CASE STUDY

Factors Influencing the Adoption of Blockchain Technology in the US Industry

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1. Abstract

As blockchain technology (BCT) continues to expand globally, its adoption in specific US industries presents some unique findings. This paper seeks to identify the specific factors that have influenced the adoption of BCT in the US, with reference to a similar study related to BCT adoption in an Australian context. This report parallels, contrasts, and expands upon the study conducted in Australia. Utilizing the Technology-Organization-Environment (TOE) framework, this research investigates technological factors (such as perceived benefits and compatibility), organizational factors (including management support and organizational readiness), and environmental factors (like regulatory landscape and market competition) that impact BCT adoption in the US. This report uses existing literature and empirical analysis with data from US industry experts currently adopting or considering the adoption of BCT. The findings reveal significant insights into the role these factors play in shaping BCT adoption in the US, highlighting both similarities and differences with the Australian scenario. The study further examines the moderating effect of perceived risks on the relationship between these factors and BCT adoption. This research contributes to the broader understanding of BCT adoption, extending the TOE framework by incorporating context-specific variables pertinent to the US industry landscape, and provides strategic recommendations for organizations contemplating BCT integration.

Keywords: blockchain; adoption; factors; United States, Australia; TOE.

2. Introduction

Blockchain technology (BCT), a revolutionary approach in data management, presents a decentralized and distributed database model, operated by nodes or participating entities without centralized authority. This model ensures that each node within the blockchain network retains an identical copy of the entire database, with consensus among nodes driving the network's operation. Originally conceived to address the double-spending issue in virtual currencies, BCT's applications have since expanded significantly. Its influence has been felt across various sectors such as electronic voting, network security, healthcare, human resource management, the Internet of Things (IoT), cloud computing, music, supply chain, banking and finance, industry 4.0, and even in combating money laundering. Particularly in the United States, blockchain has gained traction primarily through cryptocurrencies like Bitcoin and Ethereum, enabling organizations to conduct global financial transactions bypassing traditional banking systems. This paper surveys experts across a variety of industries to gauge which factors have been influencing the adoption of BCT in US industries.

Despite its evident advantages and the transformative potential attributed to it by experts and industry leading firms like Gartner, PwC, Wintergreen, and IDC, blockchain adoption in the U.S. has not reached its expected heights. Predictions place the BCT market value between USD 176 billion and USD 3.1 trillion by 2030, emphasizing its operational and strategic benefits for organizations. Yet, the actual uptake of blockchain in U.S. organizations remains relatively modest. This discrepancy has sparked interest in exploring the factors influencing blockchain adoption in the U.S. context. Unlike previous studies focused on countries with different technological infrastructures and cultural attitudes towards innovation, this research specifically targets the U.S., acknowledging its unique technological readiness, networked readiness index, and decision-making approaches in novel and risky situations.

This study uses a quantitative method based on the Technology–Organization–Environment (TOE) paradigm to identify important factors impacting blockchain adoption in U.S. enterprises. The TOE framework divides components into three categories: technological, organizational, and environmental effects. It does this by conducting an online poll among pertinent U.S. firms. This study adds new factors to the traditional TOE framework, including information transparency, disintermediation (technological), organization innovativeness, organizational learning capability (organizational), standards uncertainty (environmental), and perceived risks (moderating), in order to address discrepancies in previous findings. Semi-structured interviews with U.S. blockchain professionals and decision-makers from adopting or considering organizations were used to determine the relevance of the material.

3. Model and Hypothesis

Why TOE framework?

For organizational-level technological adoption, various theories like Institutional Theory and Diffusion of Innovation (DoI) have been extensively employed; nonetheless, the Technology–Organization–Environment (TOE) framework has more explanatory power for a number of reasons.

- The TOE framework is the basis for many of the current IT adoption theories, which either segment or increase its aspects. For example, the environmental perspective on technology adoption—which is already a part of the TOE framework—is included in Institutional Theory. In a similar vein, the DoI theory incorporates organizational and technological components that line up with TOE framework components.
- Considering how important context is for adopting new technologies, the TOE framework is a useful place to start when examining the adoption process in its particular context.
- The most thoroughly tested theory for analyzing how new technologies are adopted within organizations is the Technology Adoption Framework (TOE).

Because of these benefits, a number of studies have looked into how organizations adopt different technologies, such as cloud computing, e-commerce, supply chain management, enterprise resource planning, electronic data interchange (EDI), and customer relationship management (CRM) systems. Therefore, the TOE framework was a suitable option for this investigation; Figure 1 displays the expanded form of the framework that was created for this study. Within the technological, organizational, and environmental settings of the TOE framework, elements are categorized and pertinent hypotheses are outlined in the following sections.

