it to do.
EU3	Our RPA accomplishes what it does accurately.
EU4	Our RPA makes me work more efficiently.
EU5	The outputs of our RPA have become integrated and necessary to my work.

__Voluntariness__

(Four-point Likert scale, ranging from "strongly disagree" to "strongly agree")

VO1	My superiors expect me to use RPA.
VO2	The use of RPA is voluntary (as opposed to being required by my superiors/professors/job or program description).
VO3	My boss does not require me to use RPA.
VO4	Although it might be helpful, using RPA is certainly not compulsory in my job.

*Indicates a question written by the researcher.

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