Project Report

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Abstract:

Over the past few decades, Blockchain technology has taken root in various aspects of United States society. While BCT owes its origin to that of the financial world and more specifically Bitcoin and Cryptocurrency, the applications of this transformative technology have since been seemingly limitless. This technology has been implemented in many industries via specific usages of BCT with respect to each of these sectors of our society. For instance, a few areas BCT has taken root in are finance, healthcare, defense, and insurance. This is just a handful of the many areas and while the benefits have been abundant, there have also been issues limiting BCT usage as well. Our research is tasked with exploring these issues in an effort to draw reason as to why these problems persist. In order to execute this process we conduct an extensive survey to gather qualitative data from a diverse multitude of BCT experts. In tandem with this data, we employ the TOE (Technology, Organizational, Environmental) framework and alongside references and our research, build various constructs as sub categorizations stemming from this broader theoretical framework. These constructs aid in breaking down the survey questions towards a fundamental characteristic which each respective question can be associated with. From this we conduct an analysis of the data coupled with these constructs and display and evaluate our findings. This procedure allows for an intricate understanding of these factors and their unique relationships with one another which collectively manifest themselves in impacting United States adoption of BCT in the relevant broader context.

Introduction

In recent years, Blockchain technology has transformed a diverse multitude of industries across the United States at a rapid pace. While this array of BCT usage is a widespread feature of modern industries, this was not always the case. BCT was first outlined in the midst of the 2008 financial crisis when an unknown Satsoshi Nakamoto penned a whitepaper titled “Bitcoin: A Peer-to-Peer Electronic Cash System”. Little is known of the identity of the author however this work would kickstart the development of BCT into the transformative technology known today. This intricate system of decentralized transaction validation and data storage has since been refined, harnessed, and ascribed towards countless sectors of our society. Finance, healthcare, supply chain, cybersecurity, agriculture, insurance, and defense are a few of seemingly limitless applications of BCT which have been thrust into our lives. While these implementations have elicited an array of benefits, issues impacting its adoption have arisen and continue to persist.

The question of understanding the nature of these issues is rather convoluted with a vast array of studies and research having been conducted in recent years. When first prompted with the notion of variation in the adoption of BCT across the world, there are several if not endless routes one could take in pursuit of reasoning for such a development. Our prompt is in reference to that of BCT adoption in the United States and therefore, this introduces a rather logical categorization by country to facilitate the viewing of these adoption rates through distinction by nation. Essentially, this allows us to work off this distinction and subsequently draw comparisons. With a focus on the United States, we opted to draw on a handful of other nations across the world to compare with. Germany, Ireland, Malaysia, and Australia were selected to serve as reference points in a comparison with the United States. Next was considering the essence of what would be compared between these countries. Since Blockchain Technology is quite demanding from a technological and network perspective we opted to compare these

nations via metrics known as the technology readiness index and the network readiness index. Along with these technical measurements, we also sought a cultural metric as tendencies of a population could be impactful. Given that BCT is a rather new and perceived complex technology, a measurement of how accepting a nation's people are to change would give impactful cultural insight in this context. A metric known as the uncertainty avoidance index measures just this and as a result we employed it as well. These metrics have been collected from multiple academic sources and these are depicted in the table below.

Country	Technology Readiness Index	Networked Readiness Index	Uncertainty Avoidance Index
United States	9.4375	76.91	46
Germany	9.4375	74.00	65
Ireland	8.03125	67.51	35
Malaysia	7.46875	56.72	36
Australia	9.71875	70.36	51

