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Adoption Of Robotic Process Automation (RPA) And Its Effect On Business Value: An Internal Auditors Perspective

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Abstract

Organizations can adapt and use RPA to automate the manual tasks associated with their financial process. The ability to automate manual tasks influences the business value, but there are few studies on the association between adopting RPA and business value. This research investigates the effects of technology-organizational-environmental (TOE) factors on adopting RPA and business value in industrial countries. This study employed the TOE framework as a determinant affecting the adoption of RPA and business value. Using the targeting audiences method, the sample was determined. The data collection strategy used an online survey with internal auditors. The survey was automatically introduced to respondents who were most likely to find it relevant, followed by adding a filter within the survey to increase the accuracy of the target sample for the field of study. The data were analyzed using SEM. The findings revealed a direct positive relationship between TOE constructs, the adoption of RPA, and business value. Furthermore, a significant favorable influence was found between RPA adoption and business value. The adoption of RPA in internal audits is driven more by organizational factors than technological and environmental factors, despite their importance and significance in the model. This study has implications for practitioners and researchers interested in investigating RPA adoption. It builds an empirical model, including several determinants that may influence the adoption of RPA, in addition to the RPA adoption effect on business value from an internal auditors perspective.

Keywords: Automation, Internal Audit, Adoption, Robotic, Business Value, Vision.

1. Introduction

This is the advent of the automation era, which signals the coming of new opportunities for integrating cutting-edge technology into internal audit operations. Internal audit departments of all sizes are introducing RPA into their operations by expanding their use of traditional analytics to include RPA. According to Kokina and Blanchette (2019), RPA results in improved quality, risk mitigation, and time savings—not to mention a better awareness of risks.RPA is the robotic automation of portions of repeatable processes using rules-based systems that mimic human behavior (Aguirre & Rodriguez, 2017). According to Gartner, "RPA tools perform [if, then, else] statements on structured data, typically using a combination of user interface interactions, or by connecting to APIs to drive client servers, mainframes or HTML code. An RPA tool works by mapping a process in the RPA tool language for the software robot to follow, with a control dashboard assigning runtime to execute the script (Kerremans, 2018). RPA is an umbrella term that refers to tools that interact with other computer systems' user interfaces as a human would. People can be replaced by machines programmed from the outside using RPA. This is more effective than the usual "inside-out" approach to information system improvement. In comparison to traditional workflow technology, the information system stays unaltered (Tornbohm & Dunie, 2017; Van der Aalst, Bichler, & Heinzl, 2018). RPA solutions are being used to repeatedly help workers who do the same things (Aguirre & Rodriguez, 2017; Van der Aalst et al., 2018). Internal auditors are recommended to utilize RPA to conduct internal audits (Furtună & Ciucioi, 2019). Therefore, internal auditors automate many activities and anticipate their usefulness will grow in their organizations (Eulerich, Pawlowski, Waddoups, & Wood, 2021). Nevertheless, RPA is not widely used by firms (Maroufkhani, Iranmanesh, & Ghobakhloo, 2022) because of the lack of clarity on its effects on business organizations. This study aims to determine the factors influencing RPA adoption and its impact on a business's value. While little research has been conducted on how RPA affects a business's value, just a few are comparable to the current study. These efforts are expected to better understandwhat drives RPA adoption and how it might boost business value (Maroufkhani et al., 2022; Rutaganda, Bergstrom, Jayashekhar, Jayasinghe, & Ahmed, 2017). To provide more recent insights into how RPA adoption may boost the business's value. As a result, the TOE framework includes new factors such as digital vision, strategy an d business value. Due to businesses' low acceptance of automation processes, it is evident that studying the factors that impact an organization's adoption of RPA is vital, particular the digital vision and strategy factors. Therefore, this study aims to understand why organizations adopt RPA in their processes and its impact on business value. As a result, the adoption of RPA by businesses will be looked at in three ways: the technological context, the organizational context, and the environmental context. These three areas will be examined, emphasizing how they affect the RPA adoption and business value. The presence of automation and RPA in today's organizations has started growing. RPA has become a part of productivity programs. However, for RPA to improve business value, it must be adopted and used by organizations. Explaining organizations' adoption of new technology is often described as one of the most mature research areas in the modern information systems (IS) literature (e.g., Hu et al. 1999).

