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The Direct Impact of Blockchain Basic Knowledge and Its Indirect Impact Through Moderating Adoption of Technology Utility Knowledge and Perceived Value to Risk Tolerance in Buying Interest of Crypto Assets

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ABSTRACT

Around the world, Blockchain as an innovation technology of computer science field has developed at a rapid pace, with various utilities across many sectors. The perceived value inherent in cryptographic products has also established crypto as a new asset class in the digital world. This phenomenon has driven an increment of public buying interest in crypto products as a new option within their investment portfolios.

This research aims to explore more deeply the factors that influence the formation of value perception in cryptographic products and to what extent the public is aware of and can tolerate the risks that arise when they decide to purchase crypto as a digital asset for investment. The main factors we examine are the basic understanding of blockchain technology and knowledge of the adoption of its usefulness as cognitive and affective factors. This research relates to the study of consumer behaviour using the CAC (Cognitive-Affective-Conative) model approach. The respondents used as samples in this research activity are the citizens of Depok City.

This research is conducted for academic and learning purposes only, and not for the purpose of influencing or encouraging the public to invest. We are not responsible for any losses, both material and non-material, arising from any investment actions taken by the public who may be influenced after reading the results of this research.

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1. BACKGROUND

Rapidly advancing era of information technology has created inclusive opportunities across various sectors, including finance. Financial transactions previously constrained by geographical barriers and middle layers can now be conducted across countries and continents within seconds. Globally, this phenomenon has accelerated financial sector digitization, particularly evident in the exponential growth of digital crypto asset ecosystems, *(OJK Institute, digital article, June 19, 2025).*

Investors now enjoy broader access to diverse digital financial instruments including Bitcoin, Ethereum, Stable coins, alternative coins, cryptographic products like Non-Fungible Tokens (NFTs), digital wallets, peer-to-peer services, and smart contracts**,** *(OJK Institute, digital article, June 19, 2025).*

OJK data reveals a 335.91% surge in crypto asset users in Indonesia during 2024, reaching 22.91 million users. Furthermore, OJK recorded 15.85 million crypto users with transaction volumes hitting IDR 32.31 trillion - reflecting a 5.18% monthly increase from May 2025's 15.07 million users. *(Source: OJK reported by Kon tan daily in their digital publication, August 5, 2025).*

As innovative digital financial products, crypto assets possess distinct characteristics compared to conventional instruments: extreme price volatility, regulatory uncertainty, potential fraud/Ponzi schemes, cybersecurity vulnerabilities, and personal data breach risks, (OJK Institute, digital article, June 19, 2025).

Therefore, before investing in crypto assets, the public must comprehend these risks through ongoing intensive financial education and literacy enhancement. *(OJK Institute, digital article, June 19, 2025).*

1.1 BLOCKCHAIN TECHNOLOGY

a) BASIC UNDERSTANDING & TECHNOLOGY MECHANISM

Like the name states, a blockchain is a chain of blocks that contain information. It is a distributed ledger that is open to anyone. A ledger is a bookkeeping system that contains all of a company's financial data. It records each and every transaction that happens from day one. It also contains the account information that company's use to prepare their financial statements. Once data has been recorded inside a block it is virtually impossible to change. Each block has three components; the data, the hash and the previous block's hash.

The data depends on what kind of block it is. The hash works the same way a fingerprint does in that it can't be duplicated and you can use it to identify a single block and all its content. If a piece of data in the block changes, so does the hash. Hashes are useful because they help in identifying any changes that have happened within a block. The hash of the previous block is what links all the blocks together like a chain. This is what makes a blockchain so secure. If we had three blocks in one chain then block three would contain block two's hash and block two would contain block one's hash. The first block only has its own hash so it's called the Genesis block. In the event that the second block is interfered with, its hash will change and that would invalidate all the blocks that come afterward because block three would not contain a valid hash. While a blockchain is inherently secure, computers are developing and increasing their capabilities on a daily basis so it's not impossible for blocks to be interfered with, *(Jeffrey Smith, 2022, page.11)*

b) HISTORY OF TECHNOLOGY

The concept behind 'Blockchain' technology was first outlined in 1991 by research scientists Stuart Haber and W. Scott Stornetta. They proposed a computationally practical method that added time stamps to digital documents, so that they could not be backdated or altered. The system was to use an encrypted chain of blocks to store the time-stamped documents. In 1992, Merkle trees were included in the design. A Merkle tree is a structure used by computer applications to organize data. This made it possible for multiple documents to be collected and stored in one block. After its development, the technology was not used and the patent ended up lapsing in 2004, *(Jeffrey Smith, 2022, page 10).*

In that same year, a computer scientist named Harold Finney launched a system called RPoW or Reusable Proof of Work. The system worked by collecting non exchangeable Hash cash-based Proof of work tokens and then generating an RSA. It is a signed token that could be passed on from person to person. Hash cash is a proof-of-work model and RSA is a technique used to encrypt a public key used for secure data transmission especially over the internet. *(Jeffrey Smith, 2022, page 10).*

In 2008, a Whitepaper was posted to a cryptography mailing list by someone, or a group of people, using the pseudonym Satoshi Nakamoto. The paper presented a decentralized, peer-to peer, electronic cash system based on the Hash cash POW algorithm, called Bitcoin. (Finance Academy, 2018). It proposed the use of a decentralized peer-to-peer protocol that could trail and validate any and all transactions, *(Jeffrey Smith, 2022, page 10).*

On the 3rd of January 2009, the first Bitcoin block was mined by Satoshi Nakamoto. It yielded him a reward of 50 Bitcoins. The first ever Bitcoin transaction took place on the 12th of January when Nakamoto sent Harold Finney 10 Bitcoins, *(Jeffrey Smith, 2022, page 10).*

c) TECHNOLOGY EVOLUTION

In 2013, a programmer named Vitalik Buterin expressed that Bitcoin needed a scripting language for building decentralized applications. He then started developing a new Blockchain-based distributed computing system called Ethereum. A distributed computing system has numerous pieces of software on several computers but run as one system. The computers in the system can either be in close proximity to each other sharing a local network, or they can be dispersed in different areas and connected by a Wide area network. Ethereum has a scripting feature called Smart Contracts. Smart Contracts are scripts that are implemented on the Ethereum Blockchain. They can be used to make transactions if specific conditions are met. They are written in specific coding languages and arranged into Bytecode. Bytecode is source code that has been simplified for a software interpreter to understand. The Ethereum Virtual machine then reads and executes the transactions. The EVM is often called a virtual CPU because it is not tangible and is run on hundreds of machines worldwide. Developers can produce apps that run inside the Ethereum Blockchain. These apps are called DApps (Decentralized Applications). There are hundreds of apps running on the Ethereum blockchain, including various social media platforms. Blockchain technology is becoming more conventional and is even used in applications outside of the cryptocurrency space, *(Jeffrey Smith, 2022, page 10-11).*

d) TECHNOLOGY CHARACTERISTIC

Blockchain is an open ledger operated by a network of anonymous participants which is Calles as miners & nodes. Blockchain technology has below key characteristic:

Transparent● All transactions are publicly traceable.

Decentralized● No central authority can manipulate the data.

Immutable● Once recorded, transactions cannot be altered or erased, *(Jeffrey Smith, 2022, page.23)*

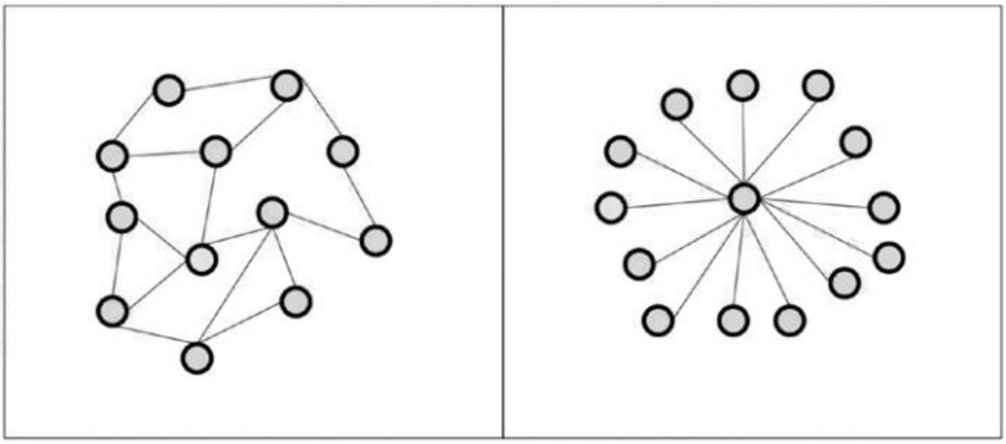
e) SECURITY CONCEPT & FUNDAMENTALS

Security concept has been adopted and enhanced by blockchain technology are below:

Confidentiality● Blockchain employs heavy encryption that is virtually impenetrable, only authorized users can access information, requires enormous time and energy to breach.

