FACTORS AFFECTING THE ADOPTION OF BLOCKHCHAIN TRACEABILITY PLATFORM IN THAILAND RUBBER SUPPLY CHAIN USING UTAUT MODEL

JEERANAN WANDEE

MASTER OF BUSINESS ADMINISTRATION
IN INTERNATIONAL LOGISTICS AND
SUPPLYCHAIN MANAGEMENT

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THIS THESIS IS A PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE DEGREE OF MASTER OF BUSINESS ADMINISTRATION IN INTERNATIONAL LOGISTICS AND SUPPLY CHAIN MANAGEMENT

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Author: Jeeranan Wandee

Examination Committee:

Assistant Professor Tosporn Arreeras, D. Eng.	Chairperson
Samatthachai Yamsa-ard, Ph. D.	Member
Damrongpol Kamhangwong, Ph. D.	Member
Sunida Tiwong, Ph. D.	Member
Puwanart Fuggate, Ph. D.	Member

Advisors: ....Advisor

(Samatthachai Yamsa-ard, Ph. D.)

....Co-Advisor

(Damrongpol Kamhangwong, Ph. D.)

Dean:

....

(Piyatida Pianluprasidh, Ph. D.)

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Jeeranan Wandee

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Author	Jeeranan Wandee
Degree	Master of Business Administration (International Logistics and Supply Chain Management)
Advisor	Samatthachai Yamsa-ard, Ph. D.
Co-Advisor	Damrongpol Kamhangwong, Ph. D.

ABSTRACT

This study aimed to identify the challenges of Thai rubber industry under the responsibility of RAOT and to test a solution which explore the acceptance of blockchain traceability platform by a proposed UTAUT model among all stakeholders in the rubber industry supply chain in Thailand. The study employed the conventional UTAUT model by incorporating the Technological Anxiety (TA) factor, which was hypothesized to influence stakeholders' acceptance of the blockchain traceability platform. The conventional UTAUT model included Social Influence (SI), Facilitating Conditions (FC), Performance Expectancy (PE), and Effort Expectancy (EE) factors, all of which were theorized to influence Behavioral Intention (BI). Data was collected from the focus group and developed a questionnaire survey of 27 statement items with 130 stakeholders' respondents. Firstly, it was found that the major challenge in the rubber industry supply chain is price fluctuation, while the imbalance between local demand and supply is a minor challenge. Moreover, this study investigated the root causes of the rubber industry's minor challenge in Thailand and identified potential solutions within the authority of RAOT. Secondly, the results were analyzed by using Structural Equation Modeling (SEM), testing the proposed UTAUT model that incorporated the TA factor. The initial results of the proposed UTAUT model were not consistent with the empirical data. In contrast, the path analysis showed that the individual factor (SI, FC, PE, TA) influenced BI, except for EE. In conclusion, FC directly influenced BI (β = 0.974; $p<0.001$) that FC could support the active stakeholders' involvement in the process of rubber supply chain. Additionally, it is also highlighting the importance of facilitating conditions (FC) e.g., IT infrastructure, updated rules and regulations, and capacity building in blockchain technology for all stakeholders in promoting acceptance. Based on these findings, the study provided recommendations for each factor, suggesting that RAOT should support and encourage the acceptance and adoption of blockchain traceability platform in Thailand's rubber supply chain. Furthermore, recommendations for future studies have been proposed based on the findings.

Keywords: UTAUT, Rubber Supply Chain, Blockchain Technology, Acceptance Behavior

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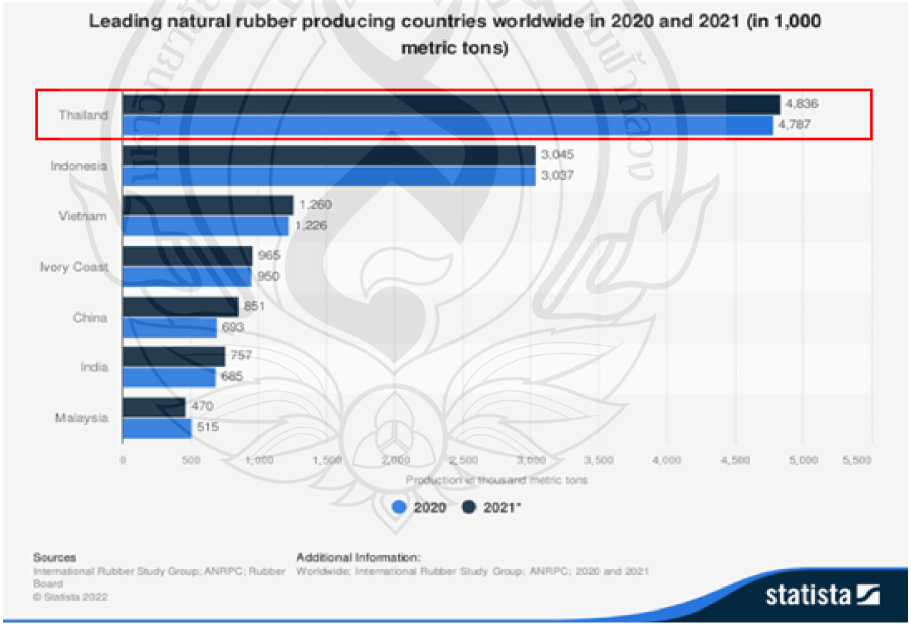
CHAPTER 1

INTRODUCTION

1.1 Background

Natural rubber is also known as India rubber, which is a milky colloid as latex, produced from the rubber tree. In 2021, Thailand is the world leading natural rubber country that produced 4.8 million metric tons with approximate of 37.5% of global rubber production (Statista Research Department, 2024). Thailand is the world's largest supplier of natural rubber, with key trading partners including China, the United States, Malaysia, Japan, and South Korea. Regarding the comparison of rubber production countries in ASEAN, Thailand is the leading producing country among Indonesia, Vietnam and Malaysia as shown in Figure 1.1.



Source Statista Research Department (2024)

Figure 1.1 Leading Natural Rubber Producing Counties Worldwide in 2020 - 2021

There is the increasing trend of rubber consumption worldwide, for instance Thailand's rubber consumption increased 12.5 percent in 2022 (Statista Research Department, 2024) due to the COVID-19 outbreak caused high demand of rubber glove for the health and hygiene self-protection. However, Thailand produced rubber mainly for exporting at 70.25 percent in 2022 (Office of Agricultural Economics [OAE], 2024). Although, Thailand holds the position of the leading producer and supplier of natural rubber worldwide, the price fluctuation of rubber is the main problem of Thai rubber producer. There is a complex issue that is caused by many factors. However, the main cause of the rubber price problem can be summarized into three main issues as follows:

1. The imbalance of demand and supply affects the selling price of rubber.
2. The economic slowdown, especially in the world's largest rubber consumer, China, the United States and Japan that cause declining the purchase rubber consumers. Furthermore, political tensions in many countries and the situation of the COVID-19 epidemic are also other factors, directly causing a price fluctuation to decline accordingly.
3. Investor's speculation in both the domestic market and the futures market is affecting trading, pricing in that market (Rubber Authority of Thailand [RAOT], 2024a).

According to the three main causes of rubber price fluctuation, Issue 1 is an internal factor that can be addressed under the authority of the Thai government, while Issues 2 and 3 are external factors that cannot be controlled. Hence, this study will focus on Issue 1 as the primary problem.

Therefore, the Thai government has established an official agency named the Rubber Authority of Thailand (RAOT) since 2015. RAOT has a responsibility for facilitating and supporting rubber industry including leveraging livelihood of farmers and all stakeholders in rubber supply chain, strengthening fair trade in rubber industry, being a center of rubber production and innovation for sustainability, and creating stable rubber pricing (RAOT, 2024a). Up to now, the RAOT has been encountering some challenges due to a lack of big data related to rubber between government organizations and external organizations. This includes stakeholder data on rubber and data on rubber trading. Addressing these data challenges is essential to effectively facilitate and support the rubber industry supply chain, as well as to forecast rubber demand and supply both domestically and internationally.

To be the leading rubber industry, there are five stakeholders to play a significant role in supporting Thai rubber industry supply chain according to the supply chain as follows:

1. Upstream Rubber Industries: Farmers

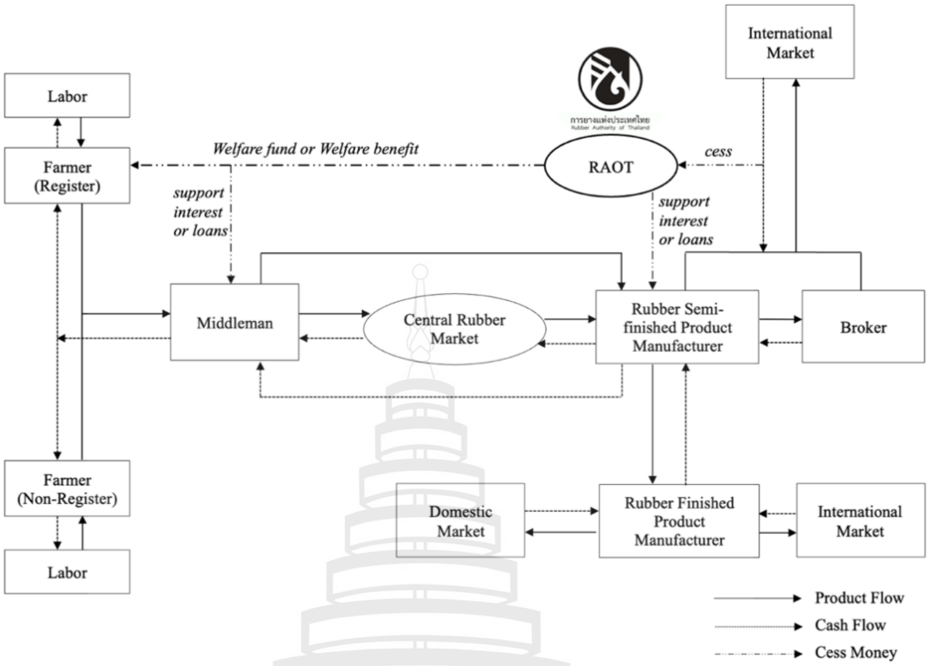
Rubber growers and tappers are involved in both the cultivation and harvesting of rubber plantations. To enhance the value of their primary production, some farmers also carry out basic processing of the latex they collect, turning it into dried rubber products like cup lumps, scrap rubber, sheets, and crepe rubber.

2. Intermediate or Midstream Rubber Industries, or Rubber Processor: Collectors.

Intermediate or midstream rubber industries, also known as rubber processors or collectors, obtain latex or processed rubber from farmers and transform it into semi-finished products. These include ribbed smoked sheets, technically specified rubber, concentrated latex, compound rubber, and skim rubber, materials that meet the necessary standards and properties for use in various downstream manufacturing processes.

3. Downstream Rubber Industries: Manufactures and Exporters

To produce rubber goods such as car tires, latex gloves, condoms, elastic materials, and other related products. Nevertheless, it still has RAOT as another stakeholder, it is playing significant role as the facilitator and supporter in Thai rubber industry under the Rubber Authority of Thailand Act, B.E. 2558 (2015). Moreover, there are two government agencies involved in the Thai rubber supply chain: (1) the Rubber Division under the Department of Agriculture (DOA), which acts as the regulator under the Rubber Control Act, B.E. 2542 (1999); and (2) the Customs Department, which oversees customs procedures as the regulator under the Customs Act, B.E. 2469 (1926). To have the clearer understanding, the relationship of all stakeholders, challenges and potential solution in Thai rubber supply chain is shown in Figure 1.2.



Source Adapted from The Corporate Strategy Division under RAOT (2024)

Figure 1.2 Rubber Industry Supply Chain in Thailand

With the advanced technology available as "Blockchain" which is the different kind of "Distributed Ledger Technology (DLT)" it is a high potential for managing big data by developing transparent, efficient and reliable management system with a good accountability. Due to the characteristics of blockchain, it is guaranteed record format security that previously recorded information cannot be changed or modified, which means every user will see all the same data. Using Cryptography principles and abilities of distributed computing to establish a trust mechanism (Raskin & Yermack, 2016).

Due to abovementioned in term of stakeholders, RAOT's challenges and a potential technological solution as "Blockchain Traceability Platform", it is important for finding what is an essential key success to the implementation of blockchain in Thai rubber industry. It may be the acceptance of all stakeholders in cooperation with the implementation process. However, it is necessary for the study to find out the factors influencing the way of all stakeholders' acceptance, the Unified Theory of Acceptance and Use of Technology (UTAUT) will be appropriate model to test the acceptance of technology among all stakeholders in rubber supply chain.

Therefore, this study will aim to explore the factors affecting the adoption of all stakeholders by implementing blockchain traceability platform in their rubber supply chain which each stakeholder will gain some benefits either directly or indirectly.

1.2 Objectives

There are 2 objectives as follows.

1.2.1 To identify the challenges of Thai rubber supply chain under the responsibility of RAOT.

1.2.2 To test a solution which explore the acceptance of the adoption of blockchain traceability platform by a proposed UTAUT model among all stakeholders in rubber supply chain in Thailand.

1.3 Hypotheses

There are five hypotheses to be tested that form the basis of the proposed UTAUT model, as illustrated in Figure 1.3, as follows.

1.3.1 Hypothesis 1 (H1 = PE ⟶ BI)

Performance Expectancy (PE) has a positive and significant direct effect on Behavioral Intention (BI) of the blockchain traceability platform. Performance Expectancy (PE) in this study is expected that the system would make the task increase effectiveness and quality (Venkatesh et al., 2003).

1.3.2 Hypothesis 2 (H2 = EE ⟶ BI)

Effort Expectancy (EE) has a positive and significant direct effect on Behavioral Intention (BI) of the blockchain traceability platform. Effort Expectancy (EE) in this study believe in the system will be easy and clear to understand (Venkatesh et al., 2003).

1.3.3 Hypothesis 3 (H3 = SI ⟶ BI)

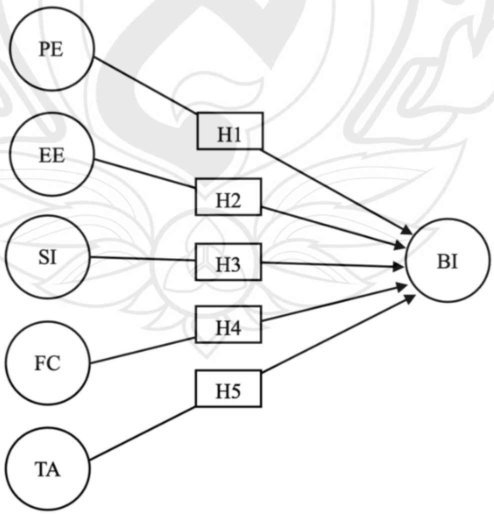
Social Influence (SI) has a positive and significant direct effect on Behavioral Intention (BI) of the blockchain traceability platform. Social Influence (SI) in this study is focused on the influence of coworkers and supporting organizations to social influence (Venkatesh et al., 2003).

1.3.4 Hypothesis 4 (H4 = FC ⟶ BI)

Facilitating Conditions (FC) has a positive and significant direct effect on Behavioral Intention (BI) of the blockchain traceability platform (Popova & Zagulova, 2022; Nain, 2021). Facilitating Conditions (FC) in this study are focus on the capacity building and the regulatory and technical infrastructure exists to support use of the system for example smart phone, computer, internet or Wi-Fi and training in blockchain technology by RAOT.

1.3.5 Hypothesis 5 (H5 = TA ⟶ BI)

Technological Anxiety (TA) has a positive and significant direct effect on Behavioral Intention (BI) of the blockchain traceability platform. In this study, Technology Anxiety (TA) refers to negative emotions and thoughts triggered by actual or imagined interactions with computer-based technology. This aligns with Bozionelos (2001), who found that computer anxiety was prevalent across all sample groups. Moreover, Technology Anxiety (TA) has been integrated into the evaluation phase of the UTAUT model, with its significance validated and highlighted in various research studies (Gunasinghe et al., 2019; Zhang & Zhang, 2024).



Source Adapted from Venkatesh et al. (2003)

Figure 1.3 Proposed UTAUT Model

1.4 Conceptual Framework

The way of doing this research is based on this conceptual framework as shown in Figure 1.4

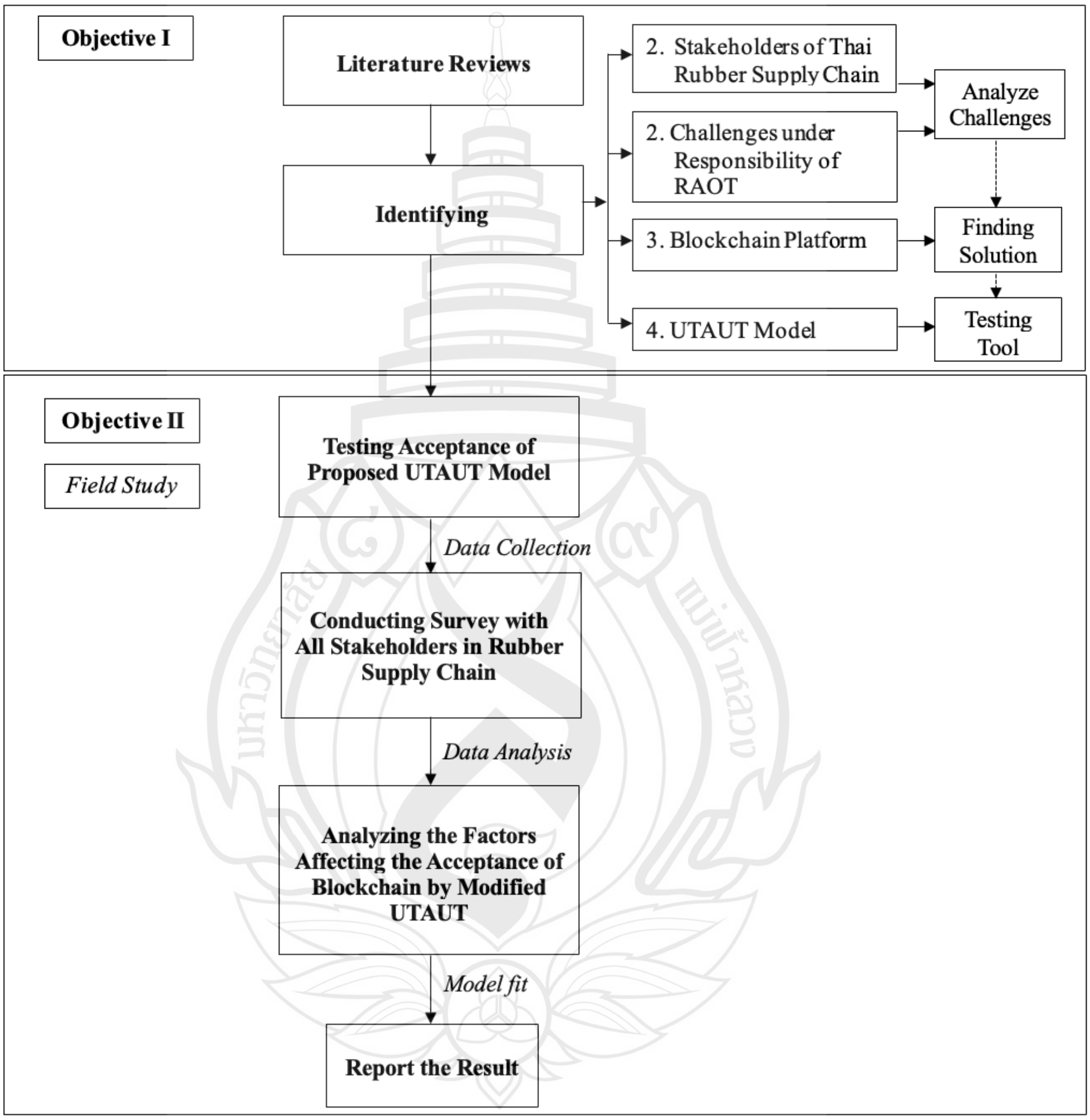


Figure 1.4 Conceptual Framework of the Study

1.5 Expected Outcomes

1.5.1 The factors that influence the acceptance of blockchain traceability platform implementation by all stakeholders in rubber industry supply chain in Thailand.

1.5.2 Suggestions to the Rubber Authority of Thailand (RAOT) to implement the possible acceptance of blockchain traceability platform.

CHAPTER 2

LITERATURE REVIEW

2.1 Rubber Industry Supply Chain in Thailand

The rubber industry supply chain in Thailand is regulated by government agencies under the Rubber Control Act, B.E. 2542 (1999), which established the Rubber Division under the Department of Agriculture (DOA) to oversee and monitor the entire rubber supply chain. The Rubber Authority of Thailand Act, B.E. 2558 (2015), established the Rubber Authority of Thailand (RAOT) to facilitate and support the entire rubber supply chain. Additionally, the Customs Department under the Customs Act, B.E. 2469 (1926), was established to facilitate global trade and provide effective control on imports, exports and transit goods as shown in Table 2.1 (RAOT, 2024b).

Table 2.1 Activities Under the Rubber Act of Rubber Supply Chain in Thailand

Stakeholders	Rubber Act	Government Agencies	Data Report
1. Farmers	- The Rubber Control Act, B.E. 2542 (1999) - The Rubber Authority of Thailand Act, B.E. 2558 (2015)	- DOA - RAOT	- Rubber Grower Registry - Rubber Cultivation Area (or Plantation Area) - Number of Rubber Trees and Rubber Varieties - Annual Production Yield - Quality Management Standard Certification

Table 2.1 (continued)

Stakeholders	**Rubber Act**	**Government Agencies**	**Data Report**
2. Collectors (Middlemen and Cooperatives)	- The Rubber Control Act, B.E. 2542 (1999) - The Rubber Authority of Thailand Act, B.E. 2558 (2015)	- DOA - RAOT	- Rubber Trader Registry (or Rubber Merchant Database) - Rubber Trading Volume Record (or Detailed Rubber Transaction Log) - Rubber Types and Traded Quality Grades
3. Manufacturers	- The Rubber Control Act, B.E. 2542 (1999) - The Rubber Authority of Thailand Act, B.E. 2558 (2015)	- DOA - RAOT	- Rubber Processing Plant Registry (or List of Registered Rubber Processing Factories) - Types of Processed Rubber Products - Processed Rubber Production Volume (or Output Quantity of Processed Rubber)

Table 2.1 (continued)

Stakeholders	Rubber Act	Government Agencies	Data Report
4. Exporters	- The Rubber Control Act, B.E. 2542 (1999) - The Rubber Authority of Thailand Act, B.E. 2558 (2015) - The Customs Act, B.E. 2469 (1926)	- DOA - RAOT - Customs	- Rubber Importers and Exporters Registry - Customs Clearance Certificate (or Custo ms Declaration Form) - Rubber Export Duty Collection (or Rubber Export Fee Levy) - Export Rubber Quality and Standard Certification

Source RAOT (2024b), DOA (2024) and Customs Department (2024)

2.1.1 Situation of Rubber Industry Supply Chain in Thailand

In 2023, Thailand was the largest producer of natural rubber in the world, producing 4.8 million tons. The total rubber plantation area in Thailand covers nearly 22.5 million rai, equivalent to 3.6 million hectares. Rubber plantations span 69 out of 77 provinces in Thailand and are distributed across all four regions with high production potential, including the Southern region 56% (14 provinces), Northeastern region 28% (20 provinces), Central region 8% (20 provinces), and Northern region 5.8% (15 provinces), respectively (OAE, 2024).

Moreover, Thailand was the leading exporter of natural rubber, exporting 3.9 million tons. This included approximately 1.6 million tons of mixed rubber, 1.5 million tons of Standard Thai Rubber (STR), also known as block rubber, and 0.78 million tons of other types such as concentrated latex and smoked rubber sheets (Rubber Division, 2024). The export value was approximately 125,000 million baht, with China being the largest consumer, accounting for 39% of total production. Other major importers included Japan, the USA, and Malaysia (Thailand's Trade Statistics, 2024).

Meanwhile, domestic rubber consumption accounted for 1.2 million tons, including 0.6 million tons for automobile tires, 0.1 million tons for latex gloves, 0.096 million tons for elastics, and other uses (Rubber Division, 2024).

2.1.2 The Flow of Rubber Industry Supply Chain in Thailand

It can be characterized into 3 levels as follows (Figure 2.1-2.2).

2.1.2.1 Upstream Rubber Supply Chain

This is a critical and essential step in the initial process of natural rubber production in Thailand. The key stakeholders in this stage are rubber farmers, who play a vital role in cultivating and tapping natural rubber.

Thailand's natural rubber industry relies on over 1.6 million farming families, cultivating approximately 22.5 million rai (3.6 million hectares) of rubber plantations. With an average yield of 214 kg per rai, the country has an annual production potential of 4.8 million tons. Rubber cultivation is widespread, covering 69 of Thailand's 77 provinces, with regional distribution as follows: the Southern region dominates production (57.5%, 14 provinces), followed by the Northeastern (28.5%, 20 provinces), Central (8.1%, 20 provinces), and Northern regions (5.9%, 15 provinces) (OAE, 2024).

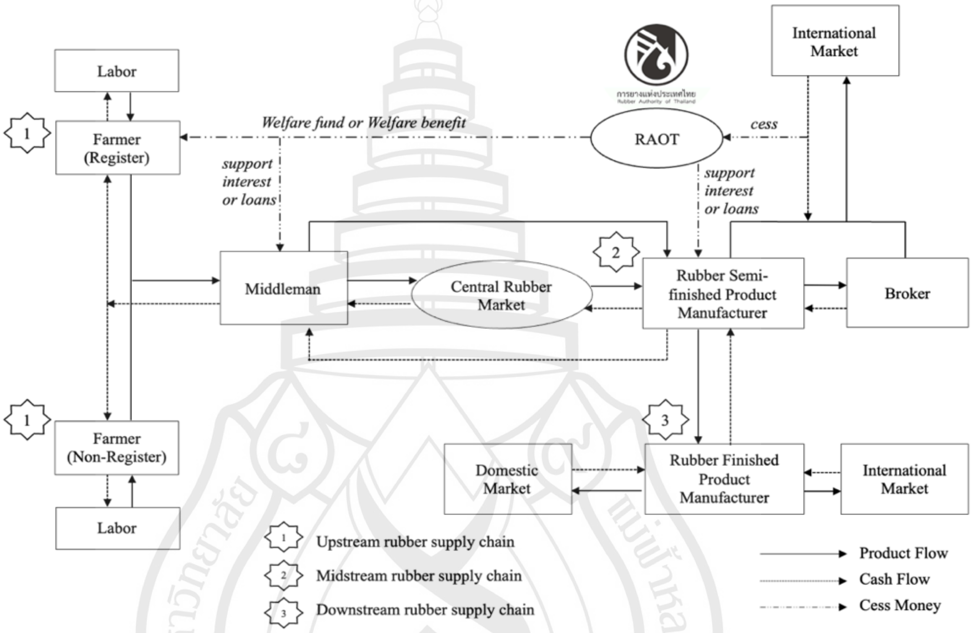
As a result, field latex (90%) and cup lump (10%) make up the main forms of primary production. To enhance the value of these raw materials, some rubber farmers carry out basic processing of their field latex to produce dried rubber products, consisting of dry rubber (83%) and latex (17%). Almost all upstream production in Thailand is used as input for the country's midstream rubber industry (Sowcharoensuk, 2024).

2.1.2.2 Midstream Rubber Supply Chain

This rubber produced on plantations is converted into semi-finished products such as Standard Thai Rubber (STR), also known as block rubber, which was the most produced type, accounting for approximately 39.6% of production from 2013 to 2017. Ribbed smoked sheets and concentrated latex were also produced, representing approximately 19.3% and 18.5% of production, respectively. Other products, including compound rubber and skim rubber, possess specific qualities and properties required as inputs for various downstream production processes.

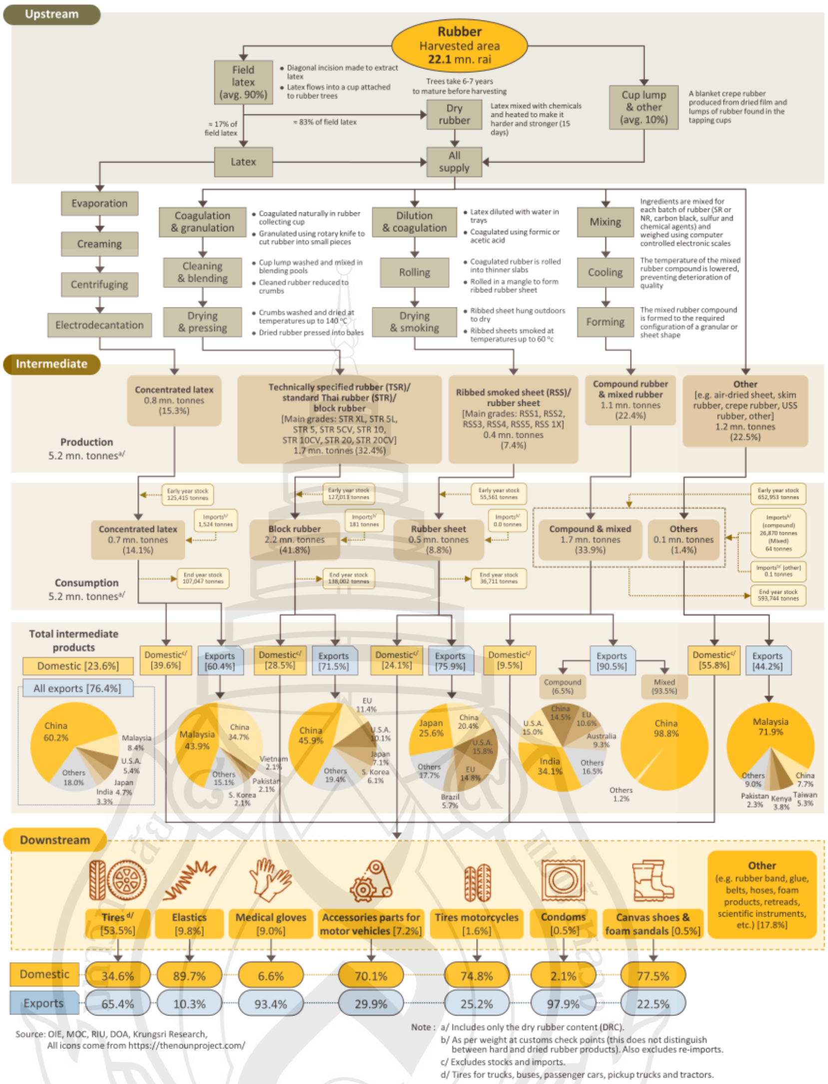
2.1.2.3 Downstream Rubber Supply Chain

This sector includes producers of goods such as automobile tires (57%), elastics (15%), latex gloves (11.6%), motorcycle tires (5.2%), and rubber bands (3.5%). However, synthetic rubber, developed by the petrochemical industry, may also be used as a substitute for midstream natural rubber products in applications where its properties are more advantageous.



Source Adapted from The Corporate Strategy Division under RAOT (2024)

Figure 2.1 Flow of Rubber Industry Supply Chain in Thailand



Source Sowcharoensuk (2024)

Figure 2.2 Products of Rubber Supply Chain in Thailand

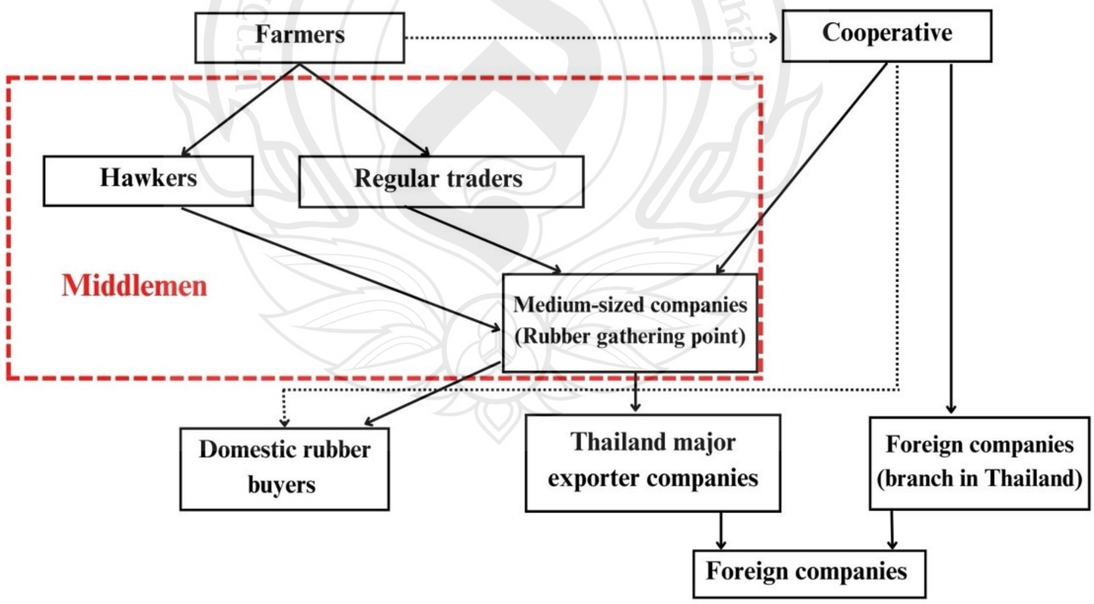
2.2 Rubber Market in Thailand

2.2.1 The System of Rubber Market in Thailand

Thailand's domestic rubber trade operates through a three-tiered market system (local, central, and agricultural futures markets), where export-oriented companies procure rubber through intermediaries rather than dealing directly with farmers. This multi-layered supply chain-involving small hawkers, traders, cooperatives, and medium-sized collectors creates systemic inefficiencies. The lack of transparent tracking mechanisms leads to unpredictable daily price volatility, quality adulteration (mixing high-grade and low-grade rubber), and exploitative practices where middlemen suppress farmgate prices.

Significantly, Thailand's upstream rubber industry functions mainly under monopolistic competition, marked by many suppliers but relatively few buyers. Rubber prices are largely dictated by collectors, causing frequent daily price fluctuations. Additionally, collectors tend to hoard rubber in anticipation of better prices before releasing it to the market.

Despite government interventions-including financial subsidies, processing support, and stockpiling-these measures offer only short-term relief. The Rubber Control Act, B.E. 2542 (1999) attempts to standardize trade practices but fails to address core data infrastructure gaps. With over 1.6 million farmers (OAE, 2022), the absence of a verifiable, centralized data system results in inconsistent record-keeping, undermining supply chain management. The opaque trading model perpetuates profit fragmentation across intermediary chains, leaving farmers economically disadvantaged and hindering sustainable price stabilization is shown in Figure 2.3.



Source Adapted from RAOT (2020)

Figure 2.3 The System of Rubber Market in Thailand

2.2.2 The Policy of Rubber Market in Thailand

The rubber market policy in Thailand is governed by the Rubber Trade License under the Rubber Control Act, B.E. 2542 (1999) (RAOT, 2024b). The main stakeholders subject to this license include middlemen, manufacturers, and exporters involved in the purchase of rubber products. The primary purpose of this policy is to ensure that all relevant stakeholders report on their rubber trading records monthly, pay annual income tax, and renew their rubber trade license annually. Furthermore, failure to comply with the policy may result in a fine of up to 10,000 baht, along with other penalties as outlined in Table 2.2.

Table 2.2 Rubber Trade License Policy

Stakeholders		Trading Activity	Duties of Rubber Trade License Policy	Penalties
Farmer		Selling Rubber Product	-	-
Collector Exporter	Middleman Manufacturer	Buying Rubber Product	1. The licensee must prepare records of rubber trading activities, monthly sales, and remaining rubber stock. These records must be submitted to the relevant authorities by the 10th of each month. The records should be prepared using Forms 5, 6, 7, and 8, as specified by law. 2. In each rubber sale or transfer, the license, date of relocation. buyer, or transporter	1. Anyone who excavates land without a permit: Shall be fined not more than 10,000 baht. 2. In cases where land is filled or rubber is brought along with other materials, including waste, tools, equipment, etc., into an illegal area: The competent official shall take appropriate action.

Table 2.2 (continued)

Stakeholders	Trading Activity	Duties of Rubber Trade License Policy	Penalties
		must allow officers to inspect the transaction, and must provide evidence of the sale, such as a rubber transport certificate, and must carry it during transportation. 3. If the licensee suspends or ceases rubber trading temporarily, they must notify the authorities in writing within 15 days, stating the reason and expected duration. 4. If the licensee relocates their rubber trading operation or changes the location, they must notify the authorities within 15 days from the 5. If the licensee wishes to renew the license, they must submit the renewal application before the license expires.	3. Anyone who submits a permit application or prepares a list of items or expense accounts incorrectly or fails to comply with the factual requirements prescribed by law: Shall be fined not more than 5,000 baht. 4. Permit holders who fail to comply with the conditions specified in the permit: Shall be fined not more than 5,000 baht.

Table 2.2 (continued)

Stakeholders	Trading Activity	Duties of Rubber Trade License Policy	Penalties
		6. If the license expires and is not renewed, but the licensee still possesses rubber, they must report the remaining rubber amount within 60 days from the expiration date. 7. If the rubber trader no longer wishes to continue the business, they must report the discontinuation in writing to the local authority within 15 days. 8. In case of death of the license`e, the heir must notify the authorities in writing within 15 days to cancel the license or apply for a new one.	

Source RAOT (2024b)

2.3 The Challenges of Rubber Industry Supply Chain in Thailand

The rubber industry supply chain in Thailand is very complicated and faces many challenges. To analyze these challenges, they can be divided into three causes that directly affect the fluctuation of rubber prices, including (1) The imbalance of demand and supply affects the selling price of rubber. (2) The economic slowdown, especially in the world's largest rubber consumer, China, the United States and Japan that cause declining the purchase rubber consumers. Furthermore, political tensions in many countries and the situation of the COVID-19 epidemic are also other factors, directly causing a price fluctuation to decline accordingly. (3) Investor's speculation in both the domestic market and the futures market is affecting trading and pricing in that market (RAOT, 2024a). To provide a clearer understanding, it can be clarified as follows.