2 Literature Review

2. TOE framework

Diverse studies employ a variety of contextually relevant factors. There is no templet of elements in the TOE framework. Therefore, certain studies extend the framework to accomplish their goals, consistent with most models and theories (Cho, Cheon, Jun, & Lee, 2021; Ganguly, 2022). However, in the context of this study, this deficiency can be viewed as a strength rather than a weakness. Despite multiple flaws identified by numerous academics, the TOE Framework enables the research and interpretation of adoption variables. It gives credibility and reliability to previous studies that came to the same conclusions based on legitimate scientific data, as shown above. Numerous factors can impact the adoption of existing or emerging organization-relevant technologies depending on the technical environment. The TOE framework defines the organizational context for adoption via the lens of organizational elements that either impede or facilitate the implementation of technological innovation. The TOE environment places the organization in the scenario in which its task is performed. Additionally, the environmental context, such as the organizational setting, might create constraints or opportunities that influence the adoption of technological developments (Bhatiasevi & Naglis, 2020; Y.-M. Wang et al., 2010). That is why the current study is going to look at how organizations from three perspectives use RPA: the technological context (compatibility and perceived uncertainty), the organizational context (vision and strategy, technology readiness, management support), and the environmental context (competitive pressure and vendor support), with an emphasis on the business value.

2.1 Technology context

2.1.1 Compatibility

Rogers (2003) defines "compatibility" as the degree to which an invention is valued to conform to the current values, requirements, and experiences of prospective adopters (Rogers 2003). In this sense, technical compatibility refers to an ongoing dynamic process that involves a continuous cycle of development and modernization until a state of compatibility between the planned technology and the existing technological environment is achieved. Several previous studies have examined the organizational and environmental influences on the adoption of computer-assisted audit tools and techniques (Siew, Rosli, & Yeow, 2020), the adoption of information technology by internal auditors in the public sector (Ahmi, Saidin, & Abdullah, 2014), and

the use and adoption of RPA in SMEs (Kumar & Kalse, 2021). Furthermore, high compatibility enables the acceptance of innovation (Al-Jabri & Sohail, 2012). Therefore, organizations will be more willing to utilize RPA if they believe it meets and fits all of their work requirements and meets the needs of innovation. As a result, this study proposes that compatibility will benefit the intention to use RPA. Thus, the study suggests suggest sowing hypothesis:
H1 Compatibility has a positive influence on RPA adoption.

2.1.2. IT Infrastructure
Comuzzi and Patel (2016) define "IT infrastructure" as the maturity of an organization's technological processes that govern, store, manage, and extract knowledge. Establishing a foundational infrastructure for RPA capabilities to facilitate effective implementation, ongoing maintenance, and risk mitigation strategy is vital. As a result, the operational and governance frameworks must be consistent with the organization's enterprise standards and leading practices. According to Ndou (2004), enhanced governanccontrolmanagement, continuous testing and monitoring, exception handling and processing, skill sets, and training are all critical components of this infrastructure. Many studies have shown that IT adoption is more successful when the foundational infrastructure is in place. Because RPA can be used to do many different things in an organization, internal auditing needs and the need to take advantage of technological opportunities with the RPA focus in internal auditing are very important. While some studies have discovered a relationship between IT infrastructure and RPA adoption (Hameed, Counsell, & Swift, 2012; Singh, Singh, & Nalwa, 2017), others have discovered no such relationship (Salah, Yusof, & Mohamed, 2021). In the study, it is thought that the foundational infrastructure of businesses will positively affect how likely they are to use RPA. The following hypothesis has been developed as a result of this discussion:
H2. IT Infrastructure has a positive influence on RPA adoption.

2.1.3. Technology Readiness
Technology readiness refers to the degree to which technological infrastructure and human resources influence the adoption of new technology(Low, Chen, & Wu, 2011). For instance, the techtechnicalrastructure comprises installed, software, network technologies, and resources necessary for operating RPA within audit firms. On the other hand, human resources refer to the availability of IT/IS knowledge and abilities of an organization's personnel to install, run, and manage RPA (Amini & Bakri, 2015). Numerous studies on IT adoption have demonstrated the role of technology readiness in adopting RPA (Jaradat, Ababneh, Faqih, & Nusairat, 2020; Parra, Talero-Sarmiento, Ortiz, & Guerrero, 2021; Priambodo, Sasmoko, Abdinagoro, & Bandur, 2021 The following hypothesis has been developed as a result of this discussion:
H3. Technology readiness has a positive influence on the RPA adoption

2.2. Organization context

2.2.1. Top Management support
Shao, Feng, and Hu (2016) argue that management support is critical for technology adoption because top management makes essential decisions for all types of organizations. According to some researchers, the top management's role in the adoption process is vital and should not be overlooked. The top management's role is to provide support, direction, and leadership to ensure that the facility's technological environment completes the work. Hsu, Liu, Tsou, and Chen (2019) previously demonstrated a positive relationship between management support and technology adoption. Support from management and team managers results in a productive and technologically advanced work environment (Thomas & Bostrom, 2010). According to the findings of this study, organizations are more likely to adopt RPA if senior management and the technology adoption top management provide direction and take the initiative to overcome barriers to technology adoption. In addition, management involvement is expected to have a positive effect on internal audit technology. Thus, organizations' readiness will positively affect their intentions to adopt RPA. The following hypothesis has been developed as a result of this discussion:
H4. Management support has a positive influence on RPA adoption.