This table details how the United States scores in a range of metrics which impact a nation's ability for BCT adoption to take hold. These metrics for the United States are depicted alongside other nations for comparison to display how the United States measures up against these other countries through the lens of these metrics. TRI is a metric which displays the level of an overall nation's technological state and capabilities. A higher score indicates a better capability and as a result, a reasonable determination can be drawn that a nation which exhibits a more developed technological state is at an increased likelihood of BCT adoption than one of a lesser state. Network readiness index is comparable to TRI in the sense that they measure an overall state of development in some regard for a nation. The difference is this metric is a

measure of an overall nation's state of network development with a higher score indicating a more advanced network. A nation with a more advanced network would be more likely to have the capacity to adopt and sustain BCT. NRI is measured on a different scale from 0-100 while TRI is 0-10. Uncertainty avoidance index is also a metric to compare nations performance however this is highly influenced by cultural phenomena while the previous metrics are less so. UAI measures how a nation's population is resistant to change and the unknown with a higher score indicating a more resistant population. A nation with a lower score would therefore be more probable to adopt new and perceived unknown ideas such as BCT. As a result, one can reasonably determine that a lower score would make a nation more likely to adopt BCT. This is measured on a scale from 0-120. The United States performs well when compared to the other nations and when viewing these scores, one can determine that the United States is at a relatively good place in these metrics to adopt BCT when compared to the standards from this data.

These studies have ranged from being predicated on quantitative data, qualitative data, and even a mix of both. In many of these studies, researchers have coupled this data alongside a variety of theoretical frameworks both individual and organizational based. After considering these studies and alongside our research into the topic, we have opted towards an organizational based theoretical depiction of interrelated concepts known as the TOE framework. This stands for Technology, Organization, and Environment. We settled onto this model as it was the most immersive, efficient, and relevant of the other theories considered as it encompassed many others while offering streamlined effectiveness in the context of factors influencing block chain adoption in the United States.

Theoretical Model, Framework, and Hypothesis:

The complex and diverse nature of these issues render achieving a solution to these issues quite difficult. Each specific application of BCT has its own properties and in turn. often exhibit unique issues as well and as a result, a thorough and objective analysis must be conducted in order to establish a semblance of understanding towards these factors affecting BCT adoption as a collective development of these specific components. Many studies, papers, and researches have been conducted on this issue and typically these utilize data analysis coupled with a relevant theoretical framework which accounts for the reasoning behind some of the factors at hand. In an effort to further our understanding in this context, we have chosen to implement a theory which encompasses much of the diversity of these issues known as the TOE framework with TOE standing for technological, organizational, and environmental. We first break down the theory in order to fundamentally understand the nuances and nature of these three general categorizations. For instance, technology, being a rather broad category, may encompass many specific BCT adoption factors however these factors are often unique and may simply fall under this "technology" categorization as a product of general similarity. In order to properly comprehend these specific issues, these broad categories must be broken down further. For instance in the context of Organization, the TOE framework notes innovativeness, learning compatibility, and top management support as three subcategories which these adoption factors fall into. For the technological contexts, it is broken down into perceived benefits, perceived compatibility, and perceived complexity. The environmental category is broken down into competition intensity, government support, trading partner readiness, and standards uncertainty. Each of these three broad categories exhibits an analogous breakdown as distinction between adoption factors is enhanced. The usage of this theoretical framework is coupled with a data analysis stemming from data gathered from experts in the BCT industry.

Research Methodology:

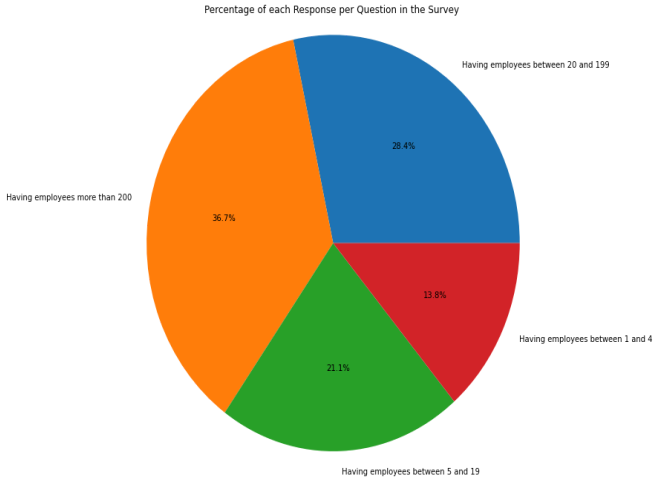
For this study, we conducted a qualitative data collection by creating a survey for BCT experts to provide responses for. For this questionnaire, we included a section of questions pertaining to the respondents background as individuals and exposure to BCT as well as experience overall in their respective industries. This section consisted of 13 questions and would be followed up with an array of questions pertaining to BCT itself. The following questions would be arranged in association with their relevant construct from the broken down TOE model. For instance, the first 5 questions are Q1a to Q1e. Their categorization as question 1 applies them towards the construct of "perceived benefits" a derivation from the technological category (This process was detailed in the modeling and hypothesis). A similar process persisted for fifteen total constructs. This essentially built in the TOE framework and its derived sub categorization into the gathering of our data.

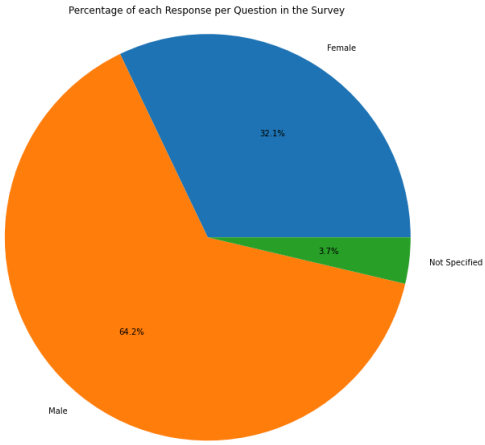
For our survey itself, the questions were constructed with this detail in mind and subsequently distributed towards BCT experts from a diverse range of backgrounds. The participants' variation in experiences and exposure meant that people from across an array of industries were involved; effectively providing us with rich insight into BCT in our survey data.

Data Processing and Analysis:

Alongside the process of gaining a fundamental understanding of the TOE framework, we conducted data preprocessing and exploratory data analysis of our survey data. In cleaning the data, we searched through it for missing values and handled them accordingly by taking the mode response for the questions. We dropped participants with inconsistent and unreasonable responses and experience. Following this refinement process, we began exploring the dataset

where we delved into the demographic data of our respondents.





As per the visuals above, you can see two distributions of respondent demographic information that was computed for two of the questions, the number of employees of their employer and gender. This process was done similarly for all the demographic questions and provided us with insightful knowledge into the participants' backgrounds. This aided in allowing us to get nuanced with the data and ensure it was well sourced and ready for the next process.

With the data cleaned and refined, we conducted factor analysis of the survey data with respect to how the BCT questions pertain to the sub categorizations of the TOE framework. Essentially, the breakdown of the theoretical framework above serves as “constructs" in a sense which the questions can be associated with. Alongside this association, we converted the qualitative response into quantitative data via Likert Scaling which standardizes the data by attributing responses to specific numerical values. Since the BCT questions follow consistent response options, this process is applicable to our data. With the data conversion and question construct relationship in place, we conducted structural equation modeling using the software SmartPls4 to gain an insight into the relationships between the questions, responses, and the constructs which they pertain to. From this analysis, generates a variety of metrics detailing the

magnitude, consistency, variance, nature and more for these relationships. These are visualized in tables in the following pages and subsequently discussed.