Integrity● Blockchain's transaction verification system ensures data cannot be altered; any changes would be detected by the entire network.

Availability● The distributed network ensures full system operation at all times; information remains accessible to authorized parties whenever needed



Picture 1: Distributed (left) vs. centralized (right) system architecture, Daniel Drescher (2017, page.11)

Decentralization● Data and functions are spread across multiple computers, to compromise the network, hackers would need to control at least 60% of network computers, as more computers join the network, transaction verification becomes easier, unauthorized access becomes more difficult. Blockchain doesn't just adopt traditional security standards, it enhances them through decentralization and advanced encryption, *(Jeffrey Smith, 2022, page.25-25)*

1.2 ADOPTION OF TECHNOLOGY UTILITY

One of the most easily understandable adoptions of blockchain technology's utility is its function for transferring monetary value between individuals across borders without intermediaries cheaper and faster. *(Jeffrey Smith, 2022, page. 7).*

In its development, blockchain technology has been utilized across various sectors as follows:

● **Financial exchanges**. The bulk of cryptocurrency exchanges on the blockchain used to happen from person to person. Now, different organizations are starting to offer decentralized cryptocurrency exchanges. These organizations have more control and can feel safe knowing that their transactions are secure.

● **Lending**. Smart contracts can be used by lenders to administer guaranteed loans. Processing these loans is faster and less expensive because Smart contracts have features that automatically set off service payments and release of funds. This also means that they can offer better interest rates.

● **Insurance**. Insurance has always been murky. Customers have never really been sure of what the fine print says and have found themselves in precarious positions because of this. Smart contracts allow for transparency between insurance providers and customers. No customer would be able to claim twice for the same incident and they could actually receive payouts faster.

● **Real estate.** Real estate involves a considerable amount of paperwork. Personal information needs verification and transfer documents need to be checked thoroughly before a sale goes through. Blockchain technology can minimize paperwork while still offering security and ensuring quicker transactions.

● **Storing personal information.** It is possible for any entity storing personal information online to experience a breach in security. Storing this information on a public ledger offers more security because it's harder to penetrate the blockchain system.

● **Storing data.** The issuing of state benefits would substantially improve if identification information was stored on a blockchain.

● **Voting.** If identity information was stored on a blockchain, people would be able to cast their votes more easily. Nobody would be able to vote twice and votes wouldn't be interfered with. It would also encourage more people to vote by being more convenient.

● **State benefits.** Storing identification information on a blockchain could aid in the dispersion of government benefits like Medicare. Blockchain's infrastructure would reduce fraud and operation costs. People would also receive their benefits a lot faster.

● **Storing and sharing medical information**. Storing medical records on a blockchain could assist in patients receiving the best medical care. Doctors would receive the latest and most accurate information on their patients thus avoiding misdiagnosis and wrongful treatment.

● **Royalties.** If there were up-to-date records on all film and music files spread over the internet, there would be a lot less piracy and artists' royalties would be paid in full and on time.

● **NFTs.** Non-fungible tokens are a way for people to own the rights to anything that can be stored as data online, but it's most prevalent in digital art. Putting NFTs on a blockchain can make certain that only a singular piece of digital art exists. It makes investing in art easier for people because there's no need to worry about storage and preservation.

● **Supply chain and logistics tracking**. Keeping track of articles as they traverse a supply chain network can help supply chain and logistics departments work better together. If all the data is stored on a blockchain network then it can't be modified and it can be accessed easily by the relevant parties.

● **Securing Internet of Things networks.** The Internet of Things or IoT, is a system of interlinked computers that have UIDs or Unique Identifiers that allow them to transmit data over a network. It works without human interaction. It's convenient, but susceptible to digital crime. It makes use of a centralized server, which makes it easier for hackers to access. The blockchain interface can enhance security by keeping login credentials on a decentralized network.

In Canada, blockchain technology has been used to credential over 500,000 businesses through its "Verifiable Organizations Network." In any country, adequate oversight and management are central to the use of blockchain - not least because unique and consistent identifiers are prerequisites for decentralized services. For example, blockchain based currency transactions are routed via public addresses that represent a transacting entity, and signed off on via a unique private key (a cryptography tool used to encrypt and decrypt code). However, the anonymity this enables may come into conflict with regulations related to identification that are designed to minimize illicit transfers of funds. As a result, blockchain based digital identity systems still face considerable technological, managerial, and regulatory issues. In addition to the scalability considerations first required in order to support billions of individual users, data integrity will be critical especially given the potential for administrators to interact with a large volume of relatively unsecure, "off-chain" data. Regulatory models will likely need to adapt, in order to accommodate new models of identity and prevent adverse related consequences such as social exclusion or widening digital divides. (World Economic Forum, 2025, intelligent blog article).

In order to make the most of blockchain technology, organizations will have to collaborate. In an acknowledgement of this fact, there has been a proliferation of industry consortia dedicated to blockchain exploration and implementation. These groups are often collaborating to an unprecedented degree, even drawing together rival businesses determined to cooperate in order to truly unlock the full potential of technology through new governance models. To-date, almost 400 such organizations have been registered, with several seeming to appear every month. The Blockchain Insurance Industry Initiative (b3i), for example, has brought together 20 key industry players such as Allianz, Liberty Mutual, and the China Pacific Insurance Company in order to explore and deploy the technology in different ways. The consortium's core activities include developing the standards and infrastructure necessary to facilitate data-sharing across separate organizations. However, collaborative models also raise new questions about intellectual property ownership, shared liability, data sharing, and more. To address such questions, consortium models generally require clear communication and alignment on roles and responsibilities. (World Economic Forum, 2025, intelligent blog article).

The intersection of automation and digital assets has enabled a so-called decentralized finance, or "DeFi," ecosystem which can potentially automate many of the processes deployed by centralized (and often costly) financial intermediaries for the purposes of lending, exchanges, and derivatives. Blockchain technology can also introduce new asset management models, if and when tangible and movable properties are registered and tokenized that is, mapped with digital references to valuable or sensitive elements for security purposes. For example, fine art and real estate could each theoretically be tokenized, making the management and ownership of these potentially pricey assets possible "on-chain." In such a system, professional agencies could be relied upon to oversee the digital management of properties and shape specialized markets for their trading, which could function much like existing financial markets. However, new and sophisticated rules are needed for the next-generation, blockchain based economy and they will have to be adequately enforced in order to help ensure the stability of digital markets and to bolster the legal protection of consumers. (World Economic Forum, 2025, intelligent blog article).

1.3 CRYPTOGRAPHY PRODUCT AS DIGITAL ASSET

Digital asset is a digital representation of value or contractual rights which can be used for payment or investment purposes, IMF-FSB Synthesis paper (2023, page.43).

From inception to the latest phase, Crypto assets explores the past, present, and future of this new asset class. It's not a hard read yet delves into much of the detail needed for a complete understanding of the benefits, and risks, of bitcoin, blockchain, and more. *(Chris Burniske and Jack Tatar, 2017, page.18).*

Those of us who work in the blockchain industry have long realized that the rise of cryptocurrencies as a legitimate asset class was inevitable. But most traditional investors have been slow on the uptick. *(Chris Burniske & Jack Tatar, 2017, page. 22)*

As a general-purpose technology, blockchain technology includes private blockchains that are going to have a profound impact on many industries and public blockchains beyond Bitcoin that are growing like gangbusters. The realm of public blockchains and their native assets is most relevant to the innovative investor, as private blockchains have not yielded an entirely new asset class that is investable to the public. *(Chris Burniske and Jack Tatar, 2017, page. 95)*

Cryptocurrencies are a powerful vertical of crypto assets, but as we laid out in the start of the last chapter, only one of three. The other two, crypto commodities and crypto tokens, are a rapidly growing segment of this budding new asset class. *(Chris Burniske and Jack Tatar, 2017, page.128).*

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Crypto has evolved into a digital asset class, substantiated by clear evidence of its adoption as a tool in innovative funding models through Initial Coin Offering (ICO) mechanisms. This development has significantly enhanced public visibility of blockchain and digital assets, enabling individuals to invest in companies through coins representing various ownership rights.