2.2.2. Digital Vision

The vision articulates what decision-makers hope to accomplish in the future due to their anticipated accomplishments. Academics have argued for nearly three decades that vision is necessary for effective leadership, strategy implementation, and organizational change. According to Kenneth Leithwood and colleagues (Thomas & Bostrom, 2010), the vision-creation process should form a fundamental and an ambitious sense of purpose that will be pursued over an extended period. As Flechsig, Anslinger, and Lasch (2021) state, leaders should assess their organizations' current state of RPA to determine where and how RPA technologies can be embedded, as well as to identify reasons for doing IT differently. To begin a technology adoption journey, It is critical to start with a vision. According to some research, there is a relationship between vision and technology adoption (Balasubramanian, 2012; Tajudeen, Jaafar, & Sulaiman, 2019). In addition, previous research shows that a clear vision for digitalization can help organizations innovate more effectively (Niemand, Rigtering, Kallmünzer, Kraus, & Matijas, 2017). However, this relationship has not been empirically tested in the context of internal auditing RPA (Niemand et al., 2017). Therefore, this study believes that the vision will positively affect the intention of RPA adoption. The following hypothesis has been developed as a result of this discussion:

H5. Digitalization vision has a positive influence on RPA adoption.

2.3.3. Strategy

According to Cook, Inayatullah, Burgman, Sutherland, and Wintle (2014), a plan helps a business move forward. According to Wang, Wang, Li, and Shi (2019), leaders should meet the strategy's requirements on time. A company's RPA plan may involve a single application or a complete transformation. While alignment and automation of internal audits are essential (Coderre, 2009; Zhang, 2019), firms may immediately focus on automating a single audit or procedure. The implementation team is recommended to start small and prioritize the most practical automation projects. Initial efforts are advised to focus on one or two objective areas that bring clear and concrete benefits to the organization. Organizations pursuing automation adoption through a data extraction process (Wenig & Anita Kim-Reinartz, 2011) to provide standardized information for use in multiple processes or audits are examples, as are organizations pursuing operational activities such as time tracking, board reporting, or certification management. Sin, Tavares, and Cardoso (2019) say firms should start with a transformation strategy to realize automation's benefits. According to studies, strategy and tech adoption are related (López-López & Giusti, 2020). Granlund and Wiktorsson (2014) say companies lack vision and strategy. No empirical studies have been done on RPA for internal auditing strategy. The study's findings suggest that the strategy will encourage RPA implementation. This conversation produced the following hypothesis:

H6. The strategy has a positive influence on RPA adoption.

2.4. Environment context

2.4.1 Competitive pressure

Competitive pressure on an organization causes it to become more similar to other organizations in the same industry, resulting in the development of simulation pressures due to this pressure (Zhuang & Yang, 2008). This process occurs by copying competitors who have successfully adopted or duplicating an innovation's adoption by a competitor in the same industry. According to this logic, the corporation may implement the planned technology to maintain its competitive edge and retain existing customers while attracting new ones. Previous research has established that competitive pressure affects technology adoption (Ahani, Rahim, & Nilashi, 2017). According to this theoretical logic and prior research, pressure from competitors operating in a similar business environment will influence an organization's intention to incorporate RPA into its operations. As a result, the researchers believe that organizations' competitive pressure will benefit their intentions to adopt RPA. The following hypothesis has been developed as a result of this discussion:

H7. Competitive pressure has a positive influence on RPA adoption.

2.4.2 Vendor support

Rogers (2003) refers to technology vendors' role in promoting new technology adoption. Vendor support can come in the form of vendors or consultants. This assistance includes training, installation, maintenance, and updates (Chatzoglou & Chatzoudes, 2017). Earlier research, such as that conducted by Bhatiasevi and Naglis (2020), established the critical importance of vendor support for successfully implementing and maintaining technology. Recognizing that they will require both short- and long-term assistance from the technology provider is essential to new technology adoption (Bruque & Moyano, 2007). Supplier support safeguards the intended technology against the negative consequences of a lack of support, such as the loss of training, implementation, maintenance, or modernization resources. A growing body of evidence demonstrates that suppliers who offer minor support for their products are less popular than those who provides the most support (Bhatiasevi & Naglis, 2020). As a result, the researchers believe that organizations' competitive pressure will benefit their intentions to adopt RPA. The following hypothesis has been proposed and tested as a result of this discussion:

H8. Vendor support has a positive influence on RPA adoption.