2.3.1 The Imbalance of Rubber Demand and Supply: Affecting the selling price of rubber.

2.3.1.1 Lack of domestic demand and supply data (RAOT, 2024a).

2.3.1.2 The supply is higher than domestic demand, causing low rubber prices (Intrasakul et al., 2017).

2.3.1.3 Plant Diseases: Diseases such as leaf blight and root rot can devastate rubber plantations, reduce the overall supply and cause prices to spike (Intrasakul et al., 2017).

2.3.1.4 Production Costs: Rising costs of labor, fertilizers, and other inputs can reduce profit margins for rubber producers, potentially leading to decreased production and higher prices (Intrasakul et al., 2017).

2.3.1.5 Technological Advances: Innovations in synthetic rubber production can affect the demand for natural rubber. If synthetic alternatives become cheaper or more efficient, the demand for natural rubber may decline, reducing prices (RAOT, 2024a; Intrasakul et al., 2017).

2.3.2 The Economic Slowdown: Especially in the world's largest rubber consumer, China, the United States and Japan that cause declining the purchase rubber consumers.

2.3.2.1 Global Economic Conditions: The demand for rubber is closely tied to the global economy. During economic booms, the demand for rubber in industries such as automotive and manufacturing increases, pushing prices up. Conversely, during economic downturns, demand decreases, leading to lower prices (Statista Research Department, 2024; Do, 2024).

2.3.2.2 Consumer Preferences: Changes in consumer preferences, such as a shift towards more sustainable and eco-friendly products, can influence the demand for natural rubber and its price. Moreover, domestic consumption remains much lower than exports, resulting in a gradual decline in the contribution of manufactured rubber and plastic products to Indonesia's GDP in recent years, in line with the drop in rubber production (Statista Research Department, 2024; Do, 2024).

2.3.3 Investor's Speculation in both the Domestic Market and the Futures Market: It affects trading and pricing in that market.

2.3.3.1 Trade Policies: Tariffs, trade agreements, and export restrictions imposed by major rubber producing or consuming countries can significantly affect rubber prices. For example, import tariffs on rubber products can decrease demand, leading to price drops (Intrasakul et al., 2017; Do, 2024).

2.3.3.2 Unfair trading, pressure on prices, weight, percentage of dry rubber, and unfair rubber quality selection, etc. (Munkong et al., 2013; Intrasakul et al., 2017; Statista Research Department, 2024).

Based on previous studies that identified the problems faced by various stakeholders in the rubber supply chain, several key issues are presented in Table 2.3 as follows.

Table 2.3 Problems of Rubber Industry Supply Chain in Different Country

Stakeholders	Countries	Problems	References
Farmer	Thailand	- The para-rubber farmers' groups were not strengthened, leading to a lack of negotiation power for rubber prices at 83.27% - The prices of rubber have been decreasing and fluctuating at 60.6% -The health problems of rubber farmers at 55.42% -The lack of professional rubber farmers at 52.31%	Intrasakul et al. (2017)

Table 2.3 (continued)

Stakeholders	Countries	Problems	References
		-The lack of knowledge in marketing and selling at 43.89%	
		-The problem of rubber disease at 40.14%	
		-The cost of para-rubber production was quite high at 39.85%.	
		-The uncontrollability of suitable areas for planting rubber was at 38.60%.	
		-The misunderstanding of production technology under the control of the Rubber Research Institute at 36.54%	
		-The lack of family workers, leading to the need to import migrant workers at 36.28%	
		-The misunderstanding of rubber tapping at 35.29%	
		-Unfair trading, pressure on prices, weight, percentage of dry rubber, and unfair rubber quality selection, etc.	Munkong et al. (2013)
	Indonesia	-Domestic consumption remains much lower than exports, resulting in a gradual decline in the contribution of manufactured rubber and plastic products to Indonesia's GDP in recent years, in line with the drop in rubber production.	Statista Research Department (2024)
	Malaysia	-The falling price of rubber, along with the heavy dependence on smallholder farmers for natural rubber production, has caused a reduction in the industry's	Statista Research Department (2024)

Table 2.3 (continued)

Stakeholders	Countries	Problems	References
		contribution to GDP compared to previous years.	
Middleman	Thailand	-The lack of rubber domestic demand and supply data	RAOT (2024a)
		-The supply is higher than the domestic demand, causing low rubber prices.	Intrasakul et al. (2017)
		-The middle market is uncovered and unsystematic across all rubber production areas.	
Industry	Thailand	-The lack of rubber domestic demand and supply data.	RAOT (2024a)
		-The Thai upstream rubber industry lacked professional expertise in technology, especially in the government sector.	Intrasakul et al. (2017)
		-The foreign entrepreneurs in the finished-product industry were moving their investments out of Thailand to other Asian countries with lower labor costs.	
		-The lack of support for small community industries and the disconnect from local farming practices.	
Exporter	Thailand	-The lack of rubber domestic demand and supply data	RAOT (2024a)
		-The use of synthetic rubber, which is lower in price, has impacted the market share of natural rubber.	Intrasakul et al. (2017)

Table 2.3 (continued)

Stakeholders	Countries	Problems	References
	Vietnam	Vietnam's rubber export prices declined, resulting in a decrease in export value compared to the same period last year. Additionally, the recovery of production activities in China was slower than expected, leading to reduced consumption and lower rubber prices.	Do (2024)
Government	Thailand	-The lack of technological advancement. -The lack of rubber domestic demand and supply data.	RAOT (2024a)
		-The management of the entire Thai rubber supply chain is unsystematic. -The unstable and unsystematic nature of the rubber industry policy affects the entire supply chain.	Intrasakul et al. (2017)

Source Intrasakul et al. (2017), Mankong et al. (2014), Statista Research Department (2024), Do (2024) and RAOT (2024a)

2.4 Thai Government Agencies in Rubber Supply Chain

It can be characterized into 3 agencies as follows (Figure 2.3).

2.4.1 Rubber Authority of Thailand (RAOT)

RAOT is a government agency operating under the Ministry of Agriculture and Cooperatives since 2015, with six core missions, including the following (1) Nation: Support the country in becoming a sustainable hub for rubber production, trade, and innovation. (2) People and Consumers: Promote awareness of the value of natural rubber use among the public and consumers. (3) Rubber Farmers: Improve the quality of life for rubber farmers. (4) Farmer Institutions: Strengthen farmer institutions and promote professional business management. (5) Rubber Entrepreneurs: Promote trade and enhance competitiveness in the rubber industry. (6) Organization: Strengthen the organization's financial stability, develop it into a knowledge-based and high-performance organization by leveraging digital technology, innovation, and good governance.

Hence, RAOT plays a role in supporting, developing, and facilitating all stakeholders in the rubber supply chain. For example, it provides financial assistance to farmers through the Rubber Plantation Welfare Fund. However, farmers must obtain permission from RAOT to plant rubber trees in accordance with the legal limits on plantation areas. RAOT also offers support in the form of rubber saplings and financial aid. Furthermore, RAOT provides financial loan support to intermediaries and the rubber industry. To be eligible for funding or loans, farmers, intermediaries, and industry stakeholders must register in the RAOT database in accordance with the Rubber Authority of Thailand Act, B.E. 2558 (2015).

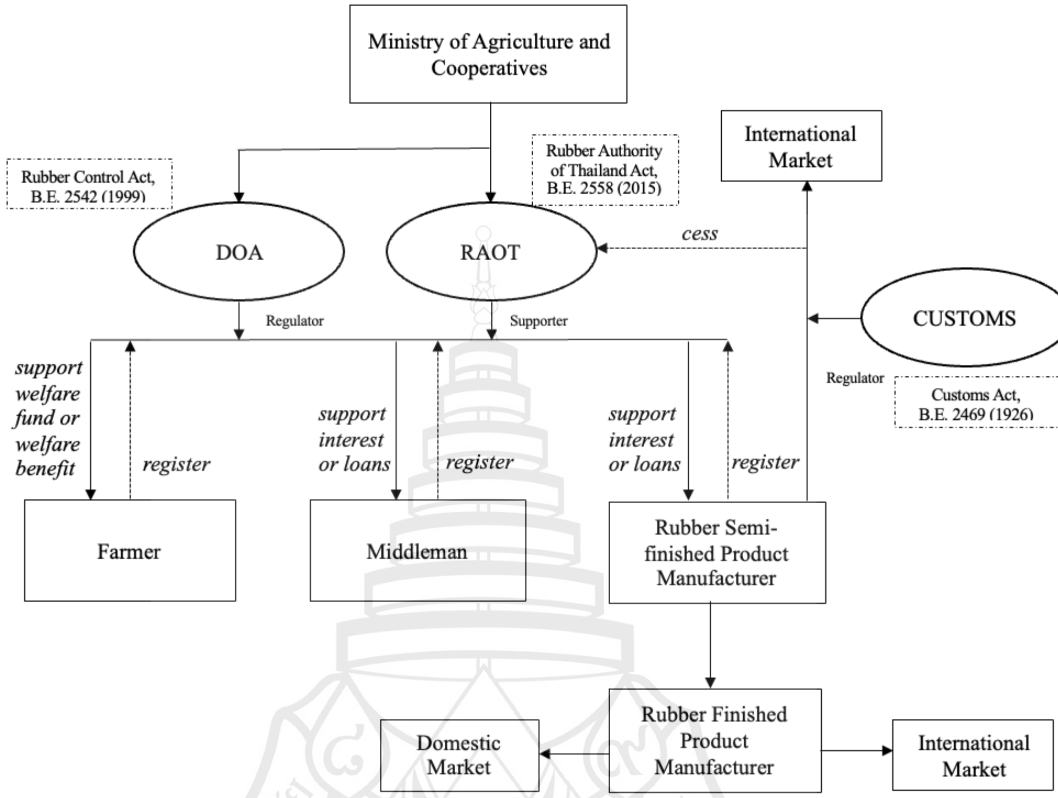
For another role of RAOT as the regulator, the exporter must pay CESS money (Centre for Experimental Social Sciences) which officially means the rubber subsidy fund. The CESS money is collected from rubber exporters by the Office of the Rubber Replanting Aid Fund under the RAOT. This fund is used to finance the replanting of low-yield rubber plantations with high-yield rubber varieties as shown in Figure 2.4.

2.4.2 Department of Agriculture (DOA)

The Rubber Division, under the Department of Agriculture (DOA), was established under the Rubber Control Act, B.E. 2542 (1999) to oversee and monitor the entire rubber supply chain. For example, it manages the issuance of Rubber Trade Licenses in accordance with the Rubber Control Act, B.E. 2542 (1999) (RAOT, 2024b), as shown in Table 2.2 and Figure 2.4, respectively.

2.4.3 Thai Customs Department

The Customs Department under the Customs Act, B.E. 2469 (1926), Customs Department (2024), was established to facilitate global trade and provide effective control on imports, exports and transit goods as shown in Figure 2.4.



Source Adapted from The Corporate Strategy Division under RAOT (2024)

Figure 2.4 Flow Chart of Rubber Authority of Thailand

2.5 Distributed Ledger Technology (DLT)

A decentralized database, often referred to as Distributed Ledger Technology (DLT), is a system where data is distributed across various computers, known as nodes. Each node maintains a copy of the ledger, which is autonomously updated whenever data is modified. DLT can represent data in various structures and does not follow a specific sequence, as different types of DLT may adopt different sequences. It operates without the need for consensus mechanisms, resulting in lower power consumption. DLT is being developed for diverse applications and does not necessarily require a currency or token to function within the network (Panwar & Bhatnagar, 2020). There are five different kinds of DLTs, namely Blockchain, Hashgraph, Holochain, DAG, and Tempo, as outlined below.

2.5.1 Blockchain: The Sequential Ledger

Blockchain is the foundational DLT, where transactions are grouped into blocks and linked in a linear, chronological chain. Each block contains a cryptographic hash of the previous one, ensuring immutability. This structure provides security and transparency, as seen in Bitcoin and Ethereum. However, its sequential nature can lead to scalability issues, as all nodes must validate each block, creating bottlenecks.

2.5.2 Hashgraph: Parallel Event-Based Consensus

Hashgraph improves by using a directed acyclic graph (DAG)-like structure where transactions (called "events") are recorded in parallel. Instead of blocks, it employs a "gossip about gossip" protocol for consensus, allowing multiple transactions to share the same timestamp. This enables high throughput, fairness, and low latency, as seen in Hedera Hashgraph. However, Hashgraph is patented, limiting its decentralization compared to public blockchains.

2.5.3 Holochain: Agent-Centric Distributed Ledger

Holochain shifts from a data-centric to an agent-centric model, where each user maintains their own chain. Transactions are validated through peer-to-peer interactions rather than global consensus, enhancing scalability and reducing energy consumption. This approach supports decentralized applications without requiring miners, making it eco-friendly. However, its security model relies heavily on user honesty, which may pose risks in adversarial environments.

2.5.4 DAG (Directed Acyclic Graph): Asynchronous Transaction Processing

Unlike blockchain’s linear structure, DAG-based ledgers (e.g., IOTA, Nano) store transactions in a topological order, where each new transaction references previous ones. This allows parallel processing, eliminating miners and enabling feeless transactions. DAGs excel in scalability and speed but face challenges in security, as they are vulnerable to certain attacks (e.g., Sybil attacks) without additional safeguards.

2.5.5 Tempo (Radix): Event-Ordered Consensus

Tempo, used by Radix, orders transactions based on actual event occurrence rather than timestamps. It employs a unique "gossip" protocol to ensure consistency across nodes, improving efficiency over traditional blockchain models. Radix aims to solve scalability without sacrificing decentralization, making it a promising alternative for high-performance decentralized finance (DeFi) applications.

2.6 The Adoption of Blockchain Technology

Blockchain is a specific type of DLT where each node in the network maintains its own copy of the ledger. When a new transaction is executed and verified, all ledgers are simultaneously updated. In blockchain, data is organized as a chain of blocks, which follows a specific sequence, making it distinct from other DLT structures. Unlike some DLTs that operate with lower power consumption, blockchain typically employs various proof-based consensus mechanisms, which require higher energy usage. The applications of blockchain are vast and span across numerous industries and governmental operations. Additionally, different blockchain platforms often utilize unique tokens and currencies within their networks, further distinguishing them in functionality and purpose (Panwar & Bhatnagar, 2020).

Blockchain technology was first proposed by Nakamoto in 2008 as Bitcoin, which is a digital currency enabling peer-to-peer (P2P) transactions without the need for centralized authorities. The concept of blockchain functions as a distributed database that operates without third parties (Chang & Chen, 2020).

The evaluation of blockchain technology was adopted from 2008 to 2015 in the field of financial applications, such as Bitcoin and other digital currencies. In 2016, the first studies on supply chain traceability and transparency, including agricultural products, were conducted. Since 2017, the growth of blockchain technology has integrated with other emerging technologies. In 2018, there was an increasing focus on studying blockchain security and privacy, distributed ledger technologies, and smart contracts. Since 2019, there have been various topics, especially focusing on blockchain acceptance and adoption (Chang & Chen, 2020).

Blockchain technology has been adopted in several fields, such as agri-food value chain management, in four main aspects: traceability, information security, manufacturing, and sustainable water management (Zhao et al., 2019).

Blockchain technology in the agricultural supply chain has shifted traditional supply chain management to a lean and agile model. In 2001, the study on the agri-food supply chain based on traceability, transparency, safety, security, food integrity, and quality assurance of the products was conducted (Salin et al., 2001).

In 2019, blockchain technology was introduced to natural rubber manufacturing by Benedict et al. (2020), who utilized the IoT-Blockchain Enabled Yield Advisory System (IBEYAS) to evaluate the yield of rubber trees at various intervals. The system alerts rubber manufacturers and relevant participants about any anomalies.

The implementation of blockchain technology in public administration can transform traditional bureaucratic processes into a more efficient system, playing a major role in the digitalization of the public sector. Many countries have integrated blockchain into their government frameworks. For example, the government of Mexico is using blockchain to decrease corruption in areas such as financial transactions, collusion, tenders, procurement, audit agencies, funding, and land registration. Similarly, the government of Turkey has adopted blockchain in various sectors, including voting, energy, land registration, IoT, healthcare, identity management, supply chain management, public financial management, and more. Other countries, such as South Korea, Estonia, Australia, the United Kingdom, and Israel, are also leveraging blockchain technology for similar purposes (Aliti et al., 2022).

Blockchain in Agriculture: Enhancing Efficiency, Transparency, and Stakeholder Engagement. Blockchain technology has emerged as a transformative tool in agriculture, addressing long-standing challenges in market efficiency, fraud reduction, and supply chain coordination. Empirical studies and real-world implementations demonstrate their potential to revolutionize the sector.

2.6.1 Improving Market Efficiency and Reducing Fraud

Research by Kouhizadeh et al. (2021) highlights how blockchain-based systems enhance market efficiency by streamlining transactions and minimizing intermediaries. The immutable nature of blockchain ensures tamper-proof data recording, significantly reducing fraud and errors in procurement processes (Tian, 2016). For instance, Lin et al. (2020) conducted a case study in agriculture where blockchain implementation improved transaction verification and product traceability, leading to faster and more reliable supply chain operations.

2.6.2 Strengthening Traceability and Accountability

Traceability platforms like IBM's Food Trust have demonstrated measurable improvements in accountability and operational efficiency (Park & Li, 2021). By enabling end-to-end visibility, blockchain allows consumers and regulators to verify product origins, reducing food fraud and ensuring compliance with safety standards. This transparency also helps balance supply and demand, mitigating price volatility (Wang et al., 2020).

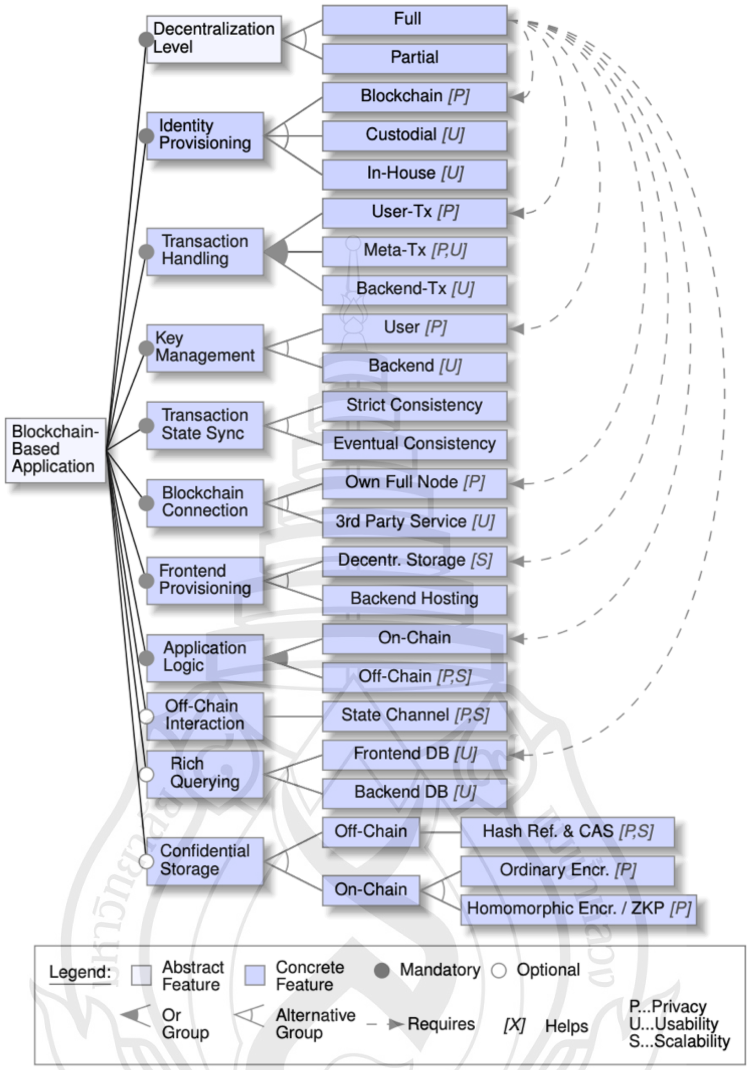
2.6.3 Stakeholder Collaboration and Adoption Challenges

However, the success of blockchain in agriculture depends on widespread stakeholder participation. Studies emphasize the necessity of early engagement with farmers, cooperatives, and legal entities to ensure system adoption (Klerkx et al., 2019). Casino et al. (2019) further argue that without buy-in from small-scale producers-who often lack digital infrastructure-blockchain solutions may fail to achieve full supply chain integration.

Blockchain technology offers a robust solution for enhancing agricultural supply chains, but its effectiveness hinges on both technological implementation and collaborative stakeholder engagement. Evidence from academic research and industry applications underscores its potential to foster transparency, efficiency, and market stability.

2.7 Blockchain-Based Application

Blockchain implementations, particularly those utilizing Ethereum, have been widely adopted across multiple sectors including finance, information security, and agri-food value chain management. As demonstrated in the study by Wöhrer et al. (2021), hybrid blockchain architectures have been successfully implemented in various business contexts. Their research not only documented these implementations but also proposed a comprehensive set of architectural design options for blockchain applications, as illustrated in Figure 2.5.



Source Wöhrer et al. (2021)

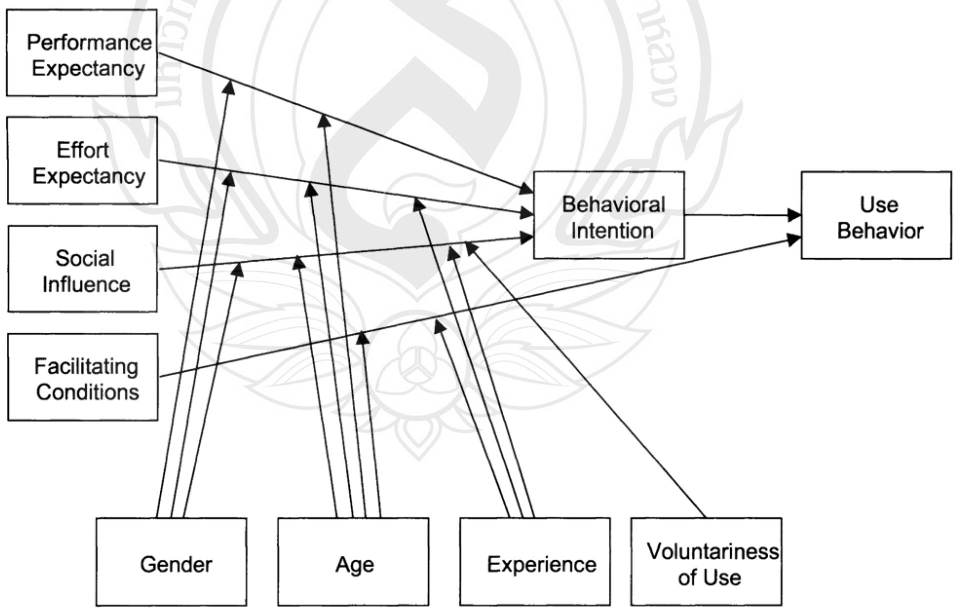
Figure 2.5 Feature Model for a Blockchain-Based Application

2.8 Unified Theory of Acceptance and Use of Technology (UTAUT)

The Unified Theory of Acceptance and Use of Technology (UTAUT) is a well-known technology acceptance model used to verify the factors influencing individual acceptance of new technology. It is a combination of eight models rooted in information systems, psychology, and sociology, which are derived from: (1) the Theory of Reasoned Action (TRA), (2) the Technology Acceptance Model (TAM), (3) the

Motivational Model (MM), (4) the Theory of Planned Behavior (TPB), (5) a model combining the Technology Acceptance Model and the Theory of Planned Behavior (C-TAM-TPB), (6) the Model of PC Utilization (MPU), (7) the Innovation Diffusion Theory (IDT), and (8) the Social Cognitive Theory (SCT) (Venkatesh et al., 2003).

The UTAUT is formulated with four core determinants of intention and usage, which depend on four moderators of key relationships and four moderators, as follows: (1) Gender, (2) Age, (3) Experience and (4) Voluntariness, as follows: (1) Performance Expectancy (PE) is the degree to which an individual believes that using the new system will help improve job performance, moderated by gender and age. (2) Effort Expectancy (EE) is the degree of ease associated with the use of the new system, moderated by gender, age, and experience. (3) Social Influence (SI) is the degree to which an individual perceives effect to others believe to use the new system, moderated by gender, age, experience and voluntariness. (4) Facilitating Conditions (FC) is the degree to which an individual believes that an organizational and technical infrastructure exists to support use of the new system, moderated by age and experience. Shown as Figure 2.6 (Venkatesh et al., 2003).

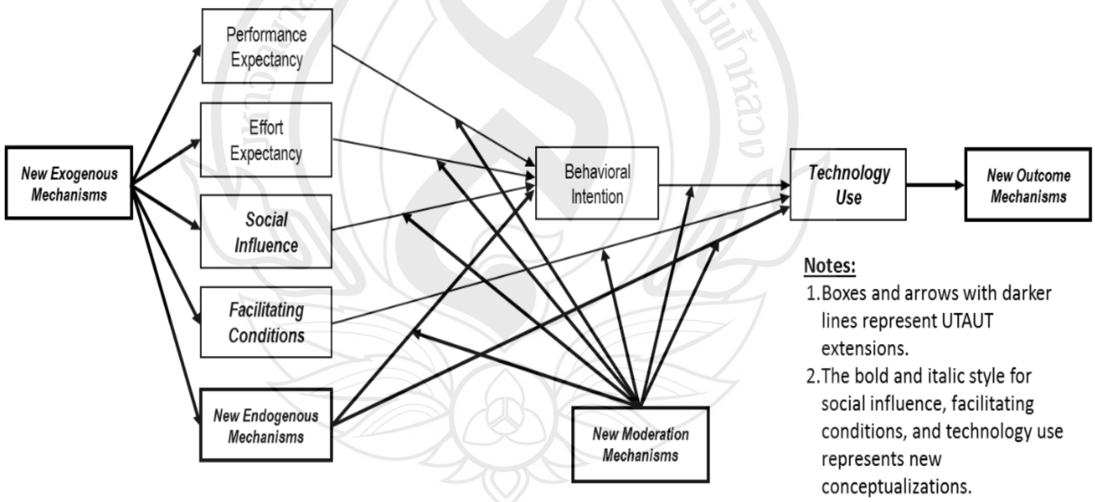


Source Venkatesh et al. (2003)

Figure 2.6 Unified Theory of Acceptance and Use of Technology (UTAUT)

The UTAUT theory is more commonly used for studying user acceptance of information systems than other theories such as TAM, DMIS, ECM, and ISSM, especially in countries like Indonesia, China, Australia, India, Malaysia, Thailand, South Africa, and Taiwan. (Nugroho et al., 2023).

The UTAUT Extension can be categorized into four primary types: (1) New exogenous mechanisms, which refer to the influence of external factors on the four exogenous variables in UTAUT (performance expectancy, effort expectancy, social influence, and facilitating conditions); (2) New endogenous mechanisms, which focus on the impact of new predictors on the two endogenous variables in UTAUT (behavioral intention and use behavior), or the enhancement of the four exogenous and two endogenous variables in the original UTAUT; (3) New moderating mechanisms, which introduce new moderating effects into the original UTAUT, including the moderation of newly established relationships; and (4) New outcome mechanisms, which add new consequences for behavioral intention and technology use to the original UTAUT. This is illustrated in Figure 2.7 (Venkatesh et al., 2016).



Source Venkatesh et al. (2016)

Figure 2.7 Extension of UTAUT

Table 2.4 Previous Research Using UTAUT Model

Author	Category Field	Factor Influenced to Behavior Intention (BI)					FC	PE	TA
		PE	SI	FC	EE	TA/ AN	Others		
Budhathoki et al. (2024)	ChatGPT adoption	√	√	√	√	AN	-	-	-
Zhang and Zhang (2024)	E-Commerce	√	-	√	-	TA	-	-	-
H et al. (2024)	AI-powered Transportation Applications	√	-	-	√	-	-	-	-
Khan et al. (2023)	E-Learning	-	√	√	-	AN	-	-	-
Petersen (2023)	Business simulation games	√	√	-	-	AN	-	-	-
Srivastava and Bhati (2023)	M-Learning	√	√	√	√	-	-	-	-
Bhati et al. (2023)	E-Banking	√	√	-	√	-	-	-	-
Popova and Zagulova (2022)	Smart City	√	-	√	-	-	-	FC	-
Umbas et al. (2022)	M-Banking	√	√	-	-	-	-	-	-
Smyth et al. (2021)	Automated Vehicles	-	-	-	-	-	-	EE	-
Kar et al. (2021)	Industrial Internet of	√	-	-	-	AN	-	-	-

Table 2.4 (continued)

Author	Category Field	Factor Influenced to Behavior Intention (BI)					FC	PE	TA
		PE	SI	FC	EE	TA/ AN	Others		
	Things and Emerging Digital Technologies								
Nain (2021)	Social Media Learning in Education	√	-	√	√	-	-	-	-
Saparudin et al. (2020)	Mobile Banking	√	√	-	√	-	-	-	-
Gunasinghe et al. (2019)	Education	√	-	-	√	TA	-	TA	-

Note TA = Technological Anxiety, AN = Anxiety

Source Gunasinghe et al. (2019), Saparudin et al. (2020), Bhati et al. (2023), H et al. (2024), Nain (2021), Srivastava and Bhati, (2023), Petersen (2023), Popova and Zagulova. (2022), Umbas et al. (2022), Budhathoki et al. (2024), Smyth et al. (2021), Kar et al. (2021), Khan et al. (2023) and Zhang and Zhang (2024)

2.9 Structural Equation Modeling (SEM)

Structural Equation Modeling (SEM) is a well-known method used to test various types of theoretical models by demonstrating relationships among observed and latent variables. The purpose of SEM analysis is to verify the extent to which the theoretical model is supported by the sample data. Therefore, if the sample data do not support the theoretical model, either the original model can be modified and retested, or new theoretical models may need to be developed and tested (Schumacker & Lomax, 2004).

The Structural Equation Model (SEM) is one of four types of models, including regression models, path models, confirmatory factor models, and structural equation models. SEM was introduced around 1972–1973 by Ward Keesling, Karl Jöreskog, and David Wiley. It was developed as the foundation for the first software program designed to estimate such models, known as LISREL (Linear Structural Relations). Today, most SEM software programs are designed for Windows operating systems, such as AMOS (SPSS), EQS, JMP, LISREL, Mplus, Mx, OpenMx, PROC CALIS (SAS), R, SEPATH (Statistica), and SEM (STATA) (Schumacker & Lomax, 2016). Moreover, between 1994-2001, SEM gained significant popularity in academic journals that published research involving multivariate methods, largely due to advancements in structural equation modeling techniques. Hence, SEM techniques have been accepted as a method for confirming or disconfirming theoretical models in quantitative research (Schumacker & Lomax, 2004).

As the study of Kline (2023) that the method of SEM divided to tree distinct families of techniques including (1) Covariance-Based SEM (CB-SEM) or Traditional SEM is most widely used and common in psychology and related fields. Traditional SEM provides a more accurate representation of real-world data by incorporating measurement error, a frequent issue in behavioral research. It is flexible enough to accommodate both exploratory and confirmatory analyses, depending on the objectives of the study. Furthermore, traditional SEM offers more extensive modeling capabilities for analyzing data collected over time (longitudinal data) than composite SEM. It works by estimating parameters in causal models composed of observed or latent variables. It does this by minimizing the difference between the actual covariance matrix and the one predicted by the theoretical model. Latent variables are modeled using shared factors, like those found in early 20th-century factor analysis techniques. Confirmatory Factor Analysis (CFA) is a key technique within this group. Several well-established software programs-such as Mplus, LISREL, AMOS, and EQS are widely recognized for their capabilities in conducting CB-SEM analyses. (2) PLS path modeling (PLS-PM) or Composite SEM, also known as Variance-Based SEM, use simpler statistical techniques and fewer assumptions by representing theoretical constructs with composite variables instead of common factors. It's popular in fields like marketing and information systems. Composite SEM focuses on maximizing explained variance (R^2), unlike traditional SEM, which doesn't always emphasize this for individual outcomes. Unlike traditional SEM, which focuses on modeling covariances, composite SEM emphasizes analyzing total variance in observed data using composites (weighted combinations of variables). The approach is based on regression techniques and is suitable for causal modeling, especially when data or theory is less developed. Confirmatory Composite Analysis (CCA) is the counterpart to CFA in this framework. From here on, the term composite SEM is used. Several well-established software programs-such as SmartPLS, ADANCO, WarpPLS, Lavaan, Mplus and LISREL are widely recognized for their capabilities in conducting PLS-SEM analyses. (3) Nonparametric SEM or Structural Causal Models (SCM) highlights the importance of counterfactuals, hypothetical outcomes under different conditions, in understanding causal relationships. It is commonly used in epidemiology, computer science, and medicine. Originating from Judea Pearl's work on Bayesian networks, SCM represents causal relationships using graphs-either DAGs (for one-way causation) or DCGs (for reciprocal causation). Unlike traditional SEM, SCM doesn't require assumptions about distributions or functional forms. It can even analyze causal structures without any data, aiding study design and control for confounding factors. This flexibility has led to new methods in mediation analysis. The SCM methos or Piecewise SEM can be conducted using standard statistical software like SPSS, eliminating the need for specialized SEM programs.

The comparative study of SEM software applications between CB-SEM and PLS-SEM revealed no significant differences in reliability and validity scores across both approaches. Therefore, the choice of model and its theoretical development by researchers should be guided by the appropriateness of the selected modeling approach, consistent with the findings of Awang et al. (2015) and Sandoval and Ramos-Diaz (2018).

2.10 Confirmatory Factor Analysis (CFA)

Confirmatory Factor Analysis (CFA) is the researcher who determines the number of factors, their relationships, and the variables linked to each factor. The research begins with a pre-defined theoretical model (Schumacker & Lomax, 2004). CFA is indeed a technique within SEM, especially as a key method within CB-SEM Kline (2023), that evaluates the relationships between observed indicators and latent variables. It is conceptually grounded in the common factor model. There are two types of analyses based on the common factor model including (1) Confirmatory Factor Analysis (CFA), which involves predetermined specifications such as the number of factors, indicator loadings, factor relationships, and indicator variances; and (2) Exploratory Factor Analysis (EFA), which examines data without prior assumptions about the number of factors or the relationships between factors and observed variables. Hence, EFA is typically used in the early stages of construct development, while CFA is employed later to confirm an established factor structure Hoyle (2023).

CHAPTER 3

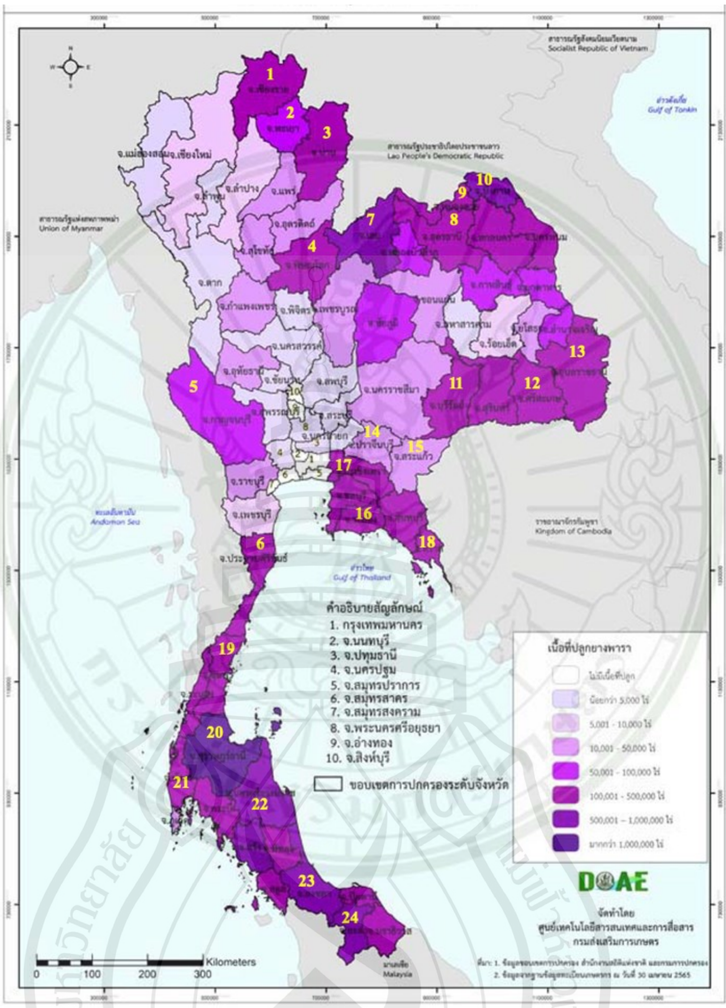
RESEARCH METHODOLOGY

This study examines the acceptance of blockchain traceability platform among all stakeholders in the rubber supply chain, including farmers, collectors, exporters, government agencies, and others. It aims to identify the factors that encourage each stakeholder to accept the blockchain platform as a traceability system for tracking the volume of rubber purchases and sales within the supply chain. The study follows the conceptual framework illustrated in Figure 1.3 and includes a review of relevant literature that supports the research objectives. The details are presented as follows:

3.1 Study Area
3.2 Data Collection
  3.2.1 Sample Groups
  3.2.2 Sample Size Formulas for Structural Equation Model (SEM)
3.3 Proposed UTAUT Model
3.4 Questionnaire Survey Construction
3.5 Statistical Data Analysis
  3.5.1 Descriptive Analysis
  3.5.2 Questionnaire Reliability
  3.5.3 Confirmation Factor Analysis (CFA)
  3.5.4 Structural Equation Model (SEM)

3.1 Study Area

This research focuses on the rubber supply chain in Thailand, covering all regions and 24 provinces, including the Northern, Central, Northeastern, Eastern, and Southern regions. The sample distribution across these regions is illustrated in Figure 3.1 and Table 3.1.