To support cryptocurrency transactions, a Web3 based digital wallet was created. This wallet functions as a storage solution for digital assets and facilitates transactions such as deposits, receipts, and transfers of cryptocurrency assets. The digital wallet contains both a private key and a public key. The private key consists of a long string of alphanumeric characters used to withdraw cryptocurrency, while the public key contains a relatively shorter alphanumeric string used to receive deposits or balance top-ups. All transactions whether deposits, transfers, or receipts of cryptocurrency are recorded on the blockchain. *(Jeffrey Smith, 2022, page. 13*).

1.4 PERCEIVED VALUE

Perceived value is the consumer's overall assessment of the utility of a product based on perceptions of what is received and what is given. Value is whatever I want in a product. Other respondents emphasized the benefits they received from the product. This second definition is essentially the same as the economist's definition of utility. Value is price and having single portions so that there is no waste. (*Zeithaml (1998), page. 13)*

Consumers depend on intrinsic attributes more than extrinsic attributes (a) at the point of consumption, (b) in pre purchase situations when intrinsic attributes are search attributes (rather than experience attributes), and (c) when the intrinsic attributes have high predictive value. (*Zeithaml (1998), page.9)*

In an increasingly digital world, it is only a matter of time until enormous amounts of value are transmitted and secured via blockchains, including the value of music and creative works. Crypt to assets makes blockchains accessible to the nontechnical by exploring their varied origin stories, use cases, and fundamental value. *(Chris Burniske and Jack Tatar, 2017, page. 19)*

Crypto assets provide a great introduction to and overview of the young yet rapidly growing universe of all things blockchain. This industry, asset class, and overall idea will make you ponder why abstract concepts like money, identity, and business function like they do in the world today, and how the innovation we're seeing will completely reshape the economy of tomorrow *(Chris Burniske and Jack Tatar, 2017, page.21)*

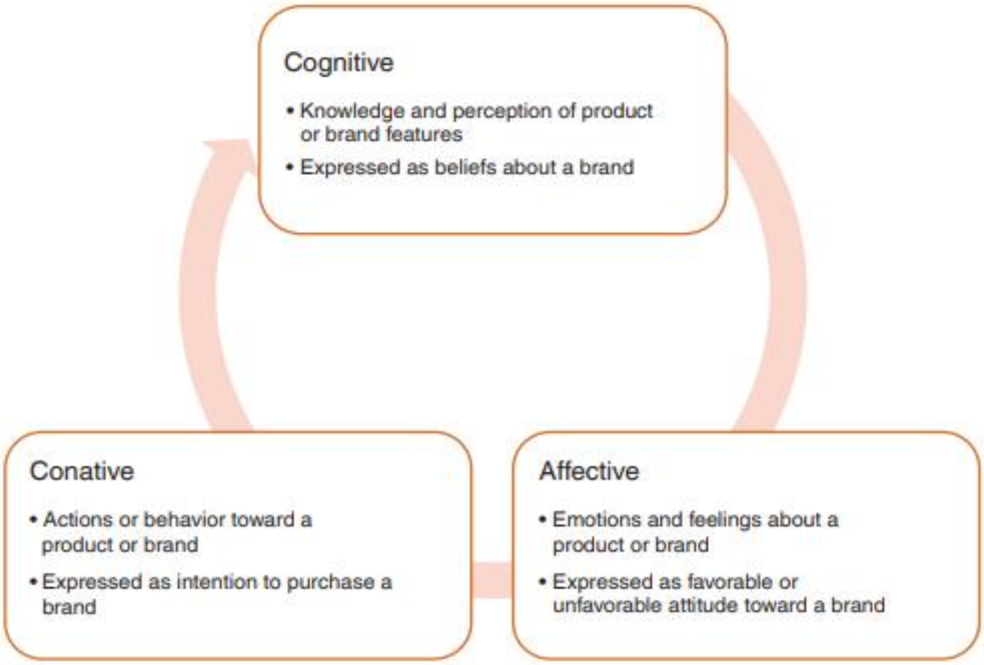
Blockchain architectures and their native assets are well on their way to becoming the next great meta-application to leverage Internet infrastructure. They already provide services that include global currencies, world computers, and decentralized social networks, among hundreds of others. *(Chris Burniske and Jack Tatar, 2017, page.55)*

Digital currency - perhaps the best-known application of blockchain technology - has a wide variety of potential uses. Bitcoin, for example, is viewed by many as a potentially critical store of value; the payments company Square said it invested $50 million in the cryptocurrency in 2020 "as in instrument of economic empowerment," around the same time that Fidelity Investments launched its first Bitcoin fund. Central Bank Digital Currencies (CBDCs) are meanwhile being explored for everything from consumer payments to inter-bank settlements. It is estimated that more than 40 central banks have or are exploring CBDC issuance, with China's on track to be the first. One particular form of digital currency, "stablecoins," is pegged to a fiat currency and is being closely watched not least due to Facebook's announced plans to issue stablecoins including a "Libra" coin that is a composite of others. In addition, a completely new funding model, initial coin offerings (ICOs), has increased the public visibility of blockchain and digital assets as people have become able to buy into companies via coins representing different entitlements. *(World Economic Forum, 2025, intelligent blog article)*

1.5 BUYING INTEREST

A consumer's emotions or feelings about a particular product or brand constitute the affective component of an attitude. These emotions and feelings are frequently treated by consumer researchers as primarily evaluative in nature; that is, they capture an individual's direct or global assessment of the attitude object (the extent to which the individual rates the attitude object as 'favorable' or 'unfavorable', 'good' or 'bad'). *(Schiffman et.al, 1991, page. 236)*

Conation, the final component of the tri component attitude model, is concerned with the likelihood or tendency that an individual will undertake a specific action or behave in a particular way with regard to the attitude object. According to some interpretations, the conative component may include the actual behavior itself. *(Schiffman et.al, 1991, page. 236)*



Picture 2: CAC – Cognitive-Affective-Conative Model, Schiffman et.al, (2019, page. 146)

The cognitive component consists of a person's cognitions that is, the knowledge and perceptions of the features of an attitude object that the person acquired from direct experience with the attitude object and information from various sources. This knowledge and perceptions commonly are expressed as beliefs. In other words, the consumer believes that the attitude object possesses or does not possess specific attributes. *(Schiffman et.al, 2019, page. 146)*

The affective component represents the consumer's emotions and feelings regarding the attitude object. These are considered evaluations because they capture the consumer's global assessment of the attitude object (i.e., the extent to which the individual rates the attitude object as "favorable" or "unfavorable," "good" or "bad") *(Schiffman et.al (2019, page. 146)*

The conative component reflects the likelihood that an individual will undertake a specific action or behave in a particular way with regard to the attitude object. In consumer research, the conative component is treated as an expression of
the consumer's intention to buy. Buying intention scales are used to assess the likelihood of a consumer purchasing a product or behaving in a certain way. *(Schiffman et.al, 2019, page. 147)*

Traditionally, consumer researchers approached decision making from a rational perspective. According to this view, people calmly and carefully integrate as much information as possible with what they already know about a product, painstakingly weigh the pluses and minuses of each alternative, and arrive at a satisfactory decision. This kind of careful, deliberate thinking is especially relevant to activities such as financial planning that call for a lot of attention to detail and many choices that impact a consumer's quality of life. *(Michael R. Solomon, 2025, page 342)*

Depending on consumer knowledge of the categories, perceptions of fit may be based on technical or manufacturing commonalties or more surface considerations such as necessary or situational complementarity**.** Consumers may transfer associations that are positive in the original product class but become negative in the extension context. Consumers may infer negative associations about an extension, perhaps even based on other inferred positive associations. *(Kotler & Keller 2016, page 349-350)*

The first part of the tri component attitude model consists of a person's cognitions, that is, the knowledge and perceptions that are acquired by a combination of direct experience with the attitude object and related information from various sources. This knowledge and resulting perceptions commonly take the form of beliefs; that is, the consumer believes that the attitude object possesses various attributes and that specific behavior will lead to specific outcomes. *(Schiffman, et.al, 1991, page.253)*

1.6 RISK TOLERANCE

The investor's risk tolerance determines the optimal tradeoff between the expected return and risk of their portfolio. More risk averse investors (lower risk tolerance) will allocate less to the optimal risky portfolio and more to the risk-free asset. *(Ziv Bodie, 2014, page.169)*

Crypto assets have been in existence for more than a decade and have displayed significant volatility. Emerging in January 2009, shortly after the Global Financial Crisis, the value of crypto-assets has fluctuated dramatically with many episodes of sharp appreciation and subsequent steep price reversions. *(IMF-FSB Synthesis paper, 2023, page.3)*