2.5. Impact of RPA adoption on Business value

Numerous factors influence the impact of technology adoption. The most critical factor to consider is the compatibility of information technology with business processes, organizational structure, and strategy. RPA adds value to internal auditing. Internal audit departments can leverage their knowledge of RPA to identify opportunities to embed automation-enabled controls within the business and apply RPA to their audit processes, according to Huang and Vasarhelyi (2019). RPA can add value to an organization through risk sampling. Data samples are frequently selected when conducting an audit because manually testing the entire population of large data sets on a single occasion is impractical. Since internal auditors manually try only a small percentage of control executions, they must choose samples that are representative of the population to be effective. Internal audit can expand audit coverage by examining entire populations of data rather than sampling, and management can have greater confidence in the design and operation of controls as a result of automated testing. According to Huang and Vasarhelyi (2019), RPA can add value to an organization through audit frequency. Due to internal audit departments' risk-based approach (as well as the time-sensitive nature of some internal audit work), not all business areas will be audited annually, and in some cases, only once every two or three years, depending on the circumstances. By implementing RPA, organizations can increase the testing frequency and, in many cases, transition to a continuous auditing model, enabling them to provide more timely insights to the business. According to Devarajan (2018), the annual risk assessment is a one-way RPA that adds value to the organization. Many internal audit departments continue to use the traditional method of conducting a yearly risk assessment before developing a yearly audit plan. This entails collecting data points from each audit area and assigning each data point a risk-based score. This can be lengthy, as it requires collecting data from each audit area across the enterprise. RPA enables the tracking of progress against the annual audit plan and the tracking and monitoring of key risk indicators (KRIs) that are considered when performing the annual risk assessment for the audit. As agile auditing becomes more widely adopted, using RPA to create a continuous monitoring and auditing program based on this model will add value to the organization. According to Eulerich, Masli, Pickerd, and Wood (2019), RPA adds value to an organization by facilitating the audit committee's reporting. The reporting process consumes a substantial amount of time for audit management. The chief audit executive (CAE) forwards audit reports to the audit committee for consideration. Traditional reports are lengthy and protracted, requiring considerable time to write and edit. RPA may enable the automation of reporting and dashboarding activities, as well as the populating of the audit committee and management report templates (RPA). As technology improves, it is expected that the business's value will rise simultaneously. This will allow for proactive reporting and insights. Therefore, this study believes that the RPA adoption in organizations will positively affect the business value.

H9. RPA adoption has a positive influence on business value.

3 Research methodology

3.1 Measurement of the factors

As previously stated, the TOE framework established the instrument's reliability and validity owing to the framework's versatility and widespread use in various studies. Additionally, the TOE framework showed the reliability and validity of the instrument. This study combines the TOE framework and Business value to create a comprehensive model. The current study used eight components when developing the TOE framework; however, it used only one construct when setting the business value. A variety of different items were prepared for measurement of the Business value. Items from previous research scales were modified to create a 7-point Likert scale ranging from "strongly disagree" to "strongly agree," with "strongly disagree" being the most extreme. The researchers arranged the items in the form of a targeted online survey.

3.2 Sampling

No sampling frame holding respondent information is suitable for the study's objectives. However, technological advancement enabled target responders who fit the study's objectives (Stokes, Vandyk, Squires, Jacob, & Gifford, 2019). Facebook has the most significant users, the most extensive global reach, the fewest subscription panels, and verifies the identity of respondents. Previous research collected survey responses through Facebook (Stokes et al., 2019). Several researchers (Brickman Bhutta, 2012; Facebook, 2022; Schneider & Harknett, 2022; Stokes et al., 2019; Zagheni, Weber, & Gummadi, 2017) have created samples of the general population using Facebook. Recently, demographers showed that Facebook's advertising platform could be used as a "digital statistic" and used it to estimate immigrant numbers by country, such as US states (Zagheni et al., 2017). Convenience sampling was used to recruit artificial intelligence-knowing internal auditors because they have a sufficient understanding of using RPA to automate manual tasks related to the financial process. Through sponsored ads on Facebook, the target population consisted of internal auditors with RPA expertise residing throughout the United States. The A-priori Sample Size Calculator for Structural Equation Models (SEM) from Daniel Soper's website has been used to determine the suggested minimum sample size (Soper, 2017). There were ten latent and 45 observable variables, with a probability of 0.05 and an expected effect size of 0.30. The suggested minimum sample size is 270 respondents, yet 7,873 respondents clicked the link on the first page to access the questionnaire. Where the questionnaire instructions describe the study's goal and the intended population, 611 respondents (7.76 %) completed the questionnaire, and 459 valid questionnaires were analyzed (75.1%). This figure exceeds the Soper-recommended sample size, suggesting that the sample size is adequate for statistical analysis.

3.3 Questionnaire Design and Demographic Profile

It contains 47 items, two of which are demographic, 35 about RPA adoption, and ten about the intention and business value, which serves as the research measurement scale. The questionnaire was developed following an extensive review of the literature on technology adoption and business value and is based on the hypothesized model depicted in Figure 1. This questionnaire was administered as a pilot test to 40 internal auditors, who all completed it and provided constructive feedback. In addition, the questionnaire was modified in response to feedback from the pilot research participants to improve readability while ensuring that it was appropriate and accurate. Table 1 summarizes the demographics of the survey respondents.