Source Adapted from Department of Agricultural Extension (2022)

Figure 3.1 The Sample Distribution in Rubber Supply Chain

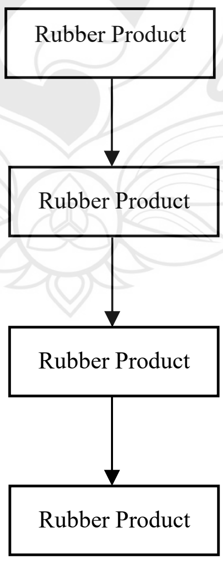
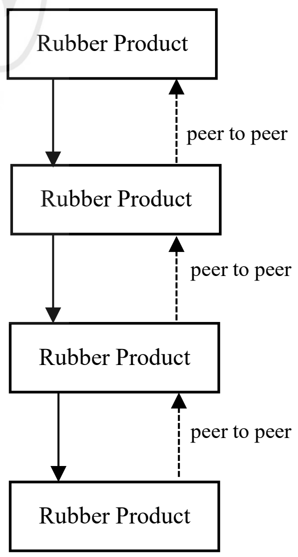
Table 3.1 The Sample Distribution in Rubber Supply Chain

Regions	Provinces
Northern	1. Chiang Rai 2. Phayao 3. Nan 4. Phitsanulok
Central	5. Kanchanaburi 6. Prachuap Khiri Khan
Northeastern	7. Loei 8. Udon Thani 9. Nong Khai 10. Bueng Kan 11. Buri Ram 12. Si Sa Ket 13. Ubon Ratchathani
Eastern	14. Prachinburi 15. Sakaeo 16. Rayong 17. Chachoengsao 18. Trat
Southern	19. Chumphon 20. Surat Thani 21. Phang Nga 22. Nakorn Srithammarat 23. Songkhla 24. Yala

3.2 Data Collection

The study carefully collected data to represent respondents from each stakeholder group, focusing on high-potential rubber production areas across the five regions of Thailand, as shown in Figure 3.1. An experimental research method was employed, involving the manipulation of independent variables through different groups of participants, each exposed to various experimental conditions. The study examines the effects of five factors based on the proposed UTAUT model, with Technology Anxiety (TA) integrated into the evaluation phase. The proposed UTAUT model includes Performance Expectancy (PE), Social Influence (SI), Facilitating Conditions (FC), Effort Expectancy (EE), and Technology Anxiety (TA). These factors were analyzed across five stakeholder groups within Thailand's rubber industry supply chain: Farmers, Collectors, Exporters, Government Agencies, and Others, depending on their roles in rubber market activities, as shown in Table 3.2.

Table 3.2 Comparing the Old and New Rubber Market Activity in Supply Chain

Stakeholder		**Old Market Activity**	**Proposed New Market Activity (Blockchain Traceability Platform)**
Farmer			
	Middleman		
Collector			
	Manufacturer		
Exporter			

Note Government agencies and other stakeholders play crucial roles in utilizing rubber market activity data.

3.2.1 Sample Groups

The research was designed using a multi-stage sampling method, combining stratified random sampling and quota sampling. Multi-stage sampling, or multi-stage cluster sampling, is a method used to collect data from large populations by selecting samples through multiple stages, starting with large groups and narrowing down to smaller units. Though less statistically precise than pure random sampling, it is more cost-effective and time efficient. The process typically involves four stages: identifying a sampling frame of distinct groups, assigning identifiers, selecting sub-groups, and finally choosing individuals using probability sampling. This method is especially useful in large-scale research (Teddlie & Yu, 2007; Makwana et al., 2023).

Stratified random sampling is a sampling technique in which a population is segmented into distinct subgroups, known as strata, based on shared attributes, and then random samples are drawn from each subgroup. This method increases the accuracy and representativeness of research by minimizing variation within each stratum. There are two main forms of this technique: proportionate and disproportionate stratified sampling including (1) Proportionate stratified sampling, the number of samples taken from each stratum corresponds to the stratum's proportion within the overall population. This method is straightforward, efficient, and particularly useful when larger strata exhibit greater variability, as it ensures an appropriate sample size from each group. (2) Disproportionate stratified sampling, in contrast, does not adhere to the natural proportions of the population. Instead, it allows researchers to assign sample sizes based on factors such as the size and variability of each stratum or the specific goals of the study. This method is more flexible and often used when subgroups warrant more focused analysis (Sekaran & Bougie, 2016; Makwana et al., 2023).

Quota sampling is a non-probability sampling technique where participants are chosen based on specific characteristics set by the researcher to ensure the sample represents the population. While it resembles stratified random sampling by dividing participants into subgroups, it differs by not using random selection. There are two types including (1) Controlled quota sampling, with strict selection guidelines, and

(2) Uncontrolled quota sampling, which allows more flexibility and is based on convenience (Sekaran & Bougie, 2016; Makwana et al., 2023).

Hence, this study adopted the proportionate stratified random sampling method based on Sekaran and Bougie (2016), where 20 percent of the population from each stratum (stakeholder groups) is considered sufficient for conducting research. The total calculated sample size was not less than 100 respondents. Additionally, quota sampling was emphasized for representing the major sectors of the rubber industry, which have a significant impact on the industry, as shown in Table 3.3.

Accordingly, a total of 130 respondents were selected from five stakeholder groups in the rubber supply chain: Farmers, Collectors, Exporters, Government Agencies, and Others (including brokers and rubber scholars), as defined below.

3.2.1.1 Farmers: There were 1,667,095 rubber farming families registered in the government database (OAE, 2022). They play a key role by growing rubber trees and producing materials such as cup lump, latex, and crepe rubber, which are sold to collectors. This study focused on large landowners, specifically those owning more than 100 rai, who represented 0.01% of the families registered in the government database.

3.2.1.2 Collectors: There were around 1,000 middlemen and manufacturer registered in the government database (RAOT, 2023). They purchase natural rubber from farmers, process it into semi-finished or finished products, and sell it to exporters or other buyers. This study focused on the 10 largest businesses registered in the government database.

3.2.1.3 Exporters: There were 38 export companies registered in the government database (RAOT, 2022). They play a key role in exporting both semi-finished products (e.g., block rubber, ribbed smoked sheets, and concentrated latex) and finished products (e.g., tires, medical rubber gloves, and elastic materials). This study focused on the 10 largest businesses registered in the government database.

3.2.1.4 Government Agencies: The government agencies involved in the Thai rubber supply chain include three key organizations:

1. The Rubber Authority of Thailand (RAOT): There is a head center located in Bangkok and around 146 branches covering all regions of Thailand (RAOT,

2021). These act as facilitators and supporters within the Thai rubber supply chain under the Rubber Authority of Thailand Act, B.E. 2558 (2015).

2. The Department of Agriculture (DOA): There is a head center located in Bangkok and around 17 branches covering all regions of Thailand (DOA, 2022). They operate under the Rubber Control Act, B.E. 2542 (1999), oversees and monitors the entire rubber supply chain.

3. The Customs Department: There is a head center located in Bangkok and around 46 branches covering all regions of Thailand (Customs Department, 2022). They regulate rubber exports under The Customs Act, B.E. 2469 (1926).

Hence, this research focused on executives, heads of rubber divisions, and staff responsible for rubber data.

3.2.1.5 Others: This group includes brokers, who facilitate trade within the supply chain, and rubber scholars, who contribute academic and technical expertise to the industry.

Table 3.3 The Calculation of Proportionate Stratified Random Sampling

No.	Rubber Stakeholders	Population (Major Sector of the Rubber Industry)	Sample (Proportionate Sampling: 20% of the Elements)
1	Farmer (F) (Land > 100 Rai)	200	20% x 200 = 40
2	Collector (C) (10 Business Largest)	100	20% x 100 = 20
3	Exporter (E) (10 Business Largest)	100	20% x 100 = 20
4	Government Agencies (G) (3 Organizations)	50	20% x 50 = 10
5	Others (O) (Broker & Scholar)	50	20% x 50 = 10
	Total	**250**	**100**

Source Sekaran and Bougie (2016)

3.2.2 Sample Size Formulas for Structural Equation Model (SEM)

This study determined the sample size for structural equation modeling (SEM) using Analytics Calculators (2024), a widely used tool for calculating sample sizes. The calculation indicated that the recommended minimum sample size was 88 stakeholders from the rubber supply chain industry in Thailand as shown in Table 3.3. This study using 3 formulas that are used to compute sample sizes for structural equation model (SEM) studies involving latent variables (Analytics Calculators, 2024).

3.2.2.1 Cumulative Distribution Function (CDF)

$$F(x;\mu,\sigma^2) = \frac{1}{2}\left[1 + \operatorname{erf}\left(\frac{x-\mu}{\sigma\sqrt{2}}\right)\right]$$

Variable definitions:

μ = mean

σ = standard deviation

erf = error function

3.2.2.2 Error Function

$$\operatorname{erf}(x) = \frac{2}{\sqrt{\pi}}\int_0^x e^{-t^2}\,dt.$$

3.2.2.3 Structural Equation Model (SEM)

$$n = \max(n_1, n_2)$$

where:

$$n_1 = \left\lceil 50\left(\frac{j}{k}\right)^2 - 450\left(\frac{j}{k}\right) + 1100 \right\rceil$$

$$n_2 = \left\lceil \frac{1}{2H}\left(A\left(\frac{\pi}{6} - B + D\right) + H + \sqrt{\left(A\left(\frac{\pi}{6} - B + D\right) + H\right)^2 + 4AH\left(\frac{\pi}{6} + \sqrt{A} + 2B - C - 2D\right)}\right) \right\rceil$$

$$A = 1 - \rho^2$$

$$B = \rho \arcsin\left(\frac{\rho}{2}\right)$$

$$C = \rho \arcsin(\rho)$$

$$D = \frac{A}{\sqrt{3 - A}}$$

$$H = \left(\frac{\delta}{z_{1-\alpha/2} - z_{1-\beta}}\right)^2$$

Variable definitions:

j = number of observed variables

k = number of latent variables

ρ = estimated Gini correlation for a bivariate normal random vector

δ = anticipated effect size

α = Sidak-corrected Type I error rate

β = Type II error rate

z = a standard normal score

This study calculates the sample size for SEM by Analytics Calculators, (2024) which is the widely instant program computed to compute sample sizes for structural equation model (SEM). The compute demonstrated that the recommended minimum sample size for this study is 88 sample of stakeholders in rubber supply chain industry in Thailand as shown in Table 3.4.

Table 3.4 Structural Equation Model (SEM) Sample Size Calculator

Variables	Number Input
Expected effect size	0.5
Latent variables	6
Observed variables	27
p-value	0.05
Statistical power	0.8
Output/ Result	
Minimum sample size to detect effect	40
Minimum sample size for model structure	88
Recommended minimum sample size	88

Source Analytics Calculators (2024)

Variable definitions:

Expected effect size = The minimum absolute anticipated effect size for the structural equation model. By convention, values of 0.1, 0.3 and 0.5 are considered small, medium and large, respectively.

Latent variables = The number of unobserved (latent) variables of the SEM.

Observed variables = The number of indicator (observed) variables of the SEM.

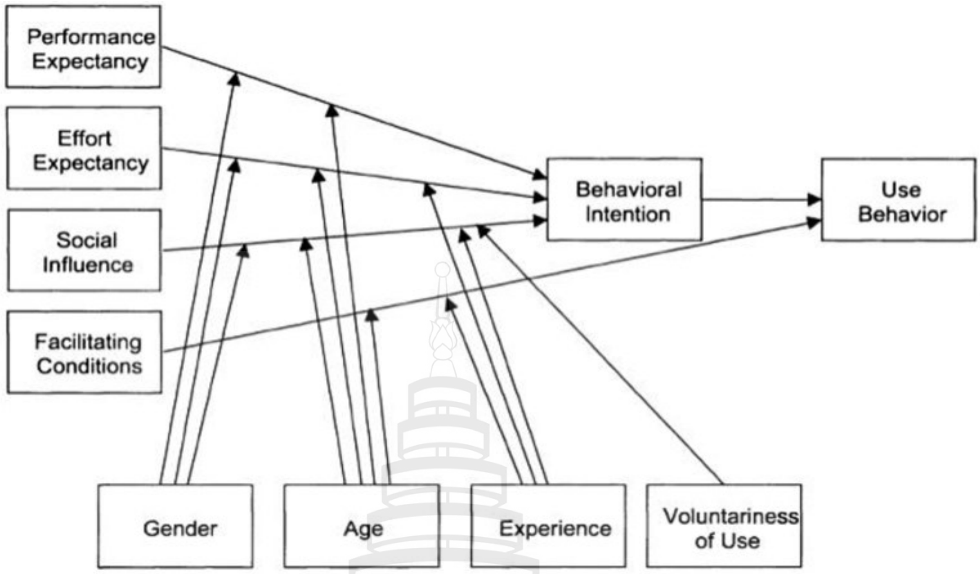
p-value = The probability level for the study. This value should typically be less than or equal to 0.05.

Statistical power = The desired statistical power level (should typically be greater than or equal to 0.8).

3.3 Proposed UTAUT Model

This study proposed a hypothesis model structure based on the Unified Theory of Acceptance and Use of Technology (UTAUT), which serves as the foundational model for non-profit activities (Venkatesh et al., 2003), as shown in Figure 3.2. The model suggests that the intention to use technology is influenced by four key constructs: performance expectancy (PE), effort expectancy (EE), social influence (SI), and facilitating conditions (FC), all of which impact behavioral intention (BI). This framework has been supported by previous research and is adopted in this study (Gunasinghe et al., 2019; Saparudin et al., 2020; Bhati et al., 2023; H et al., 2024; Nain, 2021; Srivastava & Bhati, 2023; Petersen, 2023; Popova & Zagulova, 2022; Umbas et al., 2022; Budhathoki et al., 2024; Kar et al., 2021; Khan et al., 2023; Zhang & Zhang, 2024).

Additionally, this study investigates the role of technology anxiety (TA) in relation to technology adoption, drawing from Bozionelos (2001), who found that computer anxiety was prevalent across various groups. TA has been incorporated into the evaluation phase of the UTAUT model, with its relevance validated and emphasized in several studies (Gunasinghe et al., 2019; Zhang & Zhang, 2024).



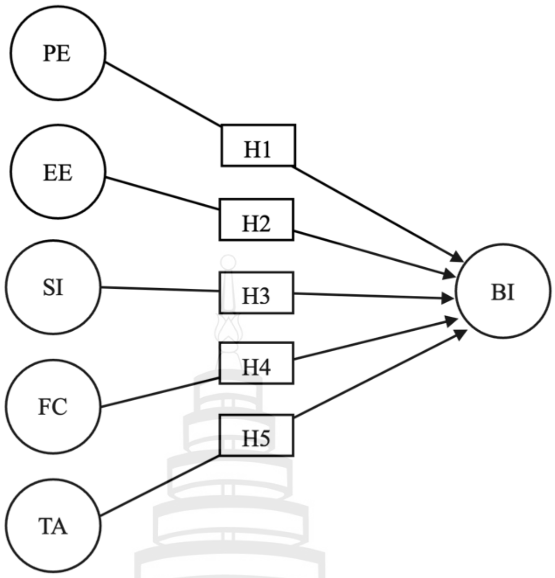
Source Venkatesh et al. (2003)

Figure 3.2 UTAUT Basic Version Model

The study was designed based on the conceptual research framework to analyze the acceptance of a blockchain traceability platform by applying the hypothetical UTAUT model, which was developed from previous studies (Gunasinghe et al., 2019; Saparudin et al., 2020; Bhati et al., 2023; H et al., 2024; Nain, 2021; Srivastava & Bhati, 2023; Petersen, 2023; Popova & Zagulova, 2022; Umbas et al., 2022; Budhathoki et al., 2024; Kar et al., 2021; Khan et al., 2023; Zhang & Zhang, 2024), as illustrated in Figure 3.3.

Since the blockchain traceability platform is a relatively new technology, its introduction to the rubber supply chain industry in Thailand may bring uncertainty. Therefore, technological anxiety could be an important factor influencing stakeholders' acceptance behavior.

In response, this study incorporates Technological Anxiety (TA), a factor whose significance has been validated and highlighted in prior research (Gunasinghe et al., 2019; Zhang & Zhang, 2024), into the UTAUT model, resulting in a revised version referred to as the Hypothetical UTAUT Model, shown in Figure 3.3. This model will be statistically tested to identify factors affecting the acceptance behavior of stakeholders in the rubber supply chain.



Source Adapted from Venkatesh et al. (2003)

Figure 3.3 Proposed UTAUT Model Based on UTAUT with Adding "Technological Anxiety"

3.4 Questionnaires Survey Construction

This study is designed by applying the concept of "Constructed Questionnaire Survey". The start of the development of the questionnaire survey is to conduct the focus group meeting with different stakeholders and experts to get key points of concern and challenges related to the study objectives. The first draft of questionnaires was designed from the opened-ended answers of interviewees that ensured a common understanding of the term "acceptance" regarding the factors affecting the behavior of stakeholders. This results from the focus group meetings were used for designing a constructed questionnaire survey that already applied in a Brazilian supply chain context. Then, the draft questionnaire had to get the comment from senior supply chain specialists (Sibona et al., 2017). Therefore, the results from focus group meetings and comments from specialists were also used as the concept to construct the questions in this questionnaire survey (Mazur & Bennett, 2008) which this study intentionally adopted. The list of constructed questions is shown in Table 3.4, and the final version of questionnaires is a tool for collecting data from the stakeholders in the form of closed-ended questions as shown in Appendix A.

The questionnaires consist of general information and specific information that focus on six factors, according to the research from Venkatesh et al. (2003). It is focused on five basic factors (factor 1-5) and the one added factor (factor 6) into the Proposed UTAUT Model of this study as follows.

1. Performance Expectancy (PE) is defined as the degree to which an individual believes that using the system will help him or her to attain gains in job performance.

2. Effort Expectancy (EE) is defined as the degree of ease associated with use of the system.

3. Social Influence (SI) is defined as the degree to which an individual perceives that it is important for users to believe in the new system.

4. Facilitating Conditions (FC) are defined as the degree to which an individual believes that an organizational and technological infrastructure exists to support the use of the system.

5. Technological Anxiety (TA) is defined by applying from the study's Bozionelos (2001) that investigated the computer anxiety involved the use of computers.

6. Behavioral Intention (BI) is defined as the decision to either accept or reject the adoption of the blockchain traceability platform as a new technology among all stakeholders in the rubber industry supply chain in Thailand.

Therefore, this study considers adapting the blockchain traceability platform as the new technology applying to be added into "Proposed UTAUT Model". The selected factors were also adapted from previously validated studies (Venkatesh et al., 2003, 2012).

Table 3.5 The List of Questions from the Focus Group Meeting and Verified by Specialists

Construct		Items
PE	PE1	Do you agree that requiring farmers and collectors to report information in a blockchain traceability platform would help ensure that the data is transparent and reliable?
	PE2	Do you agree that requiring farmers and collectors to report every rubber transaction in a blockchain traceability platform would be beneficial?
	PE3	Do you agree that requiring farmers and collectors to report every rubber transaction in a blockchain traceability platform would be effective?
	PE4	Do you agree that a government agency needs to have reliable big data on rubber?
	PE5	Do you agree that a blockchain traceability platform can meet the requirements for deforestation-free products set by the European Union?
	PE6	Do you agree that displaying a daily summary of rubber transactions in a blockchain traceability platform would provide insights into the supply and demand levels?
	PE7	Do you agree that disclosing information about all producers would help in accessing sources of raw materials?
EE	EE1	Do you agree that a blockchain traceability platform would work well with many users, such as 1.6 million farmers?
	EE2	Do you agree that you will be able to use the blockchain traceability platform by yourself?
	EE3	Do you agree that you will be able to use the blockchain traceability platform by yourself and adapt to changes in digital technology?
	EE4	Do you agree that reporting rubber trading information in the blockchain traceability platform will be redundant by reporting rubber trading values to the Rubber Control Center, Department of Agriculture?
SI	SI1	Do you agree that age will affect the use of the blockchain traceability platform?
	SI2	Do you agree to start using the blockchain traceability platform with agricultural groups first, such as cooperatives and legal entities?
	SI3	Do you agree that if the government mandates stakeholders in the rubber industry to use the blockchain traceability platform for rubber trading?
FC	FC1	Do you agree that you have the equipment to use the blockchain traceability platform, such as a smartphone or a computer?
	FC2	Do you agree that the Government Agency is ready to assist with equipment and personnel?
	FC3	Do you agree that the internet is accessible in all areas?

Table 3.5 (continued)

Construct		Items
TA	TA1	Do you agree that farmers who grow rubber trees in natural forest areas would not use blockchain traceability platforms due to concerns about data disclosure?
	TA2	Do you agree that some rubber collectors might not use blockchain traceability platforms due to concerns about tax collection from the Revenue Department?
	TA3	Do you agree that disclosing information on a blockchain traceability platform could lead to a loss of benefits?
	TA4	Do you agree that some rubber collectors may not use blockchain traceability platforms due to concerns about government inspection?
	TA5	Do you agree that exporters and processors of rubber products might not use blockchain traceability platform due to concerns about the price of raw rubber?
BI	BI1	Do you agree that you are willing to use blockchain traceability platform?
	BI2	Do you agree that there will be many users of blockchain traceability platform?
	BI3	Do you agree that blockchain traceability platform will be beneficial to stakeholders in the rubber supply chain?
	BI4	Do you agree that you are willing to use blockchain traceability platform?
	BI5	Do you agree that you are willing to cooperate with the government in using blockchain traceability platform?

The measure of scales is based on a 7-point Likert, ranging from "strongly disagree" to "strongly agree". The 7-point scale provides more varieties of options which in turn increase the probability of achieving the objectives according to the people's perception and belief are as follows (Joshi et al., 2015).

1 = Strongly disagree
2 = Disagree
3 = Somewhat disagree
4 = Neither agree nor disagree
5 = Somewhat agree
6 = Agree
7 = Strongly agree

The final version of questionnaires was sent out to the target stakeholders in different groups including Farmers, Collectors, Government Agencies, Exporters, and

Others to ensure that the samples truly are represented. Then, the data collected will be analyzed by statistical methods to test the hypothesis.

3.5 Statistical Data Analysis

This study was conducted through the prescript step as follows (1) Descriptive Analysis (2) Questionnaire Reliability and Validity and (3) Confirmatory Factor Analysis (CFA) and (4) Structural Equation Model (SEM) are as shown in Figure 3.4.

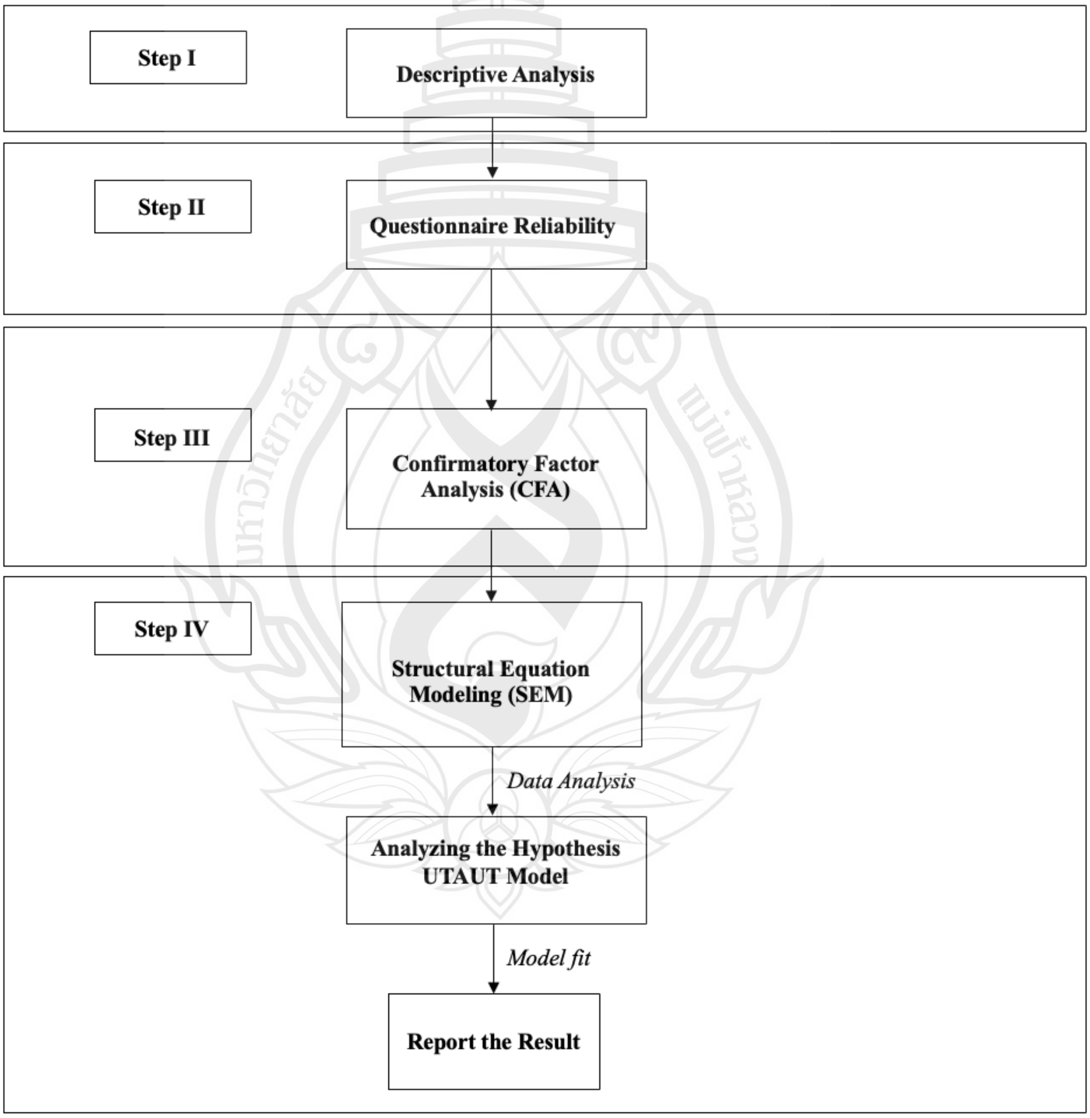


Figure 3.4 Statistical Data Analysis Framework

3.5.1 Descriptive Analysis

Descriptive statistics are subjected to an analysis of variance (*ANOVA*) to carried out comparisons to group the different average of each user.

3.5.2 Questionnaire Reliability

The questionnaires' reliability will be determined on how reliable or consistent questionnaires perform such as (1) Instrument Reliability and Validity and (2) Factor Analysis as follows (Shrestha, 2021).

3.5.2.1 Instrument Reliability and Validity

1. Cronbach's Alpha

The reliability of a questionnaire is examined with Cronbach's alpha. It provides a simple way to measure whether a score is reliable (Shrestha, 2021).

$$\alpha = \frac{n\overline{r}}{1+\overline{r}\left(n-1\right)}$$

n = the number of items

$r\bar{r}$ = the mean correlation between the items

Cronbach's alpha ranges between 0 and 1. In general, Cronbach's alpha value is more than 0.7 is considered acceptable.

2. Convergent Validity

This is used to measure the level of correlation of multiple indicators of the same construct that agree (Shrestha, 2021).

3. Average Variance Extracted (AVE)

This is a measure of the amount of variance that is taken by a construction in relation to the amount of variance due to measurement error (Fornell & Larcker, 1981).

$$AVE = \frac{\sum_{i=1}^{n} \lambda_i^2}{n}$$

n = the number of the items

λi = the factor loading of item i

d. Composite Reliability (CR)

This is a measure of internal consistency in scale items (Netemeyer et al., 2003).

$$CR=\frac{\sum_{i=1}^{n}\lambda_i^2}{\sum_{i=1}^{n}\lambda_i^2+\sum_{i=1}^{n}Var(e_i)}$$

n = the number of the items

λi = the factor loading of item i

Var (ei) = the variance of the error of the item i

The value of AVE and CR ranges from 0 to 1, where a higher value indicates a higher reliability level. AVE is more than or equal to 0.5 confirms the convergent validity.

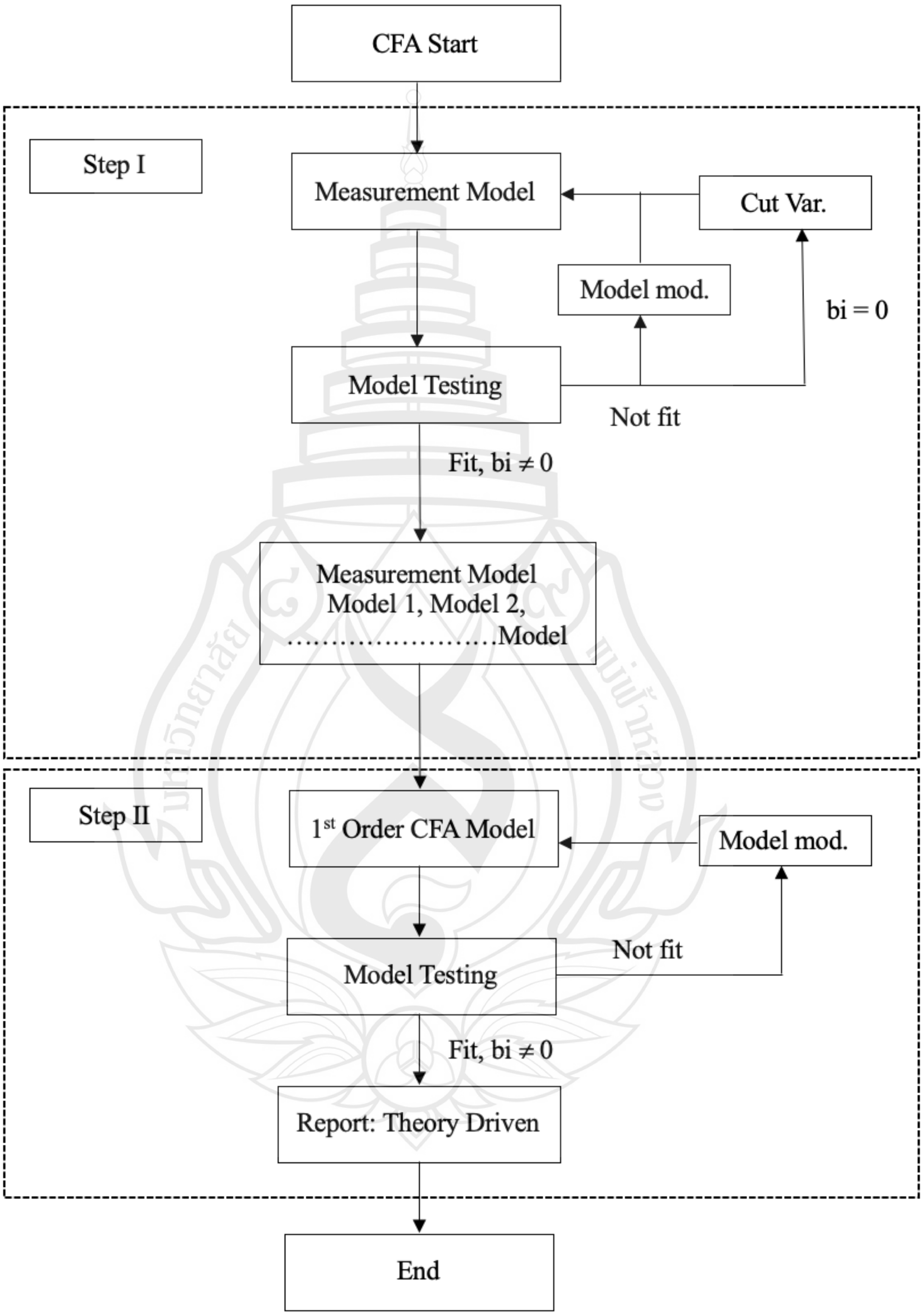
3.5.3 Confirmatory Factor Analysis (CFA)

This study employs First-Order Confirmatory Factor Analysis (CFA) based on Suksawang's (2020) methodology to validate measurement models. The analysis serves three primary purposes: (1) verifying theoretical consistency between variable structures and conceptual frameworks, (2) confirming the structural validity of measurement instruments, and (3) assessing the relative weights of observed variables.

The CFA process involves four key stages: model specification (defining theoretical relationships and creating path diagrams), model testing (evaluating fit using multiple indices including χ^2/df, GFI, CFI, RMSEA and SRMR), model modification (adjusting for error covariance and removing insignificant variables), and result interpretation (analyzing factor loadings and reliability).

Strict evaluation criteria are applied, with excellent model fit indicated by $\chi^2/df < 3$, CFI/TLI/GFI > 0.95, RMSEA < 0.05, and SRMR < 0.08. When models fail to meet these standards, corrective actions include permitting correlated errors between specific observed variables and eliminating variables with statistically insignificant factor loadings.

This rigorous analytical approach ensures the development of precise measurement instruments that accurately capture latent constructs while maintaining strong theoretical foundations. The methodology provides a systematic framework for validating measurement models, particularly useful for studies examining complex, multi-dimensional constructs in behavioral and social sciences. The study follows in the footsteps as shown in Figure 3.5.



Source Adapted from Suksawang (2020)

Figure 3.5 Confirmatory Factor Analysis (CFA)

3.5.4 Structural Equation Modeling (SEM)

Structural Equation Modeling (SEM) is widely popular for illustrating relationships among observed and latent variables in various theoretical models. It provides a quantitative method for testing hypotheses proposed by researchers. In essence, SEM allows researchers to hypothesize and test various theoretical models systematically (Schumacker & Lomax, 2016).

The proposed modified UTAUT model for the general population, based on UTAUT, will be analyzed and verified using a Structural Equation Model (SEM) in five steps, following Schumacker and Lomax's structural thinking framework (Suksawang, 2020), as illustrated in Figure 3.6

This statistical analysis will utilize Excel and JAMOVI Software (Version 2.6) (The Jamovi Project, 2024), developed as an open-source alternative to proprietary statistical software such as SPSS. JAMOVI is a modern and user-friendly statistical tool designed to make data analysis straightforward and accessible. It is entirely free, open source, and licensed under the GNU General Public License (GPL). Additionally, JAMOVI is gaining popularity alongside other established tools like LISREL, AMOS, and Mplus.

The statistical significance will be addressed in step 4 of Model Testing within Schumacker and Lomax's structural thinking framework (Suksawang, 2020). This step involves verifying the consistency between Matrix S and Matrix Σ. The model testing analysis will be divided into three main parts as follows:

3.5.4.1 Evaluation of Model Consistency with Empirical Data

This involves assessing the overall fit of the developed structural equation model with empirical data through three key aspects:

1. Chi-square Ratios

Ratios between 2 and 5 are considered indicative of a reasonable fit (Marsh & Hocevar, 1985), with a *p*-value greater than 0.05.

2. Goodness-of-Fit Index (GFI) or Fit Indices

Includes indices such as GFI, AGFI, TLI, and NFI, with values greater than 0.05 considered acceptable.

3. Estimation Error

Metrics such as RMSEA, RMR, and SRMR should have values less than 0.05 to indicate an adequate fit.

3.5.4.2 Examination of Individual Parameters

The t-values of individual parameters will be analyzed following the Rule of Thumb.

1. Absolute |t| values larger than 1.96 indicate significance at the 0.05 level.

2. Absolute |t| values larger than 2.58 indicate significance at the 0.01 level.

3.5.4.3 Assessment of Parameter Reasonableness

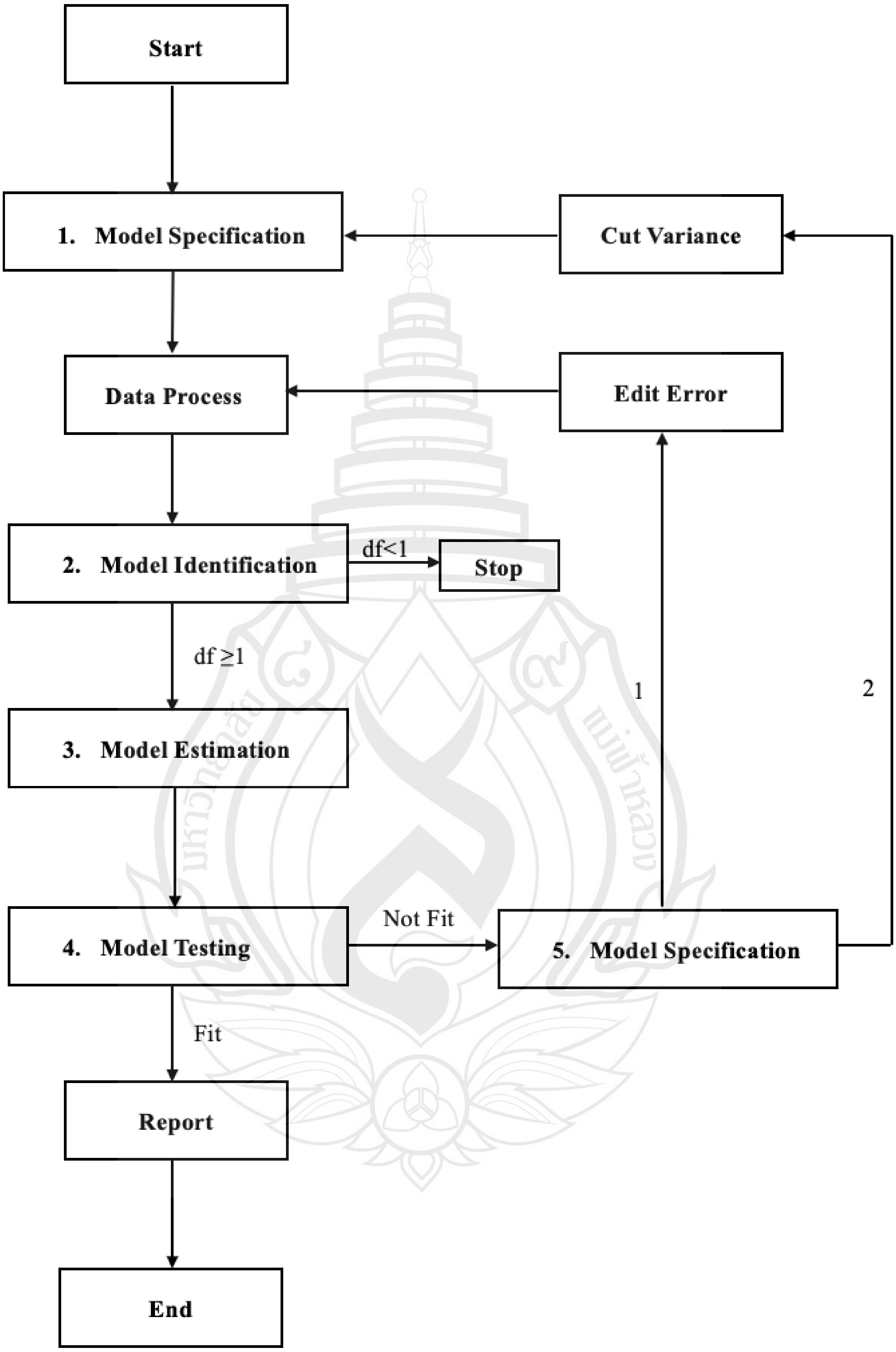
The size and direction of individual parameters will be evaluated for logical consistency and alignment with the formulated hypotheses. However, if the overall fit in Step 4 of model testing does not meet expectations, the next step is model modification. The model modification process is divided into two aspects as follows.