For the uninitiated, the world of crypto currencies is fraught with risks and pitfalls. No one should venture into this world without preparation. *(Chris Burniske and Jack Tatar, 2017, page.18)*

From inception to the latest phase, Crypto assets explores the past, present, and future of this new asset class. It's not a hard read yet delves into much of the detail needed for a complete understanding of the benefits, and risks, of bitcoin, blockchain, and more. *(Chris Burniske and Jack Tatar, 2017, page.18)*

Serious investment professionals should read Crypto assets if they want to understand and value the first new asset class of the twenty-first century. *(Chris Burniske and Jack Tatar 2017, page.18)*

Upon launch, crypto assets tend to be extremely volatile because they are thinly traded markets. *(Chris Burniske and Jack Tatar, 2017, page.184)*

We categorize five main patterns that lead to markets destabilizing: the speculation of crowds, this time is different, Ponzi schemes, misleading information from asset issuers and cornering. *(Chris Burniske and Jack Tatar, 2017, page. 251)*

To make matters worse, when markets are overheating is usually when misleading asset issuers, Ponzi operators, and market manipulators come out to play. *(Chris Burniske and Jack Tatar, 2017, page.184)*

Given the emerging nature of the crypto asset markets, it's important to recognize that there is less regulation (some would say none) in this arena, and therefore bad behavior can persist for longer than it may in more mature markets. *(Chris Burniske and Jack Tatar, 2017, page. 274)*

1.8 DISCLAIMER & OBJECTIVE OF RESEARCH

a) DISCLAIMER

- This research is not intended to encourage or influence someone to invest
- Any financial or nonfinancial losses incurred due to investment actions influenced by the results of this academic research are not our responsibility

b) OBJECTIVE OF RESEARCH

The objectives of this research are as follows:

- Providing a basic understanding of blockchain technology

- Providing an understanding of blockchain technology utility applications
- Providing an understanding of cryptography product as a valuable digital asset
- Providing an understanding of the risks associated with owning cryptography product as a digital asset
- For academic purposes

1.9 PROBLEM STATEMENT

The research is started with below questions:

- Does the understanding of utility adoption align with the basic understanding of blockchain technology?
- Does the basic understanding of blockchain technology and its utility adoption influence the perceived value inherent in cryptography product as a digital asset?
- Do the factors of basic understanding of blockchain technology, its utility adoption, and perceived value affect to risk tolerance in buying interest of cryptography product as digital asset?

1.10. SCOPE OF WORK & DISCLAIMER

The scope of this research are as follows:

- Focuses on the context of buying interest of cryptography product as digital asset using the Cognition, Affection, and Conation (CAC) model within the consumer behaviour framework.
- The research subjects/target are residents of Kota Depok as the population.

1.11. HYPOTHESIS

This research has hypothesis as below:

- **H1:** Basic Knowledge of Blockchain Technology influences directly to Risk Tolerance in Buying interest of Cryptography Product.
- **H2:** Basic Knowledge of Blockchain Technology influences Perceived Value of Cryptography Product and then influences Risk Tolerance in Buying Interest of Cryptography Product.
- **H3:** Basic Knowledge of Blockchain Technology influences Knowledge of Adoption of Blockchain Technology and then influences Risk Tolerance in Buying Interest of Cryptography Product
- **H4:** Basic Knowledge of Blockchain Technology influences Knowledge of Adoption of Blockchain Technology Utility and then influences Risk Tolerance in Buying Interest of Cryptography Product.

2. METODOLOGY

2.1 MULTIPLE REGRESSION & PATH ANALYSIS

Multiple regression analysis is a statistical technique that can be used to analyze the relationship between a single dependent (criterion) variable and several independent (predictor) variables. *(Joseph F. Hair, Jr et.al, 2014, page.285)*

Statistical models are the form of analysis where a specific model is proposed (e.g., dependent and independent variables to be analyzed by the general linear model), the model is then estimated and a statistical inference is made as to its generalizability to the population through statistical tests. Operates in opposite fashion from data mining models which generally have little model specification and no statistical inference, *(Joseph F. Hair, Jr et.al, 2014, page.3)*

Specification of the variates is critical, since many times researchers only focus on how various methods operate in terms of estimating the model of interest. And while technique selection is an important issue, many times the “success or failure” of a research project is dictated by the approach the researcher takes to specification of the variate. Including hundreds or even thousands of variables in an attempt to completely cover all the possible impacts may actually hinder the ability of the model to recover more generalized effects and thus the efficacy of the results. Thus, the more control the researcher retains on which variables are inputs to the model allows for more specificity in how the model answers the specific research question. *(Joseph F. Hair, Jr et.al, 2014, page.16)*

Variable selection is necessary Even with researcher control in specifying the variate, empirical models provide flexibility in testing alternative or competing models which vary in the number of variables included. Any estimated model can have a number of “competing or alternative” models that provide equal or even greater predictive accuracy by including a different set of variables. This is disconcerting to beginning researchers when they find there are many models that work just as well as their selected model, but have different variables and effects. Moreover, the possibility of several alternative models increases as the number of variables grows larger. So, researchers should try a number of alternative models in specifying their research, perhaps formulating several alternative models that vary based on whether the researcher controls the process or the software. Chapter 5 explores this consideration by estimating a range of model forms. *(Joseph F. Hair, Jr et.al, 2014, page.16).*

Multivariate analysis of variance (MANOVA) is a statistical technique that can be used to simultaneously explore the relationship between several categorical independent variables (usually referred to as treatments) and two or more metric dependent variables. *(Joseph F. Hair, Jr et.al, 2014, page.26)*

Multiple regression is the appropriate method of analysis when the research problem involves a single metric dependent variable presumed to be related to two or more metric independent variables. *(Joseph F. Hair, Jr et.al, 2014, page.26)*

Path analysis seeks to determine the strength of the paths shown in path diagrams. Path diagram is A visual representation of a model and the complete set of relationships among the model’s constructs. Dependence relationships are depicted by straight arrows, with the arrow emanating from the predictor variable and the arrowhead pointing to the dependent. *(Joseph F. Hair, Jr et.al, 2014, page.606)*

Path analysis procedures provide estimates for each depicted relationship (arrow) in the model. *(Joseph F. Hair, Jr et.al, 2014, page.622)*

Multivariate analysis is Analysis of multiple variables in a single relationship or set of relationships. *(Joseph F. Hair, Jr et.al, 2014, page.3)*

2.2 RESEARCH VARIABLES

This research operates with below variables:

Context	Variables	Dimension & Indicators
	Basic Knowledge of Blockchain Technology (X1)	Cognition factors: Familiarity of Information, basic definition, basic concept understanding, creation background

Buying Interest in Consumer Behavior: ***Cognition, Affection & Conation Approach.***	Knowledge of Adoption of Blockchain Technology Utility (X2)	Cognition & Affection factors: Functionality, product applied/adoption, future of use, product benefit (con's)
	Perceived Value of Cryptography Product (Z)	Cognition & Affection factors: value perception/ believing to product value, trust to product, confident to product
	Risk Tolerance in Buying Interest of Cryptography Product (Y)	Conation factors: interested, plan to be/buy/own, realize to risks

Table 1: Operand Research Variable

2.3 RESEARCH INSTRUMENT

Data analysis involves the identification and measurement of variation in a set of variables, either among themselves or between a dependent variable and one or more independent variables. Instrument is tool to measure, because in the research we cannot identify variation unless it can be measured. Measurement is important in accurately representing the concept of interest and is instrumental in the selection of the appropriate multivariate method of analysis. *(Joseph F. Hair, Jr et.al, 2014, page.11)*

A researcher operationalizes a latent construct by selecting its measurement scale items and scale type. In survey research, operationalizing a latent construct result in a series of scaled indicator items in a common format such as a Likert scale or a semantic differential scale. *(Joseph F. Hair, Jr et.al, 2014, page.627)*

In this academic research, the instrument used to collect primary data is a questionnaire designed to measure respondents' opinions. Responses are recorded using a 5-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree).

2.4 DATA & SAMPLE

Data can be classified into one of two categories as nonmetric (qualitative) and metric (quantitative) as based on the type of attributes or characteristics they represent. Every subject or object can be compared with another in terms of a "greater than" or "less than" relationship. The numbers utilized in ordinal scales, however, are really non quantitative because they indicate only relative positions in an ordered series. Ordinal scales provide no measure of the actual amount or magnitude in absolute terms, only the order of the values. The researcher knows the order, but not the amount of difference between the values. *(Joseph F. Hair, Jr et.al, 2014, page.11)*

The data to be analyzed in this research consists of primary data obtained from a one-time online questionnaire distribution, resulting in cross-sectional data for analysis.