Table 1: Demographic Information

Profile of the companies		Freq.	%	Profile of the companies		Freq.	%
Respondent Age	20-30 Years	69	15.0%	Number of Employees	< 50	194	42.3%
	31-40 Years	138	30.1%		50 - 100	101	22.0%

	40+ years	252	54.9%		100 - 249	108	23.5%
Total		459	100.0%		>250	56	12.2%
Highest Education	Bachelors	330	71.9%	Gender	Male	239	52.1%
	Associate	55	12.0%		Female	220	47.9%
	Masters	51	11.1%	Total		459	100.0 %
	High School	9	2.0%	Adoption	Yes	391	83%
	Other Degrees	14	3.1%		No	68	17%
Total		459	100.0%	Total		459	78.2%

3.4 Measurement Validity

Factor analysis was used to analyze the data. When principal component analyses (PCAs) and varimax rotations are used, the Kaiser-Meyer-Olkin (KMO) value is 0.81, which is higher than the suggested 0.50 value and identical to the previous value (Hill, 2011). The test results indicated that the test was successful, with factor loadings ranging from 0.764 to 0.931 (Table 2). In addition, Cronbach's alpha values for all variables were more significant than the commonly accepted threshold value of 0.70 (Taber, 2018). The results indicate that there are no cross-loads.

Table 2:Factor Analysis

	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**
INF4	0.918							
INF1	0.917							
INF3	0.916							
INF6	0.916							
INF5	0.913							
INF2	0.909							
VEN4		0.892						
VEN2		0.872						
VEN1		0.867						
VEN3		0.866						
VEN6		0.852						
VEN5		0.843						
MAN5			0.91					
MAN3			0.895					
MAN4			0.894					
MAN1			0.879					
MAN6			0.852					
MAN2			0.835					
CHA4				0.931				
CHA3				0.929				
CHA2				0.928				
CHA1				0.916				
PRE2					0.877			
PRE3					0.868			
PRE1					0.826			
PRE4					0.774			
VIS3						0.873		
VIS2						0.859		
VIS1						0.842		
COM1							0.831	

COM2								0.826	
COM3								0.822	
STR3									0.819
STR2									0.8
STR1									0.764
Kaiser-Meyer-Olkin Measure of Sampling Adequacy.				0.893					
Bartlett's Test of Sphericity		Approx. Chi-Square		17119.608					
		df		595					
		Sig.		0.000					
Cronbach’s alpha for the constructs				>0.7					

3.5 Convergent Validity

Structural equation modeling (SEM) with AMOS 24 was used in this study to assess the structural model's convergent and discriminant validity and the model's hypotheses. Convergent validity assesses the degree of agreement between multiple indicators of the same construct. It is also referred to as agreement validity. To determine convergent validity (Table 3), one must consider the indicator's factor loading, composite reliability (CR), and average variance extracted (AVE) (Blunch, 2012). The value is between 0 and 1. To be considered adequate for convergent validity, the AVE value should be greater than 0.50 (see Table 3) (Blunch, 2012).

3.6 Evaluation of outer model

Cross-loadings were calculated for each item to determine its reliability. It was found that the factor loading values on their constructs were high, higher than the 0.70 value that was used as a cut-off. This also demonstrates the item's high reliability, which supports the item's initial assignment to the specified latent construct. In this way, it contributes to the validity of convergent claims in an indirect manner. In addition, this indicates that the constructs and items share a quantifiable variance (Blunch, 2012).

According to Table 3, the CR values for all constructs exceed 0.70, and the AVE values for all constructs range between 0.646 and 0.766. Discriminant validity was determined by Farrell and Rudd (2009) by comparing the square root of each AVE on the diagonal to the correlation coefficients (off-diagonal) for each construct in the relevant rows and columns. By and large, there are no reservations about this measurement's validity.

Table 3: Validity Analysis

CR	AVE	MSV	MaxR(H)	1	2	3	4	5	6	7	8	
1	0.97	0.86	0.23	0.97	**0.93**							
2	0.94	0.73	0.36	0.96	0.01	**0.85**						
3	0.95	0.77	0.23	0.97	0.482***	0.01	**0.88**					
4	0.96	0.85	0.13	0.96	-0.04	0.088†	-0.04	**0.92**				
5	0.90	0.69	0.23	0.92	0.00	0.135**	-0.03	0.357***	**0.83**			
6	0.91	0.77	0.36	0.91	0.00	0.206***	0.06	0.120*	0.474***	**0.88**		
7	0.93	0.80	0.36	0.93	0.04	0.601***	0.07	0.07	0.226***	0.332***	**0.90**	
8	0.82	0.61	0.36	0.83	0.05	0.31	0.05	0.06	0.28	0.60	0.48	**0.78**

3.7 Discriminant Validity: Heterotrait-monotrait (HTMT) criterion

Correlations between measures of potentially overlapping constructs indicate an item's ability to discriminate between them or to measure distinct concepts. Table 4 and Figure 1 show the results of the HTMT analysis. The Henseler, Ringle, and Sarstedt (2015) formula make it relatively simple to calculate the output. According to the HTMT results, the values in Table 4 indicate that when the HTMT 0.85 criteria are used, there are no problems with discriminant validity, which is consistent with the study's findings. As a result, the HTMT criterion is concerned with the absence of collinearity between latent constructs (multicollinearity).