1. Considering measurement error caused by the instruments use

In this aspect, modifications can be made without affecting the proposed UTAUT model.

2. Considering the removal or addition of certain parameters in the model

This approach may lead to changes in the structural framework of the proposed UTAUT model. This situation typically arises due to insufficient literature review or inadequate reference to previous research. After addressing each aspect, the overall fit of the modified model should be reassessed to ensure it meets the expected criteria for model testing (Suksawang, 2020).



Source Adapted from Suksawang (2020)

Figure 3.6 Structural Equation Modeling by Schumacker and Lomax's Structural Thinking Framework

CHAPETR 4

RESEARCH RESULTS

This research aims to study a sample group of 130 rubber stakeholders in Thailand, comprising experts with more than five years of experience in rubber, drawn from five regions of the country. The research results are composed of the following sub-topics.

4.1 Secondary Data Analysis

4.1.1 The Challenges of Rubber Under the Authority of RAOT

4.1.2 Possible Solutions in the Challenges of Rubber Supply Chain in Thailand

4.2 Descriptive Statistic Analysis

4.2.1 Respondent's General Information

4.2.2 Respondent from five Regions of Thailand

4.3 Questionnaire Reliability Analysis

4.4 Measurement Model Analysis

4.5 Confirmatory Factor Analysis (CFA)

4.6 Structural Equation Model Analysis

4.6.1 Proposed UTAUT Model Analysis

4.6.2 Path Analysis of Each Factor from the Proposed UTAUT Model

4.1 Secondary Data Analysis

According to Chapter 2 (2.3), the literature review found that each stakeholder in the supply chain faces its own challenges based on their roles, existing conditions, knowledge of marketing and trading, and other factors. Therefore, this study identifies the priority problems that should be addressed for government support, which are officially under RAOT's roles and responsibilities as follows.

4.1.1 The Challenges of Rubber Under the Authority of RAOT

The challenges facing the rubber industry in Thailand are complex and stem from various factors affecting each stakeholder. All stakeholders should be involved in finding the best solution. This study focuses solely on the challenges that fall under the authority of RAOT, specifically addressing the fluctuation in rubber prices and identifying the most effective solutions.

The factors contributing to the fluctuation in rubber prices are as follows: (1) The imbalance between rubber demand and supply, (2) Economic crises, particularly in China, the USA, and Japan, which are the leading rubber-consuming countries, and (3) Profit speculation in the local and futures markets. The imbalance between rubber demand and supply in the local market is a challenge that RAOT can address under the Rubber Authority of Thailand Act, B.E. 2558 (2015). However, addressing the other two challenges, which are beyond RAOT's authority, requires support and collaboration with relevant countries as shown in Table 4.1.

An analysis of the root causes of this imbalance reveals the complexity of Thailand's rubber market. Notably, the upstream rubber industry in Thailand predominantly operates as a monopolistic competition market, characterized by many suppliers and a limited number of buyers. One significant impact of past policies is the implementation of the rubber trading license, which affects collectors (middlemen and manufacturers) who are responsible for purchasing and processing rubber products. This policy has led to several issues as follows (1) Inaccurately Verified Report (2) Illegal Trading (3) Lack of Rubber Trading Data (4) Lack of Big Data/ Open Data in Rubber Trading.

Rubber prices are heavily influenced by collectors, leading to daily fluctuations. Furthermore, collectors often stockpile rubber to wait for higher prices before selling. Although the government agencies have made efforts to address these issues within its authority, the implemented solutions have not been sustainable. As the authority of RAOT aims to address the root causes by focusing on big data management, especially open data. These data-related challenges are essential to overcome to effectively facilitate and support the rubber industry supply chain, as well as to forecast rubber demand and supply both domestically and internationally as shown in Figure 4.1.

In summary, the fluctuation in rubber prices poses a significant challenge for the Thai rubber industry, which falls under the responsibility of RAOT. This issue stems from an imbalance in rubber demand and supply within the local market, which RAOT is authorized to address under the Rubber Authority of Thailand Act, B.E. 2558 (2015).

Table 4.1 Secondary Data Analysis

No.	Rubber Challenges	Sub-Rubber Challenges	Authority of RAOT under the Act, B.E. 2558 (2015)
1	The imbalance of demand and supply affects the selling price of rubber	1. Lack of domestic demand and supply data (RAOT, 2024a). 2. The supply is higher than domestic demand, causing low rubber prices (Intrasakul et al., 2017). 3. Plant Diseases: Diseases such as leaf blight and root rot can devastate rubber plantations, reduce the overall supply and cause prices to spike (Intrasakul et al., 2017). 4. Production Costs: Rising costs of labor, fertilizers, and other inputs can reduce profit margins for rubber producers, potentially leading to decreased production and higher prices (Intrasakul et al., 2017). 5. Technological Advances: Innovations in synthetic rubber production can affect the demand for natural rubber. If synthetic alternatives become cheaper or more efficient, the demand for natural rubber may decline, reducing prices (RAOT, 2024a; Intrasakul et al., 2017).	1. Nation: Support the country in becoming a sustainable hub for rubber production, trade, and innovation. 2. People and Consumers: Promote awareness of the value of natural rubber use among the public and consumers. 3. Rubber Farmers: Improve the quality of life for rubber farmers. 4. Farmer Institutions: Strengthen farmer institutions and promote professional business management. 5) Rubber Entrepreneurs: Promote trade and enhance competitiveness in the rubber industry. 6. Organization: Strengthen the organization’s financial stability, develop it into a knowledge-based and high-performance organization by leveraging digital technology, innovation, and good governance.

Table 4.1 (continued)

No.	Rubber Challenges	Sub-Rubber Challenges	Authority of RAOT under the Act, B.E. 2558 (2015)
2	The economic slowdown, especially in the world's largest rubber consumer, China, the United States and Japan that cause declining the purchase rubber consumers.	1. Global Economic Conditions: The demand for rubber is closely tied to the global economy. During economic booms, the demand for rubber in industries such as automotive and manufacturing increases, pushing prices up. Conversely, during economic downturns, demand decreases, leading to lower prices (Statista Research Department, 2024; Do, 2024). 2. Consumer Preferences: Changes in consumer preferences, such as a shift towards more sustainable and eco-friendly products, can influence the demand for natural rubber and its price. Moreover, domestic consumption remains much lower than exports, resulting in a gradual decline in the contribution of manufactured rubber and plastic products to Indonesia's GDP in recent years, in line with the drop in rubber production (Statista Research Department, 2024; Do, 2024).	These challenges are beyond the control of RAOT under the ACT, B.E. 2558 (2015), as they stem from global economic factors, which are external influences.

Table 4.1 (continued)

No.	Rubber Challenges	Sub-Rubber Challenges	Authority of RAOT under the Act, B.E. 2558 (2015)
3	Investor's speculation in both the domestic market and the futures market is affecting trading, pricing in that market	1. Trade Policies: Tariffs, trade agreements, and export restrictions imposed by major rubber producing or consuming countries can significantly affect rubber prices. For example, import tariffs on rubber products can decrease demand, leading to price drops (Intrasakul et al., 2017; Do, 2024). 2. Unfair trading, pressure on prices, weight, percentage of dry rubber, and unfair rubber quality selection, etc (Munkong et al., 2013; Intrasakul et al., 2017; Statista Research Department, 2024).	These challenges are beyond the control of RAOT under the ACT, B.E. 2558 (2015), as they arise from investor-related factors, which are influenced by individual preferences and personal decisions.

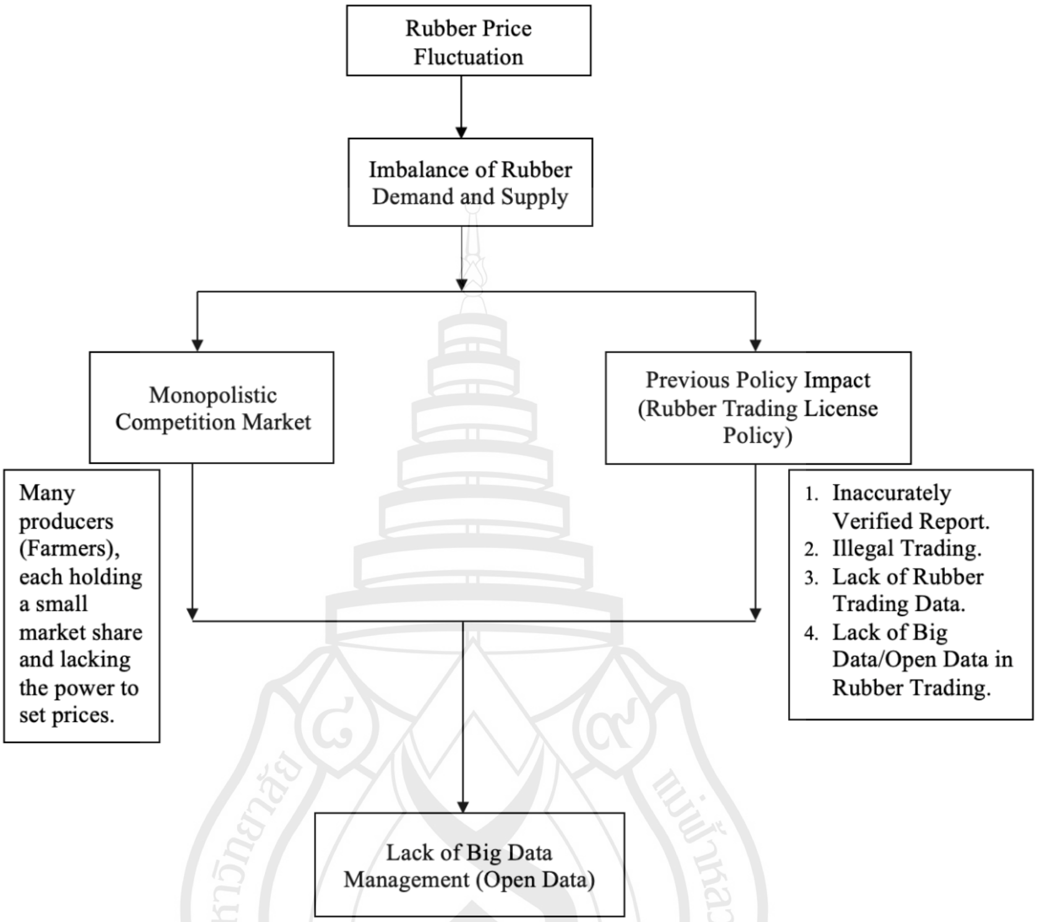


Figure 4.1 Root Causes of Imbalance Rubber Demand and Supply in Thailand

4.1.2 Possible Solutions in the Challenges of Rubber Supply Chain in Thailand

The primary cause of rubber price fluctuations is the imbalance between domestic demand and supply. Currently, government agencies lack a big data tracking system to monitor the actual daily demand and supply of rubber. As a solution for big data management, RAOT is interested in adopting advanced technologies such as blockchain, a form of Distributed Ledger Technology (DLT). Blockchain offers significant potential for managing big data by providing a transparent, efficient, and reliable system with strong accountability. Therefore, RAOT, under the Rubber Authority of Thailand Act, B.E. 2558 (2015), has committed to adopting advanced blockchain technology to address these challenges in the era of technological disruption.

Due to the characteristics of blockchain technology, it provides a secure and immutable record format, ensuring that previously recorded information cannot be changed or modified. All users will have access to the same data, ensuring transparency. By employing cryptographic principles and the capabilities of distributed computing, the platform establishes a trust mechanism (Raskin & Yermack, 2016).

Hence, to explore the acceptance of the Blockchain Traceability Platform by all stakeholders in the Thai rubber industry, a solution will be tested using a modified UTAUT model. RAOT, under the authority of the Rubber Authority of Thailand Act, B.E. 2558 (2015), plans to adopt a DLT-blockchain technology platform to transform the Thai rubber market. This platform is expected to address major challenges in the rubber industry, including the accurate recording of big data on rubber purchasing. It holds significant potential for managing big data by developing a transparent, efficient, and reliable management system with strong accountability.

4.2 Descriptive Statistic Analysis

4.2.1 Respondent's General Information

The validity of the questionnaires distributed to the respondents was assessed according to the principles outlined in Chapter 3, Research Methodology. In this study, a questionnaire survey consisting of 27 statement items was distributed to a total of 130 respondents. The demographic analysis reveals that most respondents are male (98%), typically serving as heads of their families and key contributors to the Thai rubber industry, while females account for only 2%. Most respondents have over five years of experience in the rubber industry, establishing them as specialists in the field. The respondents' age range is predominantly between 51-65 years. Their occupations are distributed as follows: farmers (31%), collectors (22%), government agencies (22%), exporters (12%), and others, including brokers and rubber scholars (13%). These findings are summarized in Table 4.2.

Table 4.2 Respondent's General Information

General Information	Items	Number	Percentage (%)
Gender	Male	128	98%
	Female	2	2%
Age range	51-65		
Experience	Over 5 years	130	100%
Stakeholders	Farmers (F)	40	31%
	Collectors (C)	29	22%
	Government Agencies (G)	29	22%
	Exporters (E)	15	12%
	Others (Broker, Rubber Scholar) (O)	17	13%
	Total	**130**	**100%**

4.2.2 Respondent from five Regions of Thailand

The respondents, drawn from five regions of Thailand, are experts in the rubber industry with more than five years of experience. Additionally, they were required to participate in a focus group discussion on blockchain technology, an advanced innovation, prior to completing the questionnaire survey. The distribution of respondents across the five regions of Thailand is as follows:

4.2.2.1 Northern Region: 18%, including Chiang Rai, Phayao, Nan, and Phitsanulok.

4.2.2.2 Central Region: 17%, including Kanchanaburi and Prachuap Khiri Khan.

4.2.2.3 Eastern Region: 31%, including Prachinburi, Sakaeo, Rayong, Chachoengsao, and Trat.

4.2.2.4 Northeastern Region: 25%, including Loei, Udon Thani, Nong Khai, Bueng Kan, Buri Ram, Si Sa Ket, and Ubon Ratchathani.

4.2.2.5 Southern Region: 39%, including Chumphon, Surat Thani, Phang Nga, Nakhon Si Thammarat, Songkhla, and Yala.

These findings are summarized in Table 4.3.

Table 4.3 Respondent from Five Regions of Thailand

Regions/ Provinces	Stakeholders Farmer (F)	Collector (C)	Government Agency (G)	Exporter (E)	Other (O)	Number	(%)
Northern Chiang Rai, Phayao, Nan and Phitsanulok	3	4	6	2	3	18	13.85
Central Kanchanaburi and Prachuap Khiri Khan	2	2	6	3	4	17	13.08
Eastern Prachinburi, Sakaeo, Rayong, Chachoengsao and Trat	15	5	5	3	3	31	23.85
Northeastern Loei, Udon Thani, Nong Khai, Bueng Kan, Buri Ram, Si Sa Ket and Ubon Ratchathani	5	8	6	3	3	25	19.23
Southern Chumphon, Surat Thani, Phang Nga, Nakornsri Thammarat, Songkhla and Yala	15	10	6	4	4	39	30
Total	**40**	**29**	**29**	**15**	**17**	**130**	**100**

4.3 Questionnaire Reliability Analysis

The study demonstrates as follows.

4.3.1 Cronbach's α

A score of 0.97 is much higher than the commonly accepted threshold of 0.7, indicating excellent internal consistency and reliability of the measurement tool.

4.3.2 Item-Rest Correlation

Scores ranging between 0.650 and 0.863 surpass the threshold of 0.2, suggesting that individual items strongly contribute to the overall reliability of the scale.

4.3.3 Mean Scores

The range of 4.24 to 6.56 suggests that participants generally expressed positive responses toward the measured constructions.

4.3.4 Standard Deviation (SD)

Values between 0.498 and 0.822 indicate reasonable variability in responses, without excessive dispersion.

The results collectively demonstrate robust reliability and positive participant feedback on the constructions being assessed. These findings align with Table 4.4 and Appendix B.

Table 4.4 Questionnaire Reliability Analysis

Item Reliability Statistics					
Items	**Mean**	**SD**	**Item-rest correlation**	**Cronbach's α**	**Result**
All	5.36	0.510	-	0.970	Reliable
PE1	5.72	0.739	0.731	0.969	Reliable
PE2	5.55	0.706	0.740	0.969	Reliable
PE3	5.74	0.721	0.742	0.969	Reliable
PE4	5.65	0.608	0.803	0.968	Reliable
PE5	5.45	0.716	0.725	0.969	Reliable
PE6	5.60	0.700	0.714	0.969	Reliable
PE7	5.58	0.755	0.728	0.969	Reliable

Table 4.4 (continued)

Item Reliability Statistics					
Items	**Mean**	**SD**	**Item-rest correlation**	**Cronbach's α**	**Result**
EE1	5.64	0.623	0.750	0.969	Reliable
EE2	5.45	0.636	0.719	0.969	Reliable
EE3	5.58	0.554	0.745	0.969	Reliable
EE4	5.34	0.822	0.696	0.969	Reliable
SI1	4.24	0.702	0.711	0.969	Reliable
SI2	4.24	0.668	0.726	0.969	Reliable
SI3	4.67	0.741	0.718	0.969	Reliable
FC1	4.58	0.581	0.779	0.969	Reliable
FC2	4.78	0.693	0.741	0.969	Reliable
FC3	5.04	0.720	0.650	0.969	Reliable
TA1	6.49	0.532	0.835	0.968	Reliable
TA2	6.33	0.652	0.674	0.969	Reliable
TA3	6.56	0.498	0.863	0.968	Reliable
TA4	6.37	0.612	0.677	0.969	Reliable
TA5	6.25	0.727	0.679	0.969	Reliable
BI1	4.72	0.729	0.790	0.968	Reliable
BI2	4.76	0.620	0.731	0.969	Reliable
BI3	4.85	0.792	0.683	0.969	Reliable
BI4	4.56	0.671	0.717	0.969	Reliable
BI5	4.96	0.762	0.761	0.969	Reliable

Note m = number of observed variables; N = applies to number of observations per group when applying CFA to multiple groups at the same time.

4.4 Measurement Model Analysis

The measurement model analysis for each latent variable was evaluated to confirm the structure of the measurement model, using JAMOVI software (Version 2.6) by The Jamovi Project (2024) and AMOS IBM26 by Arbuckle (2019). The results should align with the criteria for model fit, which require a *p*-value > 0.05, Relative Chi-Square of less than 2, RMSEA values below 0.08, CFI values above 0.99, N < 250 and 12 < m (Hair et al., 2019). The results for the six variables are as follows.

1. Technological Anxiety (TA): Chi-Square ($\chi 2$) = 0.135, df = 3, Relative Chi-Square = 0.045, *p*-value = 0.987, RMSEA = 0.000, CFI = 1.000, indicating a good fit.

2. Performance Expectancy (PE): Chi-Square ($\chi 2$) = 1.92, df = 8, Relative Chi-Square = 0.24, *p*-value = 0.983, RMSEA = 0.000, CFI = 1.000, indicating a good fit.

3. Effort Expectancy (EE): Chi-Square ($\chi 2$) = 0.844, df = 1, Relative Chi-Square = 0.844, *p*-value = 0.358, RMSEA = 0.000, CFI = 1.000, indicating a good fit.

4. Social Influence (SI): Chi-Square ($\chi 2$) = 0.682, df = 1, Relative Chi-Square = 0.682, *p*-value = 0.409, RMSEA = 0.000, CFI = 1.000, indicating a good fit.

5. Facilitating Conditions (FC): Chi-Square ($\chi 2$) = 0.073, df = 3, Relative Chi-Square =, *p*-value = 0.995, RMSEA = 0.000, CFI = 1.000, indicating a good fit.

6. Behavioral Intention (BI): Chi-Square ($\chi 2$) = 0.073, df = 3, Relative Chi-Square = 0.024, *p*-value = 0.995, RMSEA = 0.000, CFI = 1.000, indicating a good fit.

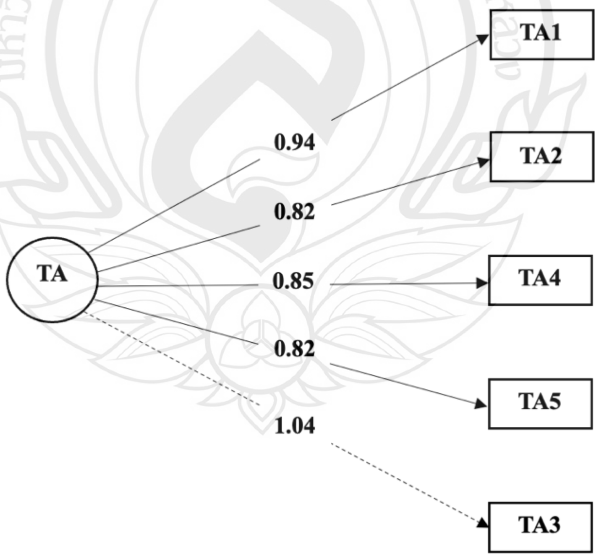
The details are shown in Table 4.5, Figure 4.2-4.7 and Appendix C.

Table 4.5 Measurement Model Analysis

Goodness of Fit Indices	Criteria Required (N< 250, m<12)	Factors					
		TA	PE	EE	SI	FC	BI
Chi-Square (χ2)	Insignificant *p*-values expected (*p*-values > 0.05)	0.135	1.92	0.844	0.682	0.163	0.073
df	-	3	8	1	1	1	3
Relative Chi-Square (χ2/df)	≤ 2	0.045	0.24	0.844	0.682	0.163	0.224
p-value	> 0.05	0.987	0.983	0.358	0.409	0.687	0.995
RMSEA	< 0.08	0.000	0.000	0.000	0.000	0.000	0.000
CFI	0.99 or better	1.000	1.000	1.000	1.000	1.000	1.000
Result		**Fit**	**Fit**	**Fit**	**Fit**	**Fit**	**Fit**

Note m = number of observed variables; N = applies to number of observations per group when applying CFA to multiple groups at the same time.

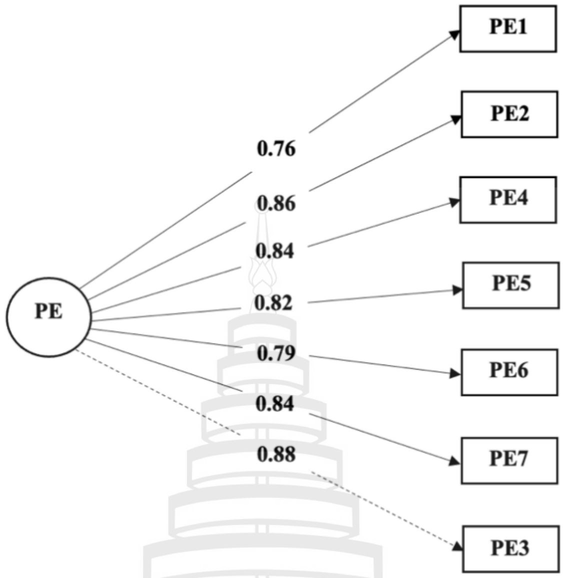
1. Technological Anxiety (TA)



Chi-Square (χ2) = 0.135, df = 3, Relative Chi-Square = 0.045, *p*-value = 0.987, RMSEA = 0.000, CFI = 1.000

Figure 4.2 Measurement Model Analysis of TA

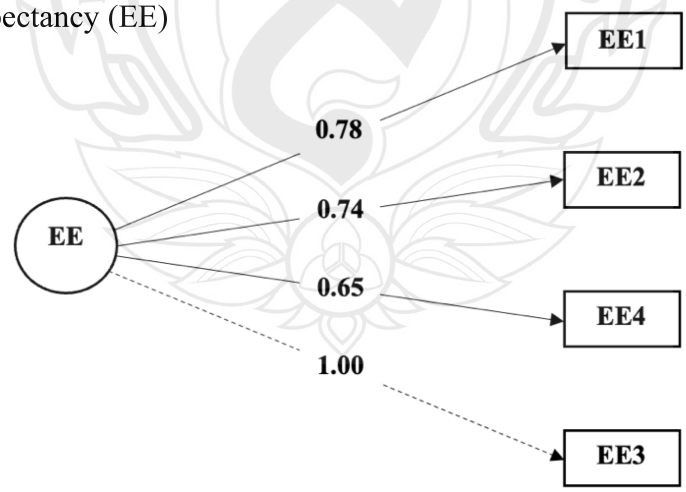
2. Performance Expectancy (PE)



Chi-Square ($\chi 2$) = 1.92, df = 8, Relative Chi-Square = 0.24, *p*-value = 0.983, RMSEA = 0.000, CFI = 1.000

Figure 4.3 Measurement Model Analysis of PE

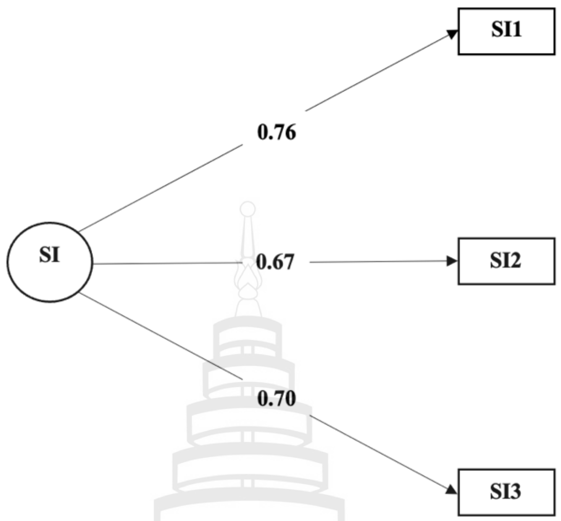
3. Effort Expectancy (EE)



Chi-Square ($\chi 2$) = 0.844, df = 1, Relative Chi-Square = 0.844, *p*-value = 0.358, RMSEA = 0.000, CFI = 1.000

Figure 4.4 Measurement Model Analysis of EE

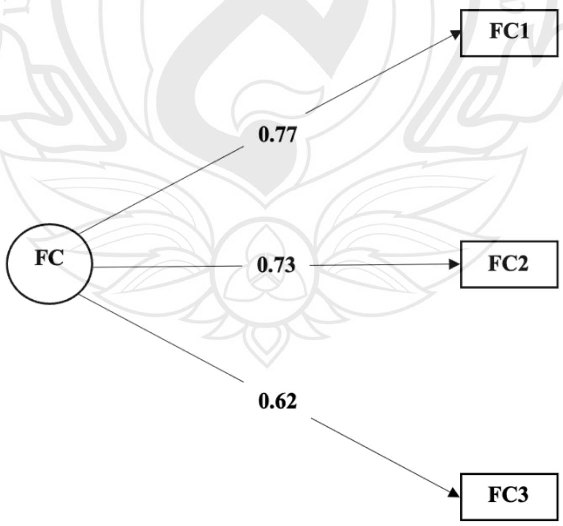
4. Social Influence (SI)



Chi-Square ($\chi 2$) = 0.682, df = 1, Relative Chi-Square = 0.682, p-value = 0.409, RMSEA = 0.000, CFI = 1.000

Figure 4.5 Measurement Model Analysis of SI

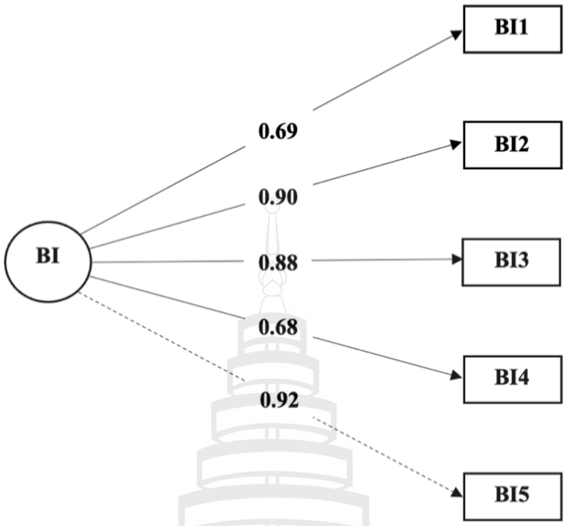
5. Facilitating Conditions (FC)



Chi-Square ($\chi 2$) = 0.073, df = 3, Relative Chi-Square = 0.824, p-value = 0.995, RMSEA = 0.000, CFI = 1.000

Figure 4.6 Measurement Model Analysis of FC

6. Behavioral Intention (BI)



Chi-Square ($\chi2$) = 0.073, df = 3, Relative Chi-Square = 0.024, *p*-value = 0.995, RMSEA = 0.000, CFI = 1.000

Figure 4.7 Measurement Model Analysis of BI

4.5 Confirmatory Factor Analysis (CFA)

The results of the Confirmatory Factor Analysis (CFA) at the first order, conducted using JAMOVI software (Version 2.6) (The Jamovi Project, 2024), show that the AVE ratios range between 0.594 and 0.763, while the CR ratios range between 0.738 and 0.912. Since these values exceed the thresholds of 0.5 and 0.7, respectively, the analysis is considered reliable.

In summary, this data demonstrates the convergent validity index, which confirms that the developed model is consistent with the empirical data. The results goodness of fit indices are as follows: Chi-Square (χ^2) = 446, df = 267, Relative Chi-Square = 1.7, *p*-value < 0.001, RMSEA = 0.072, SRMR = 0.064, CFI = 0.997, and TLI = 0.997. These results align with the criteria for model fit, which require a Relative Chi-Square of less than 2, RMSEA or SRMR values below 0.08, CFI or TLI values above 0.97, N < 250 and 12 < m < 30 (Hair et al., 2019).

Therefore, it can be concluded that the developed model is consistent with the empirical data. In summary, the developed model includes six factors, with the most strongly influenced indicators for each factor listed as follows.

1. Technological Anxiety (TA): Most strongly influenced by the indicators TA1, TA5, TA2, and TA4, respectively.

2. Performance Expectancy (PE): Most strongly influenced by the indicators PE1, PE3, PE2, PE7, PE5 and PE6 respectively.

3. Effort Expectancy (EE): Most strongly influenced by the indicators EE1, EE2 and EE4 respectively.

4. Social Influence (SI): Most strongly influenced by the indicators SI3 and SI1 respectively.

5. Facilitating Conditions (FC): Most strongly influenced by the indicators FC1 and FC3 respectively.

6. Behavioral Intention (BI): Most strongly influenced by the indicators BI5, BI3, BI2 and BI4 respectively.

The details are shown in Table 4.6, Figure 4.8 and Appendix D.

Table 4.6 Confirmatory Factor Analysis (CFA)

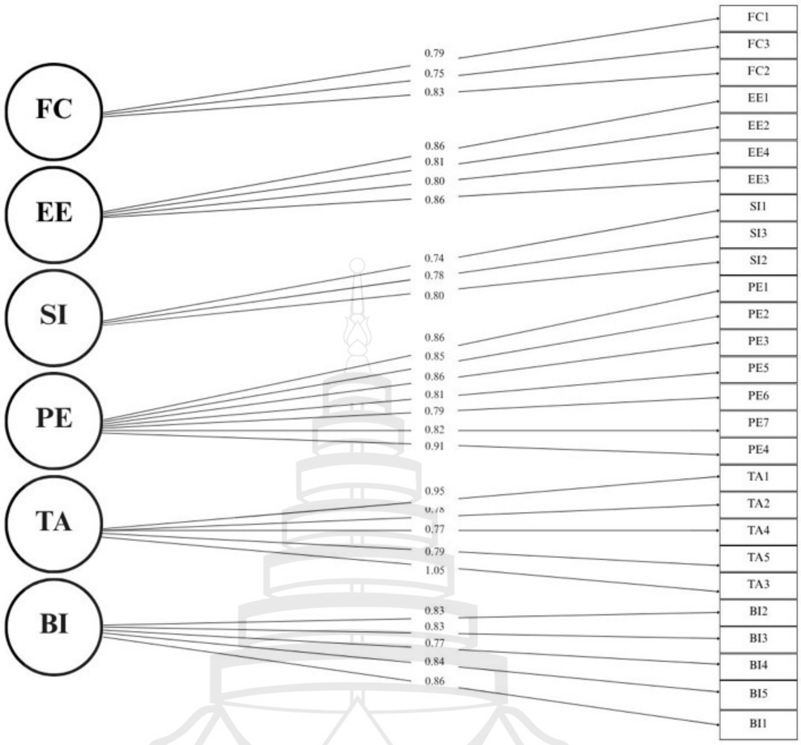
Construct	**b**	**β**	**S.E.**	**CR (>0.7)**	**AVE (>0.5)**	**Result**
TA				0.890	0.763	Reliable
TA3	1.000	1.047	0.0000			
TA5	0.751	0.786	0.0401			
TA4	0.733	0.767	0.0422			
TA2	0.744	0.780	0.0397			
TA1	0.907	0.949	0.0320			
PE				0.912	0.709	Reliable
PE4	1.000	0.906	0.0000			
PE7	0.904	0.820	0.0444			
PE6	0.869	0.788	0.0511			
PE5	0.895	0.811	0.0480			
PE3	0.945	0.857	0.0347			

Table 4.6 (continued)

Construct	b	β	S.E.	CR (>0.7)	AVE (>0.5)	Result
PE2	0.936	0.848	0.0372			
PE1	0.947	0.858	0.0455			
EE				0.802	0.690	Reliable
EE3	1.000	0.858	0.0000			
EE4	0.931	0.799	0.0603			
EE2	0.940	0.807	0.0586			
EE1	0.998	0.857	0.0569			
SI				0.747	0.594	Reliable
SI2	1.000	0.797	0.0000			
SI3	0.976	0.778	0.0505			
SI1	0.925	0.737	0.0526			
FC				0.738	0.626	Reliable
FC2	1.000	0.829	0.0000			
FC3	0.904	0.749	0.0447			
FC1	0.956	0.793	0.0577			
BI				0.874	0.683	Reliable
BI1	1.000	0.857	0.0000			
BI5	0.984	0.843	0.0365			
BI4	0.901	0.772	0.0527			
BI3	0.971	0.832	0.0389			
BI2	0.963	0.825	0.0341			

Chi-Square ($\chi 2$) = 446, df = 267, Relative Chi-Square= 1.7, *p*-value = <0.001, RMSEA = 0.072, SRMR = 0.064, CFI = 0.997, TLI = 0.997

Note m = number of observed variables; N = applies to number of observations per group when applying CFA to multiple groups at the same time.



Chi-Square ($\chi 2$) = 446, df = 267, Relative Chi-Square= 1.7, *p*-value = <0.001, RMSEA = 0.072, SRMR = 0.064, CFI = 0.997, TLI = 0.997

Figure 4.8 Confirmatory Factor Analysis (CFA)

4.6 Structural Equation Model Analysis

4.6.1 The Proposed UTAUT Model Analysis

The analysis of the path analysis of the Proposed UTAUT Model was conducted using JAMOVI software (Version 2.6) (The Jamovi Project, 2024), considering the β ratios, z ratios, and *p*-values. The acceptance criteria require that the values of β do not exceed the threshold of 1 and are in a positive direction, with z > 1.96 being significant at 0.05 or z > 2.58 being significant at 0.01, as the rule of thumb. These results must align with the criteria for model fit with N < 250 and 12 < m < 30 which require a Relative Chi-Square of less than 2, RMSEA or SRMR values below 0.08, CFI or TLI values above 0.97 (Hair et al., 2019).

Therefore, it can be concluded that the developed model is not consistent with the empirical data. In summary, the developed model includes five hypotheses with the criteria for model fit Chi-Square ($\chi2$) = 220, df = 214, Relative Chi-Square= 1.8, *p*-value = 0.377, RMSEA = 0.015, SRMR = 0.049, CFI = 1.000, TLI = 1.000. The influenced indicators for each hypothesis are listed as follows.

1. Hypothesis 1 (PE → BI): The result of β = 0.955 with the positive direction, z = 0.802, *p*-value = 0.422, indicating that Hypothesis 1 is rejected.

2. Hypothesis 2 (EE → BI): The result of β = 0.652 with the positive direction, z = 1.305, p-value = 0.192, indicating that Hypothesis 2 is rejected.

3. Hypothesis 3 (SI → BI): The result of β = -0.803 with the negative direction, z = -0.191, p-value = 0.848, indicating that Hypothesis 3 is rejected.

4. Hypothesis 4 (FC → BI): The result of β = -0.009 with the negative direction, z = -0.004, p-value = 0.997, indicating that Hypothesis 4 is rejected.