The research population comprises residents of Depok City, with an initial sample size of 401 respondents. After data screening, the filtered sample consisted of 300 respondents. From these 300 samples, 99 extreme outliers were identified. Consequently, 201 sample data points qualified for regression analysis.

2.4.1 DATA NORMALITY TEST

Normality is degree to which the distribution of the sample data corresponds to a normal distribution, *Joseph F. Hair, Jr et.al, (2014, page.48)*

The severity of non-normality is based on two dimensions: the shape of the offending and the sample size. Normality can have serious effects in small samples (fewer than 50 cases), but the impact effectively diminishes when sample sizes reach 200 cases or more. It results in a similar effect here, in that larger sample sizes reduce the detrimental effects of non-normality. In small samples of 50 or fewer observations, and especially if the sample size is less than 30 or so, significant departures from normality can have a substantial impact on the results. For sample sizes of 200 or more, however, these same effects may be negligible. ".as the sample sizes become large, the researcher can be less concerned about non-normal variables, except as they might lead to other assumption violations that do have an impact in other way." *(Joseph F. Hair, Jr et.al, 2014, page.94)*

2.4.2 CONSTRUCTS RELIABILITY AND VALIDITY TEST

Reliability is extent to which a variable or set of variables is consistent in what it is intended to measure. If multiple measurements are taken, the reliable measures will all be consistent in their values. It differs from validity in that it relates not to what should be measured, but instead to how it is measured. *(Joseph F. Hair, Jr et.al, 2014, page.3)*

Reliability is a measure of the degree to which a set of measured variables is internally consistent based on how highly interrelated the indicators are with each other. In other words, it represents the extent to which the indicators all measure the same thing. Reliability does not guarantee, however, that the measures indicate only one thing. In general, reliability is inversely related to measurement error. That is, as reliability increases the relationships between a construct and the indicators are larger, meaning that the construct explains more of the variance in each indicator. Thus, high reliability is associated with lower measurement error. *(Joseph F. Hair, Jr et.al, 2014, page.786)*

While Cronbach's alpha is a widely used method of assessing reliability. Higher values indicate higher levels of reliability when interpreting internal consistency reliability results. For example, values between 0.60 and 0.70 are "acceptable in exploratory research," whereas results between 0.70 and 0.95 represent "satisfactory to good" reliability levels. *(Joseph F. Hair, Jr et.al, 2014, page.775)*

High construct reliability indicates that internal consistency exists > 0.70, meaning that the measures all consistently represent the same latent construct. *(Joseph F. Hair, Jr et.al, 2014, page.676)*

Validity is extent to which a measure or set of measures correctly represents the concept of study—the degree to which it is free from any systematic or nonrandom error. Validity is concerned with how well the concept is defined by the measure(s), whereas reliability relates to the consistency of the measure. *(Joseph F. Hair, Jr et.al, 2014, page.3)*

Construct validity is broad approach to ensure the validity of a set of items as representative of a conceptual definition. Includes specific sub-elements of convergent validity, discriminant validity and nomological validity. *(Joseph F. Hair, Jr et.al, 2014, page.122)*

Construct validity is the extent to which sets of measured items accurately reflect the theoretical latent constructs they are designed to measure. Thus, construct validity deals with the accuracy of measurement. *(Joseph F. Hair, Jr et.al, 2014, page.675)*

Construct Validity having ensured that a scale (1) conforms to its conceptual definition, (2) is unidimensional, and (3) meets the necessary levels of reliability, the researcher must make one final assessment: construct validity. Construct validity is the extent to which a scale or set of measures accurately represents the concept of interest. We already described one form of construct validity—content or face validity—in the discussion of conceptual definitions. Other forms of validity are measured empirically by the correlation between theoretically defined sets of variables. The three most widely accepted forms of validity are convergent, discriminant, and nomological validity. *(Joseph F. Hair, Jr et.al, 2014, page.162)*

Pearson value are used to show whether or not there is a relationship between one variable and another variable.

One of indicator that can be used to measure the requirement of a linear relationship is the Pearson correlation, although this method has limitations. *(Joseph F. Hair, Jr et.al, 2014, page.46*)

2.5. ESTIMATING & ASSESSING GOODNESS OF FIT MODEL

2.5.1 MODEL ESTIMATION AND HYPOTHESIS TEST

a) F – TEST APPROACH

In addition to testing for the difference from a base model, there is also a test for the significance of any of the estimated coefficients. This test, if significant, reflects that at least one of the estimated coefficients is significant. This is similar in nature to the overall model F test in multiple regression. *(Joseph F. Hair, Jr et.al, 2014, page.564)*

b) PSEUDO R2 MEASURES

In addition to the statistical chi-square tests, several different "R2 - like" measures have been developed and are presented in various statistical programs to represent overall model fit. These pseudo-R 2 measures are interpreted in a manner similar to the coefficient of determination in multiple regression. A pseudo-R 2 value can be easily derived for logistic regression similar to the R 2 value in regression analysis. *(Joseph F. Hair, Jr et.al, 2014, page.564)*

c) t – TEST APPROACH

An independent variable is considered to influence a dependent variable based on the significance value in the coefficient matrix. If the calculated significance value is < 0.05 (assuming a 5% significance level), then the independent variable can be said to have a significant effect on the dependent variable in the linear regression model. Conversely, if the calculated significance value is > 0.05 (assuming a 5% significance level), then the independent variable is considered to have no significant effect on the dependent variable in the linear regression model.

This is consistent with Wood's statement in his book, when a specific alternative is not stated, it is usually considered to be two-sided. In the remainder of this text, the default will be a two-sided alternative, and 5% will be the default significance level. When carrying out empirical econometric analysis, it is always a good idea to be explicit about the alternative and the significance level. If H0 is rejected in favor at the 5% level, we usually say that "x; is statistically significant, or statistically different from zero, at the 5% level." If Ho is not rejected, we say that "x; is statistically insignificant at the 5% level. *(Jeffrey M. Wooldridge, 2016, page.115)*

2.5.2 ASSUMPTION OF CLASICAL MODEL TEST

For the techniques based on statistical inference, the assumptions of multivariate normality, linearity, independence of the error terms, and equality of variances must all be met, Joseph F. Hair, Jr et.al, (2014, page.33).

2.5.2.1 NORMALITY ASSUMPTION TEST

The assumption of normality applies only to the error terms/residuals, any attempt to remedy non-normality involves assessing the non-normality of the independent or dependent variables or both. They differ from residual plots in that the standardized residuals are compared with the normal distribution. (Joseph F. Hair, Jr et.al, 2014, page.291)

One of the methods used to determine data normality is by calculating the skewness and kurtosis of the data:

Skewness Measure of the symmetry of a distribution; in most instances the comparison is made to a normal distribution. A positively skewed distribution has relatively few large values and tails off to the right, and a negatively skewed distribution has relatively few small values and tails off to the left. Skewness values falling outside the range of 21 to 11 indicate a substantially skewed distribution. (Joseph F. Hair, Jr et.al, 2014, page.48)

Kurtosis Measure of the peaked Ness or flatness of a distribution when compared with a normal distribution. A positive value indicates a relatively peaked distribution, and a negative value indicates a relatively flat distribution. (Joseph F. Hair, Jr et.al, 2014, page.48)

The most fundamental assumption in multivariate analysis is normality, referring to the shape of the data distribution for an individual metric variable and its correspondence to the normal distribution, the benchmark for statistical methods. If the variation from the normal distribution is sufficiently large, all resulting statistical tests are invalid, because normality is required to use the F and t statistics. Both the univariate and the multivariate statistical methods discussed in this text are based on the assumption of univariate normality, with the multivariate methods also assuming multivariate normality. (Joseph F. Hair, Jr et.al, 2014, page.94)

Researchers have a number of different approaches to assess normality, but they primarily can be classified as either graphical or statistical. Graphical methods were developed to enable normality assessment without the need for complex computations. They provide the researcher with a more "in depth" perspective of the distributional characteristics than a single quantitative value, but they are also limited in making specific distinctions since graphical interpretations are less precise that statistical measures. (Joseph F. Hair, Jr et.al, 2014, page.94)

The severity of non-normality is based on two dimensions: the shape of the offending distribution and the sample size. Normality can have serious effects in small samples (fewer than 50 cases), but the impact effectively diminishes when sample sizes reach 200 cases or more. It results in a similar effect here, in that larger sample sizes reduce the detrimental effects of non-normality. In small samples of 50 or fewer observations, and especially if the sample size is less than 30 or so, significant departures from normality can have a substantial impact on the results. For sample sizes of 200 or more, however, these same effects may be negligible. ".as the sample sizes become large, the researcher can be less concerned about non-normal variables, except as they might lead to other assumption violations that do have an impact in other way." (Joseph F. Hair, Jr et.al, 2014, page.94)