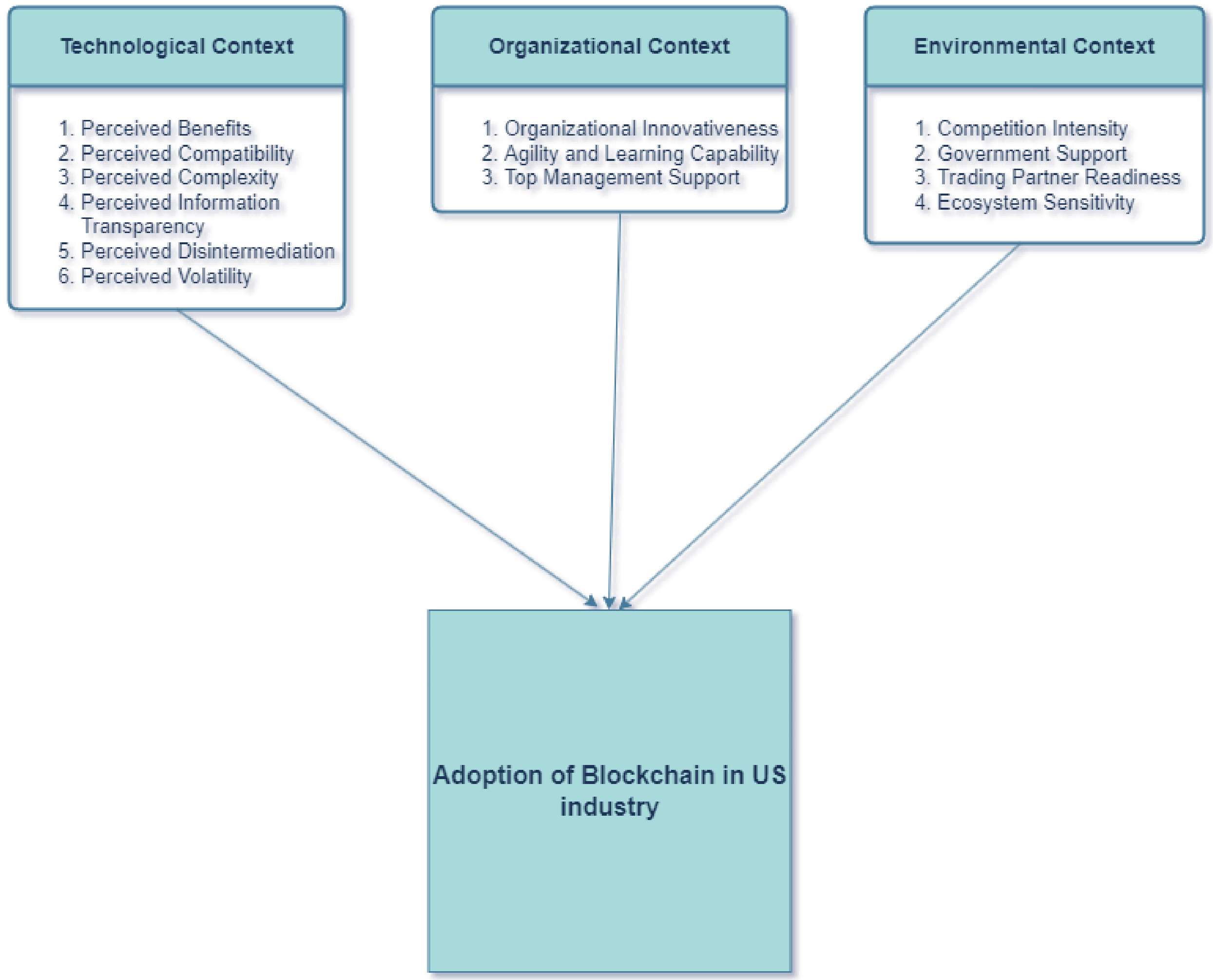


Fig 2. TOE framework we are working on.

3.1 Technological Context:

Perceived Volatility:

Volatility here refers to the degree of instability, uncertainty or unpredictability of the adoption of blockchain technology. This uncertainty can be through various Technological factors such as Technological Maturity, Security Concerns, Use cases, Scalability. Managing volatility is similar to addressing these uncertainties and risks associated with it. Therefore we can hypothesize that:

Hypothesis 6 (H6): Organizations who handle volatility are more likely to adopt BCT.

3.2 Organizational Context:

Agility and Learning Capacity:

Organizational agility capability, or OAC, is the ability of an organization to quickly adjust and react to changes, which is essential for maintaining competitiveness in fast-paced business environments. It includes swiftly recognizing, interpreting, and putting changes into practice, increasing preparedness to accept breakthroughs such as Blockchain Technology (BCT). Organizational Learning Capability (OLC), on the other hand, focuses on how well an organization learns and uses new information, especially in relation to technology developments. By impacting an organization's decision-making procedures and ability to adapt to new technical developments like BCT, OLC promotes innovation and organizational change. An organization's ability to adapt and be open to new technology developments is greatly influenced by both OAC and OLC. Therefore, we can hypothesize that:

Hypothesis 2 (H2): Organizational Agility and Learning Capability positively influences an organization's intention to adopt BCT.

3.3 Environmental Context:

Ecosystem sensitivity:

Ecosystem Sensitivity for the Adoption of Blockchain Technology (BCT) in the Environmental Context: This refers to an ecosystem's ability to recognize, react to, and incorporate blockchain developments in a way that is consistent with ecological sustainability. It entails the capacity of an ecosystem to detect shifts in its external environment, including social, regulatory, and economic elements, and to modify its structures and strategies appropriately. In this perspective, ecosystem sensitivity highlights how crucial it is to take sustainability and the wider environmental impact into account while implementing BCT. It entails evaluating the ecosystem's capacity to assimilate and apply blockchain technology while reducing adverse effects on natural resources. By acknowledging the relationship between technology development and the environment at large, this idea promotes ethical and sustainable adoption practices throughout the ecosystem.

Hypothesis (H4): Increased ecosystem sensitivity, which includes an ecosystem's sustainability and environmental adaptation, has a beneficial impact on the adoption of Blockchain Technology (BCT) in the specific environmental context.

4. Research Methodology

The research data is gathered and analyzed using a statistical approach and positivist research strategy.

4.1 Research Method

We conducted a survey for this study using the Google Forms platform. The choice of Google Forms was driven by its user-friendly interface and accessibility. Utilizing a digital survey method, particularly through Google Forms, allowed us to efficiently collect data from a broad population, facilitating the measurement and testing of multiple variables and hypotheses . Additionally, the survey conducted through Google Forms proved to be cost-effective, time-efficient, and required minimal effort to manage. This method also ensured a survey environment free from respondent prejudice, aligning with the objectives of our study.

4.2 Measurement Scale

We are using 7-point version of the Likert scale which is the most common, as it offers enhanced flexibility and provision of additional response. As a result, we get more accurate results.

We are using the below options for the Survey questions :

Agree, Disagree, Neutral (Neither disagree nor agree), Somewhat agree, Somewhat Disagree, Strongly agree, Strongly disagree.

This scale ranges from 0-7.