Table 4: HTMT Analysis

1	2	3	4	5	6	7	8
1							
2	0.006						
3	0.468	0.003					
4	0.034	0.092	0.04				
5	0.01	0.126	0.033	0.39			
6	0.002	0.183	0.064	0.12	0.461		
7	0.039	0.592	0.064	0.067	0.221	0.33	
8	0.053	0.317	0.038	0.042	0.265	0.577	0.483

3.8 Specific Bias And Common Method Bias

The Amos Plugin specific bias and common method bias (CMB) were used to conduct the bias test (Gaskin & Lim, 2016a, 2016b). The results indicated that bias tests could not detect any specific reaction distortions affecting the study's model in the original or TOE framework (Table 5).

Table 5: Zero Constraints Test

	X^2	DF	Delta	p-value
Unconstrained Model	565.421	495	X^2=0.000	1
Zero Constrained Model	565.421	495	DF=0	

When it comes to fit statistics, the result noted that when he reviewed them, all of the fit statistics in Table 6 indicated an excellent fit. The Chi-square test revealed a value of 1678.09 and a probability level of 0.000. For example, if the probability level is.05 or less, the data departure from the model is significant at the.05 levels. The TLI is typically compared and used with the CFI fit index. TLI is equal to 0.957. While the typical range of TLI is zero to one, it is not limited to that range (Blunch, 2012; Hu & Bentler, 1999). The CFI is identical to that developed by McDonald and Marsh (1990), except that it is truncated to fall within the range of zero to one to estimate the model's non-centrality parameter. CFI values close to 1 indicate a perfect fit. In terms of SRMR, it is 0.047. This parameter is the difference between an observed correlation and the model-generated implied correlation matrix.

Table 6: Model Fit Measures

Measure	Estimate	Threshold	Interpretation	Terrible	Acceptable	Excellent
CMIN	1678.092	--	--	--	--	--
DF	931	--	--	--	--	--
CMIN/DF	1.802	Between 1 and 3	Excellent	<0.90	<0.95	>0.95
Chi-square sig	0	p < or =0.05	Sig			

CFI	0.96	>0.95	Excellent	>0.10	>0.08	<0.08
SRMR	0.047	<0.08	Excellent	>0.08	>0.06	<0.06
RMSEA	0.042	<0.06	Excellent	<0.01	<0.05	>0.05
PClose	1	>0.05	Excellent	> 5	> 3	> 1
TLI	0.957	Close to 1	Very good			1

As a result, the average magnitude of the discrepancies between observed and expected correlations can be used in a variety of situations as an absolute measure of the (model) fit criterion. A good fit is defined as a value of 0.06 or 0.08 or less. The root means square error of fit (RMSEA) is 0.042, and it is an absolute fit index, which indicates how far from perfection a hypothesized model is. In comparison, incremental fit indices such as the CFI and TLI compare the fit of a hypothesized model to that of a baseline model (i.e., a model with the worst fit). A root mean square error (RMSEA) of less than 0.06 indicates an excellent fit. According to Hu and Bentler (1999), the best results should be obtained by combining measures such as CFI > 0.95 and SRMR 0.08. The RMSEA for this study was 0.06; the GFI for this study was 0.951; the NFI for this study was 0.950; the CFI for this study was 0.978; the SRMR for this study was 0.047; the RMI for this study was 0.015; the PClose for this study was 0.999, and the RMSEA for this study was 0.035. These findings contribute to the body of evidence. All of these statistics come dangerously close to meeting widely recommended standards (Blunch, 2012; Gaskin & Lim, 2016a, 2016b; Hu & Bentler, 1999).