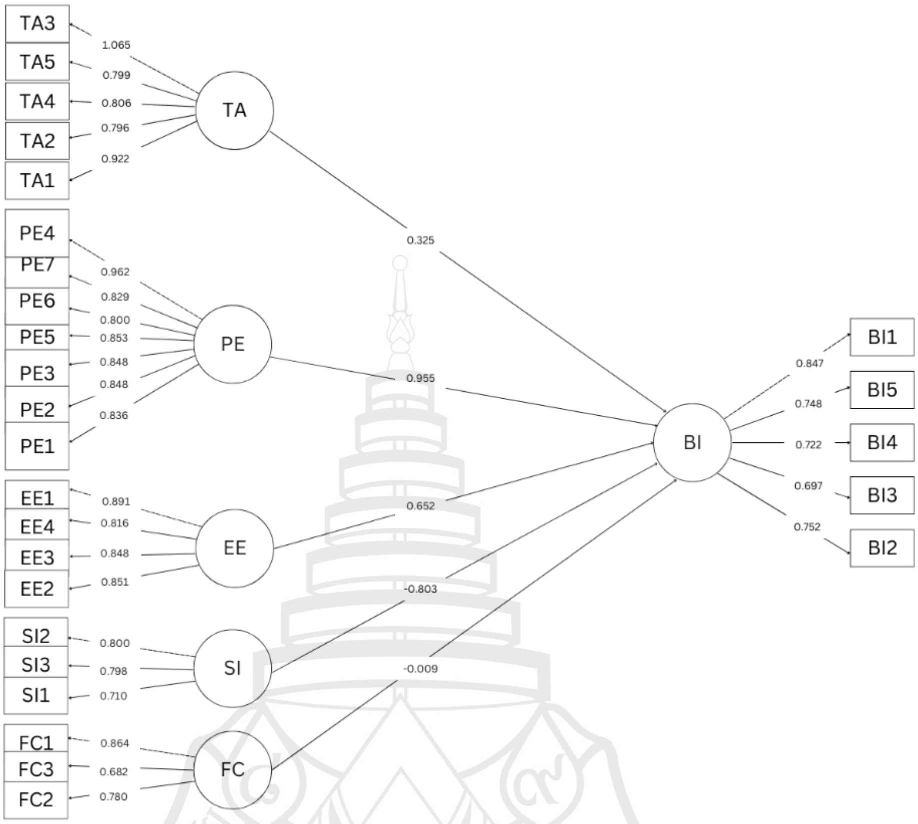
5. Hypothesis 5 (TA → BI): The result of β = 0.325 with the positive direction, z = 0.304, *p*-value = 0.762, indicating that Hypothesis 5 is rejected.

However, the proposed UTAUT model was not consistent with the empirical data and could not be accepted. One possible explanation for these results is that PE, EE, SI, FC, and TA may have had indirect rather than direct influences on BI, whereas the proposed UTAUT model was designed to test only their direct effects, as shown in Table 4.7, Figure 4.9 and Appendix E.

Table 4.7 Structural Equation Model Analysis of the Proposed UTAUT Model

Hypothesis	**Construct path**	**β**	**z**	***p*-value**	**Result**
H1	PE → BI	0.955	0.802	0.422	Rejected
H2	EE → BI	0.652	1.305	0.192	Rejected
H3	SI → BI	-0.803	-0.191	0.848	Rejected
H4	FC → BI	-0.009	-0.004	0.997	Rejected
H5	TA → BI	0.325	0.304	0.762	Rejected

Note m = number of observed variables; N = applies to number of observations per group when applying CFA to multiple groups at the same time.



Chi-Square ($\chi 2$) = 220, df = 214, Relative Chi-Square= 1.8, *p*-value = 0.377,

RMSEA = 0.015, SRMR = 0.049, CFI = 1.000, TLI = 1.000

Figure 4.9 Structural Equation Model Analysis of the Proposed UTAUT Model

4.6.2 The Path Analysis of Each Factor from the Proposed UTAUT Model

According to the analysis, the Structural Equation Model was not consistent with the empirical data. Therefore, it is necessary to test the path analysis of each factor from the proposed UTAUT model to verify whether each factor directly influences Behavioral Intention (BI).

The analysis of the path analysis of the proposed UTAUT model was conducted using JAMOVI software (Version 2.6) (The Jamovi Project, 2024), considering the β ratios, z ratios, and *p*-values. The acceptance criteria require that the values of β do not exceed the threshold of 1 and are in a positive direction, with $z > 1.96$ being significant at 0.05 or $z > 2.58$ being significant at 0.01, as the rule of thumb. These results must align with the criteria for model fit with $N < 250$ and $m < 12$ which require a *p*-value >

0.05, Relative Chi-Square of less than 2, RMSEA values below 0.08, CFI values above 0.99 (Hair et al., 2019).

Therefore, it can be concluded that the path analysis of each factor shows that four out of five are consistent with the empirical data, while one is not. In summary, the path analysis of the proposed UTAUT model includes five factors, with the most strongly influenced indicators for each factor listed as follows.

1. PE ➔ BI: The result of β = 0.956 with the positive direction, z = 19.20 *p*-value <0.001. The criteria for model fit Chi-Square (χ2) = 59.9, df = 46, Relative Chi-Square = 1.30, *p*-value = 0.083, RMSEA = 0.048, CFI = 0.999, indicating PE influences directly BI and significant at 0.001.

2. EE ➔ BI: The result of β = 1.060 with the positive direction, z = 12.80 p-value <0.001. The criteria for model fit Chi-Square (χ2) = 2.5, df = 14, Relative Chi-Square = 0.18, *p*-value = 1, RMSEA = 0.000, CFI = 1.000, indicating EE does not influence directly BI.

3. SI ➔ BI: The result of β = 0.994 with the positive direction, z = 10.90 p-value <0.001. The criteria for model fit Chi-Square (χ2) = 4.46, df = 14, Relative Chi-Square= 0.32, *p*-value = 0.992, RMSEA = 0.000, CFI = 1.000, indicating SI influences directly BI and significant at 0.001.

4. FC ➔ BI: The result of β = 0.974 with the positive direction, z = 11.90 p-value <0.001. The criteria for model fit Chi-Square (χ2) = 21.7, df = 17, Relative Chi-Square = 1.28, *p*-value = 0.195, RMSEA = 0.046, CFI = 0.999, indicating FC influences directly BI and significant at 0.001.

5. TA ➔ BI: The result of β = 0.950 with the positive direction, z = 23.00, *p*-value <0.001. The criteria for model fit Chi-Square (χ2) = 30.4, df = 30, Relative Chi-Square = 1.01, *p*-value = 0.444, RMSEA = 0.011, CFI = 1.000, indicating TA influences directly BI and significant at 0.001.

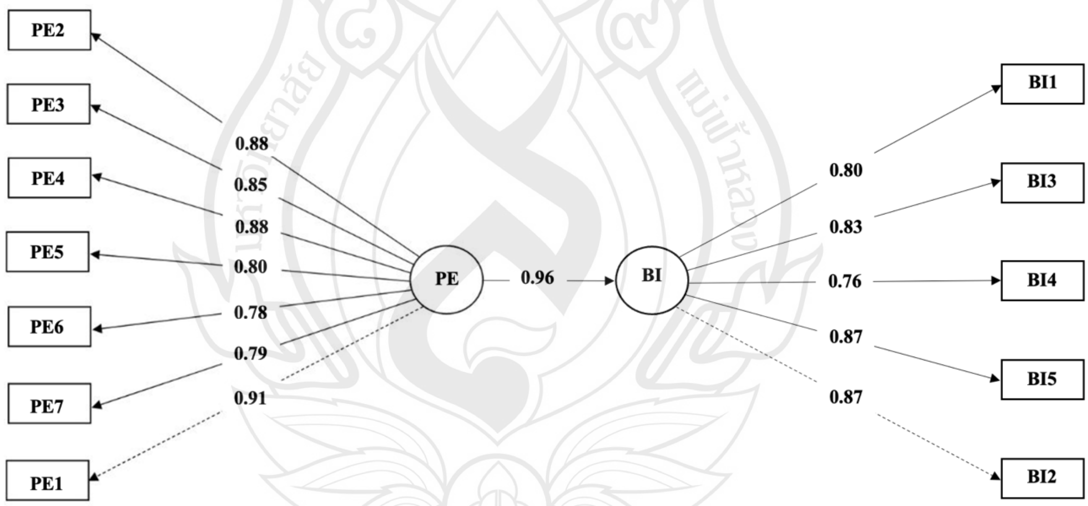
Hence, the results demonstrated that out of the five factors, four were influenced directly BI (PE, SI, FC, and TA), while one was not influenced directly (EE), as shown in Table 4.8, Figure 4.10-4.14 and Appendix F.

In summary, the factors affecting the adoption of blockchain traceability platform in Thailand rubber supply chain using UTAUT model are Social Influence (SI), Facilitating Conditions (FC), Performance Expectancy (PE), and Technological Anxiety (TA), respectively. While Effort Expectancy (EE) is not affecting the adoption of blockchain traceability platform in Thailand rubber supply chain using UTAUT model.

Table 4.8 Path Analysis of Each Factor from the Proposed UTAUT Model

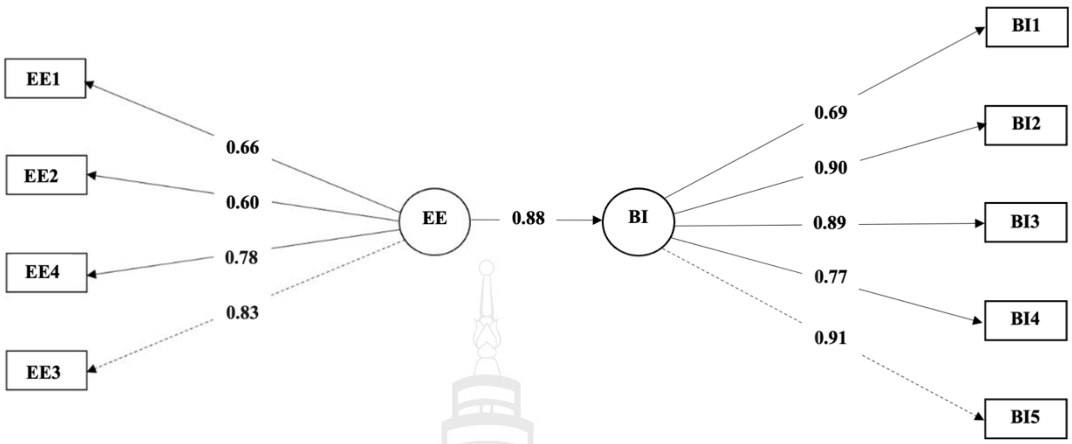
Construct path	**β**	**z**	***p*-value**	**Result**
PE → BI	0.956	19.20	<0.001	Accepted
EE → BI	1.060	12.80	<0.001	Rejected
SI → BI	0.994	10.90	<0.001	Accepted
FC → BI	0.974	11.90	<0.001	Accepted
TA → BI	0.950	23.00	<0.001	Accepted

Note m = number of observed variables; N = applies to number of observations per group when applying CFA to multiple groups at the same time.



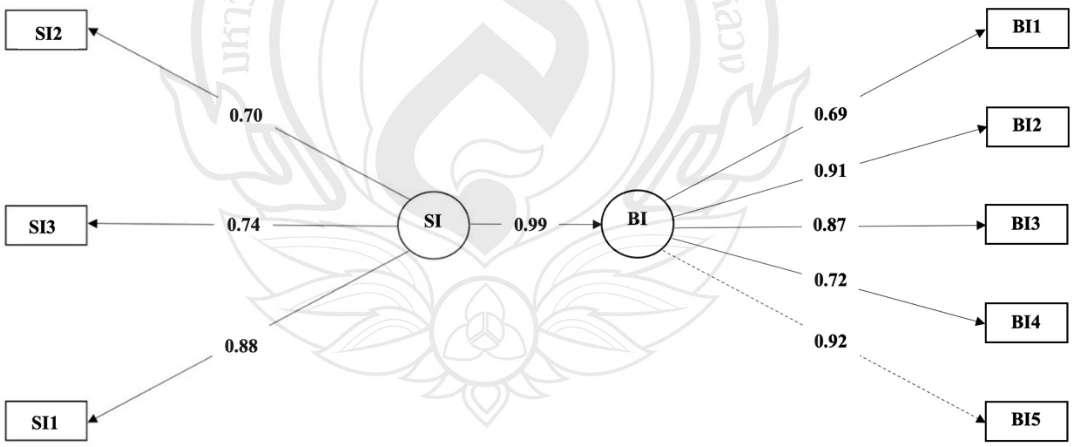
Chi-Square ($\chi 2$) = 59.9, df = 46, Relative Chi-Square= 1.30, *p*-value = 0.083, RMSEA = 0.048, CFI = 0.999

Figure 4.10 Path Analysis of PE to BI



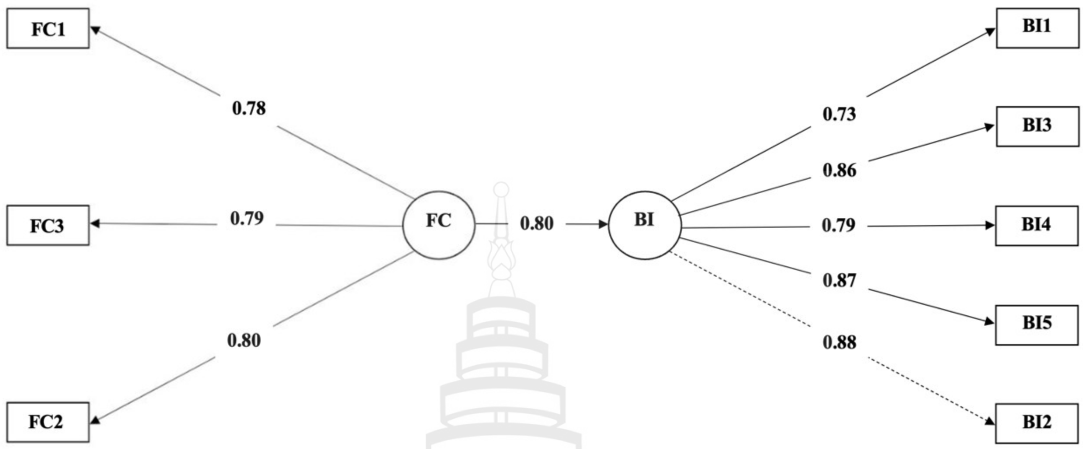
Chi-Square (χ2) = 2.5, df = 14, Relative Chi-Square= 0.18, *p*-value = 1, RMSEA = 0.000, CFI = 1.000

Figure 4.11 Path Analysis of EE to BI



Chi-Square (χ2) = 4.46, df = 14, Relative Chi-Square= 0.32, *p*-value = 0.992, RMSEA = 0.000, CFI = 1.000

Figure 4.12 Path Analysis of SI to BI



Chi-Square ($\chi2$) = 21.7, df = 17, Relative Chi-Square= 1.28, *p*-value = 0.195, RMSEA = 0.046, CFI = 0.999

Figure 4.13 Path Analysis of FC to BI

Chi-Square ($\chi2$) = 30.4, df = 30, Relative Chi-Square = 1.01, *p*-value = 0.444, RMSEA = 0.011, CFI = 1.000

Figure 4.14 Path Analysis of TA to BI

CHAPTER 5

CONCLUSION AND DISCUSSION

This research conclusion and discussion are composed of the following sub-topics.

5.1 Discussion the Result

5.1.1 Challenges and Solutions for Rubber Under the Authority of RAOT

5.1.2 Structural Equation Model Analysis of the Proposed UTAUT Model

5.1.3 Path Analysis of Each Factor from the Proposed UTAUT Model

5.2 Conclusion the Hypothesis

5.3 Conclusion of the Objectives

5.4 Suggestions to the Rubber Authority of Thailand (RAOT)

5.5 Limitation and Further Recommendation of the Study

5.1 Discussion the Result

This section presents the research findings based on a study of 130 rubber stakeholders in Thailand. The sample includes industry experts with over five years of experience, representing five regions of the country. The results are organized and discussed under specific subtopics.

5.1.1 The Challenges and Solutions for Rubber Under the Authority of RAOT

As the three main causes of rubber price fluctuations including (1) The imbalance between rubber demand and supply, (2) Economic crises, particularly in China, the USA, and Japan, which are the leading rubber-consuming countries, and (3) Profit speculation in the local and futures markets. Issue 1 is identified as an internal factor that falls under RAOT's authority and can be addressed under the Act, B.E. 2558 (2015). In contrast, Issues 2 and 3 are external factors beyond RAOT's control.

Therefore, this study focuses on Issue 1 as the primary problem as shown in Table 4.1 and Figure 4.1.

To determine the root causes of the imbalance between rubber demand and supply, RAOT considered the impact of previous policies and the current market structure, which reflects monopolistic competition, characterized by many producers, each with a small market share and limited power to influence prices. One significant impact of past policy is the implementation of the rubber trading license. This policy affects collectors (middlemen and manufacturers), who play a key role in buying and processing rubber products, as shown in Figure 4.2.

RAOT, or the Rubber Authority of Thailand, is an official government agency responsible for facilitating and supporting the rubber industry. Its roles under the Rubber Authority of Thailand Act, B.E. 2558 (2015) especially (1) Improving the livelihoods of farmers and stakeholders across the rubber supply chain. (2) Promoting fair trade and serving as a center for rubber production and innovation for sustainability. And (3) Contributing to stable rubber pricing.

Hence, RAOT aims to tackle these root causes by focusing on big data management, particularly using open data. Overcoming these data-related challenges is essential to effectively support the rubber supply chain and to forecast rubber demand and supply both domestically and internationally. As a tool for big data management, RAOT is exploring advanced technologies such as blockchain, a form of Distributed Ledger Technology (DLT). Blockchain holds significant potential for managing big data by enabling a transparent, efficient, and reliable system with strong accountability.

5.1.2 The Structural Equation Model Analysis of the Proposed UTAUT Model

However, the proposed UTAUT model is not consistent with the empirical data and, therefore, cannot be accepted. One possible explanation for this result is that TA (Technological Anxiety), PE (Performance Expectancy), EE (Effort Expectancy), SI (Social Influence), and FC (Facilitating Conditions) may have indirect rather than direct effects on BI (Behavioral Intention). This aligns with findings from previous studies by Gunasinghe et al. (2019), Popova and Zagulova (2022), and Smyth et al. (2021). In contrast, the proposed UTAUT model was designed to test only direct relationships, as illustrated in Table 4.7 and Figure 4.9.

5.1.3 The Path Analysis of Each Factor from the Proposed UTAUT Model

The study found that the key individual factors influencing Behavioral Intention (BI) to adopt the blockchain traceability platform in Thailand's rubber supply chain, based on the UTAUT model, were Performance Expectancy (PE), Social Influence (SI), Facilitating Conditions (FC), and Technological Anxiety (TA), respectively. In contrast, Effort Expectancy (EE) was not found to have a significant effect on adoption.

5.1.3.1 The Effect of Performance Expectancy (PE) on the Behavior Intention (BI) to Adopt the Blockchain Traceability Platform

PE refers to the extent to which an individual believes that using a new system will enhance job performance, with this relationship moderated by gender and age (Venkatesh et al., 2003). The path coefficient of PE on acceptance blockchain traceability platform was $\beta = 0.956$ with probability value of <0.001, indicating a positive and significant influence of PE on the intention to accept the blockchain traceability platform, as shown in Table 4.8 and Figure 4.10 This outcome corresponds with earlier researches of Gunasinghe et al. (2019), Saparudin et al. (2020), H et al., 2024; Nain. (2021), Srivastava and Bhati (2023), Bhati et al. (2023), Petersen (2023), Popova and Zagulova (2022), Umbas et al. (2022), Budhathoki et al. (2024), Kar et al. (2021), Zhang & Zhang, 2024).

5.1.3.2 The Effect of Effort Expectancy (EE) on the Behavior Intention (BI) to Adopt the Blockchain Traceability Platform

Effort Expectancy (EE) refers to the degree of ease associated with using a new system, with this relationship moderated by gender, age, and experience (Venkatesh et al., 2003). The path coefficient of EE on the acceptance of the blockchain traceability platform was $\beta = 1.060$, with a probability value of <0.001, indicating that EE had a non-significant influence on the intention to accept the blockchain traceability platform and was therefore rejected, as shown in Table 4.8 and Figure 4.11. Hence, users perceive that the system is not easy to use because blockchain traceability platform is an advanced technology, making it difficult to understand. This observation is supported by prior research of Umbas et al. (2022).

5.1.3.3 The Effect of Social Influence (SI) on Behavioral Intention (BI) to Adopt the Blockchain Traceability Platform

SI refers to the extent to which an individual perceives that others' beliefs influence their decision to use a new system, with this relationship moderated by gender, age, experience, and voluntariness (Venkatesh et al., 2003). The path coefficient of SI on the acceptance of the blockchain traceability platform was $\beta = 0.994$, with a probability value of <0.001, indicating a positive and significant influence of SI on the intention to accept the blockchain traceability platform, as shown in Table 4.8 and Figure 4.12 This result aligns with previous studies of Saparudin et al. (2020), Bhati et al. (2023), Srivastava and Bhati (2023), Petersen (2023), Umbas et al. (2022), Budhathoki et al. (2024) and Khan et al. (2023).

5.1.3.4 The Effect of Facilitating Conditions (FC) on Behavior Intention (BI) to Adopt the Blockchain Traceability Platform

FC refers to the extent to which an individual believes that an organization's system and technical infrastructure support the use of a new system, with this relationship moderated by age and experience (Venkatesh et al., 2003). The path coefficient of FC on acceptance blockchain traceability platform was $\beta = 0.974$ with probability value of <0.001, indicating a positive and significant influence of FC on the intention to accept the blockchain traceability platform, as shown in Table 4.8 and Figure 4.13 This finding is consistent with previous studies of Bhati et al. (2023), Nain (2021), Srivastava and Bhati (2023), Popova and Zagulova (2022), Budhathoki et al. (2024), Khan et al. (2023) and Zhang & Zhang, 2024).

5.1.3.5 The Effect of Technological Anxiety (TA) on the Behavior Intention (BI) to Adopt the Blockchain Traceability Platform

Technological Anxiety (TA) is defined based on Bozionelos (2001) study, which investigated computer anxiety related to the use of computers. Therefore, this study considers adapting the blockchain traceability platform as a new technology to be incorporated into the proposed UTAUT model. The path coefficient of TA on acceptance blockchain traceability platform was $\beta = 0.950$ with probability value of <0.001, indicating a positive and significant influence of TA on the intention to accept the blockchain traceability platform, as shown in Table 4.8 and Figure 4.14. This evidence reinforces the findings of previous studies of Bozionelos (2001), Gunasinghe et al. (2019) and Zhang & Zhang, 2024).

5.2 Conclusion the Hypotheses

Five hypotheses were tested based on the proposed UTAUT model; however, the results indicated that the model was not consistent with the empirical data and, therefore, could not be accepted. One possible explanation for this outcome is that the factors (Technological Anxiety (TA), Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), and Facilitating Conditions (FC)) may influence Behavioral Intention (BI) indirectly rather than directly. This interpretation aligns with previous studies by Gunasinghe et al. (2019), Popova and Zagulova (2022), and Smyth et al. (2021). In contrast, the original UTAUT model was constructed to assess only direct relationships, as shown in Table 4.7 and Figure 4.9.

Consequently, the study conducted a path analysis of each factor in the proposed UTAUT model to determine whether each directly influences Behavioral Intention (BI) to adopt a blockchain traceability platform in Thailand's rubber supply chain. Based on the proposed UTAUT model, the key individual factors found to have a direct influence on BI were Social Influence (SI), Facilitating Conditions (FC), Performance Expectancy (PE), and Technological Anxiety (TA), respectively. However, Effort Expectancy (EE) did not demonstrate a statistically significant impact on adoption, as illustrated in Table 4.8 and Figures 4.10 through 4.14.

5.3 Conclusion the Objectives

This study proposes a hypothesized model structure based on the UTAUT framework, incorporating the "Technological Anxiety (TA)" factor from Bozionelos (2001), to analyze the factors affecting the adoption of a blockchain traceability platform in rubber supply chain industry Thailand. This discussion addresses two research objectives, with the analysis of each factor presented as follows.

5.3.1 Objective 1: To Identify the Challenges of Thai Rubber Industry Under the Responsibility of RAOT

Rubber price fluctuations present a major challenge for Thailand's rubber industry, a concern overseen by the Rubber Authority of Thailand (RAOT) under the Rubber Authority of Thailand Act, B.E. 2558 (2015). The root cause lies in the imbalance between domestic rubber demand and supply, largely due to the market's monopolistic competition structure, many suppliers but few buyers.

A key contributing factor is the implementation of the rubber trading license policy, which impacts collectors (middlemen and manufacturers). This policy has resulted in several issues: (1) inaccurately verified reports, (2) illegal trading, (3) lack of rubber trading data, and (4) lack of big data/open data systems.

Collectors heavily influence rubber prices and often stockpile products, causing daily price fluctuations. Although government agencies have attempted to address these problems, the solutions have not been sustainable. RAOT now aims to tackle the root causes through big data management, particularly by emphasizing open data. Addressing these data-related challenges is critical to strengthening the rubber supply chain and improving the accuracy of domestic and international demand and supply forecasting, as illustrated in Table 4.1 and Figure 4.1.

In summary, the findings highlight the complexity of challenges within Thailand's rubber supply chain. The major challenge is rubber price fluctuation, while a minor challenge is the imbalance between rubber demand and supply. The root causes of these issues stem from past policies, particularly the rubber trading license system and monopolistic market competition. These challenges are compounded by difficulties in accurately recording large volumes of data related to rubber transactions.

To address these issues, there is significant potential in leveraging advanced technology to develop a transparent, efficient, and accountable big data management system. One promising solution is the adoption of blockchain technology, particularly for managing domestic rubber trading data. This aligns with the mission of the Rubber Authority of Thailand (RAOT), under the authority granted by the Rubber Authority of Thailand Act, B.E. 2558 (2015), to embrace technological advancements. RAOT plans to implement a blockchain traceability platform to reform the Thai rubber market. This platform aims to address the root causes and ensure sustainability while tackling both major and minor challenges in the industry.

5.3.2 Objective 2: To Test a Solution which Explore the Acceptance of Blockchain Traceability Platform by a Proposed UTAUT Model Among All Stakeholders in Thai Rubber Industry

The proposed UTAUT model did not align with the empirical data and, as such, was not supported. A potential reason for this outcome is that Technological Anxiety (TA), Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), and Facilitating Conditions (FC) may influence Behavioral Intention (BI) indirectly rather than directly. This observation is consistent with the findings of earlier studies by Gunasinghe et al. (2019), Popova and Zagulova (2022), and Smyth et al. (2021). Notably, the original UTAUT model used in this study was structured to examine only direct effects.

Accordingly, this study reveals that the main individual factors influencing Behavioral Intention (BI) to adopt the blockchain traceability platform in Thailand's rubber supply chain which based on the proposed UTAUT model are Social Influence (SI), Facilitating Conditions (FC), Performance Expectancy (PE), and Technological Anxiety (TA), respectively. Conversely, Effort Expectancy (EE) did not show a significant impact on adoption. This suggests that users perceive the platform as difficult to use, likely due to the complex nature of blockchain technology, which poses challenges in comprehension. These findings are consistent with those of Umbas et al. (2022).

In summary, the factors affecting the adoption of blockchain traceability platform in Thailand rubber supply chain using UTAUT model are Social Influence (SI), Facilitating Conditions (FC), Performance Expectancy (PE), and Technological Anxiety (TA), respectively. While Effort Expectancy (EE) is not affecting the adoption of blockchain traceability platform in Thailand rubber supply chain using UTAUT model.

5.4 Suggestions to the Rubber Authority of Thailand (RAOT)

The suggestions to the RAOT are based on an analysis of the Proposed UTAUT Model, which identifies and prioritizes key factors influencing the acceptance of a blockchain traceability platform in rubber industry supply chain in Thailand. These factors include “Facilitating Conditions (FC)”, “Social Influence (SI)”, “Technological Anxiety (TA)”, “Effort Expectancy (EE)” and “Performance Expectancy (PE)” respectively, guiding the implementation of the new system accordingly.

5.4.1 Facilitating Conditions (FC)

5.4.1.1 Capacity Building

To train government staff on blockchain traceability platform and applications, conduct workshops for rubber farmers (targeting 1.6 M farming households) to improve technological literacy and address technology access gaps despite 80% device ownership.

5.4.1.2 Regulatory & Infrastructure Development

To modernize the Rubber Control Act (1999) to streamline blockchain-based reporting and build robust technical infrastructure to support blockchain implementation.

5.4.1.3 Data-Driven Market Enhancement

To develop comprehensive big data systems are as follows enable better business decisions, unlock new market opportunities and create competitive market conditions.

5.4.2 Social Influence (SI)

5.4.2.1 Proactive Communication & Engagement

To launch targeted awareness campaigns highlighting blockchain traceability platform benefits (price stabilization through improved supply-demand balance, enhanced data accuracy for better decision-making and transparent supply chain management), prioritize engagement with all stakeholder tiers (farmers, cooperatives, legal entities) and emphasize solutions for 1.6M rubber-farming families.

5.4.2.2 Capacity Building Initiatives

To implement age-appropriate digital literacy programs, design hands-on training workshops tailored to farmers' technological competencies and develop progressive learning modules for different tech-literacy levels.

5.4.2.3 Incentivized Participation Framework

To introduce compliance rewards for RAOT-registered members, establish flexible regulatory adaptations (non-ALRO land farmers and unregistered stakeholders) and create tiered participation benefits to encourage broader adoption.

5.4.3 Technological Anxiety (TA)

5.4.3.1 Inclusive Participation Framework

To ensure system flexibility for independent farmers, especially in non-group affiliated growers, farmers cultivating non-ALRO lands and stakeholders with legal status concerns.

5.4.3.2 Data Governance Assurance

To implement PDPA-compliant data protection protocols, address registration hesitancy by clarifying the number of mandatory membership fees and transparent tax obligation guidelines.

5.4.3.3 Market Transparency Features

To develop open-data tools for price prediction using real-time supply-demand analytics and localized market intelligence.

5.4.3.4 Risk Mitigation Capabilities

To bridge information gaps between domestic market realities and international futures markets (AFET/ TOCOM/ SICOM/ SHFE) and provide reliable long-term investment indicators.

5.4.4 Effort Expectancy (EE)

5.4.4.1 Intuitive User Experience

To prioritize simple, accessible interface design requiring minimal training and implement clear navigation and instructions for all user types.

5.4.4.2 Operational Efficiency

To streamline processes to save time for all stakeholders and eliminate redundant tasks and to duplicate data entry requirements.

5.4.4.3 Scalable Performance

To build robust architecture capable of handling 1.6 million farmer profiles and high-volume transaction processing and to ensure system reliability with near-zero error rates.

5.4.5 Performance Expectancy (PE)

5.4.5.1 Transparent Communication

To clearly articulate system benefits to drive user adoption and demonstrate value proposition for all stakeholder groups.

5.4.5.2 Market Transparency & Compliance

To implement open-data standards for real-time (domestic transaction visibility, supply-demand analytics and new market opportunity identification) and enable EU deforestation-free certification compliance.

5.4.5.3 Operational Efficiency

To eliminate duplicate reporting under Rubber Control Act (1999) and streamline purchase reporting requirements.

5.4.5.4 Accessibility Assurance

To guarantee cost-free access with no membership fees and no mandatory payment requirements and to maintain zero financial barriers to entry.

5.5 Limitation and Further Recommendation of the Study

This study is the first in Thailand to apply a blockchain traceability platform to the rubber supply chain, focusing on a major sector of the rubber industry by specifically targeting large landowners owning more than 100 rai, as well as the 10 largest businesses registered in the government database, including farmers, collectors, factories, exporters, government agencies, brokers, and experts, all of whom have a significant impact on the industry. Due to its broad scope, the research faces several challenges and limitations, including the complexity of the rubber supply chain industry and the high cost of technology and data servers. It is recommended that future research focus on smaller-scale operations, particularly rubber farmers (1,667,095 farming families) most of whom own areas of 20–30 rai and are registered in the government database or other stakeholder groups.

The recommendation for future studies: First, the results indicate that the proposed UTAUT model had no significant influence on the intention to adopt the blockchain traceability platform and was therefore rejected, as shown in Figure 4.5. Consequently, the proposed UTAUT model is not consistent with the empirical data and cannot be accepted. One possible explanation for this outcome is that TA (Technological Anxiety), PE (Performance Expectancy), EE (Effort Expectancy), SI (Social Influence), and FC (Facilitating Conditions) may have indirect rather than direct effects on BI (Behavioral Intention), whereas the current model was designed to test only direct relationships. Therefore, future research should consider developing and testing an alternative UTAUT model that better fits the empirical data.

Second, as RAOT continues to develop the prototype blockchain platform, it is recommended that a follow-up survey be conducted to analyze stakeholders' behavior after they have had practical experience using the technology. This approach will provide valuable insights and contribute significantly to the advancement of Thailand's rubber industry.

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APPENDIX A

QUESTIONNAIRE SURVEY

This questionnaire is a part of my study of Master of Business Administration Program in International Logistics and Supply Chain Management (A2) at School of Management, Mae Fah Luang University in Chaing Rai, Thailand. The title of research study is "Factors Affecting the Adoption of Blockchain Traceability Platform in Thailand Rubber Supply Chain Using UTAUT Model". As I am a researcher, I would like to share the objectives of this research that are to identify the challenges of Thai rubber industry under the responsibility of RAOT, to explore the factors affecting the adoption of blockchain traceability platform by stakeholders. The blockchain traceability platform is an application designed to facilitate, monitor and give a feedback of rubber supply chain in Thailand. This application will support all stakeholders to be able to access the information of whole supply chain as well as the tendency of demand and supply in Thai rubber industry. The researcher would like to have cooperation from you to respond truly to all questions based on your understanding, knowledge and experience towards the rubber supply chain process. All your information shared will be kept confidential according to PDPA (Personal Data Protection Act B.E. 2562 (2019)). If you clearly understand and agree to answer all questions in this questionnaire upon the above condition, please kindly sign on this form for confirmation of understanding and voluntary participation.

I understand all details and conditions and
□ I agree
□ I disagree
Thank you so much for your cooperation.
Jeeranan Wandee
Student of M.B.A. Program in International Logistics and Supply Chain Management
School of Management, Mae Fah Luang University

****

This questionnaire is composed of two parts and please kind √ your answer into a box.

Part 1: General information

1.1 Gender

□ Male

□ Female

1.2 Age (Year)

□ 15-35

□ 36-50

□ 51-65

□ >65

1.3 Occupation

□ Farmer (F)

□ Collector (C)

□ Government agency (G)

□ Exporter (E)

□ Others (O)

1.4 Location/ Station/ Region

□ Northern (Chiang Rai, Payao, Nan and Phitsanulok)

□ Central (Kanchanaburi and Prachuap Khiri Khan)

□ Northeastern (Loei, Udon Thani, Nong Khai, Bueng Kan, Buri Ram, Si Sa Ket and Ubon Ratchatani)

□ Eastern (Prachinburi, Sakaeo, Rayong, Chachoengsao and Trat)

□ Southern (Chumphon, Surat Thani, Phang Nga, Nakon Srithammarat, Songkhla and Yala)

Part 2: Specific Information

The next list of questions will be focused on different factors that affecting the acceptance of blockchain traceability platform on the use behavior of stakeholders in the rubber industry supply chain. Therefore, each question will be emphasized on different factors and sub-factors that you can answer according to the level of agreement in the range of 1 (strongly disagree) to 7 (strongly agree) scale as the details below.

1 = Strong disagree

2 = Disagree

3 = Somewhat disagree

4 = Neither agree nor disagree

5 = Somewhat agree

6 = Agree

7 = Strong agree

Table A 2.1 Performance Expectancy (PE)

No.	Factor	Content	1	2	3	4	5	6	7
2.1.1	PE1	Do you agree that requiring farmers and rubber traders to report information in a blockchain traceability platform would help ensure that the data is transparent and reliable?							
2.1.2	PE2	Do you agree that requiring farmers and rubber traders to report every rubber transaction in a blockchain traceability platform would be beneficial?							
2.1.3	PE3	Do you agree that requiring farmers and rubber traders to report every rubber transaction in a blockchain traceability platform would be effective?							
2.1.4	PE4	Do you agree that a government agency needs to have reliable big data on rubber?							
2.1.5	PE5	Do you agree that a blockchain traceability platform can meet the requirements for deforestation-free products set by the European Union?							
2.1.6	PE6	Do you agree that displaying a daily summary of rubber transactions in a blockchain traceability platform would provide insights into the supply and demand levels?							
2.1.7	PE7	Do you agree that disclosing information about all producers would help in accessing sources of raw materials?							

Table A 2.2 Effort Expectancy (EE)

No.	Factor	Content	1	2	3	4	5	6	7
2.2.1	EE1	Do you agree that a blockchain traceability platform would work well with many users, such as 2 million farmers?							
2.2.2	EE2	Do you agree that you will be able to use the blockchain traceability platform by yourself?							
2.2.3	EE3	Do you agree that you will be able to use the blockchain traceability platform by yourself and adapt to changes in digital technology?							
2.2.4	EE4	Do you agree that reporting rubber trading information in the blockchain traceability platform will be redundant with reporting rubber trading values to the Rubber Control Center, Department of Agriculture?							

Table A 2.3 Social Influence (SI)

No.	Factor	Content	1	2	3	4	5	6	7
2.3.1	SI1	Do you agree that age will affect the use of the blockchain traceability platform?							
2.3.2	SI2	Do you agree to start using the blockchain traceability platform with agricultural groups first, such as cooperatives and legal entities?							
2.3.3	SI3	Do you agree that if the government mandates stakeholders in the rubber industry to use the blockchain traceability platform for rubber trading?							

Table A 2.4 Facilitating Conditions (FC)

No.	Factor	Content	1	2	3	4	5	6	7
2.4.1	FC1	Do you agree that you have the equipment to use the blockchain traceability platform, such as a smartphone or a computer?							
2.4.2	FC2	Do you agree that the Government Agency is ready to assist with equipment and personnel?							
2.4.3	FC3	Do you agree that the internet is accessible in all areas?							

Table A 2.5 Technological Anxiety (TA)

No.	Factor	Content	1	2	3	4	5	6	7
2.5.1	TA1	Do you agree that farmers who grow rubber trees in natural forest areas would not use blockchain traceability platform due to concerns about data disclosure?							