To examining the normal probability plot, one can also use statistical tests to assess normality. A simple test is a rule of thumb based on the skewness and kurtosis values (available as part of the basic descriptive statistics for a variable computed by all statistical programs), The statistic value (z) for the skewness value is calculated as:

$$z_{\text{skewness}} = \frac{\text{skewness}}{\sqrt{\frac{6}{N}}} \qquad z_{\text{kurtosis}} = \frac{\text{kurtosis}}{\sqrt{\frac{24}{N}}}$$

If either calculated z value exceeds the specified critical value, then the distribution is non-normal in terms of that characteristic. The critical value is from a z distribution, based on the significance level we desire. (Joseph F. Hair, Jr et.al, 2014, page.95-96)

Graphical analyses (i.e., partial regression plots, residual plots, and normal probability plots) are the most widely used methods of assessing assumptions for the variate. Most remedies for problems found in the variate must be accomplished by modifying one or more independent variables. (Joseph F. Hair, Jr et.al, 2014, page.292)

2.5.2.2 LINEARITY ASSUMPTION TEST

Used to express the concept that the model possesses the properties of additivity and homogeneity. In a simple sense, linear models predict values that fall in a straight line by having a constant unit change (slope) of the dependent variable for a constant unit change of the independent variable. In the population model Y = b0 + b1X1 + e, the effect of a change of 1 in X1 is to add b1 (a constant) units to Y. (Joseph F. Hair, Jr et.al, 2014, page.47)

Linearity assumption test is condition in the case of individual variables, this linearity relates to the patterns of association between each pair of variables and the ability of the correlation coefficient to adequately represent the relationship. (Joseph F. Hair, Jr et.al, 2014, page.128)

The linearity of the relationship between dependent and independent variables represents the degree to which the change in the dependent variable is associated with the independent variable. The regression coefficient is assumed to be constant across the range of values for the independent variable. The concept of correlation, the measure of association underlying regression analysis, is based on a linear relationship, thus making it a critical issue in representing the "true" relationship between variables in the analysis. Moreover, violations of the linearity assumption are not overcome by increasing the sample size, as is the case with other assumptions (e.g., normality). (Joseph F. Hair, Jr et.al, 2014, page.288)

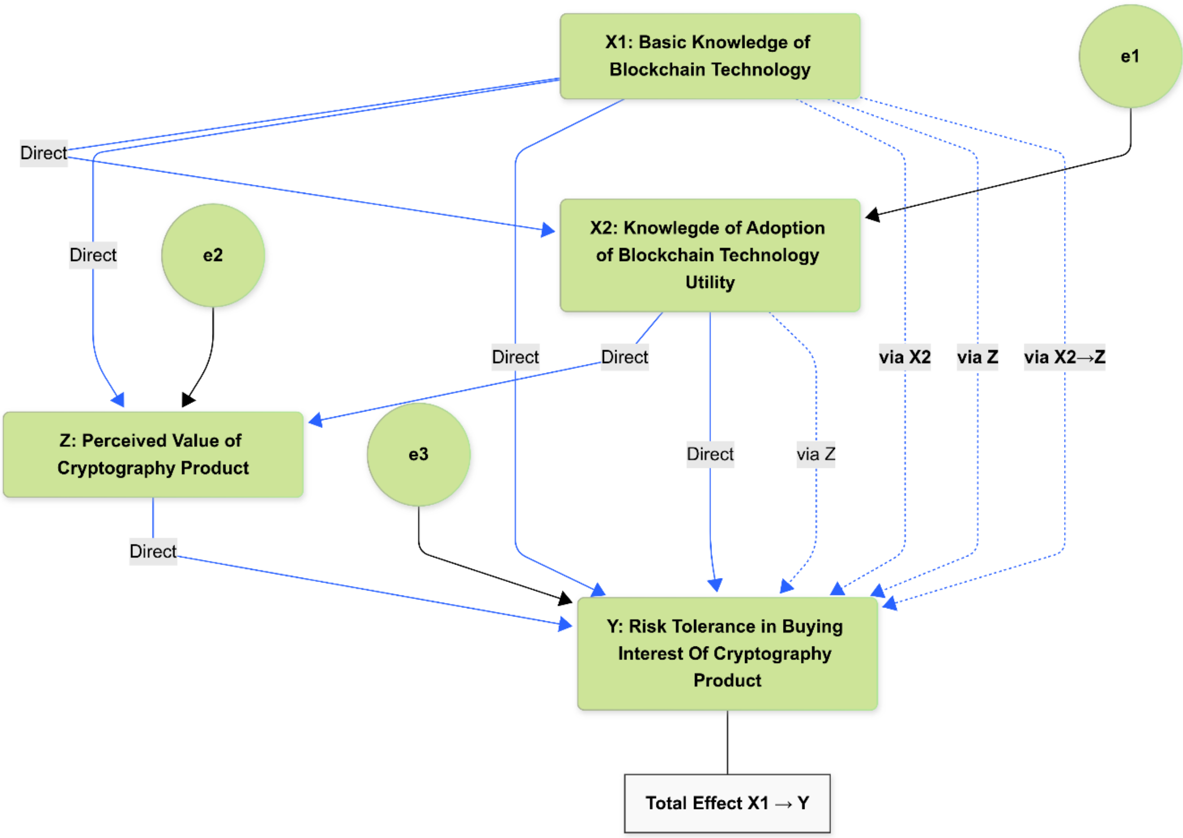
$$\text{Lagrange Multiplier Statistic (LM)} = \frac{(n-k+r)(\text{RRSS}-\text{URSS})}{\text{RRSS}} \sim \chi_r^2$$

Letting RRSS and URSS denote the restricted and unrestricted residual sums of squares, where k is the number of regressors in the unrestricted model and r is the number of restrictions. (Damodaran N. Gujarati, et.al, 2009, page.276)

3. ANALYSIS

3.1 PATH ANALYSIS DIAGRAM

Path diagrams are the basis for path analysis, the procedure for empirical estimation of the strength of each relationship (path) depicted in the path diagram. Path analysis calculates the strength of the relationships using only a correlation or covariance matrix as input. *(Joseph F. Hair, Jr et.al, 2014, page.650)*



Picture 2: Path Diagram Analysis

Path diagram has description as below:

- **H1:** Basic Knowledge of Blockchain Technology influences directly to Risk Tolerance in Buying Interest of Cryptography Product
- **H2:** Basic Knowledge of Blockchain Technology influences Perceived Value of Cryptography Product and then influences Risk Tolerance in Buying Interest of Cryptography Product
- **H3:** Basic Knowledge of Blockchain Technology influences Knowledge of Adoption of Blockchain Technology and then influences Risk Tolerance in Buying Interest of Cryptography Product
- **H4:** Basic Knowledge of Blockchain Technology influences Knowledge of Adoption of Blockchain Technology Utility and then influences Risk Tolerance in Buying Interest of Cryptography Product

EQUATIONS:

X2 : aX1 + e1 ……………………………………..…………………………………...……*(1)*

Y : b1X1 + b2X2 + bZ + e2 …………………………………………...………………...*(2)*

Z : c1X1 + c2X2 + e3 ……………..………………………………………………………..*(3)*

3.2. DATA ANALYSIS

3.2.1 CONSTRUCTS RELIABILITY & VALIDITY TEST

One of way to obtain the values of Cronbach's Alpha and Pearson Correlation in the SPSS application is by performing bivariate correlation analysis on the data. The following are the results of the bivariate correlation analysis in the SPSS application:

Questionnaire Items	Response on Likert Scale
	Cronbach's Alpha
BASIC KNOWLEDGE OF BLOCKCHAIN TECHNOLOGY (X1)	
I understand the basic definition of blockchain technology	0.860
I know that blockchain is decentralized and transparent	0.869
Blockchain and cryptography are future technology	0.881
Blockchain is synonymous with technology that provides transparency to every owner	0.857
I believe that blockchain can improve data security	0.888
Cronbach's Alpha of variable's construct	89.4%
KNOWLEDGE OF ADOPTION OF BLOCKCHAIN TECHNOLOGY UTILITY (X2)	
Cryptographic products are synonymous with data security	0.954
Cryptographic products are characterized by encryption mechanisms in transaction processes	0.957
I am familiar with blockchain implementations (e.g., Bitcoin, Ethereum, NFT)	0.956
Blockchain is beneficial for supply chain business processes	0.955
I am optimistic that blockchain can improve business and government efficiency	0.955
Blockchain can transform the financial sector (e.g., bank less transactions)	0.954
I have heard about WEB3 products that provide users full authority over content ownership, access, and online activities	0.956
I have heard about smart contract technology that automates transaction mechanisms transparently	0.961
I have heard about NFT technology that provides authentication features for creative works like documents, art, and audio-video	0.958
I know that official certificates/documents can be converted and verified using blockchain technology	0.957
Cronbach's Alpha of variable's construct	96.10%
PERCEIVED VALUE OF CRYPTOGRAPHY PRODUCT (Z)	
Cryptography is synonymous with monetizable products	0.936
Crypto is emblematic of future digital currency	0.934
I am interested investing in crypto assets (Bitcoin, Ethereum, etc.)	0.931
I believe crypto can be a profitable alternative investment	0.938