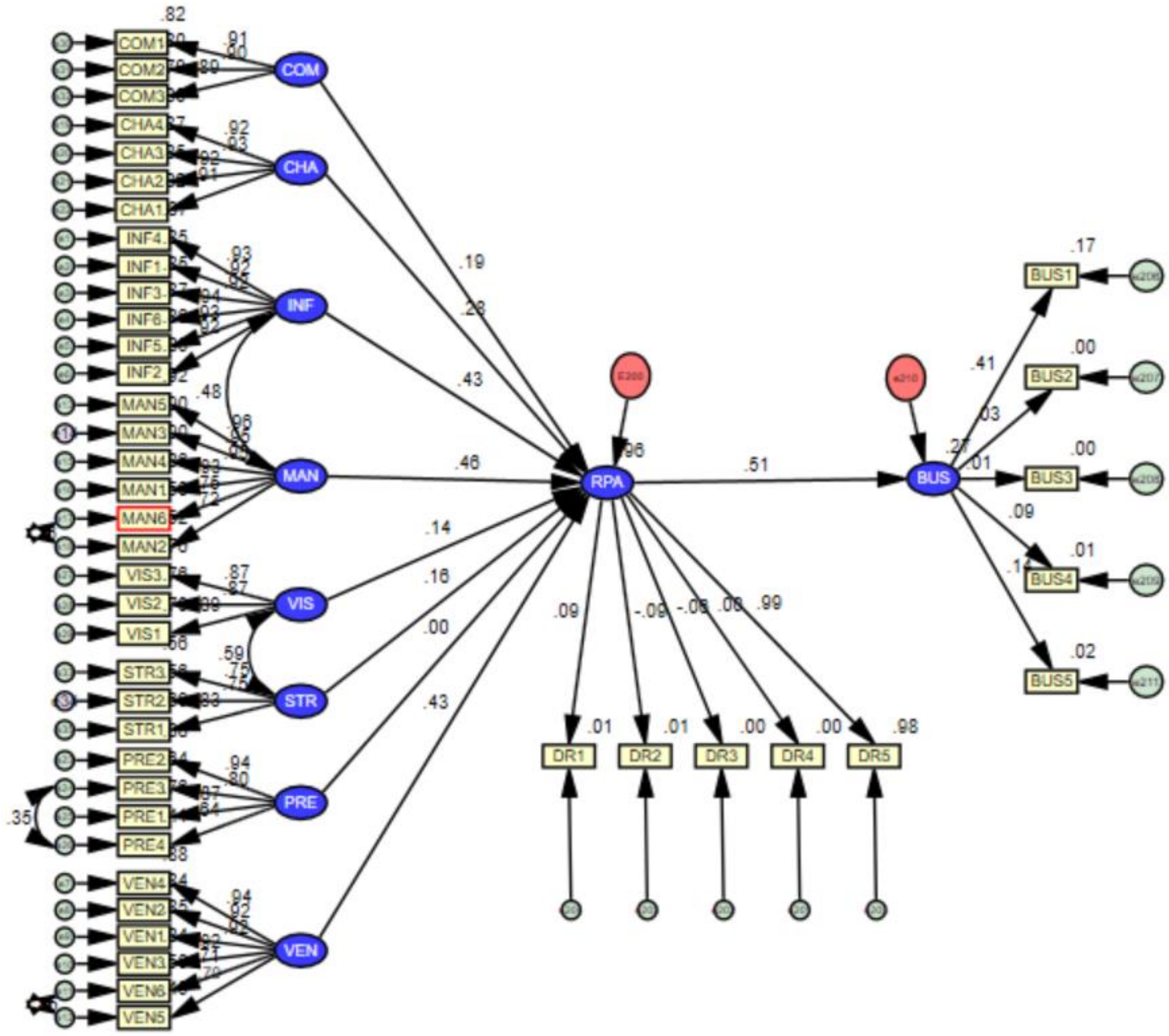

Figure 2: Study Model

3.9 Intention toward RPA

The test statistic C.R. (Critical Value) is used to determine the statistical significance of parameter estimates derived from SEM. It is defined as the parameter estimate divided by the parameter estimate's standard error (S.E.). The C.R. value must be greater than or equal to 1.96 at a 0.05 level of significance. The parameter can be considered irrelevant to the model's performance if this value is less than. Each factor has a factor loading greater than or equal to +1.96, which is statistically significant except for the competitive pressure (C.R. =0.131, p=0.896). Table (7) shows that all of the study model's hypotheses are valid. Furthermore, they have a statistically significant positive effect ((Compatibility, 0.188), (Technology readiness, 0.282), (I.T. Infrastructure, 0.428), (Management support, 0.464), (Digitalization Vision, 0.139) (Strategy, 0.159), and (Vendor support, 0.432) (RPA, 0.515)) as shown in Table in table 7, except for the hypothesis (H7) related to competitive pressure (Competitive pressure, 0.002). Unsurprisingly, the intent to adopt RPA resulted in this outcome. This finding is consistent with the notion that intention toward adoption can be derived from the characteristics of technology, organization, and environment in the context of IT usage. Recent empirical studies have revealed that the revised TOE framework frequently omits certain factors used in the framework, such as complexity and government regulations. However, this study contributed to the literature because it integrated the digital vision and strategy with the TOE framework, in addition to expanding the model by studying the impact of adopting RPA on the business value in the organization.