No.	Factor	Content	1	2	3	4	5	6	7
2.5.2	TA2	Do you agree that some rubber collectors might not use blockchain traceability platform due to concerns about tax collection from the Revenue Department?							
2.5.3	TA3	Do you agree that disclosing information on a blockchain traceability platform could lead to a loss of benefits?							
2.5.4	TA4	Do you agree that some rubber traders may not use blockchain traceability platform due to concerns about government inspection?							
2.5.5	TA5	Do you agree that exporters and processors of rubber products might not use blockchain traceability platform due to concerns about the price of raw rubber?							

Table A 2.6 Behavioral Intention (BI)

No.	Factor	Content	1	2	3	4	5	6	7
2.6.1	BI1	Do you agree that you are willing to use blockchain traceability platform?							
2.6.2	BI2	Do you agree that there will be many users of blockchain traceability platform?							
2.6.3	BI3	Do you agree that blockchain traceability platform will be beneficial to stakeholders in the rubber supply chain?							
2.6.4	BI4	Do you agree that you are intending to use blockchain traceability platform?							
2.6.5	BI5	Do you agree that you are willing to cooperate with the government in using blockchain traceability platform?							

Thank you for your support and cooperation.

****

APPENDIX B

QUESTIONAIRE RELIABILITY ANALYSIS

Results

Reliability Analysis

Scale Reliability Statistics

	Mean	SD	Cronbach's α
scale	5.36	0.510	0.970

[3]

Item Reliability Statistics

	Mean	SD	Item-rest correlation
PE1	5.72	0.739	0.731
PE2	5.55	0.706	0.740
PE3	5.74	0.721	0.742
PE4	5.65	0.608	0.803
PE5	5.45	0.716	0.725
PE6	5.60	0.700	0.714
PE7	5.58	0.755	0.728
EE1	5.64	0.623	0.750
EE2	5.45	0.636	0.719
EE3	5.58	0.554	0.745
EE4	5.34	0.822	0.696
SI1	4.24	0.702	0.711
SI2	4.24	0.668	0.726
SI3	4.67	0.741	0.718
FC1	4.58	0.581	0.779
FC2	4.78	0.693	0.741
FC3	5.04	0.720	0.650
TA1	6.49	0.532	0.835
TA2	6.33	0.652	0.674
TA3	6.56	0.498	0.863
TA4	6.37	0.612	0.677
TA5	6.25	0.727	0.679
BI1	4.72	0.729	0.790
BI2	4.76	0.620	0.731
BI3	4.85	0.792	0.683
BI4	4.56	0.671	0.717
BI5	4.96	0.762	0.761

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APPENDIX C

MEASUREMENT MODEL ANALYSIS

Measurement Model Analysis of TA

Results

Structural Equation Models

Models Info

Estimation Method	**DWLS**
Optimization Method	**NLMINB**
Number of observations	**130**
Free parameters	**16**
Standard errors	**Robust**
Scaled test	**Mean adjusted scaled and shifted**
Converged	**TRUE**
Iterations	**19**
Model	**TA=~TA3+TA5+TA4+TA2+TA1**
	TA4~~TA2
	TA5~~TA1

Note. Variable (TA3,TA5,TA4,TA2,TA1) has been coerced to ordered type.
Note. lavaan->lav_object_post_check(): some estimated ov variances are negative **[3] [4]**

Overall Tests

Model tests

Label	X^2	df	p
User Model	0.135	3	0.987
Baseline Model	6136.868	10	<.001
Scaled User	0.782	3	0.854
Scaled Baseline	4492.767	10	<.001

Fit indices

			95% Confidence Intervals		
Type	**SRMR**	**RMSEA**	**Lower**	**Upper**	**RMSEA p**
Classical	0.006	0.000	0.000	0.000	0.992
Robust	0.005				
Scaled	0.005	0.000	0.000	0.081	0.903

User model versus baseline model

	Model	Scaled
Comparative Fit Index (CFI)	1.000	1.000
Tucker-Lewis Index (TLI)	1.002	1.002
Bentler-Bonett Non-normed Fit Index (NNFI)	1.002	1.002
Relative Noncentrality Index (RNI)	1.000	1.000
Bentler-Bonett Normed Fit Index (NFI)	1.000	1.000
Bollen's Relative Fit Index (RFI)	1.000	0.999
Bollen's Incremental Fit Index (IFI)	1.000	1.000
Parsimony Normed Fit Index (PNFI)	0.300	0.300

Estimates

Measurement model

				95% Confidence Intervals				
Latent	**Observed**	**Estimate**	**SE**	**Lower**	**Upper**	**β**	**z**	**p**
TA	**TA3**	1.000	0.0000	1.000	1.000	1.042		
	TA5	0.783	0.0506	0.684	0.882	0.816	15.5	<.001
	TA4	0.816	0.0484	0.721	0.911	0.850	16.9	<.001
	TA2	0.784	0.0447	0.696	0.871	0.817	17.5	<.001
	TA1	0.898	0.0359	0.827	0.968	0.936	25.0	<.001

Variances and Covariances

				95% Confidence Intervals				
Variable 1	**Variable 2**	**Estimate**	**SE**	**Lower**	**Upper**	**β**	**z**	**p**
TA4	TA2	0.1596	0.0507	0.0603	0.25891	0.5252	3.15	0.002
TA5	TA1	-0.1003	0.0484	-0.1952	-0.00544	-0.4914	-2.07	0.038
TA3	TA3	-0.0861	0.0000	-0.0861	-0.08607	-0.0861		
TA5	TA5	0.3344	0.0000	0.3344	0.33445	0.3344		
TA4	TA4	0.2772	0.0000	0.2772	0.27723	0.2772		
TA2	TA2	0.3331	0.0000	0.3331	0.33307	0.3331		
TA1	TA1	0.1246	0.0000	0.1246	0.12457	0.1246		
TA	TA	1.0861	0.0429	1.0020	1.17015	1.0000	25.32	<.001

Intercepts

Variable	Intercept	SE	95% Confidence Intervals Lower	Upper	z	p
TA3	0.000	0.000	0.000	0.000		
TA5	0.000	0.000	0.000	0.000		
TA4	0.000	0.000	0.000	0.000		
TA2	0.000	0.000	0.000	0.000		
TA1	0.000	0.000	0.000	0.000		
TA	0.000	0.000	0.000	0.000		

Thresholds

Variable	Step	Thresholds	SE	95% Confidence Intervals Lower	Upper	z	p
TA3	t1	-0.155	0.111	-0.372	0.062	-1.397	0.162
TA5	t1	-0.957	0.131	-1.214	-0.701	-7.316	<.001
TA5	t2	0.214	0.111	-0.004	0.432	1.921	0.055
TA4	t1	-1.482	0.168	-1.811	-1.153	-8.825	<.001
TA4	t2	0.155	0.111	-0.062	0.372	1.397	0.162
TA2	t1	-1.282	0.151	-1.577	-0.987	-8.515	<.001
TA2	t2	0.174	0.111	-0.043	0.392	1.572	0.116
TA1	t1	-2.160	0.280	-2.709	-1.611	-7.715	<.001
TA1	t2	-0.019	0.110	-0.236	0.197	-0.175	0.861

Modifcation indices

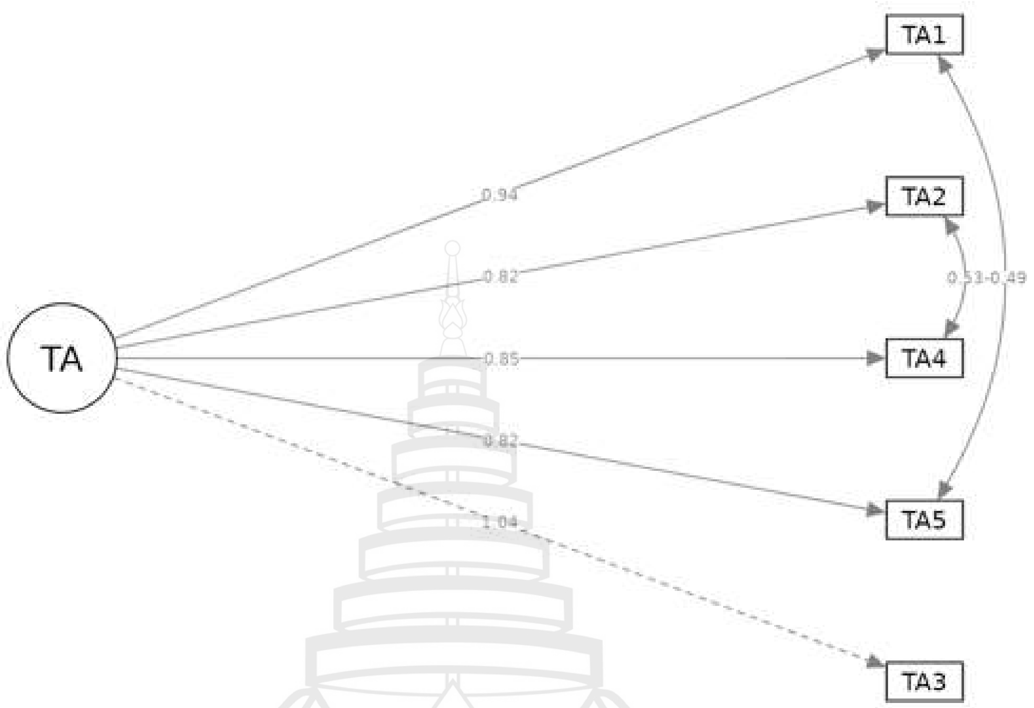
Modification indices

	Modif. index	EPC	sEPC (LV)	sEPC (all)	sEPC (nox)

Note. No modification indices above threshold

Path Model

Path diagrams



[5]

semljgui

This analysis has been cancelled.

Structural Equation Models

Measurement Model Analysis of PE

Results

Structural Equation Models

Models info

Estimation Method	DWLS
Optimization Method	NLMINB
Number of observations	130
Free parameters	33
Standard errors	Robust
Scaled test	Mean adjusted scaled and shifted
Converged	TRUE
Iterations	25
Model	PE=~PE3+PE7+PE6+PE5+PE4+PE2+PE1
	PE6~~PE1
	PE4~~PE2
	PE4~~PE3
	PE2~~PE1
	PE5~~PE1
	PE6~~PE4

Note. Variable (PE3,PE7,PE6,PE5,PE4,PE2,PE1) has been coerced to ordered type.
[3] [4]

Overall Tests

Model tests

Label	X^2	df	p
User Model	1.82	8	0.983
Baseline Model	3888.31	21	<.001
Scaled User	4.05	8	0.853
Scaled Baseline	2503.51	21	<.001

Fit indices

			95% Confidence Intervals		
Type	SRMR	RMSEA	Lower	Upper	RMSEA p
Classical	0.017	0.000	0.000	0.000	0.904
Robust	0.013	0.000	0.000	0.066	0.929
Scaled	0.013	0.000	0.000	0.057	0.935

User model versus baseline model

	Model	Scaled	Robust
Comparative Fit Index (CFI)	1.000	1.000	1.000
Tucker-Lewis Index (TLI)	1.004	1.004	1.072
Bentler-Bonett Non-normed Fit Index (NNFI)	1.004	1.004	1.072
Relative Noncentrality Index (RNI)	1.002	1.002	1.027
Bentler-Bonett Normed Fit Index (NFI)	0.999	0.998	
Bollen's Relative Fit Index (RFI)	0.999	0.996	
Bollen's Incremental Fit Index (IFI)	1.002	1.002	
Parsimony Normed Fit Index (PNFI)	0.381	0.380	

Estimates

Measurement model

				95% Confidence Intervals				
Latent	Observed	Estimate	SE	Lower	Upper	β	z	p
PE	PE3	1.000	0.0000	1.000	1.00	0.882		
	PE7	0.950	0.0414	0.869	1.03	0.838	22.9	<.001
	PE6	0.897	0.0531	0.793	1.00	0.791	16.9	<.001
	PE5	0.928	0.0624	0.806	1.05	0.818	14.9	<.001
	PE4	0.957	0.0494	0.860	1.05	0.843	19.4	<.001
	PE2	0.971	0.0565	0.860	1.08	0.856	17.2	<.001
	PE1	0.865	0.0737	0.720	1.01	0.762	11.7	<.001

Variances and Covariances

				95% Confidence Intervals				
Variable 1	Variable 2	Estimate	SE	Lower	Upper	β	z	p
PE6	PE1	0.1980	0.0680	0.0646	0.3313	0.500	2.91	0.004
PE4	PE2	0.1324	0.0566	0.0214	0.2433	0.470	2.34	0.019
PE3	PE4	0.0641	0.0532	-0.0401	0.1684	0.253	1.21	0.228
PE2	PE1	0.1200	0.0383	0.0450	0.1950	0.358	3.14	0.002
PE5	PE1	0.0842	0.0609	-0.0351	0.2034	0.226	1.38	0.167
PE6	PE4	-0.0748	0.0321	-0.1378	-0.0118	-0.227	-2.33	0.020
PE3	PE3	0.2228	0.0000	0.2228	0.2228	0.223		
PE7	PE7	0.2985	0.0000	0.2985	0.2985	0.298		
PE6	PE6	0.3751	0.0000	0.3751	0.3751	0.375		
PE5	PE5	0.3301	0.0000	0.3301	0.3301	0.330		
PE4	PE4	0.2887	0.0000	0.2887	0.2887	0.289		
PE2	PE2	0.2677	0.0000	0.2677	0.2677	0.268		
PE1	PE1	0.4189	0.0000	0.4189	0.4189	0.419		
PE	PE	0.7772	0.0517	0.6756	0.8785	1.000	15.03	<.001

Intercepts

			95% Confidence Intervals			
Variable	Intercept	SE	Lower	Upper	z	p
PE3	0.000	0.000	0.000	0.000		
PE7	0.000	0.000	0.000	0.000		
PE6	0.000	0.000	0.000	0.000		
PE5	0.000	0.000	0.000	0.000		
PE4	0.000	0.000	0.000	0.000		
PE2	0.000	0.000	0.000	0.000		
PE1	0.000	0.000	0.000	0.000		
PE	0.000	0.000	0.000	0.000		

Thresholds

				95% Confidence Intervals			
Variable	Step	Thresholds	SE	Lower	Upper	z	p
PE3	t1	-1.994	0.242	-2.468	-1.520	-8.242	<.001
PE3	t2	-0.314	0.112	-0.534	-0.093	-2.791	0.005
PE3	t3	1.087	0.138	0.817	1.357	7.898	<.001
PE7	t1	-1.482	0.168	-1.811	-1.153	-8.825	<.001
PE7	t2	-0.155	0.111	-0.372	0.062	-1.397	0.162
PE7	t3	1.327	0.154	1.025	1.629	8.614	<.001
PE6	t1	-1.870	0.219	-2.298	-1.441	-8.544	<.001
PE6	t2	-0.097	0.111	-0.313	0.120	-0.874	0.382
PE6	t3	1.327	0.154	1.025	1.629	8.614	<.001
PE5	t1	-1.482	0.168	-1.811	-1.153	-8.825	<.001
PE5	t2	0.097	0.111	-0.120	0.313	0.874	0.382
PE5	t3	1.542	0.174	1.201	1.883	8.855	<.001
PE4	t1	-0.194	0.111	-0.412	0.024	-1.748	0.081
PE4	t2	1.482	0.168	1.153	1.811	8.825	<.001
PE2	t1	-1.769	0.203	-2.168	-1.371	-8.720	<.001
PE2	t2	0.000	0.110	-0.216	0.216	0.000	1.000
PE2	t3	1.375	0.158	1.065	1.684	8.700	<.001
PE1	t1	-2.423	0.363	-3.135	-1.711	-6.671	<.001
PE1	t2	-0.214	0.111	-0.432	0.004	-1.921	0.055
PE1	t3	1.053	0.136	0.787	1.319	7.758	<.001

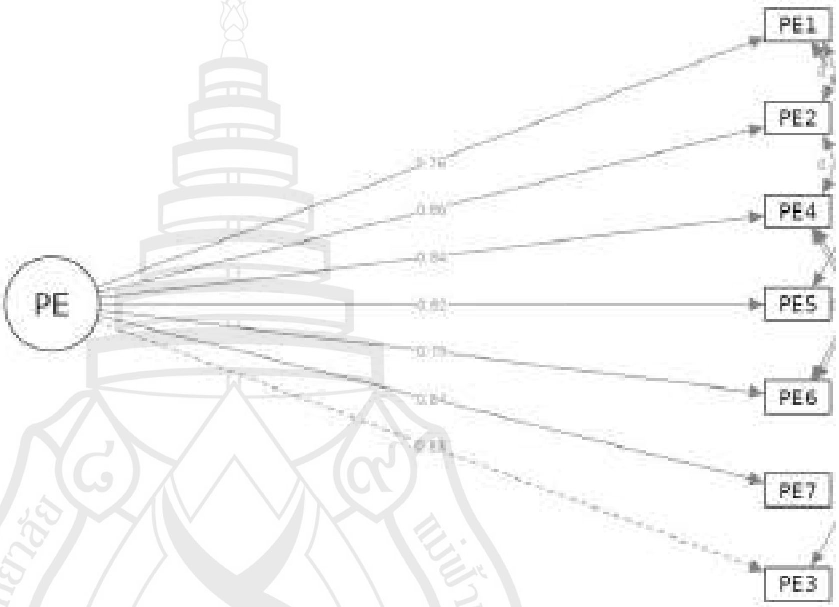
Modifcation indices

Modification indices

	Modif. index	EPC	sEPC (LV)	sEPC (all)	sEPC (nox)

Path Model

Path diagrams



[5]

References

[1] The jamovi project (2024). *jamovi*. (Version 2.6) [Computer Software]. Retrieved from https://www.jamovi.org.

[2] R Core Team (2024). *R: A Language and environment for statistical computing*. (Version 4.4) [Computer software]. Retrieved from https://cran.r-project.org. (R packages retrieved from CRAN snapshot 2024-08-07).

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Measurement Model Analysis of BI

Models Info

Estimation Method	**DWLS**	.
Optimization Method	**NLMINB**	
Number of observations	**130**	
Free parameters	**21**	
Standard errors	**Robust**	
Scaled test	**Mean adjusted scaled and shifted**	
Converged	**TRUE**	
Iterations	**17**	
Model	**BI=~BI5+BI4+BI3+BI2+BI1**	
	BI4~~BI1	
	BI4~~BI2	

Note. Variable (BI5,BI4,BI3,BI2,BI1) has been coerced to ordered type.

Note. lavaan->lav_model_vcov(): The variance-covariance matrix of the estimated parameters (vcov) does not appear to be positive definite! The smallest eigenvalue (= -2.818926e-17) is smaller than zero. This may be a symptom that the model is not identified.

[3] [4]

Overall Tests

Model tests

Label	X²	df	p
User Model	0.0730	3	0.995
Baseline Model	1725.4084	10	< .001
Scaled User	0.4651	3	0.926
Scaled Baseline	1344.3729	10	< .001

Fit indices

			95% Confidence Intervals		
Type	SRMR	RMSEA	Lower	Upper	RMSEA p
Classical	0.004	0.000	0.000	0.000	0.997
Robust	0.003	0.000	0.000	0.000	0.984
Scaled	0.003	0.000	0.000	0.047	0.953

User model versus baseline model

	Model	Scaled	Robust
Comparative Fit Index (CFI)	1.000	1.000	1.000
Tucker-Lewis Index (TLI)	1.006	1.006	1.052
Bentler-Bonett Non-normed Fit Index (NNFI)	1.006	1.006	1.052
Relative Noncentrality Index (RNI)	1.002	1.002	1.016
Bentler-Bonett Normed Fit Index (NFI)	1.000	1.000	
Bollen's Relative Fit Index (RFI)	1.000	0.999	
Bollen's Incremental Fit Index (IFI)	1.002	1.002	
Parsimony Normed Fit Index (PNFI)	0.300	0.300	

Estimates

Measurement model

				95% Confidence Intervals				
Latent	**Observed**	**Estimate**	**SE**	**Lower**	**Upper**	**β**	**z**	**p**
BI	**BI5**	1.000	0.0000	1.000	1.000	0.920		
	BI4	0.734	0.0692	0.598	0.870	0.675	10.6	<.001
	BI3	0.957	0.0440	0.871	1.043	0.881	21.7	<.001
	BI2	0.974	0.0494	0.877	1.071	0.896	19.7	<.001
	BI1	0.752	0.0653	0.624	0.880	0.692	11.5	<.001

Variances and Covariances

				95% Confidence Intervals				
Variable 1	**Variable 2**	**Estimate**	**SE**	**Lower**	**Upper**	**β**	**z**	**p**
BI4	BI1	0.1438	0.0624	0.0214	0.266	0.270	2.30	0.021
BI4	BI2	0.0814	0.0658	-0.0475	0.210	0.249	1.24	0.216
BI5	BI5	0.1531	0.0000	0.1531	0.153	0.153		
BI4	BI4	0.5439	0.0000	0.5439	0.544	0.544		
BI3	BI3	0.2247	0.0000	0.2247	0.225	0.225		
BI2	BI2	0.1966	0.0000	0.1966	0.197	0.197		
BI1	BI1	0.5217	0.0000	0.5217	0.522	0.522		
BI	BI	0.8469	0.0515	0.7460	0.948	1.000	16.45	<.001

Intercepts

			95% Confidence Intervals			
Variable	Intercept	SE	Lower	Upper	z	p
BI5	0.000	0.000	0.000	0.000		
BI4	0.000	0.000	0.000	0.000		
BI3	0.000	0.000	0.000	0.000		
BI2	0.000	0.000	0.000	0.000		
BI1	0.000	0.000	0.000	0.000		
BI	0.000	0.000	0.000	0.000		

Thresholds

				95% Confidence Intervals			
Variable	Step	Thresholds	SE	Lower	Upper	z	p
BI5	t1	-0.524	0.116	-0.752	-0.297	-4.519	<.001
BI5	t2	0.662	0.120	0.428	0.897	5.538	<.001
BI5	t3	2.423	0.363	1.711	3.135	6.671	<.001
BI4	t1	-1.769	0.203	-2.166	-1.371	-8.720	<.001
BI4	t2	-0.097	0.111	-0.313	0.120	-0.874	0.382
BI4	t3	1.542	0.174	1.201	1.883	8.855	<.001
BI3	t1	-0.375	0.113	-0.597	-0.153	-3.312	<.001
BI3	t2	0.927	0.129	0.673	1.181	7.163	<.001
BI3	t3	2.423	0.363	1.711	3.135	6.671	<.001
BI2	t1	-0.417	0.114	-0.640	-0.193	-3.658	<.001
BI2	t2	1.282	0.151	0.987	1.577	8.515	<.001
BI1	t1	-1.994	0.242	-2.468	-1.520	-8.242	<.001
BI1	t2	-0.253	0.112	-0.472	-0.035	-2.269	0.023
BI1	t3	1.087	0.138	0.817	1.357	7.898	<.001

Modifcation indices

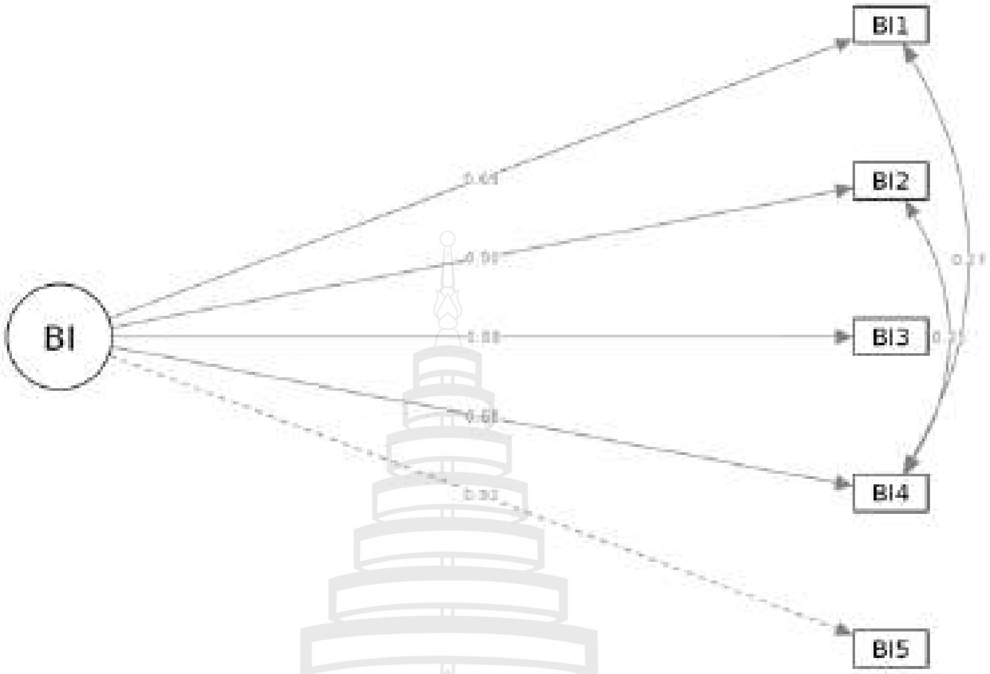
Modification Indices

	Modif. index	EPC	sEPC (LV)	sEPC (all)	sEPC (nox)

Note. No modification indices above threshold

Path Model

Path diagrams



[5]

Structural Equation Models

Measurement Model Analysis of EE

Models Info

Estimation Method	**DWLS**
Optimization Method	**NLMINB**
Number of observations	**130**
Free parameters	**17**
Standard errors	**Robust**
Scaled test	**Mean adjusted scaled and shifted**
Converged	**TRUE**
Iterations	**15**
Model	**EE=~EE3+EE4+EE2+EE1** **EE2~~EE1**

Note. Variable (EE3,EE4,EE2,EE1) has been coerced to ordered type.
[3] [4]

Overall Tests

Model tests

Label	X^2	df	p
User Model	0.844	1	0.358
Baseline Model	1151.719	6	<.001
Scaled User	1.547	1	0.214
Scaled Baseline	1005.312	6	<.001

Fit indices

			95% Confidence Intervals		
Type	**SRMR**	**RMSEA**	**Lower**	**Upper**	**RMSEA p**
Classical	0.022	0.000	0.000	0.226	0.431
Robust	0.015	0.123	0.000	0.464	0.228
Scaled	0.015	0.065	0.000	0.254	0.285

User model versus baseline model

	Model	Scaled	Robust
Comparative Fit Index (CFI)	1.000	0.999	0.994
Tucker-Lewis Index (TLI)	1.001	0.997	0.963
Bentler-Bonett Non-normed Fit Index (NNFI)	1.001	0.997	0.963
Relative Noncentrality Index (RNI)	1.000	0.999	0.994
Bentler-Bonett Normed Fit Index (NFI)	0.999	0.998	
Bollen's Relative Fit Index (RFI)	0.996	0.991	
Bollen's Incremental Fit Index (IFI)	1.000	0.999	
Parsimony Normed Fit Index (PNFI)	0.167	0.166	

Estimates

Measurement model

				95% Confidence Intervals				
Latent	**Observed**	**Estimate**	**SE**	**Lower**	**Upper**	**β**	**z**	**p**
EE	**EE3**	1.000	0.0000	1.000	1.000	0.995		
	EE4	0.650	0.0752	0.503	0.798	0.647	8.65	<.001
	EE2	0.748	0.1022	0.547	0.948	0.744	7.31	<.001
	EE1	0.786	0.0997	0.591	0.982	0.782	7.88	<.001

Variances and Covariances

				95% Confidence Intervals				
Variable 1	**Variable 2**	**Estimate**	**SE**	**Lower**	**Upper**	**β**	**z**	**p**
EE2	EE1	0.16309	0.0768	0.01256	0.31362	0.39204	2.12	0.034
EE3	EE3	0.00927	0.0000	0.00927	0.00927	0.00927		
EE4	EE4	0.58102	0.0000	0.58102	0.58102	0.58102		
EE2	EE2	0.44628	0.0000	0.44628	0.44628	0.44628		
EE1	EE1	0.38778	0.0000	0.38778	0.38778	0.38778		
EE	EE	0.99073	0.1280	0.73990	1.24157	1.00000	7.74	<.001

Intercepts

			95% Confidence Intervals			
Variable	**Intercept**	**SE**	**Lower**	**Upper**	**z**	**p**
EE3	0.000	0.000	0.000	0.000		
EE4	0.000	0.000	0.000	0.000		
EE2	0.000	0.000	0.000	0.000		
EE1	0.000	0.000	0.000	0.000		
EE	0.000	0.000	0.000	0.000		

Thresholds

Variable	Step	Thresholds	SE	95% Confidence Intervals Lower	Upper	z	p
EE3	t1	-2.423	0.363	-3.135	-1.711	-6.671	<.001
EE3	t2	-0.174	0.111	-0.392	0.043	-1.572	0.116
EE3	t3	1.994	0.242	1.520	2.468	8.242	<.001
EE4	t1	-1.087	0.138	-1.357	-0.817	-7.898	<.001
EE4	t2	0.273	0.112	0.054	0.493	2.443	0.015
EE4	t3	1.375	0.158	1.065	1.684	8.700	<.001
EE2	t1	-1.542	0.174	-1.883	-1.201	-8.855	<.001
EE2	t2	0.000	0.110	-0.216	0.216	0.000	1.000
EE2	t3	2.160	0.280	1.611	2.709	7.715	<.001
EE1	t1	-2.423	0.363	-3.135	-1.711	-6.671	<.001
EE1	t2	-0.194	0.111	-0.412	0.024	-1.746	0.081
EE1	t3	1.482	0.168	1.153	1.811	8.825	<.001

Modifcation indices

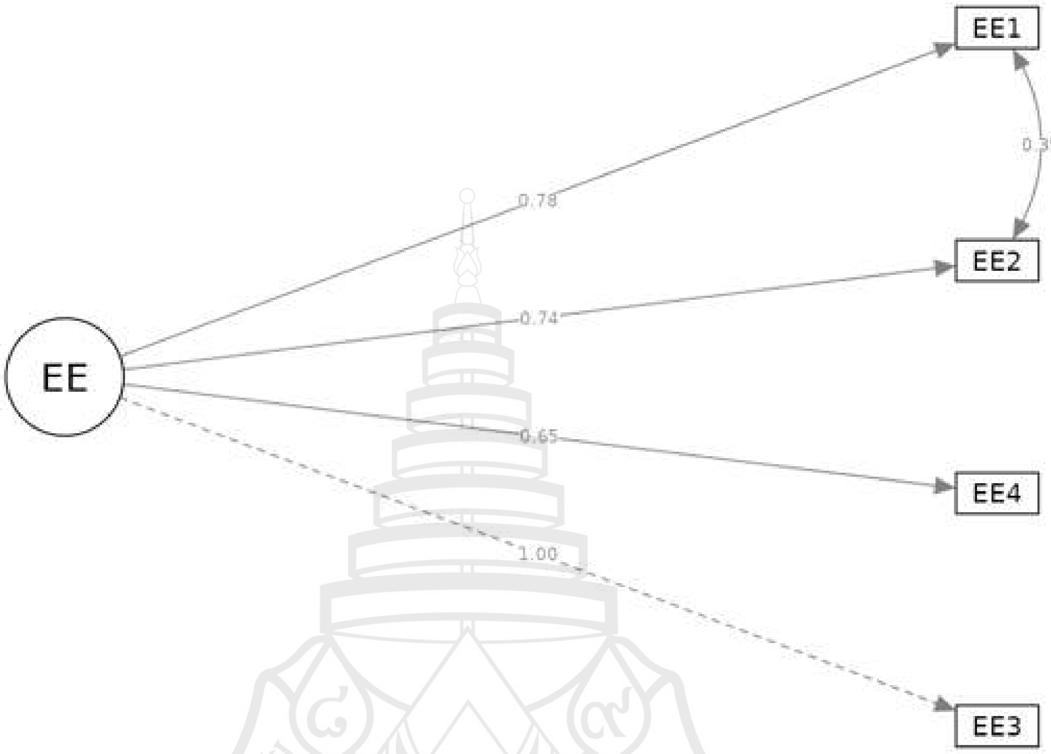
Modification indices

	Modif. index	EPC	sEPC (LV)	sEPC (all)	sEPC (nox)

Note. No modification indices above threshold

Path Model

Path diagrams



[5]

References

[1] The jamovi project (2024). *jamovi*. (Version 2.6) [Computer Software]. Retrieved from https://www.jamovi.org.

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[4] Rosseel, Y. (2019). lavaan: An R Package for Structural Equation Modeling. *Journal of Statistical Software, 48(2), 1-36*. link.

[5] Epskamp S. , Stuber S., Nak J., Veenman M., Jorgensen T.D. (2019). *semPlot: Path Diagrams and Visual Analysis of Various SEM Packages' Output*. [R Package]. Retrieved from https://CRAN.R-project.org/package=semPlot.

Measurement Model Analysis of FC

FC Measurement Model

Estimate
Groups
Analysis Summary
Group number 1 (Group number 1)
Notes for Group (Group number 1)
The model is recursive.
Sample size = 130
Variable Summary (Group number 1)
Your model contains the following variables (Group number 1)
Observed, endogenous variables
FC1
FC2
FC3
Unobserved, exogenous variables
FC
e1
e2
e3
Variable counts (Group number 1)

Number of variables in your model:	7
Number of observed variables:	3
Number of unobserved variables:	4
Number of exogenous variables:	4
Number of endogenous variables:	3

Parameter Summary (Group number 1)

	Weights	Covariances	Variances	Means	Intercepts	Total
Fixed	4	0	1	0	0	5
Labeled	0	0	0	0	0	0
Unlabeled	2	0	3	0	0	5
Total	6	0	4	0	0	10

Models
Default model (Default model)
Notes for Model (Default model)
Computation of degrees of freedom (Default model)

Number of distinct sample moments:	6
Number of distinct parameters to be estimated:	5
Degrees of freedom (6 - 5):	1

Result (Default model)
Minimum was achieved
Chi-square = .163
Degrees of freedom = 1
Probability level = .687
Group number 1 (Group number 1 - Default model)
Estimates (Group number 1 - Default model)
Scalar Estimates (Group number 1 - Default model)
Maximum Likelihood Estimates
Regression Weights: (Group number 1 - Default model)

			Estimate	S.E.	C.R.	P	Label
FC1	<---	FC	1.000				
FC2	<---	FC	1.126	.160	7.041	***	
FC3	<---	FC	.991	.161	6.158	***	

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

	Estimate

FC1	<---	FC	.766
FC2	<---	FC	.727
FC3	<---	FC	.616

Variances: (Group number 1 - Default model)

	Estimate	S.E.	C.R.	P	Label
FC	.199	.041	4.807	***	
e1	.140				
e2	.225	.044	5.132	***	
e3	.319	.050	6.414	***	

Minimization History (Default model)

Iteration		Negative eigenvalues	Condition #	Smallest eigenvalue	Diameter	F	NTries	Ratio
0	e	0	61.795		9999.000	79.730	0	9999.000
1	e	0	90.271		1.002	29.129	5	.000
2	e	0	8.283		.625	11.986	4	.000
3	e	0	5.678		.485	1.339	1	1.025
4	e	0	6.395		.099	.169	1	1.035
5	e	0	6.325		.009	.163	1	1.009
6	e	0	6.324		.000	.163	1	1.000

Model Fit Summary

CMIN

Model	NPAR	CMIN	DF	P	CMIN/DF
Default model	3	.183	1	.669	.183
Saturated model	6	.000	0		
Independence model	3	90.733	3	.000	30.244

RMR, GFI

Model	RMR	GFI	AGFI	PGFI
Default model	.003	.999	.995	.167
Saturated model	.000	1.000		
Independence model	.152	.669	.337	.334

Baseline Comparisons

Model	NFI Delta1	RFI rho1	IFI Delta2	TLI rho2	CFI
Default model	.998	.995	1.006	1.029	1.000
Saturated model	1.000		1.000		1.000
Independence model	.000	.000	.000	.000	.000

Parsimony-Adjusted Measures

Model	PRATIO	PNFI	PCFI
Default model	.333	.333	.333
Saturated model	.000	.000	.000
Independence model	1.000	.000	.000

NCP

Model	NCP	LO 90	HI 90

Default model	.000	.000	3.671
Saturated model	.000	.000	.000
Independence model	87.733	60.282	122.607

FMIN

Model	FMIN	F0	LO 90	HI 90
Default model	.001	.000	.000	.030
Saturated model	.000	.000	.000	.000
Independence model	.703	.680	.467	.950

RMSEA

Model	RMSEA	LO 90	HI 90	PCLOSE
Default model	.000	.000	.173	.731
Independence model	.478	.393	.563	.000

AIC

Model	AIC	BCC	BIC	CAIC
Default model	10.163	10.483	24.500	29.500
Saturated model	12.000	12.384	29.205	35.205
Independence model	96.733	96.925	105.336	108.336

ECVI

Model	ECVI	LO 90	HI 90	MECVI
Default model	.079	.085	.115	.081
Saturated model	.093	.093	.093	.096
Independence model	.750	.537	1.020	.751

HOELTER

Model	HOELTER .05	HOELTER .01
Default model	3046	1263
Independence model	11	17

Execution time summary

Minimization:	.029
Miscellaneous:	.076
Bootstrap:	.000
Total:	.105

Model Fit

Groups

Group number 1 (Group number 1)

Notes for Group (Group number 1)

The model is recursive.