Crypto offers higher return potential compared to stocks	0.934
Crypto investments are easily accessible anytime	0.936
Certain crypto products can serve as a hedge against inflation	0.932
I prefer Crypto over conventional investments	0.932
Cronbach’s Alpha of variable’s construct	94.2%
RISK TOLERANCE IN BUYING INTEREST OF CRYPTOGRAPHY PRODUCT AS DIGITAL ASSET (Y)	
I would consider crypto investment if clear guidance were available	0.839
I am interested investing in crypto assets despite the risks due to their high volatility for long-term investment	0.836
I am interested investing in crypto assets despite the risks of hacking and scams	0.855
Political instability affects crypto valuation	0.846

Table 2: Data Reliability Test based on questionnaire result

Based on the results of the correlation test using the SPSS application, the results were obtained with Cronbach's Alpha values for each indicator as a construct of the variable with values greater than 0.7. This indicates that each indicator can be a construct that can explain the concept of the variable.

Pearson correlation value:

	X1	**X2**	**Z**	**Y**
X1	1	0,939	0,932	0,894
X2	0,939	1	0,930	0,912
Z	0,932	0,930	1	0,931
Y	0,894	0,912	0,930	1

Table 3: Data Validity Test based on questionnaire result

Based on the results of the correlation test using the SPSS application, the results were obtained with Pearson’s correlation values for each variable are with values greater than 0.7. This indicates that each variable’s relationship is strong and positives.

3.2.2 OUTLIER DATA SCREENING

Missing data are a nuisance to researchers and primarily result from errors in data collection/data entry or from the omission of answers by respondents. Classifying missing data and the reasons underlying their presence are addressed through a series of steps that not only identify the impacts of the missing data, but that also provide remedies for dealing with it in the analysis. Outliers, or extreme responses, may unduly influence the outcome of any multivariate analysis. (Joseph F. Hair, Jr et.al, 2014, page.46)

Outliers, or anomalies in the parlance of data mining, are observations with a unique combination of characteristics identifiable as distinctly different from what is normal. (Joseph F. Hair, Jr et.al, 2014, page.80)

In univariate methods, outlier can be found by examining all metric variables to identify unique or extreme observation. For small samples (80 or fewer observations), outliers typically are defined as cases with standard scores of 2.5 or greater. For larger sample sizes, increase the threshold value of standard scores up to 4. If standard scores are not used, identify cases falling outside the ranges of 2.5 versus 4 standard deviations, depending on the sample size with these univariate, bivariate, and multivariate diagnostic methods, the researcher has a complementary set of perspectives with which to examine observations as to their status as outliers. Each of these methods can provide a unique perspective on the observations and be used in a concerted manner to identify outliers. (Joseph F. Hair, Jr et.al, 2014, page.90)

3.2.3 DATA NORMALITY TEST

In the normality test of the sample data, the results obtained were not normal. However, with a sample data size of 201, the sample data normality test is not crucial, or the condition of data non-normality can still be tolerated. *This refers to the opinion of Joseph F. Hair, Jr. et al. in their book published in 2014*

The severity of non-normality is based on two dimensions: the shape of the offending distribution and the sample size. Normality can have serious effects in small samples (fewer than 50 cases), but the impact effectively diminishes when sample sizes reach 200 cases or more. It results in a similar effect here, in that larger sample sizes reduce the detrimental effects of non-normality. In small samples of 50 or fewer observations, and especially if the sample size is less than 30 or so, significant departures from normality can have a substantial impact on the results. For sample sizes of 200 or more, however, these same effects may be negligible. ".as the sample sizes become large, the researcher can be less concerned about non-normal variables, except as they might lead to other assumption violations that do have an impact in other way." *(Joseph F. Hair, Jr et.al, 2014, page.94)*

3.2.4. REGRESSION ANALYSIS

3.2.4.1 MODEL ESTIMATION & HYPHOTESIS

After the removal of incorrect and outlier data, the data is ready to be analyzed using the SPSS application. The following is a summary of the output results from the data analysis using regression analysis in SPSS:

Description	Equation 1	Equation 2	Equation 3
Model	**X2: aX1 + e1**	**Z: b1X1 + b2X2 + e2**	**Y = c1X1 + c2X2 + c3Z + e3**
Significant level at	**5%**	**5%**	**5%**
ANOVA (F-test)			
F-value	**1.470,67**	**832,120**	**501,165**
Sig. Value	**0,000 (sig. value)**	**0,000 (sig. value)**	**0,000 (sig. value)**
Model Summary			
R	**0,939**	**0.945**	**0,940**
R Square	**0,881**	**0,893**	**0,884**
Coefficient (t-Test)			
Constant	**0,021**	**0,243**	**0,024**
Standardized Coeff. & Sig of X1	**0,939; 0.000 (sig. value)**	**0,499; 0,000 (sig. value)**	**-0,096; 0,230 (sig. value)**
Standardized Coeff. & Sig of X2		**0.462; 0,000 (sig. value)**	**0,395; 0,000 (sig. value)**
Standardized Coeff. & Sig of Z			**0,653; 0,000 (sig. value)**
e Value			
$\sqrt{(1-R^2)}$	**0,344**	**0,325**	**0,340**
Model with coefficient	**X2: 0,939X1**	**Z: 0,434X1 + 0,498X2**	**Y: -0,096X1 + 0,395X2 + 0,653Z**

Table 4: Model Estimation (Source: Modified SPSS output)

Table. 4 above displays the data results from linear regression processing using the SPSS application. The results can be explained as follows:

Equation 1, X2: 0,939X1 with R Square values as 0,881 and 0,344 as e1 value

Equation 2, Z: 0,434X1 + 0,498X2 with R Square values 0,893 and 0,325 as e2 value
Equation 3, Y: -0,096X1 + 0,395X2 + 0,653Z with R Square values 0,884 and 0,340 as e3 value

Thus, the interpretation of the path analysis result in figure 2 can be done as follows:

Equation	Direct Effect	Indirect Effect	Total Effect
X1's direct impact to Y	**-0, 096**		**-0,096**
X1's indirect impact to Y through X2		**0,939 * 0,395**	**0,370**
X1's indirect impact to Y through X2 to Z		**0, 939 * 0,498 * 0,653**	**0,305**
X1's indirect impact to Y through Z		**0,434 * 0,653**	**0,383**
Simultaneously of X1 Impact to Y			**0,863**

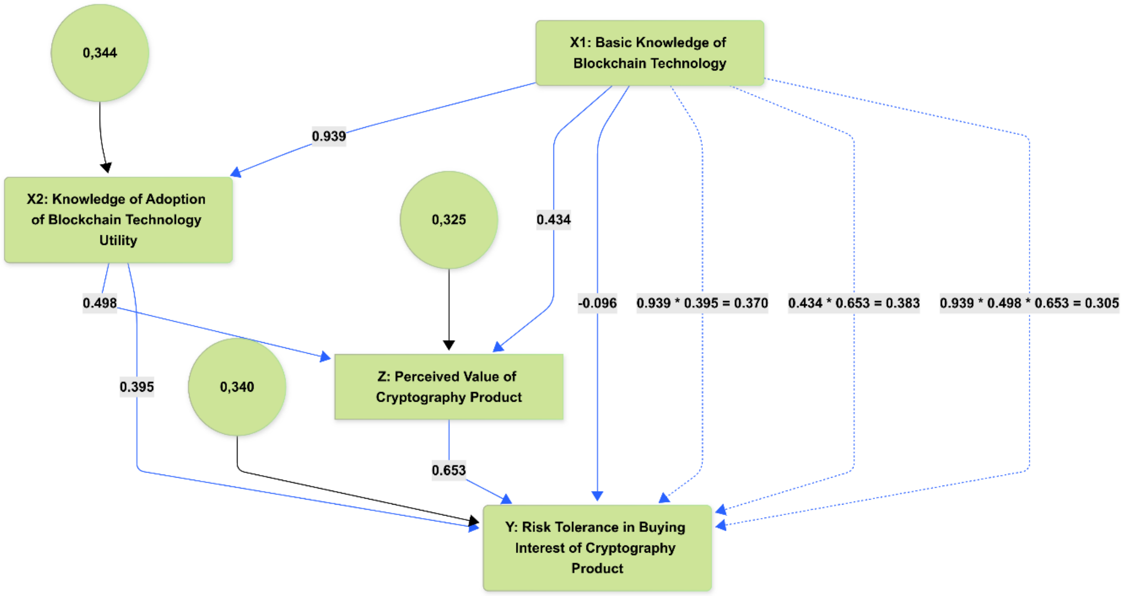
Table 5: Impact Calculation

Table 5 shows the estimation results of the influence of variable X1 on Y. This can be explained as follows:

- X1 has direct effect on Y of -0.096.
- X1 has an indirect effect on Y through X2 of 0.370.
- X1 has an indirect effect on Y through Z of 0.383.
- X1 has an indirect effect on Y through X2 and then through Z of 0.305.