The hypothesis regarding the compatibility of RPA with the organization's work procedures and Its relevance to current audit requirements is accepted. It has a positive impact on RPA adoption (C.R. = 10.659, p = 0.000). The hypothesis regarding the technology readiness of RPA adoption, such as financial resources, necessary I.T. resources, training, and technical help, is acceptable and positively impacts the adoption of RPA (C.R. = 11.383, p = 0.000). The hypothesis regarding the impact of IT infrastructure on RPA adoption, represented by enhanced governance establishing roles, responsibilities, and change management, continuous testing and monitoring, exception handling and processing, and skill sets and training, has a positive impact on RPA adoption (C.R. = 11.383, p = 0.000). The hypothesis regarding the impact of management support on RPA adoption, represented by senior management's association with competitive strategies, willingness to assume the risks, financial resource allocation, automation support, and direct supervision from the top management, has a positive impact on RPA adoption (C.R. = 11.64, p = 0.000).

Table 7: Standardized Regression Weights: (Group number 1 - Default model)

			Estimate
RPA	<---	Compatibility	0.188
RPA	<---	Technology readiness	0.282
RPA	<---	IT Infrastructure	0.428
RPA	<---	Management support	0.464
RPA	<---	Digitalization Vision	0.139
RPA	<---	Strategy	0.159
RPA	<---	Competitive pressure	0.002
RPA	<---	Vendor support	0.432
BUS	<---	RPA	0.515

The hypothesis regarding the impact of the digitalization vision on RPA adoption, which represents the availability of a clear vision, engaging employees with the digital vision, and assessing the current status of RPA, has a positive impact on RPA adoption (C.R. = 6.243, p = 0.000). The hypothesis regarding the effect of strategy on RPA adoption represented a clear strategy for implementing RPA, focusing on the most beneficial automation initiatives and meeting the strategic requirements to maximize the benefits of automation, and had a positive impact on RPA adoption (C.R. = 6.503, p = 0.000). The hypothesis regarding the effect of vendor support on RPA adoption, represented by providing timely technical assistance, quality of technical assistance, and high-quality training, has a positive impact on RPA adoption (C.R. = 11.676, p = 0.000). There is a relationship between adopting RPA and the Business value of an organization, which is shown by the ability of RPA to add value to an organization through expanded audit sampling, testing frequency, risk assessment, and reporting to the audit committee. This link was found by looking at the correlation between the adoption of RPA and the Business value (Table 7). This conclusion is consistent with Hegde and Rokseth (2020).

Table 8: Regression Weights: (Group number 1 - Default model)

			Estimate	S.E.	C.R.	P
RPA	<---	Compatibility	.510	.044	11.645	***
RPA	<---	Technology readiness	1.368	0.128	10.659	***
RPA	<---	Infrastructure	1.908	0.168	11.383	***
RPA	<---	Management	1.657	0.142	11.64	***
RPA	<---	Vision	0.851	0.136	6.243	***
RPA	<---	Strategy	1.421	0.219	6.503	***
RPA	<---	Pressure	0.011	0.083	0.131	0.896
RPA	<---	Vendor	1.955	0.167	11.676	***
BUS	<---	RPA	0.022	0.005	4.237	***

4 Conclusion

This study adds to the body of knowledge on robotic adoption RPA at the organizational level in industrialized economies, notably the United States. This study expands and links the TOE framework with influencers from the DOI theory to examine the expanding phenomena of RPA adoption and its impact on business value. The current study adds fresh evidence to the existing literature by providing empirical support from the standpoint of RPA adoption and its impact on business value. Although the direct effects of TOE constructs on RPA adoption have been researched previously, the digital vision, strategy, and RPA adoption impact on organizations' business value has seldom been investigated. This difference is relevant given that subsequent technologies may grow increasingly similar, with organizations preferring to adopt distinctive platforms for similar reasons. Thus, the present study used an integrative framework to evaluate the antecedents of RPA adoption utilizing the TOE framework and their influence on organizations' business value. The present study provides a complete comprehension of elements, permitting owners and managers to cognize the true impact of RPA adoption. In addition, this study expedites their understanding of how the appropriate administration of RPA adoption can boost organizations' business value in the US. When it comes to extended audit sampling, testing frequency, risk assessment, and reporting to the audit committee, the results show that RPA adoption significantly impacts an organization's business value. The present study shows the beneficial connection between adopting RPA and business value. In addition, noted that owners/managers can inspire organizations toward RPA adoption and owning a digital vision and strategy that prepares the company in the future to adopt sophisticated technology, including RPA. Finally, TOE constructions allow organizations to adopt RPA quickly because these qualities offer an excellent environment to adopt RPA. As few studies advocated, these organizations utilize RPA just because of others in the industry. As a result of this wasteful conduct by organizations, it is possible that RPA adoption will not yield the expected results. According to this study, organizations should have a clear digital vision, strategy, and understanding of how RPA adoption should be implemented and what results it may create. The researchers used a sampling technique known as "convenience sampling." This method was enhanced further by targeting the study population and including filters in the questionnaire. The targeting strategy also increased the response rate and reduced the time required to collect data.

Therefore, it can be concluded that the current method is superior to non-probability sampling conducted without improvement, and the result is outstanding compared to the non-probability sample shown without modification. In any case, this method requires extensive investigation by future studies to demonstrate its efficacy.

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