Sample size = 130

Variable Summary (Group number 1)

Your model contains the following variables (Group number 1)

Observed, endogenous variables

FC1

FC2

FC3

Unobserved, exogenous variables

FC

e1

e2

e3

Variable counts (Group number 1)

Number of variables in your model:	7
Number of observed variables:	3
Number of unobserved variables:	4
Number of exogenous variables:	4
Number of endogenous variables:	3

Parameter Summary (Group number 1)

	Weights	Covariances	Variances	Means	Intercepts	Total
Fixed	4	0	1	0	0	5
Labeled	0	0	0	0	0	0
Unlabeled	2	0	3	0	0	5
Total	6	0	4	0	0	10

Models

Default model (Default model)

Notes for Model (Default model)

Computation of degrees of freedom (Default model)

Number of distinct sample moments:	6
Number of distinct parameters to be estimated:	5
Degrees of freedom (6 - 5):	1

Result (Default model)

Minimum was achieved

Chi-square = .183

Degrees of freedom = 1

Probability level = .687

Group number 1 (Group number 1 - Default model)

Estimates (Group number 1 - Default model)

Scalar Estimates (Group number 1 - Default model)

Maximum Likelihood Estimates

Regression Weights: (Group number 1 - Default model)

			Estimate	S.E.	C.R.	P	Label
FC1	<---	FC	1.000				
FC2	<---	FC	1.128	.160	7.041	***	
FC3	<---	FC	.991	.161	6.158	***	

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

			Estimate
FC1	<---	FC	.766
FC2	<---	FC	.727
FC3	<---	FC	.818

Variances: (Group number 1 - Default model)

	Estimate	S.E.	C.R.	P	Label
FC	.199	.041	4.807	***	
e1	.140				
e2	.225	.044	5.132	***	
e3	.319	.050	6.414	***	

Minimization History (Default model)

Iteration		Negative eigenvalues	Condition #	Smallest eigenvalue	Diameter	F	NTries	Ratio
0	e	0	63.795		9999.000	79.730	0	9999.000
1	e	0	80.271		1.002	20.529	5	.000
2	e	0	9.285		.625	11.986	4	.000
3	e	0	5.678		.485	1.339	1	1.025
4	e	0	6.395		.099	.169	1	1.033
5	e	0	6.325		.009	.163	1	1.009
6	e	0	6.324		.000	.163	1	1.000

Model Fit Summary

CMIN

Model	NPAR	CMIN	DF	P	CMIN/DF
Default model	5	.163	1	.687	.163
Saturated model	6	.000	0		
Independence model	3	90.733	3	.000	30.244

RMR, GFI

Model	RMR	GFI	AGFI	PGFI
Default model	.003	.999	.995	.167
Saturated model	.000	1.000		
Independence model	.152	.669	.337	.334

Baseline Comparisons

Model	NFI Delta1	RFI rho1	IFI Delta2	TLI rho2	CFI
Default model	.998	.995	1.009	1.029	1.000
Saturated model	1.000		1.000		1.000
Independence model	.000	.000	.000	.000	.000

Parsimony-Adjusted Measures

Model	PRATIO	PNFI	PCFI
Default model	.333	.333	.333
Saturated model	.000	.000	.000
Independence model	1.000	.000	.000

NCP

Model	NCP	LO 90	HI 90
Default model	.000	.000	3.871
Saturated model	.000	.000	.000
Independence model	87.733	60.282	122.607

FMIN

Model	FMIN	F0	LO 90	HI 90
Default model	.001	.000	.000	.030
Saturated model	.000	.000	.000	.000
Independence model	.703	.680	.467	.950

RMSEA

Model	RMSEA	LO 90	HI 90	PCLOSE
Default model	.000	.000	.173	.731
Independence model	.476	.395	.563	.000

AIC

Model	AIC	BCC	BIC	CAIC
Default model	10.169	10.483	24.300	29.300
Saturated model	12.000	12.384	29.205	35.205
Independence model	96.733	96.925	105.336	108.336

ECVI

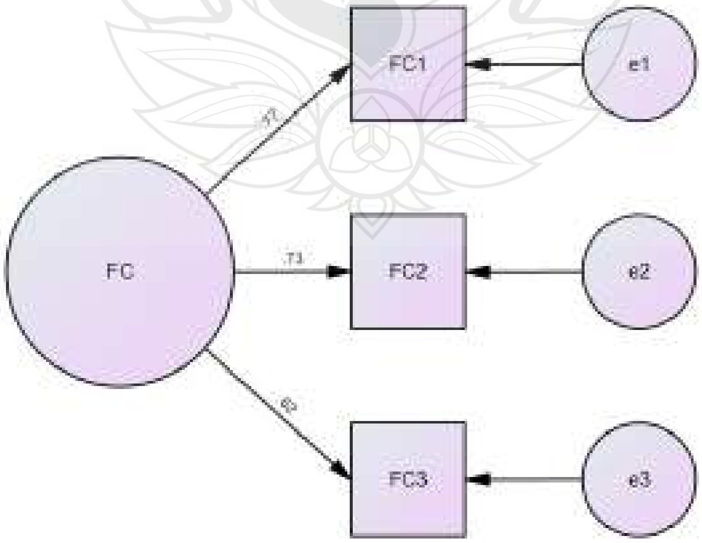
Model	ECVI	LO 90	HI 90	MECVI
Default model	.079	.085	.115	.081
Saturated model	.093	.093	.093	.096
Independence model	.750	.537	1.020	.751

HOELTER

Model	HOELTER .05	HOELTER .01
Default model	3048	5263
Independence model	12	17

Execution time summary

Minimization:	.029
Miscellaneous:	.076
Bootstrap:	.000
Total:	.105



Measurement Model Analysis of SI

SI Measurement Model

Estimate
Groups
Group number 1 (Group number 1)
Notes for Group (Group number 1)
The model is recursive.
Sample size = 130
Variable Summary (Group number 1)
Your model contains the following variables (Group number 1)
Observed, endogenous variables
SI1
SI2
SI3
Unobserved, exogenous variables
SI
e1
e2
e3
Variable counts (Group number 1)

Number of variables in your model:	7
Number of observed variables:	3
Number of unobserved variables:	4
Number of exogenous variables:	4
Number of endogenous variables:	3

Parameter Summary (Group number 1)

	Weights	Covariances	Variances	Means	Intercepts	Total
Fixed	4	0	1	0	0	5
Labeled	0	0	0	0	0	0
Unlabeled	2	0	3	0	0	5
Total	6	0	4	0	0	10

Models
Default model (Default model)
Notes for Model (Default model)
Computation of degrees of freedom (Default model)

Number of distinct sample moments:	6
Number of distinct parameters to be estimated:	5
Degrees of freedom (6 - 5):	1

Result (Default model)
Minimum was achieved
Chi-square = .682
Degrees of freedom = 1
Probability level = .409
Group number 1 (Group number 1 - Default model)
Estimates (Group number 1 - Default model)
Scalar Estimates (Group number 1 - Default model)
Maximum Likelihood Estimates
Regression Weights: (Group number 1 - Default model)

			Estimate	S.E.	C.R.	P	Label
SI1	<---	SI	1.000				
SI2	<---	SI	.845	.128	6.628	***	
SI3	<---	SI	.974	.143	6.831	***	

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

			Estimate
SI1	<---	SI	.763

SI2	<---	S1	.670
SI3	<---	S1	.696

Variances: (Group number 1 - Default model)

	Estimate	S.E.	C.R.	P	Label
SI	.279	.058	4.784	***	
e1	.200				
e2	.244	.041	5.885	***	
e3	.280	.050	5.568	***	

Modification Indices (Group number 1 - Default model)

Covariances: (Group number 1 - Default model)

	M.I.	Par Change

Variances: (Group number 1 - Default model)

	M.I.	Par Change

Regression Weights: (Group number 1 - Default model)

	M.I.	Par Change

Minimization History (Default model)

Iteration		Negative eigenvalues	Condition #	Smallest eigenvalue	Diameter	F	NTries	Ratio
0	e	0	30.206		9999.000	77.639	0	9999.000
1	e	0	9.506		.929	28.518	4	.000
2	e	0	5.223		.926	12.474	3	.000
3	e	0	6.446		.453	1.471	1	.854
4	e	0	6.667		.077	.699	1	1.016
5	e	0	6.367		.017	.682	1	1.011
6	e	0	6.352		.000	.682	1	1.000

Model Fit Summary

CMIN

Model	NPAR	CMIN	DF	P	CMIN/DF
Default model	5	.682	1	.409	.682
Saturated model	6	.000	0		
Independence model	3	88.131	3	.000	29.377

RMR, GFI

Model	RMR	GFI	AGFI	PGFI
Default model	.008	.996	.979	.166
Saturated model	.000	1.000		
Independence model	.173	.670	.340	.335

Baseline Comparisons

Model	NFI Delta1	RFI rho1	IFI Delta2	TLI rho2	CFI
Default model	.992	.977	1.004	1.011	1.000
Saturated model	1.000		1.000		1.000
Independence model	.000	.000	.000	.000	.000

Parsimony-Adjusted Measures

Model	PRATIO	PNFI	PCFI

Default model	.333	.331	.333
Saturated model	.000	.000	.000
Independence model	1.000	.000	.000

NCP

Model	NCP	LO 90	HI 90
Default model	.000	.000	6.082
Saturated model	.000	.000	.000
Independence model	85.131	58.135	119.549

FMIN

Model	FMIN	F0	LO 90	HI 90
Default model	.065	.000	.000	.047
Saturated model	.000	.000	.000	.000
Independence model	.683	.660	.451	.927

RMSEA

Model	RMSEA	LO 90	HI 90	PCLOSE
Default model	.000	.000	.217	.480
Independence model	.469	.388	.556	.000

AIC

Model	AIC	BCC	BIC	CAIC
Default model	10.682	11.002	25.020	30.020
Saturated model	12.000	12.384	29.205	35.205
Independence model	94.131	94.323	102.733	105.733

ECVI

Model	ECVI	LO 90	HI 90	MECVI
Default model	.083	.085	.132	.085
Saturated model	.093	.093	.093	.096
Independence model	.730	.520	.997	.731

HOELTER

Model	HOELTER .05	HOELTER .01
Default model	727	1255
Independence model	12	17

Execution time summary

Minimization:	.020
Miscellaneous:	.084
Bootstrap:	.000
Total:	.104

Model Fit

Groups
Group number 1 (Group number 1)
Notes for Group (Group number 1)
The model is recursive.
Sample size = 130

Variable Summary (Group number 1)

Your model contains the following variables (Group number 1)

Observed, endogenous variables

SI1

SI2

SI3

Unobserved, exogenous variables

SI

e1

e2

e3

Variable counts (Group number 1)

Number of variables in your model:	7
Number of observed variables:	3
Number of unobserved variables:	4
Number of exogenous variables:	4
Number of endogenous variables:	3

Parameter Summary (Group number 1)

	Weights	Covariances	Variances	Means	Intercepts	Total
Fixed	4	0	1	0	0	5
Labeled	0	0	0	0	0	0
Unlabeled	2	0	3	0	0	5
Total	6	0	4	0	0	10

Models

Default model (Default model)

Notes for Model (Default model)

Computation of degrees of freedom (Default model)

Number of distinct sample moments:	6
Number of distinct parameters to be estimated:	5
Degrees of freedom (6 - 5):	1

Result (Default model)

Minimum was achieved

Chi-square = .682

Degrees of freedom = 1

Probability level = .409

Group number 1 (Group number 1 - Default model)

Estimates (Group number 1 - Default model)

Scalar Estimates (Group number 1 - Default model)

Maximum Likelihood Estimates

Regression Weights: (Group number 1 - Default model)

			Estimate	S.E.	C.R.	P	Label
SI1	<---	SI	1.000				
SI2	<---	SI	.843	.124	6.628	***	
SI3	<---	SI	.974	.143	6.831	***	

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

			Estimate
SI1	<---	SI	.763
SI2	<---	SI	.670
SI3	<---	SI	.686

Variances: (Group number 1 - Default model)

	Estimate	S.E.	C.R.	P	Label

SI	.279	.058	4.784	***
e1	.200			
e2	.244	.041	5.885	***
e3	.280	.050	5.568	***

Modification Indices (Group number 1 - Default model)

Covariances: (Group number 1 - Default model)

	M.I.	Par Change

Variances: (Group number 1 - Default model)

	M.I.	Par Change

Regression Weights: (Group number 1 - Default model)

	M.I.	Par Change

Minimization History (Default model)

Iteration		Negative eigenvalues	Condition #	Smallest eigenvalue	Diameter	F	NTries	Ratio
0	e	0	30.306		9999.000	77.639	0	9999.000
1	e	0	9.508		.929	28.518	4	.000
2	e	0	5.229		.926	12.474	3	.000
3	e	0	6.446		.453	1.471	1	.854
4	e	0	6.667		.077	.699	1	1.016
5	e	0	6.367		.017	.682	1	1.015
6	e	0	6.352		.000	.682	1	1.000

Model Fit Summary

CMIN

Model	NPAR	CMIN	DF	P	CMIN/DF
Default model	5	.682	1	.409	.682
Saturated model	6	.000	0		
Independence model	3	88.131	3	.000	29.377

RMR, GFI

Model	RMR	GFI	AGFI	PGFI
Default model	.008	.996	.979	.166
Saturated model	.000	1.000		
Independence model	.173	.670	.340	.335

Baseline Comparisons

Model	NFI Delta1	RFI rho1	IFI Delta2	TLI rho2	CFI
Default model	.992	.977	1.004	1.011	1.000
Saturated model	1.000		1.000		1.000
Independence model	.000	.000	.000	.000	.000

Parsimony-Adjusted Measures

Model	PRATIO	PNFI	PCFI
Default model	.333	.331	.333
Saturated model	.000	.000	.000
Independence model	1.000	.000	.000

NCP

Model	NCP	LO 90	HI 90
Default model	.000	.000	6.082
Saturated model	.000	.000	.000
Independence model	85.131	58.135	119.549

FMIN

Model	FMIN	F0	LO 90	HI 90
Default model	.005	.000	.000	.047
Saturated model	.000	.000	.000	.000
Independence model	.683	.660	.451	.927

RMSEA

Model	RMSEA	LO 90	HI 90	PCLOSE
Default model	.000	.000	.217	.480
Independence model	.469	.388	.556	.000

AIC

Model	AIC	BCC	BIC	CAIC
Default model	10.682	11.002	25.020	30.020
Saturated model	12.000	12.384	29.205	35.205
Independence model	94.131	94.323	102.733	105.733

ECVI

Model	ECVI	LO 90	HI 90	MECVI
Default model	.083	.085	.132	.085
Saturated model	.093	.093	.093	.096
Independence model	.730	.520	.997	.731

HOELTER

Model	HOELTER .05	HOELTER .01
Default model	727	1255
Independence model	12	17

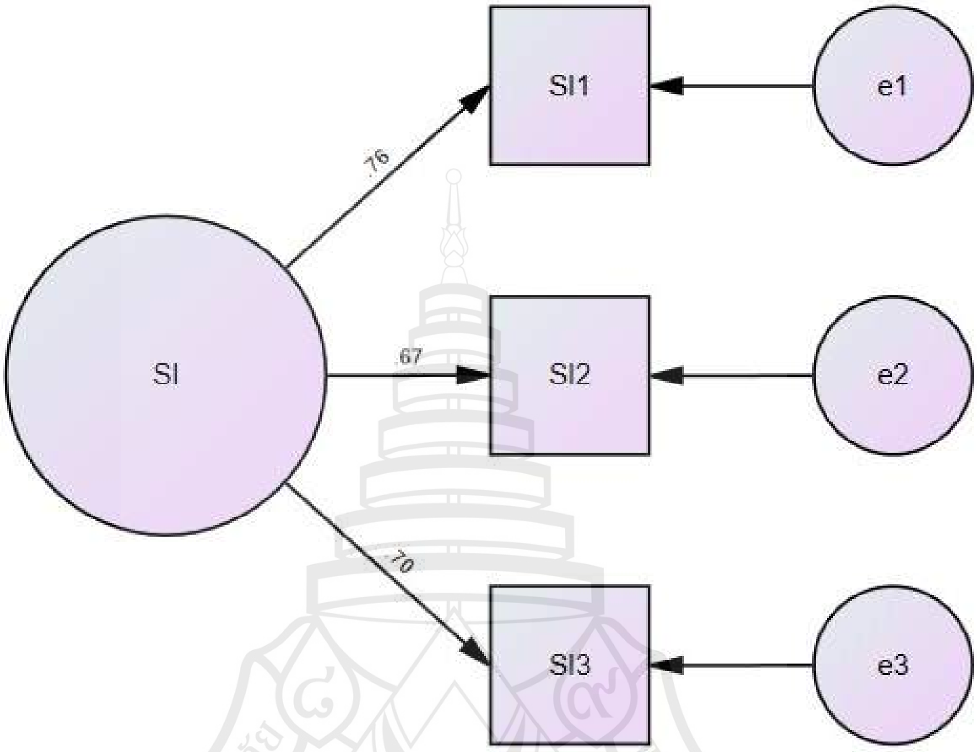
Execution time summary

Minimization: .020

Miscellaneous: .084

Bootstrap: .000

Total: .104


SI1
e1
.76
SI
.67
SI2
e2
.70
SI3
e3

APPENDIX D

CONFIRMATORY FACTOR ANALYSIS

Results

Structural Equation Modelling

Estimation Method	DWLS
Optimization Method	NLMINB
Number of observations	130
Free parameters	155
Standard errors	Robust
Scaled test	Mean adjusted scaled and shifted
Converged	TRUE
Iterations	94
Model	BI=~BI1+BI5+BI4+BI3+BI2
	TA=~TA3+TA5+TA4+TA2+TA1
	PE=~PE4+PE7+PE6+PE5+PE3+PE2+PE1
	SI=~SI2+SI3+SI1
	EE=~EE3+EE4+EE2+EE1
	FC=~FC2+FC3+FC1
	BI3~~SI1
	BI2~~TA3
	SI2~~FC1
	EE3~~FC1
	BI5~~SI1
	PE4~~EE2
	EE2~~FC1
	PE4~~FC1
	BI1~~FC1
	EE1~~FC1
	TA4~~TA2
	TA2~~EE2
	SI1~~EE4
	TA4~~EE2
	SI1~~EE3
	TA5~~PE4
	TA3~~FC1
	TA2~~FC1
	SI2~~EE3
	TA1~~FC1
	TA1~~SI1

Note. Variable (BI1,BI5,BI4,BI3,BI2,TA3,TA5,TA4,TA2,TA1,PE4,PE7,PE6,PE5,PE3,PE2,PE1,SI2,SI3,SI1,EE3,EE4,EE2,EE
coerced to ordered type.

Note. lavaan->lav_samplestats_step2(): correlation between variables TA1 and BI2 is (nearly) 1.0

Note. lavaan->lav_model_vcov(): The variance-covariance matrix of the estimated parameters (vcov) does not ap
definite! The smallest eigenvalue (= -3.360391e-17) is smaller than zero. This may be a symptom that the model

Note. lavaan->lav_object_post_check(): some estimated ov variances are negative

Note. Covariance matrix of latent variables is not positive definite.

[3] [4]

Models Info

PE5~~FC1
BI2~~SI1
BI4~~EE4
TA4~~FC1
BI5~~EE3
PE5~~SI2
BI1~~SI2
PE7~~FC2
BI4~~FC3
BI5~~PE6
BI4~~PE6
PE4~~SI3
PE5~~FC2
PE7~~SI3
TA4~~EE1
BI5~~TA2
BI3~~EE4
TA4~~PE4
SI2~~FC2
BI1~~PE5
TA5~~PE2

Note. Variable (BI1,BI5,BI4,BI3,BI2,TA3,TA5,TA4,TA2,TA1,PE4,PE7,PE6,PE5,PE3,PE2,PE1,SI2,SI3,SI1,EE3,EE4,EE2,EE
coerced to ordered type.

Note. lavaan->lav_samplestats_step2(): correlation between variables TA1 and BI2 is (nearly) 1.0

Note. lavaan->lav_model_vcov(): The variance-covariance matrix of the estimated parameters (vcov) does not ap
definite! The smallest eigenvalue (= -3.360391e-17) is smaller than zero. This may be a symptom that the model

Note. lavaan->lav_object_post_check(): some estimated ov variances are negative

Note. Covariance matrix of latent variables is not positive definite.

[3] [4]

Overall Tests

Model tests

Label	X²	df	p
User Model	446	267	<.001
Baseline Model	68478	351	<.001
Scaled User	474	267	<.001
Scaled Baseline	22429	351	<.001

Models Info

PE5~~FC1

BI2~~SI1

BI4~~EE4

TA4~~FC1

BI5~~EE3

PE5~~SI2

BI1~~SI2

PE7~~FC2

BI4~~FC3

BI5~~PE6

BI4~~PE6

PE4~~SI3

PE5~~FC2

PE7~~SI3

TA4~~EE1

BI5~~TA2

BI3~~EE4

TA4~~PE4

SI2~~FC2

BI1~~PE5

TA5~~PE2

Note. Variable (BI1,BI5,BI4,BI3,BI2,TA3,TA5,TA4,TA2,TA1,PE4,PE7,PE6,PE5,PE3,PE2,PE1,SI2,SI3,SI1,EE3,EE4,EE2,EE coerced to ordered type.

Note. lavaan->lav_samplestats_step2(): correlation between variables TA1 and BI2 is (nearly) 1.0

Note. lavaan->lav_model_vcov(): The variance-covariance matrix of the estimated parameters (vcov) does not ap definite! The smallest eigenvalue (= -3.360391e-17) is smaller than zero. This may be a symptom that the model

Note. lavaan->lav_object_post_check(): some estimated ov variances are negative

Note. Covariance matrix of latent variables is not positive definite.

[3] [4]

Overall Tests

Model tests

Label	X²	df	p
User Model	446	267	<.001
Baseline Model	68478	351	<.001
Scaled User	474	267	<.001
Scaled Baseline	22429	351	<.001

Fit indices

Type	SRMR	RMSEA	95% Confidence Intervals Lower	Upper	RMSEA p
Classical	0.064	0.072	0.060	0.084	0.002
Robust	0.059				
Scaled	0.059	0.078	0.066	0.089	<.001

User model versus baseline model

	Model	Scaled
Comparative Fit Index (CFI)	0.997	0.991
Tucker-Lewis Index (TLI)	0.997	0.988
Bentler-Bonett Non-normed Fit Index (NNFI)	0.997	0.988
Relative Noncentrality Index (RNI)	0.997	0.991
Bentler-Bonett Normed Fit Index (NFI)	0.993	0.979
Bollen's Relative Fit Index (RFI)	0.991	0.972
Bollen's Incremental Fit Index (IFI)	0.997	0.991
Parsimony Normed Fit Index (PNFI)	0.756	0.745

Estimates

Measurement model

				95% Confidence Intervals				
Latent	**Observed**	**Estimate**	**SE**	**Lower**	**Upper**	**β**	**z**	**p**
BI	**BI1**	1.000	0.0000	1.000	1.000	0.857		
	BI5	0.984	0.0365	0.912	1.055	0.843	27.0	<.001
	BI4	0.901	0.0527	0.798	1.004	0.772	17.1	<.001
	BI3	0.971	0.0389	0.895	1.047	0.832	25.0	<.001
	BI2	0.963	0.0341	0.896	1.030	0.825	28.2	<.001
TA	**TA3**	1.000	0.0000	1.000	1.000	1.047		
	TA5	0.751	0.0401	0.672	0.829	0.786	18.7	<.001
	TA4	0.733	0.0422	0.650	0.815	0.767	17.4	<.001
	TA2	0.744	0.0397	0.666	0.822	0.780	18.7	<.001
	TA1	0.907	0.0320	0.844	0.969	0.949	28.3	<.001
PE	**PE4**	1.000	0.0000	1.000	1.000	0.906		
	PE7	0.904	0.0444	0.817	0.991	0.820	20.4	<.001
	PE6	0.869	0.0511	0.769	0.969	0.788	17.0	<.001
	PE5	0.895	0.0480	0.801	0.989	0.811	18.7	<.001
	PE3	0.945	0.0347	0.877	1.013	0.857	27.2	<.001
	PE2	0.936	0.0372	0.863	1.009	0.848	25.2	<.001
	PE1	0.947	0.0455	0.858	1.036	0.858	20.8	<.001
SI	**SI2**	1.000	0.0000	1.000	1.000	0.797		
	SI3	0.976	0.0505	0.877	1.075	0.778	19.3	<.001
	SI1	0.925	0.0526	0.821	1.028	0.737	17.6	<.001
EE	**EE3**	1.000	0.0000	1.000	1.000	0.858		
	EE4	0.931	0.0603	0.812	1.049	0.799	15.4	<.001
	EE2	0.940	0.0586	0.825	1.055	0.807	16.0	<.001
	EE1	0.998	0.0569	0.887	1.110	0.857	17.6	<.001
FC	**FC2**	1.000	0.0000	1.000	1.000	0.829		
	FC3	0.904	0.0447	0.816	0.991	0.749	20.2	<.001
	FC1	0.956	0.0577	0.843	1.069	0.793	16.6	<.001

Variances and Covariances

Variable 1	Variable 2	Estimate	SE	95% Confidence Intervals Lower	Upper	β	z	p
BI3	SI1	0.2565	0.0505	0.15760	0.3554	0.6842	5.08	<.001
BI2	TA3	0.1028	0.0379	0.02848	0.1771	0.5850	2.71	0.007
SI2	FC1	0.2025	0.0443	0.11557	0.2894	0.5502	4.57	<.001
EE3	FC1	0.2266	0.0507	0.12714	0.3261	0.7246	4.47	<.001
BI5	SI1	0.2310	0.0546	0.12398	0.3381	0.6358	4.23	<.001
PE4	EE2	0.2743	0.0317	0.21224	0.3364	1.0983	8.66	<.001
EE2	FC1	0.2345	0.0442	0.14794	0.3210	0.6511	5.31	<.001
PE4	FC1	0.1782	0.0382	0.10345	0.2530	0.6917	4.67	<.001
BI1	FC1	0.1675	0.0410	0.08712	0.2479	0.5335	4.08	<.001
EE1	FC1	0.1832	0.0533	0.07868	0.2877	0.5831	3.44	<.001
TA4	TA2	0.2557	0.0459	0.16578	0.3457	0.6367	5.57	<.001
TA2	EE2	0.2300	0.0338	0.16388	0.2962	0.6216	6.81	<.001
SI1	EE4	0.1648	0.0470	0.07275	0.2569	0.4052	3.51	<.001
TA4	EE2	0.2674	0.0455	0.17822	0.3566	0.7058	5.88	<.001
SI1	EE3	0.1816	0.0496	0.08430	0.2789	0.5236	3.66	<.001
TA5	PE4	0.2327	0.0425	0.14941	0.3161	0.8910	5.47	<.001
TA3	FC1	0.0923	0.0363	0.02104	0.1635	0.4866	2.54	0.011
TA2	FC1	0.1243	0.0397	0.04654	0.2020	0.3255	3.13	0.002
SI2	EE3	0.1055	0.0431	0.02108	0.1899	0.3403	2.45	0.014
TA1	FC1	0.0763	0.0468	-0.01542	0.1681	0.3989	1.63	0.103
TA1	SI1	0.0864	0.0381	0.01165	0.1611	0.4068	2.27	0.023
PE5	FC1	0.1746	0.0431	0.09019	0.2590	0.4901	4.05	<.001
BI2	SI1	0.1788	0.0561	0.06875	0.2888	0.4683	3.18	0.001
BI4	EE4	0.1859	0.0427	0.10212	0.2696	0.4863	4.35	<.001
TA4	FC1	0.1358	0.0563	0.02552	0.2461	0.3474	2.41	0.016
BI5	EE3	0.0985	0.0365	0.02696	0.1700	0.3570	2.70	0.007
PE5	SI2	0.1456	0.0523	0.04317	0.2481	0.4126	2.79	0.005
BI1	SI2	0.1100	0.0491	0.01367	0.2063	0.3535	2.24	0.025
PE7	FC2	0.1500	0.0575	0.03727	0.2628	0.4684	2.61	0.009
BI4	FC3	0.1437	0.0495	0.04673	0.2407	0.3418	2.90	0.004
BI5	PE6	0.1806	0.0507	0.08118	0.2800	0.5451	3.56	<.001
BI4	PE6	0.1765	0.0559	0.06694	0.2861	0.4509	3.16	0.002
PE4	SI3	0.1274	0.0422	0.04457	0.2101	0.4792	3.02	0.003
PE5	FC2	0.1308	0.0556	0.02174	0.2399	0.4003	2.35	0.019
PE7	SI3	0.1258	0.0536	0.02074	0.2308	0.3492	2.35	0.019
TA4	EE1	0.1933	0.0329	0.12887	0.2577	0.5848	5.88	<.001
BI5	TA2	-0.2220	0.0567	-0.33310	-0.1109	-0.6593	-3.92	<.001
BI3	EE4	0.0840	0.0444	-0.00307	0.1710	0.2516	1.89	0.059
TA4	PE4	0.1671	0.0418	0.08517	0.2490	0.6163	4.00	<.001
SI2	FC2	0.0635	0.0578	-0.04987	0.1768	0.1880	1.10	0.272
BI1	PE5	0.1647	0.0385	0.08924	0.2402	0.5470	4.28	<.001
TA5	PE2	0.1490	0.0410	0.06865	0.2294	0.4553	3.63	<.001
BI1	BI1	0.2655	0.0000	0.26550	0.2655	0.2655		
BI5	BI5	0.2889	0.0000	0.28893	0.2889	0.2889		
BI4	BI4	0.4036	0.0000	0.40358	0.4036	0.4036		
BI3	BI3	0.3077	0.0000	0.30768	0.3077	0.3077		
BI2	BI2	0.3190	0.0000	0.31904	0.3190	0.3190		
TA3	TA3	-0.0968	0.0000	-0.09675	-0.0968	-0.0968		

Variances and Covariances

TA5	TA5	0.3817	0.0000	0.38174	0.3817	0.3817		
TA4	TA4	0.4112	0.0000	0.41119	0.4112	0.4112		
TA2	TA2	0.3924	0.0000	0.39236	0.3924	0.3924		
TA1	TA1	0.0986	0.0000	0.09863	0.0986	0.0986		
PE4	PE4	0.1787	0.0000	0.17872	0.1787	0.1787		
PE7	PE7	0.3283	0.0000	0.32828	0.3283	0.3283		
PE6	PE6	0.3798	0.0000	0.37979	0.3798	0.3798		
PE5	PE5	0.3416	0.0000	0.34162	0.3416	0.3416		
PE3	PE3	0.2660	0.0000	0.26600	0.2660	0.2660		
PE2	PE2	0.2806	0.0000	0.28056	0.2806	0.2806		
PE1	PE1	0.2633	0.0000	0.26327	0.2633	0.2633		
SI2	SI2	0.3647	0.0000	0.36467	0.3647	0.3647		
SI3	SI3	0.3952	0.0000	0.39519	0.3952	0.3952		
SI1	SI1	0.4569	0.0000	0.45692	0.4569	0.4569		
EE3	EE3	0.2633	0.0000	0.26331	0.2633	0.2633		
EE4	EE4	0.3621	0.0000	0.36209	0.3621	0.3621		
EE2	EE2	0.3491	0.0000	0.34911	0.3491	0.3491		
EE1	EE1	0.2657	0.0000	0.26574	0.2657	0.2657		
FC2	FC2	0.3126	0.0000	0.31262	0.3126	0.3126		
FC3	FC3	0.4387	0.0000	0.43872	0.4387	0.4387		
FC1	FC1	0.3715	0.0000	0.37147	0.3715	0.3715		
BI	BI	0.7345	0.0457	0.64497	0.8240	1.0000	16.08	<.001
TA	TA	1.0968	0.0360	1.02624	1.1673	1.0000	30.49	<.001
PE	PE	0.8213	0.0456	0.73195	0.9106	1.0000	18.02	<.001
SI	SI	0.6353	0.0560	0.52548	0.7452	1.0000	11.34	<.001
EE	EE	0.7367	0.0611	0.61698	0.8564	1.0000	12.06	<.001
FC	FC	0.6874	0.0554	0.57877	0.7960	1.0000	12.40	<.001
BI	TA	0.8983	0.0331	0.83341	0.9631	1.0008	27.14	<.001
BI	PE	0.7505	0.0297	0.69232	0.8086	0.9663	25.29	<.001
BI	SI	0.6732	0.0327	0.60919	0.7372	0.9855	20.61	<.001
BI	EE	0.7296	0.0367	0.65771	0.8016	0.9919	19.88	<.001
BI	FC	0.7095	0.0335	0.64378	0.7753	0.9986	21.15	<.001
TA	PE	0.8860	0.0324	0.82258	0.9495	0.9336	27.36	<.001
TA	SI	0.8262	0.0299	0.76766	0.8847	0.9898	27.66	<.001
TA	EE	0.8707	0.0406	0.79110	0.9504	0.9687	21.43	<.001
TA	FC	0.8606	0.0453	0.77184	0.9494	0.9912	19.00	<.001
PE	SI	0.7164	0.0302	0.65713	0.7756	0.9917	23.70	<.001
PE	EE	0.6947	0.0344	0.62719	0.7622	0.8931	20.18	<.001
PE	FC	0.7409	0.0343	0.67388	0.8081	0.9861	21.63	<.001
SI	EE	0.6816	0.0344	0.61412	0.7490	0.9962	19.81	<.001
SI	FC	0.7045	0.0405	0.62525	0.7838	1.0661	17.41	<.001
EE	FC	0.6833	0.0372	0.61043	0.7561	0.9601	18.39	<.001

Intercepts

Variable	Intercept	SE	95% Confidence Intervals Lower	Upper	z	p
BI1	0.000	0.000	0.000	0.000		
BI5	0.000	0.000	0.000	0.000		
BI4	0.000	0.000	0.000	0.000		
BI3	0.000	0.000	0.000	0.000		
BI2	0.000	0.000	0.000	0.000		
TA3	0.000	0.000	0.000	0.000		
TA5	0.000	0.000	0.000	0.000		
TA4	0.000	0.000	0.000	0.000		
TA2	0.000	0.000	0.000	0.000		
TA1	0.000	0.000	0.000	0.000		
PE4	0.000	0.000	0.000	0.000		
PE7	0.000	0.000	0.000	0.000		
PE6	0.000	0.000	0.000	0.000		
PE5	0.000	0.000	0.000	0.000		
PE3	0.000	0.000	0.000	0.000		
PE2	0.000	0.000	0.000	0.000		
PE1	0.000	0.000	0.000	0.000		
SI2	0.000	0.000	0.000	0.000		
SI3	0.000	0.000	0.000	0.000		
SI1	0.000	0.000	0.000	0.000		
EE3	0.000	0.000	0.000	0.000		
EE4	0.000	0.000	0.000	0.000		
EE2	0.000	0.000	0.000	0.000		
EE1	0.000	0.000	0.000	0.000		
FC2	0.000	0.000	0.000	0.000		
FC3	0.000	0.000	0.000	0.000		
FC1	0.000	0.000	0.000	0.000		
BI	0.000	0.000	0.000	0.000		
TA	0.000	0.000	0.000	0.000		
PE	0.000	0.000	0.000	0.000		
SI	0.000	0.000	0.000	0.000		
EE	0.000	0.000	0.000	0.000		
FC	0.000	0.000	0.000	0.000		

Thresholds

				95% Confidence Intervals			
Variable	Step	Thresholds	SE	Lower	Upper	z	p
BI1	t1	-1.994	0.242	-2.468	-1.520	-8.242	<.001
BI1	t2	-0.253	0.112	-0.472	-0.035	-2.269	0.023
BI1	t3	1.087	0.138	0.817	1.357	7.898	<.001
BI5	t1	-0.524	0.116	-0.752	-0.297	-4.519	<.001
BI5	t2	0.662	0.120	0.428	0.897	5.538	<.001
BI5	t3	2.423	0.363	1.711	3.135	6.671	<.001
BI4	t1	-1.769	0.203	-2.166	-1.371	-8.720	<.001
BI4	t2	-0.097	0.111	-0.313	0.120	-0.874	0.382
BI4	t3	1.542	0.174	1.201	1.883	8.855	<.001
BI3	t1	-0.375	0.113	-0.597	-0.153	-3.312	<.001
BI3	t2	0.927	0.129	0.673	1.181	7.163	<.001
BI3	t3	2.423	0.363	1.711	3.135	6.671	<.001
BI2	t1	-0.417	0.114	-0.640	-0.193	-3.658	<.001
BI2	t2	1.282	0.151	0.987	1.577	8.515	<.001
TA3	t1	-0.155	0.111	-0.372	0.062	-1.397	0.162
TA5	t1	-0.957	0.131	-1.214	-0.701	-7.316	<.001
TA5	t2	0.214	0.111	-0.004	0.432	1.921	0.055
TA4	t1	-1.482	0.168	-1.811	-1.153	-8.825	<.001
TA4	t2	0.155	0.111	-0.062	0.372	1.397	0.162
TA2	t1	-1.282	0.151	-1.577	-0.987	-8.515	<.001
TA2	t2	0.174	0.111	-0.043	0.392	1.572	0.116
TA1	t1	-2.160	0.280	-2.709	-1.611	-7.715	<.001
TA1	t2	-0.019	0.110	-0.236	0.197	-0.175	0.861
PE4	t1	-0.194	0.111	-0.412	0.024	-1.746	0.081
PE4	t2	1.482	0.168	1.153	1.811	8.825	<.001
PE7	t1	-1.482	0.168	-1.811	-1.153	-8.825	<.001
PE7	t2	-0.155	0.111	-0.372	0.062	-1.397	0.162
PE7	t3	1.327	0.154	1.025	1.629	8.614	<.001
PE6	t1	-1.870	0.219	-2.298	-1.441	-8.544	<.001
PE6	t2	-0.097	0.111	-0.313	0.120	-0.874	0.382
PE6	t3	1.327	0.154	1.025	1.629	8.614	<.001
PE5	t1	-1.482	0.168	-1.811	-1.153	-8.825	<.001
PE5	t2	0.097	0.111	-0.120	0.313	0.874	0.382
PE5	t3	1.542	0.174	1.201	1.883	8.855	<.001
PE3	t1	-1.994	0.242	-2.468	-1.520	-8.242	<.001
PE3	t2	-0.314	0.112	-0.534	-0.093	-2.791	0.005
PE3	t3	1.087	0.138	0.817	1.357	7.898	<.001
PE2	t1	-1.769	0.203	-2.166	-1.371	-8.720	<.001
PE2	t2	0.000	0.110	-0.216	0.216	0.000	1.000
PE2	t3	1.375	0.158	1.065	1.684	8.700	<.001
PE1	t1	-2.423	0.363	-3.135	-1.711	-6.671	<.001
PE1	t2	-0.214	0.111	-0.432	0.004	-1.921	0.055
PE1	t3	1.053	0.136	0.787	1.319	7.758	<.001
SI2	t1	-1.123	0.140	-1.397	-0.849	-8.034	<.001