Construct with Measuring Items	Outer Loadings	AVE	CR	Cronbach's Alpha
Competative Intensity(CI)		0.755	0.852	839
12.a	0.851553842			
12.b	0.899032619			
12.c	0.855			
perceived complexity(PCM)		0.656	0.81	0.748
3.a	0.684			
3.b	0.883			
3.c	0.85			
Governament support (GS)		0.654	0.822	0.759
10.a	0.86			
10.b	0.773			
10.c	0.791			
Intention to adopt BCT (INT)		0.549	0.585	0.583
15.a	0.65			
15.b	0.791			
15.c	0.774			
organization Innovativeness (OI)		0.66	0.756	0.742
8.a	0.808			
8.b	0.886			
8.c	0.736			
Organization Agility Learning Capability (OALC)		0.483	0.832	0.823
9.a	0.665			
9.b	0.742			
9.c	0.732			
9.d	0.707			
9.e	0.623			
9.f	0.691			
9.g	0.7			
perceived Benefits (PB)		0.609	0.847	0.839
1.a	0.8			
1.b	0.821			
1.c	0.782			
1.d	0.714			
1.e	0.78			
perceived Compatibility (PC)		0.671	0.803	0.758
2.a	0.873			
2.b	0.86			
2.c	0.714			
perceived Disintermediation (PD)		0.695	0.766	0.756
5.a	0.719			
5.b	0.83			
5.c	0.804			
5.d	0.678			
perceived information transparency (PIT)		0.578	0.779	0.78
4.a	0.807			
4.b	0.841			
4.c	0.851			
perceived Risks (PR)		0.677	0.769	0.762
14.a	0.804			
14.b	0.865			
14.c	0.798			

AVE Matrix	PB	GS	TP	CI	ES	PR	INT	PC	PCM	PIT	PD	PV	TMS	OI	OALC
PB	0.78														
GS	0.61	0.809													
TP	0.388	0.414	0.83												
CI	0.336	0.285	0.447	0.869											
ES	0.469	0.363	0.182	0.298	0.807										
PR	0.392	0.339	0.405	0.604	0.386	0.823									
INT	0.514	0.431	0.428	0.631	0.576	0.665	0.741								
PC	0.481	0.334	0.435	0.311	0.326	0.495	0.463	0.819							
PCM	0.267	0.294	0.219	0.252	0.279	0.335	0.335	0.336	0.81						
PIT	0.362	0.3	0.276	0.496	0.378	0.594	0.606	0.431	0.303	0.833					
PD	0.401	0.272	0.38	0.36	0.393	0.523	0.455	0.563	0.28	0.527	0.76				
PV	0.529	0.563	0.466	0.545	0.447	0.486	0.586	0.41	0.41	0.318	0.405	0.752			
TMS	0.478	0.407	0.382	0.516	0.325	0.598	0.575	0.452	0.349	0.508	0.358	0.594	0.834		
OI	0.511	0.332	0.399	0.399	0.244	0.433	0.501	0.346	0.403	0.408	0.439	0.317	0.377	0.812	
OALC	0.553	0.519	0.306	0.28	0.52	0.336	0.494	0.496	0.226	0.307	0.514	0.402	0.302	0.352	0.695

Relationship	PathCoefficient
PB→INT	-0.034
PC→INT	0.057
PIT→INT	0.221
PD→INT	-0.14
OI→INT	0.132
OALC→INT	0.179
TMS→INT	0.094
CI→INT	0.191
GS→INT	-0.022
TPR→INT	0.021
PR→INT	0.11
PB→PR→INT	0.124
PC→PR→INT	0.086
PIT→PR→INT	0.331
PD→PR→INT	-0.124
OI→PR→INT	-0.066
OALC→PR→INT	-0.118
TMS→PR→INT	-0.114
CI→PR→INT	-0.004
GS→PR→INT	0.051
TPR→PR→INT	-0.002

Discussion of Results from the Factor Analysis:

As a result of our factor analysis, the metrics above provide valuable insight into the nature of the responses and their respective constructs. From the first table, the outer loadings detail a breakdown under the constructs relative to each question where it notes how substantial each question actually pertains to its greater construct. A higher value indicates a stronger relationship and this is seen with the outer loadings as these values above remain solid for the majority of questions. Cronbach's Alpha depicts the level of consistency regarding how well a set of questions which are intended to measure a certain construct actually do. In our metrics above, we can see 0.839 for the value for the initial constrict indicating a good level of consistency. For intention to adopt BCT, this value is .583 which is lower compared to the other features showing it exhibits less consistency among its questions and their responses. The remaining constructs fall between these two. The composite reality, can note this consistency in a sense however this is done by collectively delving into the factor loadings of the SEM procedure to produce a metric of how well they resonate with their construct. In a similar sense, the CR for perceived benefits is strongest with .852 along with intention to adopt as the weakest with .585. Average Variance Extracted uses the measurement error determined in order to compare against the total variance that a construct exhibits to depict the validity of the construct with regards to its realized applicability to its associated questions. In the metrics above we see the strongest being perceived benefit with a value of .755 and the weakest being organization agility learning capability with a score of .483.

In the second table, we depict the level of correlation which a construct exhibits when compared against the square root of its respective AVE. Essentially, a larger number, typically over .5, shows that the construct’s internal variance is primarily due to the factors it is composed

of as opposed to measurement error indicating stronger convergent validity between constructs. In this table, the diagonal values depict a construct compared with its own AVE that has been square rooted. The values off the diagonal compare the constructs with each other in this capacity. We can see this with PD, perceived disadvantages, and PV, perceived value. This has a value of .752 which is rather strong compared to the others and shows that PV and PD fluctuate in a similar manner as their variance coincide rather often. On the other hand, TP, trading partner readiness, and ES, environmental support have a value of .182. This shows that these constructs' fluctuations resemble weak similarity and effectively showing the developments which impact each construct are quite different. As per the matrix above, this analysis can be conducted on each relationship depicted.

In the third table, we depict pathways which are symbolic for a specific relationship between constructs. Alongside each relation reference, a correlation value is shown with respect to its associated pathway. Essentially, the magnitude of the correlation denotes the strength of the relationship between constructs with the sign indicating if it is a positive or inverse relation. This can be visualized with an example from the table, PB to INT. This is symbolic for the connection between perceived benefits and intention to adopt where one can see a value of -0.034. This indicates a weak inverse interrelation between these constructs and could serve to substantiate these subfactors as bearing minimal impact on each other. Pinpointing a sole reason as to the driving force for this relation is difficult as it could be due to a myriad of factors and the correlation is close to nothing as is; however, the fact that these constructs are part of different broader categories may play a role in how the connection materialized form the data. Using another example, PIT to INT, this shows the relationship between persuasive innovation tendencies and intention to adopt and has a correlation value of .221. Relative to the other

connections, this is a strong positive relation between the two constructs and this makes sense as taking convincing actions to innovate would likely see an impact on increasing an organization's intention to adopt as they are being convinced. In addition, these two are part of the broader organizational categorization. Overall, this table notes an array of different pathways each with their own correlations which can be interpreted in comparable means as has been shown.

Conclusion:

Overall, this meticulous process provided us with an intricate understanding of the nature of our survey data and how it corresponds to their associated constructs derived from the TOE framework. Garnering this insight from data gathered from experts in Blockchain technology allows these results to be quite impactful since they stem from those readily working in a variety of industries today. Our analysis from this data paired with its association to the constructs shed insightful light into how well the questions and their responses actually pertained to the construct and the nature of the relationships between these features themselves. Essentially, from this we can conclude that the survey responses showed that the constructs used bear solid relevance when analyzed in comparison to real world data. We also learned that this relevance fluctuates between features which perceived benefits being one of the stronger performers and other such as intention to adopt being weaker. This variation was not limited in just comparing the factors themselves as their respective relationships with each other also fluctuated tremendously indicating some constructs have tendencies to impact others in varying positive or negative capacities. In turn, this means many of these constructs, in an isolated and or more collective state, could essentially be used as factors which do influence blockchain adoption in the United States to the range of extents shown by this analysis.

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