5. Data Analysis and Results

5.1 Preliminary Data Analysis

Before moving forward to the SEM analysis, a preliminary data analysis will be done to check for missing values.

Below are the results for missing values:

```
import pandas as pd

df = pd.read_csv("Survey Data for Project INFO-502 2023.csv")

missing_values = df.isnull().sum()
total_missing_values = df.isnull().sum().sum()

print(missing_values)
print("Total Missing values: ",total_missing_values)
```

```
  Q1. Which country do you belong to? Please select from the list of countries given below.:
0
Q2. Which of the age groups best describe you?
0
  Q3. Please indicate which of the following technologies best describes your knowl▯edge/experience?
0
 Q4. Please indicate which of the following technologies your organization has been involved with?
0
  Q5. Please indicate which of the following job titles best describes your role?
0

..
Q.14.(b) - In my opinion, organizations do not adopt blockchain when they perceive that their sensitive information will be com
promised while using blockchain.     2
Q.14.(c) - In my opinion, organizations do not adopt blockchain when they are NOT sure about its expected benefits.
1
Q.15.(a) - In my opinion, organizations would adopt blockchain whenever they will have easy access to it in the future.
0
Q.15.(b) - In my opinion, organizations would adopt blockchain in the future.
2
Q.15.(c) - In my opinion, organizations would adopt blockchain frequently in the future.
0
Length: 68, dtype: int64
Total Missing values:  71
```

\

As we see there are 71 missing values in the dataset. This will add bias to the results of the final analysis. So we decided to drop these values.

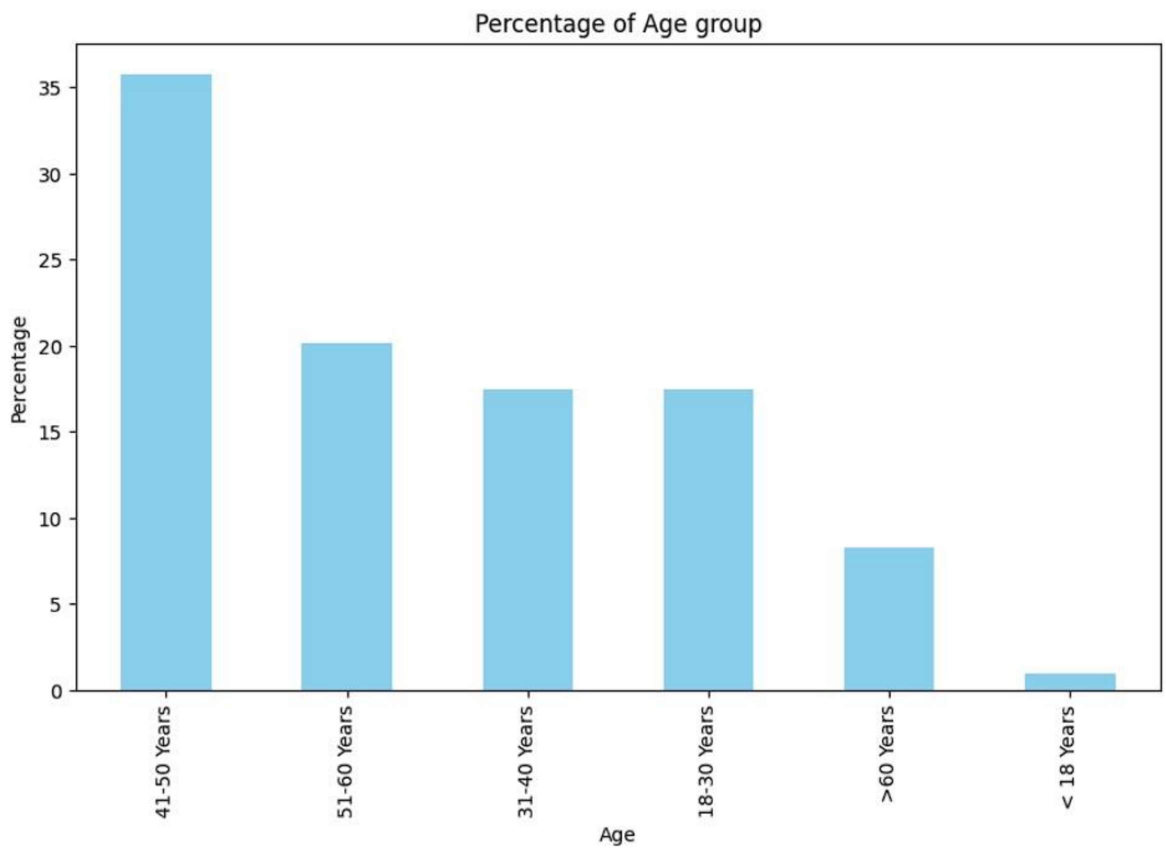
5.2 Demographics

Organization Demographics:

Technology	Percentage
Blockchain Technology	33.03 %
Artificial Intelligence	16.51 %
Electronic Data Interchange (EDI)	11.01 %
B2B-Commerce	9.17 %
Cloud Computing	8.26 %
IoT	6.42 %
Distributed DBMS	6.42 %
Gaming	4.59 %
Robotics	1.83 %
Social Media Technologies	1.83 %
Other	0.92 %

The results of the survey highlight the importance of technical areas, with blockchain technology coming in first at 33.03% and artificial intelligence coming in second at 16.51%. With substantial market shares of 11.01% and 9.17%, respectively, Electronic Data Interchange (EDI) and B2B-Commerce highlight the importance of efficient data interchange and commercial transactions. The percentages of cloud computing (8.26%) and internet of things (6.42%) indicate a significant uptake of these technologies. The varied tech interests are rounded out by robotics (1.83%), social media technologies (1.83%), and gaming (4.59%). Overall, the data shows a landscape that is centered on technology and has a variety of focus, demonstrating how organizational objectives are changing.