Therefore, the total effect of X1 on Y is 0.863. *(Imam Ghazali 2013, page.250)*

Thus, it can be illustrated in a diagram as follows:



Picture 3: Coefficient Path Analysis

3.2.4.2 NORMALITY ASSUMPTION TEST

One of way to test the classical assumption of normality is by examining the normality of the residuals in each linear equation within the model. The following are the results of data processing in the SPSS application using the linear regression feature:

Description	Equation 1	Equation 2	Equation 3
Model	X2: 0,939X1 + 0,344	Z: 0,434X1 + 0,498X2 + 0,325	Y: -0,096X1 + 0,395X2 + 0,653Z + 0,340
Significant level at	5%	5%	5%
N (No of Observation)	201	201	201
Unstandardized Residual			
Skewness	-0,223	0,047	0,020
Kurtosis	-0,119	0,662	0,172
Normal Z-Score	+/- 1,96	+/- 1,96	+/- 1,96
Z-Skewness	-.1,29	0,27	0,11
Z-Kurtosis	-0,34	1,91	0,49
Conclusion	Pass of normality test	Pass of normality test	Pass of normality test

Table 6: Assumption of Normality Test Result (source: Modified SPSS Output)

For the model normality test, a method was used that calculates the Z-skewness and Z-kurtosis values, with the statistical Skewness and Kurtosis values obtained from the analysis results in SPSS.

- **Equation 1:** The calculated Skewness (Z-skewness) and Kurtosis (Z-kurtosis) values are |-1.29| and |-0.34| respectively. Since these values are smaller than the normal Z-score critical value of |1.96| for a dataset with 201 samples at a 5% significance level, Equation 1 is considered to have passed the normality assumption test.
- **Equation 2:** The calculated Skewness (Z-skewness) and Kurtosis (Z-kurtosis) values are |0.27| and |1.91| respectively. Since these values are smaller than the normal Z-score critical value of |1.96| for a dataset with 201 samples at a 5% significance level, Equation 2 is considered to have passed the normality assumption test.
- **Equation 3:** The calculated Skewness (Z-skewness) and Kurtosis (Z-kurtosis) values are |0.11| and |0.49| respectively. Since these values are smaller than the normal Z-score critical value of |1.96| for a dataset with 201 samples at a 5% significance level, Equation 3 is considered to have passed the normality assumption test.

3.2.4.3 LINEARITY ASSUMPTION TEST

One of way to test the classical assumption of model linearity is by using the Lagrange Multiplier Test method. The following are the results of data processing in the SPSS application for conducting the linearity test:

Description	Equation 1	Equation 2	Equation 3
Model	X2: 0,939X1 + 0,344	Z: 0,434X1 + 0,498X2 + 0,325	Y: -0,096X1 + 0,395X2 + 0,653Z + 0,340
Significant level at	5%	5%	5%
N (No of Observation)	201	201	201
R Square			
Origin	0,881	0,893	0,884

Lagrange Multiplier Test	**0,000**	**0,000**	**0,000**
Chi-Square			
Table (5%; df=200)	**233,994**	**233,994**	**233,994**
Lagrange Multiplier Test	**0**	**0**	**0**
Conclusion	**Pass of linearity test**	**Pass of linearity test**	**Pass of linearity test**

Table 7: Assumption of Linearity Test Result (source: Modified SPSS Output)

For the model linearity assumption test, the Lagrange Multiplier Test method was used. The first step involves obtaining the residuals from the original equation, which is believed to be correctly specified as a linear model. These residuals are then regressed against the original model to obtain an R-squared value, which we refer to as the Lagrange Multiplier Test R-squared. If this R-squared value multiplied by the number of observations is smaller than the critical Chi-Square value for N observations, then the model is said to be linear and does not suffer from misspecification. (Imam Ghazali 2013, page. 162 – 163)

- Equation 1: Based on the Lagrange Multiplier Test results, the obtained R-squared value was 0.000. This value is smaller when compared to the calculated chi-square value (LM Test R-squared X 201 Observations), which is 0.000 X 201 = 0 (smaller than the critical Chi-Square value of 233.994). Therefore, the linear regression model for Equation 1 has met the linearity assumption.
- Equation 2: Based on the Lagrange Multiplier Test results, the obtained R-squared value was 0.000. This value is smaller when compared to the calculated chi-square value (LM Test R-squared X 201 Observations), which is 0.000 X 201 = 0 (smaller than the critical Chi-Square value of 233.994). Therefore, the linear regression model for Equation 2 has met the linearity assumption.
- Equation 3: Based on the Lagrange Multiplier Test results, the obtained R-squared value was 0.000. This value is smaller when compared to the calculated chi-square value (LM Test R-squared X 201 Observations), which is 0.000 X 201 = 0 (smaller than the critical Chi-Square value of 233.994). Therefore, the linear regression model for Equation 3 has met the linearity assumption.

4. RESULT OF ANALYSIS

Based on the data analysis results in Table. 5 and Table. 6 and also their explanations, it can be concluded that:

- **H1:** Basic Knowledge of Blockchain Technology influences directly to Risk Tolerance in Buying Interest of Cryptography Product. ***This hypothesis is acceptable.***
- **H2:** Basic Knowledge of Blockchain Technology influences Perceived Value of Cryptography Product and then influences Risk Tolerance in Buying Interest of Cryptography Product. ***This hypothesis is acceptable***
- **H3:** Basic Knowledge of Blockchain Technology influences Knowledge of Adoption of Blockchain Technology and then influences Risk Tolerance in Buying Interest of Cryptography Product. ***This hypothesis is acceptable***
- **H4:** Basic Knowledge of Blockchain Technology influences Knowledge of Adoption of Blockchain Technology Utility and then influences Risk Tolerance in Buying Interest of Cryptography Product. ***This hypothesis is acceptable***

5. CONCLUSIONS & RECOMMENDATION

a) CONCLUSIONS:

Based on the results of the path analysis, it was found that the total effect value of basic blockchain knowledge on risk tolerance regarding the intention to buy crypto assets is 0.863. This value is obtained from the direct effect of basic blockchain knowledge of -0.096, the indirect effect through knowledge of utility adoption of 0.380, the indirect effect through perceived value of 0.383, and the indirect effect through knowledge of technology utility adoption which is then mediated through perceived value of 0.305.

With the largest indirect effect on risk tolerance coming from perceived value, this indicates that the allure of value inherent in crypto assets is more dominant than knowledge of the function, utility, or application of the blockchain technology itself. This is especially true given the negative influence of basic knowledge about blockchain technology. This situation presents a potential risk for investment behaviour, particularly within digital asset class portfolios like cryptographic products.

Furthermore, this risk is amplified by the proliferation of new blockchain networks which require new members to act as human nodes to strengthen them. Therefore, enhancing foundational understanding and utility adoption of blockchain becomes highly relevant.

b) RECOMMENDATION:

We fully recognize that this research still requires refinement. Therefore, we welcome suggestions and input. Furthermore, for educational and learning purposes, allow us to provide recommendations for future researchers with related topics, such as:

1. Research is needed on FOMO (fear of missing out) behaviour in buying interest of crypto assets.
2. Further research is needed on cryptographic products that have high reliability and utility levels to support their value and have a proven long term track record of providing returns to investors. This aims to protect the public from potential investment losses.
3. More research is required on the application and use of blockchain technology.
4. Research is needed on the integrity of the organizers and developers of new blockchain networks, as well as their reliability and future utility.

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