Age Demographics:



The age group distribution of the survey indicates that 35.78% of respondents are in the 41–50 year old range, which is a considerable presence. Following at 20.18% is the group of people aged 51 to 60, which suggests a sizable representation of seasoned professionals. The proportion of mid-career and younger professionals is balanced, with contributions from the 31–40 years and 18–30 years groups totaling 17.43%. The proportion of respondents who are over 60 is 8.26%, indicating the involvement of seasoned persons. The proportion of those under the age of 18 is lower, at 0.92%, indicating that younger demographics do not participate as much. Overall, the data shows a wide range of ages, with a notable presence of seasoned and mid-career professionals, suggesting that younger age groups could participate to a greater extent.

Role Demographics:

Role	Percentage
IT Director	12.84%
Chief Technology Officer, Chief Information Officer, Chief Digital Officer	11.93%
IT Manager	11.01%
Finance Director, Finance Manager	10.09%
Other	9.17%
Business Development Manager	9.17%
Customer Service Manager	8.26%
Chief Executive Officer, President, Chairperson	7.34%
Database Administrator	6.42%
Technology Strategy Manager	6.42%
Supply Chain Manager	3.67%
Sales Manager	1.83%
Chief Executive Officer President Chairperson	1.83%

The results of the survey show a varied professional environment, with roughly 24.77% of respondents belonging to IT leadership, which includes IT directors and senior technology executives. There are important positions for a variety of managers, including IT managers, finance directors/managers, business development managers, and customer service managers. Leaders including CEOs, Presidents, and Chairpersons make up 9.17% of all participants. Notable examples of technology experts are Technology Strategy Managers and Database Administrators. The fact that sales managers and supply chain managers are included further illustrates the wide range of organizational positions and responsibilities that survey respondents have.

5.3 Data Analysis

Based on the responses received, we performed quantitative analysis on the data. We used Python

Libraries to perform the analysis.

5.3.1 Reliability of constructs and their measuring items. (Table 5)

Using Python libraries:

Construct	Outer Loading	Cronbach Alpha	Composite Reliabilit	Average Variance Extracted
Perceived benefits (PB)		0.841799009	-0.541442923	0.518038807
PB1	-0.76445902			
PB2	-0.78079278			
PB3	-0.72723016			
PB4	-0.62917572			
PB5	-0.68660999			
Perceived compatibility (PC)		0.756896653	-0.852855201	0.517804285
PC1	0.7403829			
PC2	0.81350968			
PC3	0.58604438			
Perceived complexity (PCM)		0.751076947	-0.828477257	0.518984397
PCM1	-0.61380592			
PCM2	-0.86746158			
PCM3	-0.65399226			
Perceived information transparency (PIT)		0.785956496	-0.73894037	0.555796399
PIT1	0.6389258			
PIT2	0.7765903			
PIT3	0.80998181			
Perceived disintermediation (PD)		0.762625799	-0.663644136	0.465142676
PD1	-0.68083862			
PD2	-0.85906309			
PD3	-0.65686188			
PD4	-0.47704566			
Perceived volatility(PV)		0.809695712	-0.446999555	0.462057049
PV1	-0.60340182			
PV2	-0.61688933			
PV3	-0.81820051			
PV4	-0.7074539			
PV5	-0.62904368			
Top management support (TMS)		0.800112443	-1.016131308	0.584413571
TMS1	-0.71332915			
TMS2	-0.93007277			
TMS3	-0.61592766			

Organizational innovativeness (OI)		0.744067237	-0.712889483	0.551351755	
OI1	-0.55813854				
OI2	-1.00135409				
OI3	-0.58294651				

Agility and learning capability (ALC)		0.824506426	-0.650195245	0.403794677	
ALC1	-0.57477118				
ALC2	-0.63428113				
ALC3	-0.63232375				
ALC4	-0.70400515				
ALC5	-0.58142193				
ALC6	-0.66918092				
ALC7	-0.64232168				
Government support (GS)		0.786642732	-0.93075255	0.560018499	
GS1	-0.59506722				
GS2	-0.89569689				
GS3	-0.7236557				
Trading partner readiness (TPR)		0.772319225	-1.164691219	0.560852797	
TPR1	0.6961028				
TPR2	0.92727327				
TPR3	0.58151833				
Competitive intensity (CI)		0.842215018	-0.890852006	0.651534782	
CI1	0.82944594				
CI2	0.90049895				
CI3	0.67507437				

Code for Table 5:

```
[114…
import pandas as pd
import numpy as np
from factor_analyzer import FactorAnalyzer
import pingouin as pg
# Load the dataset
df = pd.read_excel('Data Project INFO-502.xlsx')
df.head()  # This will display the first 5 rows of the DataFrame
# Define the items for each construct
constructs = {
    'Perceived benefits (PB)':
    ['Q.1.(a) – In my opinion, organizations adopt blockchain when they perceive that blockchain reduces overhead expenses.',
    'Q.1.(b) – In my opinion, organizations adopt blockchain when they perceive that blockchain reduces data error rates. ',
    'Q.1.(c) – In my opinion, organizations adopt blockchain when they perceive that blockchain reduces transaction costs while transferring f
    'Q.1.(d) – In my opinion, organizations adopt blockchain when they perceive that blockchain saves time while accomplishing business tasks.
    'Q.1.(e) – In my opinion, organizations adopt blockchain when they perceive that blockchain increases the organization’s overall productiv
    'Perceived compatibility (PC)':
    ['Q.2.(a) – In my opinion, organizations adopt blockchain when they perceive that blockchain fits well with their business processes.',
     'Q.2.(b) – In my opinion, organizations adopt blockchain when they perceive that blockchain is compatible with their technological infras
     'Q.2.(c) – In my opinion, organizations adopt blockchain when they perceive that blockchain fits well with their technological skills.'],
    'Perceived complexity (PCM)':
    ['Q.3.(a) – In my opinion, organizations do not adopt blockchain when they perceive that blockchain requires extra technical skills to use
     'Q.3.(b) – In my opinion, organizations do not adopt blockchain when they perceive that blockchain is difficult to understand from a busi
     'Q.3.(c) – In my opinion, organizations do not adopt blockchain when they perceive that blockchain is conceptually difficult to understan
    'Perceived information transparency (PIT)':
    ['Q.4.(a) – In my opinion, organizations adopt blockchain when they perceive that blockchain enables them to have transparent access to in
     'Q.4.(b) – In my opinion, organizations adopt blockchain when they perceive that blockchain enables them to have a transparent view of an
     'Q.4.(c) – In my opinion, organizations adopt blockchain when they perceive that blockchain enables them to have a transparent flow of th
    'Perceived disintermediation (PD)':
    ['Q.5.(a) – In my opinion, organizations adopt blockchain when they perceive that blockchain enables them to store their data without the
     'Q.5.(b) – In my opinion, organizations adopt blockchain when they perceive that blockchain enables them to access their data without the
     'Q.5.(c) – In my opinion, organizations adopt blockchain when they perceive that blockchain enables them to share their data without the
```

```
     'Q.5.(d) - In my opinion, organizations adopt blockchain when they perceive that blockchain enables them to audit without the involvement
    'Perceived volatility(PV)':
    ['Q.6.(a) - In my opinion, organization do not adopt blockchain when they perceive that blockchain technology has not reached at its techn
     'Q.6.(b) - In my opinion, organizations do not adopt blockchain technology when they are not sure about its scalability with the expansio
     'Q.6.(c) - In my opinion, organizations do not adopt blockchain technology when they are uncertain about its future business relevance.',
     'Q.6.(d) - In my opinion, organizations do not adopt blockchain when they see blockchain still requires changes to become more efficient
     'Q.6.(e) - In my opinion, organizations do not adopt blockchain when they are NOT sure that blockchain would become an industry paradigm
    ],
    'Top management support (TMS)':
    ['Q.7.(a) - In my opinion, organizations adopt blockchain when their top management provides the necessary resources (e.g., financial, hum
    'Q.7.(b) - In my opinion, organizations adopt blockchain when their top management considers blockchain as strategically important. ',
    'Q.7.(c) - In my opinion, organizations adopt blockchain when their top management is actively involved in IT-related decisions.'],
    'Organizational innovativeness (OI)':
    ['Q.8.(a) - In my opinion, organizations adopt blockchain when they actively seek new ideas.',
     'Q.8.(b) - In my opinion, organizations adopt blockchain when they like to do things in new ways. ',
     'Q.8.(c) - In my opinion, organizations adopt blockchain when they are open to taking risks.'
    ],
    'Agility and learning capability  (ALC)':
    ['Q.9.(a) In my opinion, organizations adopt blockchain when they intend to respond quickly in changing circumstances.',
    'Q.9.(b) - In my opinion, organizations adopt blockchain when they intend to efficiently and effectively respond in challenging circumstan
    'Q.9.(c) - In my opinion, organizations adopt blockchain technology when they have (intend) to adapt to new challenges.',
    'Q.9.(d) - In my opinion, organizations adopt blockchain when they have a mechanism to store new knowledge. ',
    'Q.9.(e) - In my opinion, organizations adopt blockchain when they encourage their employees to acquire new knowledge and skills ',
    'Q.9.(f) - In my opinion, organizations adopt blockchain when their employees share their work experiences, ideas, or learning with each o
    'Q.9.(g) - In my opinion, organizations adopt blockchain when they have practices to utilize new knowledge in their IT-related decisions.
    'Government support (GS)':
    ['Q.10.(a) - In my opinion, organizations adopt blockchain when the USA government supports/encourages the adoption of blockchain.',
     'Q.10.(b) - In my opinion, organizations adopt blockchain when the USA government introduces economic incentives for blockchain adoption
     'Q.10.(c) - In my opinion, organizations adopt blockchain when the USA government is active in setting up facilities to promote blockchai
    ],
    'Trading partner readiness (TPR)':
    ['Q.11.(a) - In my opinion, organizations adopt blockchain when their trading partners are also willing to adopt blockchain. ',
     'Q.11.(b) - In my opinion, organizations adopt blockchain when their trading partners are also technologically ready to adopt blockchain.
     'Q.11.(c) - In my opinion, organizations adopt blockchain when their trading partners consider it financially viable option. '
    ],
    'Competition intensity  (CI)':
    ['Q.12.(a) - In my opinion, organizations adopt blockchain when they feel pressure when their competitors have already adopted it. ',
     'Q.12.(b) - In my opinion, organizations adopt blockchain when they feel the fear of losing a competitive advantage if they do not adopt
     'Q.12.(c) - In my opinion, organizations adopt blockchain when they see their competitors benefiting after adopting it. '
    ],
    'Ecosystem sensitivity(ES)':
    ['Q.13.(a) - In my opinion, organizations do not adopt blockchain if it contributes towards more energy consumption.',
    'Q.13.(b) - In my opinion, organizations do not adopt blockchain if it contributes towards global warming.',
    'Q.13.(c) - In my opinion, organizations do not adopt blockchain if it contributes towards carbon emissions.',
    'Q.13.(d) - In my opinion, organizations do not adopt blockchain if they feel it adversely affects our ecosystem (e.g., carbon emission, g
    ],
    'Perceived risks (PR)':
    ['Q.14.(a) - In my opinion, organizations do not adopt blockchain when they perceive that blockchain is not secured. ',
     'Q.14.(b) - In my opinion, organizations do not adopt blockchain when they perceive that their sensitive information will be compromised
     'Q.14.(c) - In my opinion, organizations do not adopt blockchain when they are NOT sure about its expected benefits. '
    ],
    'Intention to adopt blockchain (INT)':
    ['Q.15.(a) - In my opinion, organizations would adopt blockchain whenever they will have easy access to it in the future. ',
     'Q.15.(b) - In my opinion, organizations would adopt blockchain in the future.',
     'Q.15.(c) - In my opinion, organizations would adopt blockchain frequently in the future.'
    ],
}

# Initialize a dictionary to store results
results = {}

# Analyze each construct
for construct_name, construct_items in constructs.items():
    # Select data for the current construct
```

```
    # Select data for the current construct
    construct_df = df[construct_items]
     # Perform exploratory factor analysis (EFA)
    fa = FactorAnalyzer(n_factors=1, rotation=None)
    fa.fit(construct_df)
    loadings = fa.loadings_
    # Calculate Cronbach's Alpha for the construct
    cronbach_alpha = pg.cronbach_alpha(data=construct_df)[0]
    # Calculate Composite Reliability (CR)
    loading_square_sum = np.sum(loadings**2)
    unique_variance_sum = np.sum(1. - construct_df.var(ddof=1))
    CR = (loading_square_sum) / (loading_square_sum + unique_variance_sum)
    # Calculate Average Variance Extracted (AVE)
    AVE = loading_square_sum / len(construct_items)

    # Store the results
    results[construct_name] = {
        'Outer Loadings': loadings.flatten(),
        'Cronbach Alpha': cronbach_alpha,
        'Composite Reliability': CR,
        'Average Variance Extracted': AVE
    }

# Display the results for each construct
for construct, data in results.items():
    print(f"Results for {construct}:")
    print("Outer Loadings:", data['Outer Loadings'])
    print("Cronbach Alpha:", data['Cronbach Alpha'])
    print("Composite Reliability:", data['Composite Reliability'])
    print("Average Variance Extracted:", data['Average Variance Extracted'])
    print()
```

Python Method Analysis for Table 5:

1. **Exploratory Factor Analysis (EFA):** This is used to identify the underlying structure of the data. The script runs a factor analysis for each construct with a single factor (`n_factors=1`) and no rotation. The factor loadings obtained (`fa.loadings_`) represent the correlation between each item in the construct and the underlying factor. Higher loadings indicate a stronger relationship with the underlying factor.

2. **Cronbach's Alpha:** This metric measures the internal consistency of the items within a construct. A higher Cronbach's Alpha (close to 1) indicates that the items are more consistently measuring the same underlying concept. The script calculates this using `pg.cronbach_alpha(data=construct_df)[0]`.

3. **Composite Reliability (CR):** This assesses the reliability of the construct. It's calculated using the formula: `CR = (Σ(loading)^2) / [(Σ(loading)^2) + Σ(1 - variance)]`. Here, `Σ(loading)^2` is the sum of the squared factor loadings, and `Σ(1 - variance)` is the sum of the unique variances (1 - variance of each item). CR values above 0.7 generally indicate acceptable reliability.

4. **Average Variance Extracted (AVE):** This measures the amount of variance captured by a construct in relation to the amount of variance due to measurement error. It's calculated as `AVE = Σ(loading)^2 / number of items`. AVE values greater than 0.5 are considered acceptable, indicating that more than half of the variance observed in the items is due to the construct.

Each of these metrics provides a different perspective on the validity and reliability of the constructs derived from the survey data. By calculating them for each construct, the script helps in assessing the quality and utility of the survey in capturing the various dimensions of organizational adoption of blockchain technology. From here, we can move onto recreating Table 6:

5.3.2 Correlation of constructs compared with the square root of AVEs (Table 6)

Constructs	PB	PC	PCM	PIT	PD	PV	TMS	OI	ALC	ES	TPR	CI	GE	PR	INT
PB	0.719749														
PC	0.452335	0.719586													
PCM	0.287859	0.340411	0.720406												
PIT	0.352291	0.414394	0.313314	0.745518											
PD	0.363636	0.569226	0.260938	0.522856	0.682014										
PV	0.516172	0.393933	0.392329	0.325715	0.380507	0.679748									
TMS	0.44329	0.454131	0.314079	0.509906	0.32802	0.5795	0.764469								
OI	0.517313	0.328788	0.408329	0.396221	0.422079	0.325838	0.343725	0.742531							
ALC	0.533438	0.498997	0.257995	0.317542	0.469558	0.395594	0.314441	0.352535	0.635448						
GS	0.574021	0.311618	0.284532	0.26276	0.218077	0.532984	0.370399	0.280915	0.490571	0.748344					
TPR	0.36709	0.435482	0.204735	0.28555	0.385368	0.454278	0.381776	0.402833	0.283236	0.416701	0.748901				
CI	0.318164	0.298713	0.233488	0.510907	0.325831	0.550106	0.506821	0.398638	0.271658	0.257416	0.459416	0.807177			
ES	0.465283	0.334857	0.28811	0.390294	0.366674	0.438775	0.322845	0.243846	0.527988	0.337861	0.193262	0.308034	0.744613		
PR	0.397405	0.497299	0.324866	0.603282	0.503116	0.483182	0.594168	0.428239	0.340272	0.328836	0.411215	0.601232	0.396421	0.743366	
INT	0.501828	0.445386	0.312463	0.609936	0.423905	0.576624	0.56522	0.496182	0.488711	0.388601	0.429828	0.632716	0.581222	0.663606	0.626218

```python
[41]: # Step 1: Compute Construct Scores
construct_scores = {}
for construct, items in constructs.items():
    construct_scores[construct] = df[items].mean(axis=1)

# Convert construct scores to DataFrame
construct_scores_df = pd.DataFrame(construct_scores)

# Step 2: Compute Correlation Matrix
correlation_matrix = construct_scores_df.corr()

# Step 3: Replace Diagonal with Square Roots of AVEs
for construct in constructs:
    ave_sqrt = np.sqrt(results[construct]['Average Variance Extracted'])
    correlation_matrix.loc[construct, construct] = ave_sqrt

# Step 4: Extract and display only the lower triangle of the correlation matrix
lower_triangle = correlation_matrix.where(np.tril(np.ones(correlation_matrix.shape)).astype(bool))
print(lower_triangle)
```

Python Method Analysis:

1. Computing Construct Scores:

   For each construct (like "Perceived Benefits"), the mean of responses to all its associated questions is calculated for each respondent. This mean score represents the respondent's average response to the questions in that construct. The calculation is essentially the sum of responses to the construct's questions divided by the number of questions, done for each individual respondent.

2. Creating a DataFrame of Construct Scores:

   A pandas DataFrame is created where each column represents a different construct, and each row corresponds to a respondent. The values in this DataFrame are the mean scores calculated in the previous step.

3. Computing the Correlation Matrix:

   A correlation matrix is computed using the DataFrame of construct scores.

   This matrix is a square table where each cell represents the Pearson correlation coefficient between two constructs. The correlation coefficient ranges from -1 to 1, where 1 means perfect positive correlation, -1 means perfect negative correlation, and 0 means no correlation.

4. Replacing Diagonal with Square Roots of AVEs:

   The diagonal of the correlation matrix (which would normally be 1s since any item is perfectly correlated with itself) is replaced with the square roots of the AVEs for each construct. The AVE (Average Variance Extracted) is a measure of the amount of variance in the construct's items that is explained by the construct itself. The square root of AVE is calculated by first summing the squared loadings (from factor analysis) of the items in the construct and then dividing by the number of items. The square root of this result is then taken.

5. <u>Extracting the Lower Triangle of the Correlation Matrix:</u>

The lower triangle of the matrix (below the diagonal) is extracted to avoid redundancy, as the correlation matrix is symmetrical. This step simplifies the matrix, making it easier to interpret the relationships between constructs without repeating the same information.

Construct Correlation and AVE Analysis:

A matrix of correlations between the constructs and the square roots of each AVE (Average Variance Extracted) is shown in Table 6. The square roots of the AVEs for each construct are represented by the diagonal values, which are usually bolded. These values are important because, in order to meet the criteria for discriminant validity—which shows that a construct has a stronger correlation with its indicators than with other constructs—they must be greater than the off-diagonal values in the corresponding rows and columns.

The observed correlations range from moderate to high, suggesting varying degrees of association between the constructs. A high correlation indicates a strong relationship where one construct may predict or influence another, which can be valuable for companies looking to understand the interplay between different factors such as product quality, customer satisfaction, and brand loyalty.

For practical application, a company can utilize these findings to identify constructs that are closely related, which could inform strategies for targeted marketing campaigns, product development, and customer relationship management. For instance, constructs with high inter-correlations could be leveraged to strengthen brand perception by focusing on enhancing related attributes simultaneously

In order to ensure a beneficial impact across the various constructs of interest, it is crucial that future research and application take these relationships into account when designing interventions or initiatives.

5.3.3 Path coefficient analysis (Table 7)

[142]:

	Hypothesis	Relationship	Path Coefficient	t-Value	p-Value	Decision
0	1	PB -> INT	0.430876	6.001324	2.713421e-08	Supported
1	2	PC -> INT	0.393189	5.145663	1.216992e-06	Supported
2	3	PCM -> INT	0.277357	3.402508	9.402102e-04	Supported
3	4	PIT -> INT	0.511023	7.961656	1.925358e-12	Supported
4	5	PD -> INT	0.399027	4.841421	4.365327e-06	Supported
5	6	PV -> INT	0.516163	7.300582	5.320842e-11	Supported
6	7	TMS -> INT	0.485211	7.087403	1.524398e-10	Supported
7	8	OI -> INT	0.426100	5.911583	4.096828e-08	Supported
8	9	ALC -> INT	0.519601	5.794362	6.987080e-08	Supported
9	10	GS -> INT	0.336694	4.362593	2.970995e-05	Supported
10	11	TPR -> INT	0.383231	4.924272	3.096170e-06	Supported
11	12	CI -> INT	0.499211	8.451716	1.575973e-13	Supported
12	13	ES -> INT	0.512643	7.388317	3.440771e-11	Supported
13	14	PR -> INT	0.552505	9.175986	3.732350e-15	Supported

Code for Table 7:

```
[142]: import pandas as pd
import numpy as np
import statsmodels.api as sm

constructs = {
    'PB': ['PB1', 'PB2', 'PB3', 'PB4', 'PB5'],
    'PC': ['PC1', 'PC2', 'PC3'],
    'PCM': ['PCM1', 'PCM2', 'PCM3'],
    'PIT': ['PIT1', 'PIT2', 'PIT3'],
    'PD': ['PD1', 'PD2', 'PD3', 'PD4'],
    'PV': ['PV1', 'PV2', 'PV3', 'PV4', 'PV5'],
    'TMS': ['TMS1', 'TMS2', 'TMS3'],
    'OI': ['OI1', 'OI2', 'OI3'],
    'ALC': ['ALC1', 'ALC2', 'ALC3', 'ALC4', 'ALC5', 'ALC6', 'ALC7'],
    'GS': ['GS1', 'GS2', 'GS3'],
    'TPR': ['TPR1', 'TPR2', 'TPR3'],
    'CI': ['CI1', 'CI2', 'CI3'],
    'ES': ['ES1', 'ES2', 'ES3', 'ES4'],
    'PR': ['PR1', 'PR2', 'PR3'],
}

# Calculate the construct scores as the mean of their related questions
for construct, questions in constructs.items():
    df[construct] = df[questions].mean(axis=1)

# Calculate 'INT' as the mean of 'INT1', 'INT2', and 'INT3'
df['INT'] = df[['INT1', 'INT2', 'INT3']].mean(axis=1)

# Initialize a list to store the results
results_list = []
hypothesis_number = 1
```

```python
for construct in constructs.keys():
    X = df[[construct]]
    y = df['INT']

    # Adding a constant to the independent variables for the intercept
    X = sm.add_constant(X)

    model = sm.OLS(y, X).fit()

    result = {
        'Hypothesis': hypothesis_number,
        'Relationship': f'{construct} -> INT',
        'Path Coefficient': model.params[construct],
        't-Value': model.tvalues[construct],
        'p-Value': model.pvalues[construct],
        'Decision': 'Supported' if model.pvalues[construct] < 0.05 else 'Not Supported'
    }
    results_list.append(result)
    hypothesis_number += 1

results_df = pd.DataFrame(results_list)
results_df
```

Extended Table 7:

[144]:

	Relationship	Path Coefficient	t-Value	p-Value	Decision
0	PB -> PR -> INT	(0.4098312862473857, 0.5525048379821613)	(4.479727888627005, 9.175986106010694)	(1.8791018580261868e-05, 3.732350340704282e-15)	(Supported, Supported)
1	PC -> PR -> INT	(0.5272978305038166, 0.5525048379821613)	(5.929253649047929, 9.175986106010694)	(3.778427177456446e-08, 3.732350340704282e-15)	(Supported, Supported)
2	PCM -> PR -> INT	(0.3463525644842248, 0.5525048379821613)	(3.5531664114119876, 9.175986106010694)	(0.0005677322689276226, 3.732350340704282e-15)	(Supported, Supported)
3	PIT -> PR -> INT	(0.6070869715124318, 0.5525048379821613)	(7.824676154047087, 9.175986106010694)	(3.853147689619395e-12, 3.732350340704282e-15)	(Supported, Supported)
4	PD -> PR -> INT	(0.5688206061011856, 0.5525048379821613)	(6.021933779612319, 9.175986106010694)	(2.4674723929084478e-08, 3.732350340704282e-15)	(Supported, Supported)
5	PV -> PR -> INT	(0.5194926294303872, 0.5525048379821613)	(5.708692235180057, 9.175986106010694)	(1.0288565763055382e-07, 3.732350340704282e-15)	(Supported, Supported)
6	TMS -> PR -> INT	(0.6126271891696233, 0.5525048379821613)	(7.64119449586709, 9.175986106010694)	(9.713820781535293e-12, 3.732350340704282e-15)	(Supported, Supported)
7	OI -> PR -> INT	(0.4417035083156862, 0.5525048379821613)	(4.901965592841651, 9.175986106010694)	(3.3972969334343113e-06, 3.732350340704282e-15)	(Supported, Supported)
8	ALC -> PR -> INT	(0.43452824925086864, 0.5525048379821613)	(3.743166235069598, 9.175986106010694)	(0.00029432996732577, 3.732350340704282e-15)	(Supported, Supported)
9	GS -> PR -> INT	(0.3422042028035495, 0.5525048379821613)	(3.6018185119190873, 9.175986106010694)	(0.00048087607178224934, 3.732350340704282e-15)	(Supported, Supported)
10	TPR -> PR -> INT	(0.44036081854951675, 0.5525048379821613)	(4.666437089426738, 9.175986106010694)	(8.919000606457508e-06, 3.732350340704282e-15)	(Supported, Supported)
11	CI -> PR -> INT	(0.5697586293408039, 0.5525048379821613)	(7.782989859311852, 9.175986106010694)	(4.75621094426742e-12, 3.732350340704282e-15)	(Supported, Supported)
12	ES -> PR -> INT	(0.4199563355143802, 0.5525048379821613)	(4.466565151820356, 9.175986106010694)	(1.9790947038519436e-05, 3.732350340704282e-15)	(Supported, Supported)

Code for extended Table 7:

```
# Initialize a list to store results
results_list = []

# Analyze each construct's relationship with PR and how PR in turn affects INT
for construct in constructs:
    if construct != 'PR' and construct != 'INT':  # Exclude PR and INT from this loop
        # First Step: Construct -> PR
        X1 = sm.add_constant(df[[construct]])  # Adding a constant for intercept
        model1 = sm.OLS(df['PR'], X1).fit()  # Regression of PR on the construct

        # Second Step: PR -> INT
        X2 = sm.add_constant(df[['PR']])  # Adding a constant for intercept
        model2 = sm.OLS(df['INT'], X2).fit()  # Regression of INT on PR

        # Collect the results for both steps
        result = {
            'Relationship': f'{construct} -> PR -> INT',
            'Path Coefficient': (model1.params[construct], model2.params['PR']),
            't-Value': (model1.tvalues[construct], model2.tvalues['PR']),
            'p-Value': (model1.pvalues[construct], model2.pvalues['PR']),
            'Decision': ('Supported' if model1.pvalues[construct] < 0.05 else 'Not Supported',
                         'Supported' if model2.pvalues['PR'] < 0.05 else 'Not Supported')
        }
        results_list.append(result)

# Convert the results list to a DataFrame
results_df = pd.DataFrame(results_list)
results_df
```

Analysis :

The "path coefficient" is a common way to show how much and in what direction each independent variable affects the dependent variable. As an example, the path coefficient for the relationship between PB and INT is 0.430876, which means that the relationship between PB and INT is positive and modest. This means that as PB goes up, so should INT.

A "t-value" is a measurement that shows how far an estimate of a parameter is from its expected value compared to its standard error. This number is used to find the p-value, which is then used to check if a result is statistically significant. It's less likely that the observed connection is just a coincidence if the absolute value of the t-statistic is high. All of the t-values in this set of data are pretty high, which means there is strong evidence against the null hypothesis, which generally means there is no effect.

With the t-value and p-value in mind, the Decision column shows whether the theory is supported. A choice of "support" means that the p-value is less than the normal level for statistical significance ($p < 0.05$), which means that the link between the independent and dependent factors is statistically significant. In this set of data, all hypotheses from H1 to H14 are supported, which means that each predicted variable has a positive effect on INT that is statistically significant. The strongest proof against the null hypothesis in this group is shown by the highest t-value (9.175986 for PR -> INT), which corresponds to the biggest path coefficient (0.552505). This means that PR is a very good indicator of INT.