Thresholds

SI2	t2	0.334	0.113	0.113	0.555	2.965	0.003
SI3	t1	-1.870	0.219	-2.298	-1.441	-8.544	<.001
SI3	t2	-0.174	0.111	-0.392	0.043	-1.572	0.116
SI3	t3	1.123	0.140	0.849	1.397	8.034	<.001
SI1	t1	-1.087	0.138	-1.357	-0.817	-7.898	<.001
SI1	t2	0.354	0.113	0.133	0.576	3.139	0.002
SI1	t3	2.160	0.280	1.611	2.709	7.715	<.001
EE3	t1	-2.423	0.363	-3.135	-1.711	-6.671	<.001
EE3	t2	-0.174	0.111	-0.392	0.043	-1.572	0.116
EE3	t3	1.994	0.242	1.520	2.468	8.242	<.001
EE4	t1	-1.087	0.138	-1.357	-0.817	-7.898	<.001
EE4	t2	0.273	0.112	0.054	0.493	2.443	0.015
EE4	t3	1.375	0.158	1.065	1.684	8.700	<.001
EE2	t1	-1.542	0.174	-1.883	-1.201	-8.855	<.001
EE2	t2	0.000	0.110	-0.216	0.216	0.000	1.000
EE2	t3	2.160	0.280	1.611	2.709	7.715	<.001
EE1	t1	-2.423	0.363	-3.135	-1.711	-6.671	<.001
EE1	t2	-0.194	0.111	-0.412	0.024	-1.746	0.081
EE1	t3	1.482	0.168	1.153	1.811	8.825	<.001
FC2	t1	-0.334	0.113	-0.555	-0.113	-2.965	0.003
FC2	t2	1.020	0.134	0.757	1.283	7.614	<.001
FC3	t1	-0.762	0.123	-1.003	-0.521	-6.203	<.001
FC3	t2	0.687	0.120	0.451	0.923	5.706	<.001
FC3	t3	2.160	0.280	1.611	2.709	7.715	<.001
FC1	t1	-2.423	0.363	-3.135	-1.711	-6.671	<.001
FC1	t2	-0.135	0.111	-0.352	0.082	-1.223	0.221
FC1	t3	1.769	0.203	1.371	2.166	8.720	<.001

Additional outputs

Reliability indices

Variable	α	Ordinal α	ω_1	ω_2	ω_3	AVE
BI	0.874	0.914	0.866	0.866	0.869	0.683
TA	0.890	0.952	0.848	0.848	0.827	0.763
PE	0.912	0.944	0.907	0.907	0.905	0.709
SI	0.747	0.815	0.741	0.741	0.739	0.594
EE	0.802	0.880	0.826	0.826	0.873	0.690
FC	0.738	0.824	0.750	0.750	0.763	0.626

[5]

Modifcation indices

Modification indices

			Modif. index	EPC	sEPC (LV)	sEPC (all)	sEPC (nox)
FC	=~	BI1	25166.2	-202.776	-168.119	-168.119	-168.119
TA	=~	BI1	14257.3	-86.830	-90.934	-90.934	-90.934
PE	=~	SI2	14066.8	-169.133	-153.276	-153.276	-153.276
SI	=~	BI1	10882.8	-90.233	-71.923	-71.923	-71.923
EE	=~	BI1	6959.8	-56.352	-48.367	-48.367	-48.367
EE	=~	SI2	4656.2	-58.059	-49.832	-49.832	-49.832
SI	=~	FC2	2971.6	-61.481	-49.006	-49.006	-49.006
BI1	~*~	BI1	2868.8	-23.927	-23.927	-1.000	-1.000
BI	=~	BI1	2868.8	-23.927	-20.506	-20.506	-20.506
PE	=~	FC2	2067.7	-37.085	-33.608	-33.608	-33.608
PE	=~	BI1	1921.9	-14.899	-13.502	-13.502	-13.502
BI	=~	FC2	1424.5	-26.298	-22.538	-22.538	-22.538
TA	=~	FC2	1254.6	-20.805	-21.788	-21.788	-21.788
FC2	~*~	FC2	884.8	-18.847	-18.847	-1.000	-1.000
EE	=~	FC2	845.2	-16.245	-13.943	-13.943	-13.943
FC	=~	FC2	806.3	-17.990	-14.916	-14.916	-14.916
TA	=~	BI2	412.6	-0.877	-0.918	-0.918	-0.918
EE	=~	BI2	409.7	-1.081	-0.928	-0.928	-0.928
FC	=~	BI2	405.6	-1.087	-0.902	-0.902	-0.902
SI	=~	BI2	401.5	-1.123	-0.895	-0.895	-0.895
PE	=~	BI2	382.3	-0.998	-0.905	-0.905	-0.905
BI2	~*~	BI2	376.5	-1.100	-1.100	-1.000	-1.000
SI	=~	EE2	193.4	-5.672	-4.521	-4.521	-4.521
SI	=~	PE4	177.8	-5.479	-4.367	-4.367	-4.367
TA	=~	EE2	177.7	-4.186	-4.384	-4.384	-4.384
BI	=~	PE4	161.9	-4.847	-4.154	-4.154	-4.154
FC	=~	PE4	144.9	-4.806	-3.984	-3.984	-3.984
BI	=~	EE2	127.8	-4.101	-3.514	-3.514	-3.514
FC	=~	EE2	116.5	-3.797	-3.148	-3.148	-3.148
EE	=~	PE4	98.1	-2.502	-2.147	-2.147	-2.147
TA	=~	PE4	94.9	-2.194	-2.298	-2.298	-2.298
EE	=~	TA1	80.8	-0.582	-0.500	-0.500	-0.500
BI	=~	TA1	79.1	-0.564	-0.483	-0.483	-0.483
PE	=~	EE2	78.7	-2.166	-1.963	-1.963	-1.963

Note. NaNs produced

Note. lavaan->lav_start_check_cov(): starting values imply NaN for a correlation value; variables involved are: BI2 TA3

Note. lavaan->lav_start_check_cov(): starting values imply a correlation larger than 1; variables involved are: PE4 EE2

Note. lavaan->lav_start_check_cov(): starting values imply a correlation larger than 1; variables involved are: BI TA

Note. lavaan->lav_start_check_cov(): starting values imply a correlation larger than 1; variables involved are: SI FC

Modification Indices

FC	=~	**TA1**	73.5	-0.563	-0.467	-0.467	-0.467
PE	=~	**TA1**	65.2	-0.489	-0.443	-0.443	-0.443
SI	=~	**TA1**	64.0	-0.547	-0.436	-0.436	-0.436
TA1	~*~	**TA1**	59.0	-0.468	-0.468	-1.000	-1.000
TA	=~	**BI4**	54.4	-0.390	-0.408	-0.408	-0.408
FC1	~*~	**FC1**	53.5	-0.528	-0.528	-1.000	-1.000
TA	=~	**FC1**	52.9	-0.422	-0.442	-0.442	-0.442
EE	=~	**FC1**	51.3	-0.501	-0.430	-0.430	-0.430
EE	=~	**BI4**	50.8	-0.468	-0.402	-0.402	-0.402
FC	=~	**BI4**	50.3	-0.472	-0.391	-0.391	-0.391
SI	=~	**BI4**	50.2	-0.489	-0.390	-0.390	-0.390
PE	=~	**FC1**	49.8	-0.464	-0.421	-0.421	-0.421
SI	=~	**FC1**	49.4	-0.521	-0.415	-0.415	-0.415
BI	=~	**FC1**	49.2	-0.489	-0.419	-0.419	-0.419
EE	=~	**BI3**	48.4	-0.512	-0.440	-0.440	-0.440
PE	=~	**BI4**	48.0	-0.434	-0.393	-0.393	-0.393
TA	=~	**BI3**	47.5	-0.408	-0.427	-0.427	-0.427
FC	=~	**BI3**	47.2	-0.512	-0.424	-0.424	-0.424
SI	=~	**BI3**	45.7	-0.522	-0.416	-0.416	-0.416
BI4	~*~	**BI4**	44.0	-0.495	-0.495	-1.000	-1.000
PE	=~	**BI3**	42.8	-0.459	-0.416	-0.416	-0.416
BI3	~*~	**BI3**	42.8	-0.507	-0.507	-1.000	-1.000
FC	=~	**BI5**	38.8	-0.522	-0.432	-0.432	-0.432
SI	=~	**BI5**	38.2	-0.536	-0.427	-0.427	-0.427
EE	=~	**BI5**	37.1	-0.503	-0.432	-0.432	-0.432
PE	=~	**BI5**	36.7	-0.475	-0.431	-0.431	-0.431
TA	=~	**BI5**	36.6	-0.403	-0.422	-0.422	-0.422
BI5	~*~	**BI5**	32.1	-0.499	-0.499	-1.000	-1.000
SI	=~	**TA2**	30.7	-0.510	-0.407	-0.407	-0.407
BI	=~	**SI1**	30.3	-0.458	-0.392	-0.392	-0.392
PE	=~	**TA2**	29.9	-0.442	-0.401	-0.401	-0.401
FC	=~	**TA2**	29.0	-0.475	-0.394	-0.394	-0.394
PE	=~	**SI1**	28.7	-0.422	-0.383	-0.383	-0.383
TA2	~*~	**TA2**	28.6	-0.554	-0.554	-1.000	-1.000
EE	=~	**SI1**	27.6	-0.445	-0.382	-0.382	-0.382
FC	=~	**SI1**	27.6	-0.447	-0.371	-0.371	-0.371

Note. NaNs produced

Note. lavaan->lav_start_check_cov(): starting values imply NaN for a correlation value; variables involved are: BI2 TA3

Note. lavaan->lav_start_check_cov(): starting values imply a correlation larger than 1; variables involved are: PE4 EE2

Note. lavaan->lav_start_check_cov(): starting values imply a correlation larger than 1; variables involved are: BI TA

Note. lavaan->lav_start_check_cov(): starting values imply a correlation larger than 1; variables involved are: SI FC

Modification indices

TA	=~	**SI1**	27.4	-0.359	-0.376	-0.376	-0.376
PE	=~	**TA5**	26.4	-0.470	-0.426	-0.426	-0.426
BI3	~~	**TA1**	26.2	-0.207	-0.207	-1.186	-1.186
TA4	~*~	**TA4**	25.3	-0.537	-0.537	-1.000	-1.000
EE	=~	**TA4**	25.2	-0.463	-0.398	-0.398	-0.398
TA	=~	**SI3**	25.1	-0.403	-0.422	-0.422	-0.422
PE	=~	**SI3**	25.0	-0.467	-0.423	-0.423	-0.423
BI	=~	**TA2**	25.0	-0.425	-0.364	-0.364	-0.364
FC	=~	**SI3**	24.9	-0.502	-0.416	-0.416	-0.416
EE	=~	**TA2**	24.9	-0.436	-0.375	-0.375	-0.375
SI	=~	**TA5**	24.4	-0.511	-0.407	-0.407	-0.407
BI4	~~	**TA1**	23.1	-0.182	-0.182	-0.915	-0.915
FC	=~	**TA5**	22.7	-0.473	-0.392	-0.392	-0.392
BI	=~	**TA5**	22.7	-0.456	-0.390	-0.390	-0.390
SI	=~	**TA4**	22.3	-0.460	-0.367	-0.367	-0.367
TA5	~*~	**TA5**	22.3	-0.523	-0.523	-1.000	-1.000
SI1	~*~	**SI1**	22.2	-0.467	-0.467	-1.000	-1.000
SI3	~*~	**SI3**	21.8	-0.517	-0.517	-1.000	-1.000
EE	=~	**SI3**	21.1	-0.456	-0.391	-0.391	-0.391
FC	=~	**TA4**	20.9	-0.427	-0.354	-0.354	-0.354
EE	=~	**TA5**	20.6	-0.445	-0.382	-0.382	-0.382
BI	=~	**SI3**	19.8	-0.436	-0.374	-0.374	-0.374
BI	=~	**TA4**	18.3	-0.385	-0.330	-0.330	-0.330
TA	=~	**FC3**	17.1	-0.378	-0.396	-0.396	-0.396
PE	=~	**TA4**	17.0	-0.355	-0.322	-0.322	-0.322
SI	=~	**FC3**	16.4	-0.479	-0.382	-0.382	-0.382
EE	=~	**FC3**	15.7	-0.437	-0.375	-0.375	-0.375
PE	=~	**FC3**	15.2	-0.413	-0.374	-0.374	-0.374
PE	=~	**EE3**	15.1	0.913	0.828	0.828	0.828
FC3	~*~	**FC3**	14.6	-0.498	-0.498	-1.000	-1.000
BI	=~	**FC3**	13.4	-0.407	-0.349	-0.349	-0.349
FC	=~	**PE2**	11.9	1.362	1.129	1.129	1.129
BI	=~	**EE3**	11.2	1.127	0.966	0.966	0.966
EE	=~	**PE2**	10.7	0.773	0.663	0.663	0.663
BI1	~~	**TA3**	10.2	-0.138	-0.138	-0.269	-0.269
TA	=~	**PE2**	10.0	0.725	0.759	0.759	0.759

Note. NaNs produced

Note. lavaan->lav_start_check_cov(): starting values imply NaN for a correlation value; variables involved are: BI2 TA3

Note. lavaan->lav_start_check_cov(): starting values imply a correlation larger than 1; variables involved are: PE4 EE2

Note. lavaan->lav_start_check_cov(): starting values imply a correlation larger than 1; variables involved are: BI TA

Note. lavaan->lav_start_check_cov(): starting values imply a correlation larger than 1; variables involved are: SI FC

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[1] The jamovi project (2024). *jamovi*. (Version 2.6) [Computer Software]. Retrieved from https://www.jamovi.org.

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[4] Rosseel, Y. (2019). lavaan: An R Package for Structural Equation Modeling. *Journal of Statistical Software, 48(2), 1-36*. link.

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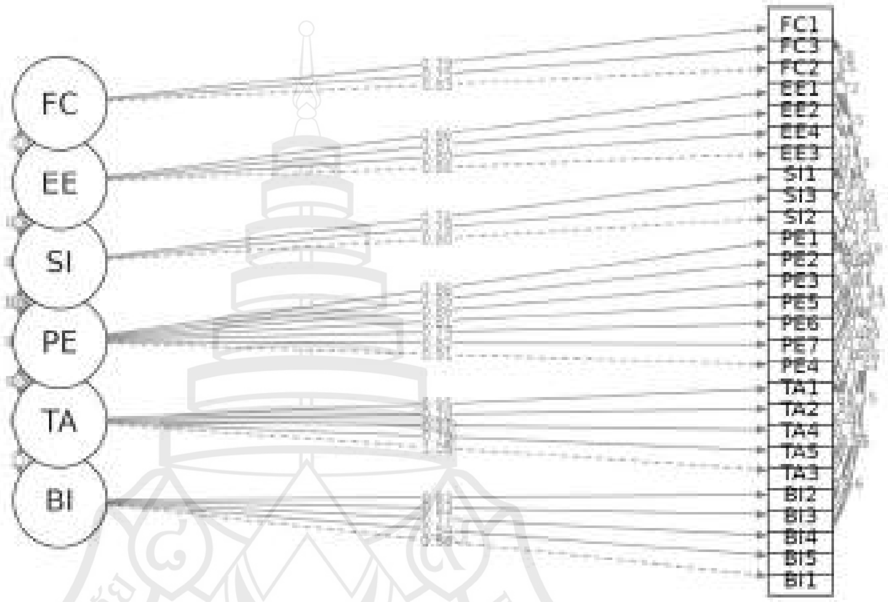
Path Model

Path diagrams



APPENDIX E

STRUCTURAL EQUATION MODEL ANALYSIS OF PROPOSED UTAUT MODEL ANALYSIS

Models Info

Estimation Method	DWLS
Optimization Method	NLMINB
Number of observations	130
Free parameters	208
Standard errors	Robust
Scaled test	Mean adjusted scaled and shifted
Converged	TRUE
Iterations	136
Model	TA=~TA3+TA5+TA4+TA2+TA1
	PE=~PE4+PE7+PE6+PE5+PE3+PE2+PE1
	EE=~EE1+EE4+EE3+EE2
	SI=~SI2+SI3+SI1
	FC=~FC1+FC3+FC2
	BI=~BI1+BI5+BI4+BI3+BI2
	BI~TA+PE+EE+SI+FC
	SI1~~BI3
	SI2~~FC1
	BI2~~FC1
	FC1~~BI5
	EE3~~FC1
	BI5~~BI3
	BI5~~BI2
	PE4~~FC1
	SI1~~BI5
	TA1~~BI3
	TA1~~BI4
	SI1~~BI2
	EE3~~BI5
	BI3~~BI2
	BI5~~BI4
	PE6~~BI5
	TA4~~TA2
	PE6~~BI4
	PE5~~FC1

Note. Model set-up: lavaan->lav_partable_flat(): duplicated elements in model syntax have been ignored: " FC1 ~

Note. Variable {TA3,TA5,TA4,TA2,TA1,PE4,PE7,PE6,PE5,PE3,PE2,PE1,EE1,EE4,EE3,EE2,SI2,SI3,SI1,FC1,FC3,FC2,BI1,
coerced to ordered type.

Note. lavaan->lav_samplestats_step2(): correlation between variables BI2 and TA1 is (nearly) 1.0

Note. lavaan->lav_model_vcov(): The variance-covariance matrix of the estimated parameters (vcov) does not ap
definite! The smallest eigenvalue (= -4.949825e-11) is smaller than zero. This may be a symptom that the model

Note. lavaan->lav_object_post_check(): some estimated ov variances are negative

Note. lavaan->lav_object_post_check(): some estimated lv variances are negative

[3] [4]

Models Info

TA2~~EE2

BI4~~BI2

TA1~~FC1

BI5~~FC1

BI4~~FC1

PE4~~EE2

EE4~~BI3

EE2~~FC1

EE4~~SI1

TA1~~BI5

EE4~~BI2

EE4~~FC1

EE3~~BI3

EE4~~BI5

EE4~~BI4

PE4~~BI4

PE1~~BI3

EE1~~BI5

PE4~~FC1

EE3~~SI1

TA2~~BI5

TA5~~BI4

FC2~~FC1

FC3~~BI4

TA1~~SI1

BI4~~BI3

PE1~~BI5

PE1~~BI2

SI2~~FC1

PE4~~BI3

PE7~~BI4

EE1~~BI2

EE1~~FC1

TA4~~EE2

PE7~~FC1

Note. Model set-up: lavaan->lav_partable_flat(): duplicated elements in model syntax have been ignored: " FC1 ~

Note. Variable (TA3,TA5,TA4,TA2,TA1,PE4,PE7,PE6,PE5,PE3,PE2,PE1,EE1,EE4,EE3,EE2,SI2,SI3,SI1,FC1,FC3,FC2,BI1,I
coerced to ordered type.

Note. lavaan->lav_samplestats_step2(): correlation between variables BI2 and TA1 is (nearly) 1.0

Note. lavaan->lav_model_vcov(): The variance-covariance matrix of the estimated parameters (vcov) does not ap
definite! The smallest eigenvalue (= -4.949825e-11) is smaller than zero. This may be a symptom that the model

Note. lavaan->lav_object_post_check(): some estimated ov variances are negative

Note. lavaan->lav_object_post_check(): some estimated lv variances are negative

[3] [4]

Models Info

PE1~~BI4
TA1~~FC3
EE2~~FC1
EE3~~SI2
TA5~~PE4
TA3~~BI5
PE2~~BI4
TA1~~FC1
EE1~~FC1
FC3~~BI3
TA2~~BI2
TA5~~BI2
FC2~~BI5
FC3~~BI5
SI1~~BI4
FC2~~BI3
PE7~~FC2
SI3~~BI3
PE1~~FC3
PE5~~SI2
SI1~~FC3
TA1~~EE3
TA2~~FC1
TA3~~BI2
TA4~~PE5
PE4~~SI3
SI2~~FC2
PE7~~SI3
TA5~~PE2
TA4~~EE1
EE3~~SI3
EE1~~SI2
PE6~~PE1
PE5~~FC2
EE4~~EE2

Note. Model set-up: lavaan->lav_partable_flat(): duplicated elements in model syntax have been ignored: " FC1 –

Note. Variable (TA3,TA5,TA4,TA2,TA1,PE4,PE7,PE6,PE5,PE3,PE2,PE1,EE1,EE4,EE3,EE2,SI2,SI3,SI1,FC1,FC3,FC2,BI1,I coerced to ordered type.

Note. lavaan->lav_samplestats_step2(): correlation between variables BI2 and TA1 is (nearly) 1.0

Note. lavaan->lav_model_vcov(): The variance-covariance matrix of the estimated parameters (vcov) does not ap definite! The smallest eigenvalue (= -4.949825e-11) is smaller than zero. This may be a symptom that the model

Note. lavaan->lav_object_post_check(): some estimated ov variances are negative

Note. lavaan->lav_object_post_check(): some estimated lv variances are negative

[3] [4]

Models Info

EE4~~EE1
PE6~~PE4
SI1~~FC2
PE6~~FC1
PE5~~FC1
TA1~~PE4
PE5~~EE2
PE4~~PE1
TA4~~EE3
PE3~~FC2
FC3~~BI2
TA1~~FC2
PE4~~PE5

Note. Model set-up: lavaan->lav_partable_flat(): duplicated elements in model syntax have been ignored: " FC1 ~

Note. Variable (TA3,TA5,TA4,TA2,TA1,PE4,PE7,PE6,PE5,PE3,PE2,PE1,EE1,EE4,EE3,EE2,SI2,SI3,SI1,FC1,FC3,FC2,BI1,I coerced to ordered type.

Note. lavaan->lav_samplestats_step2(): correlation between variables BI2 and TA1 is (nearly) 1.0

Note. lavaan->lav_model_vcov(): The variance-covariance matrix of the estimated parameters (vcov) does not ap definite! The smallest eigenvalue (= -4.949825e-11) is smaller than zero. This may be a symptom that the model

Note. lavaan->lav_object_post_check(): some estimated ov variances are negative

Note. lavaan->lav_object_post_check(): some estimated lv variances are negative

[3] [4]

Overall Tests

Model tests

Label	X^2	df	p
User Model	220	214	0.377
Baseline Model	68478	351	<.001
Scaled User	289	214	<.001
Scaled Baseline	22429	351	<.001

Fit indices

			95% Confidence Intervals		
Type	SRMR	RMSEA	Lower	Upper	RMSEA p
Classical	0.049	0.015	0.000	0.040	0.995
Robust	0.045				
Scaled	0.045	0.052	0.035	0.067	0.398

User model versus baseline model

	Model	Scaled
Comparative Fit Index (CFI)	1.000	0.997
Tucker-Lewis Index (TLI)	1.000	0.994
Bentler-Bonett Non-normed Fit Index (NNFI)	1.000	0.994
Relative Noncentrality Index (RNI)	1.000	0.997
Bentler-Bonett Normed Fit Index (NFI)	0.997	0.987
Bollen's Relative Fit Index (RFI)	0.995	0.979
Bollen's Incremental Fit Index (IFI)	1.000	0.997
Parsimony Normed Fit Index (PNFI)	0.608	0.602

Estimates

Parameters estimates

				95% Confidence Intervals				
Dep	**Pred**	**Estimate**	**SE**	**Lower**	**Upper**	**β**	**z**	**p**
BI	TA	0.25836	0.851	-1.410	1.93	0.32484	0.30350	0.762
BI	PE	0.84104	1.048	-1.213	2.90	0.95529	0.80237	0.422
BI	EE	0.61916	0.474	-0.311	1.55	0.65165	1.30489	0.192
BI	SI	-0.85004	4.433	-9.539	7.84	-0.80278	-0.19174	0.848
BI	FC	-0.00878	2.385	-4.683	4.67	-0.00895	-0.00368	0.997

Measurement model

Latent	Observed	Estimate	SE	95% Confidence Intervals Lower	95% Confidence Intervals Upper	β	z	p
TA	**TA3**	1.000	0.0000	1.000	1.000	1.065		
	TA5	0.750	0.0398	0.672	0.828	0.799	18.9	<.001
	TA4	0.757	0.0387	0.681	0.832	0.806	19.6	<.001
	TA2	0.748	0.0391	0.671	0.824	0.796	19.1	<.001
	TA1	0.866	0.0317	0.803	0.928	0.922	27.3	<.001
PE	**PE4**	1.000	0.0000	1.000	1.000	0.962		
	PE7	0.862	0.0416	0.780	0.943	0.829	20.7	<.001
	PE6	0.832	0.0481	0.737	0.926	0.800	17.3	<.001
	PE5	0.887	0.0439	0.801	0.973	0.853	20.2	<.001
	PE3	0.882	0.0313	0.820	0.943	0.848	28.2	<.001
	PE2	0.882	0.0339	0.815	0.948	0.848	26.0	<.001
	PE1	0.869	0.0428	0.785	0.953	0.836	20.3	<.001
EE	**EE1**	1.000	0.0000	1.000	1.000	0.891		
	EE4	0.915	0.0603	0.797	1.033	0.816	15.2	<.001
	EE3	0.951	0.0548	0.844	1.059	0.848	17.4	<.001
	EE2	0.955	0.0543	0.848	1.061	0.851	17.6	<.001
SI	**SI2**	1.000	0.0000	1.000	1.000	0.800		
	SI3	0.998	0.0509	0.898	1.097	0.798	19.6	<.001
	SI1	0.887	0.0513	0.787	0.988	0.710	17.3	<.001
FC	**FC1**	1.000	0.0000	1.000	1.000	0.864		
	FC3	0.790	0.0572	0.677	0.902	0.682	13.8	<.001
	FC2	0.903	0.0503	0.805	1.002	0.780	18.0	<.001
BI	**BI1**	1.000	0.0000	1.000	1.000	0.847		
	BI5	0.883	0.0417	0.802	0.965	0.748	21.2	<.001
	BI4	0.852	0.0503	0.754	0.951	0.722	16.9	<.001
	BI3	0.823	0.0374	0.750	0.897	0.697	22.0	<.001
	BI2	0.887	0.0358	0.817	0.957	0.752	24.8	<.001

Variances and Covariances

Variable 1	Variable 2	Estimate	SE	95% Confidence Intervals Lower	Upper	β	z	p
SI1	BI3	0.3344	0.0508	0.23490	0.43387	0.6619	6.587	<.001
SI2	FC1	0.1938	0.0480	0.09969	0.28800	0.6405	4.035	<.001
FC1	BI2	-0.0857	0.0493	-0.18225	0.01087	-0.2576	-1.739	0.082
FC1	BI5	-0.1146	0.0407	-0.19428	-0.03485	-0.3425	-2.817	0.005
EE3	FC1	0.1398	0.0546	0.03275	0.24685	0.5230	2.560	0.010
BI5	BI3	0.2948	0.0634	0.17047	0.41918	0.6198	4.647	<.001
BI5	BI2	0.2608	0.0589	0.14539	0.37625	0.5958	4.429	<.001
PE4	FC1	0.0681	0.0368	-0.00402	0.14020	0.4943	1.851	0.064
SI1	BI5	0.2786	0.0583	0.16439	0.39274	0.5958	4.782	<.001
TA1	BI3	0.2287	0.0417	0.14686	0.31047	0.8227	5.479	<.001
TA1	BI4	0.1387	0.0279	0.08412	0.19334	0.5171	4.979	<.001
SI1	BI2	0.2107	0.0553	0.10229	0.31909	0.4532	3.809	<.001
EE3	BI5	0.1762	0.0416	0.09473	0.25770	0.5010	4.239	<.001
BI3	BI2	0.2582	0.0669	0.12708	0.38938	0.5460	3.859	<.001
BI5	BI4	0.0801	0.0568	-0.03120	0.19131	0.1743	1.410	0.158
PE6	BI5	0.2079	0.0528	0.10444	0.31135	0.5223	3.939	<.001
TA4	TA2	0.2125	0.0450	0.12423	0.30075	0.5927	4.719	<.001
PE6	BI4	0.1714	0.0574	0.05883	0.28397	0.4129	2.984	0.003
PE5	FC1	0.0831	0.0440	-0.00313	0.16930	0.3157	1.889	0.059
TA2	EE2	0.2221	0.0335	0.15646	0.28772	0.6984	6.632	<.001
BI4	BI2	0.1442	0.0420	0.06193	0.22648	0.3159	3.435	<.001
TA1	FC1	0.0375	0.0421	-0.04488	0.11997	0.1921	0.893	0.372
FC1	BI4	-0.0214	0.0361	-0.09201	0.04931	-0.0612	-0.592	0.554
PE4	EE2	0.2148	0.0311	0.15389	0.27570	1.4964	6.913	<.001
EE4	BI3	0.1692	0.0482	0.07475	0.26361	0.4081	3.511	<.001
EE2	FC1	0.1059	0.0517	0.00449	0.20731	0.3998	2.047	0.041
EE4	SI1	0.2024	0.0490	0.10631	0.29854	0.4967	4.128	<.001
TA1	BI5	0.1559	0.0522	0.05359	0.25824	0.6060	2.986	0.003
EE4	BI2	0.1452	0.0456	0.05587	0.23448	0.3805	3.186	0.001
EE4	FC1	-0.1027	0.0506	-0.20179	-0.00352	-0.3520	-2.030	0.042
EE3	BI3	0.1898	0.0332	0.12469	0.25500	0.4996	5.711	<.001
EE4	BI5	0.1139	0.0491	0.01775	0.21010	0.2969	2.322	0.020
EE4	BI4	0.2034	0.0451	0.11500	0.29182	0.5083	4.509	<.001
PE4	BI4	-0.1400	0.0313	-0.20133	-0.07862	-0.7404	-4.471	<.001
PE1	BI3	0.2193	0.0635	0.09476	0.34376	0.5570	3.452	<.001
EE1	BI5	-0.0699	0.0458	-0.15965	0.01978	-0.2325	-1.528	0.127
EE3	SI1	0.2414	0.0488	0.14569	0.33707	0.6461	4.944	<.001
TA2	BI5	-0.1674	0.0523	-0.26981	-0.06495	-0.4168	-3.203	0.001
TA5	BI4	-0.0997	0.0510	-0.19962	1.24e-4	-0.2397	-1.958	0.050
FC1	FC2	0.0352	0.0681	-0.09826	0.16872	0.1117	0.517	0.605
FC3	BI4	0.1710	0.0586	0.05606	0.28589	0.3378	2.916	0.004
TA1	SI1	0.1384	0.0375	0.06492	0.21190	0.5066	3.691	<.001
BI4	BI3	0.0929	0.0584	-0.02161	0.20733	0.1872	1.590	0.112
PE1	BI5	0.1599	0.0680	0.02668	0.29304	0.4388	2.353	0.019
PE1	BI2	-0.0452	0.0264	-0.09684	0.00648	-0.1247	-1.714	0.086
PE4	BI3	0.0690	0.0525	-0.03389	0.17194	0.3525	1.315	0.189
PE7	BI4	-0.0607	0.0343	-0.12788	0.00651	-0.1569	-1.770	0.077
EE1	BI2	-0.0413	0.0477	-0.13475	0.05208	-0.1382	-0.867	0.386

Variances and Covariances

EE1	FC1	0.0574	0.0555	-0.05138	0.16616	0.2511	1.034	0.301
TA4	EE2	0.2425	0.0449	0.15442	0.33057	0.7791	5.396	<.001
PE7	FC1	-0.1033	0.0355	-0.17286	-0.03366	-0.3663	-2.908	0.004
PE1	BI4	0.0963	0.0454	0.00733	0.18536	0.2536	2.121	0.034
TA1	FC3	0.1819	0.0580	0.06817	0.29565	0.6414	3.135	0.002
EE3	SI2	0.1441	0.0453	0.05524	0.23286	0.4527	3.179	0.001
TA5	PE4	0.1826	0.0429	0.09856	0.26669	1.1114	4.258	<.001
TA3	BI5	0.0506	0.0555	-0.05822	0.15936	0.2083	0.911	0.362
PE2	BI4	-0.0612	0.0417	-0.14286	0.02045	-0.1671	-1.469	0.142
FC3	BI3	0.1420	0.0643	0.01608	0.26800	0.2709	2.210	0.027
TA2	BI2	-0.0733	0.0508	-0.17292	0.02635	-0.1835	-1.442	0.149
TA5	BI2	0.0795	0.0572	-0.03253	0.19159	0.2004	1.391	0.164
FC2	BI5	0.0884	0.0669	-0.04263	0.21945	0.2129	1.322	0.186
FC3	BI5	0.0308	0.0593	-0.08541	0.14693	0.0634	0.519	0.604
SI1	BI4	0.0877	0.0432	0.00297	0.17250	0.1799	2.029	0.042
FC2	BI3	0.0542	0.0715	-0.08595	0.19432	0.1208	0.758	0.449
PE7	FC2	0.1828	0.0576	0.06995	0.29564	0.5225	3.175	0.001
SI3	BI3	0.0531	0.0743	-0.09256	0.19872	0.1229	0.714	0.475
PE1	FC3	0.1563	0.0369	0.08402	0.22853	0.3891	4.239	<.001
PE5	SI2	0.1159	0.0512	0.01547	0.21630	0.3698	2.262	0.024
SI1	FC3	0.1738	0.0539	0.06817	0.27945	0.3372	3.225	0.001
TA1	EE3	0.1861	0.0371	0.11331	0.25892	0.9055	5.010	<.001
TA2	FC1	0.0590	0.0377	-0.01483	0.13283	0.1934	1.566	0.117
TA3	BI2	0.1572	0.0407	0.07738	0.23693	0.6511	3.861	<.001
TA4	PE5	-0.2339	0.0509	-0.33365	-0.13421	-0.7565	-4.598	<.001
PE4	SI3	0.0711	0.0413	-0.00989	0.15216	0.4320	1.721	0.085
SI2	FC2	0.1517	0.0579	0.03818	0.26521	0.4039	2.619	0.009
PE7	SI3	0.1070	0.0531	0.00287	0.21112	0.3175	2.014	0.044
TA5	PE2	0.1407	0.0408	0.06080	0.22069	0.4420	3.451	<.001
TA4	EE1	0.1759	0.0315	0.11407	0.23771	0.6551	5.576	<.001
EE3	SI3	-0.1286	0.0408	-0.20853	-0.04863	-0.4024	-3.152	0.002
EE1	SI2	0.1057	0.0503	0.00702	0.20429	0.3883	2.100	0.036
PE6	PE1	0.1319	0.0604	0.01351	0.25039	0.4006	2.183	0.029
PE5	FC2	0.1386	0.0570	0.02684	0.25032	0.4242	2.431	0.015
EE4	EE2	-0.2699	0.0633	-0.39396	-0.14593	-0.8883	-4.266	<.001
EE1	EE4	-0.1870	0.0567	-0.29817	-0.07584	-0.7133	-3.297	<.001
PE4	PE6	-0.1778	0.0277	-0.23202	-0.12353	-1.0848	-6.424	<.001
SI1	FC2	0.1619	0.0538	0.05650	0.26732	0.3672	3.011	0.003
PE6	FC1	-0.1486	0.0333	-0.21389	-0.08335	-0.4914	-4.463	<.001
TA1	PE4	-0.1183	0.0272	-0.17161	-0.06493	-1.1166	-4.346	<.001
PE5	EE2	-0.1480	0.0465	-0.23918	-0.05690	-0.5397	-3.184	0.001
PE4	PE1	-0.1623	0.0273	-0.21581	-0.10875	-1.0818	-5.942	<.001
TA4	EE3	0.1227	0.0443	0.03582	0.20950	0.3906	2.769	0.006
PE3	FC2	0.1524	0.0544	0.04573	0.25902	0.4594	2.800	0.005
FC3	BI2	0.0588	0.0763	-0.09077	0.20831	0.1218	0.770	0.441
TA1	FC2	0.1126	0.0408	0.03263	0.19254	0.4641	2.760	0.006
PE4	PE5	-0.1474	0.0370	-0.22005	-0.07484	-1.0338	-3.980	<.001
TA3	TA3	-0.1339	0.0000	-0.13386	-0.13386	-0.1339		
TA5	TA5	0.3617	0.0000	0.36175	0.36175	0.3617		
TA4	TA4	0.3509	0.0000	0.35088	0.35088	0.3509		
TA2	TA2	0.3663	0.0000	0.36626	0.36626	0.3663		
TA1	TA1	0.1503	0.0000	0.15033	0.15033	0.1503		

Variances and Covariances

PE4	PE4	0.0746	0.0000	0.07463	0.07463	0.0746		
PE7	PE7	0.3125	0.0000	0.31254	0.31254	0.3125		
PE6	PE6	0.3598	0.0000	0.35983	0.35983	0.3598		
PE5	PE5	0.2725	0.0000	0.27253	0.27253	0.2725		
PE3	PE3	0.2809	0.0000	0.28095	0.28095	0.2809		
PE2	PE2	0.2803	0.0000	0.28027	0.28027	0.2803		
PE1	PE1	0.3015	0.0000	0.30152	0.30152	0.3015		
EE1	EE1	0.2055	0.0000	0.20548	0.20548	0.2055		
EE4	EE4	0.3345	0.0000	0.33448	0.33448	0.3345		
EE3	EE3	0.2811	0.0000	0.28105	0.28105	0.2811		
EE2	EE2	0.2761	0.0000	0.27608	0.27608	0.2761		
SI2	SI2	0.3603	0.0000	0.36028	0.36028	0.3603		
SI3	SI3	0.3633	0.0000	0.36330	0.36330	0.3633		
SI1	SI1	0.4966	0.0000	0.49659	0.49659	0.4966		
FC1	FC1	0.2542	0.0000	0.25421	0.25421	0.2542		
FC3	FC3	0.5351	0.0000	0.53507	0.53507	0.5351		
FC2	FC2	0.3915	0.0000	0.39154	0.39154	0.3915		
BI1	BI1	0.2827	0.0000	0.28274	0.28274	0.2827		
BI5	BI5	0.4403	0.0000	0.44026	0.44026	0.4403		
BI4	BI4	0.4788	0.0000	0.47884	0.47884	0.4788		
BI3	BI3	0.5139	0.0000	0.51388	0.51388	0.5139		
BI2	BI2	0.4352	0.0000	0.43522	0.43522	0.4352		
TA	TA	1.1339	0.0364	1.06260	1.20513	1.0000	31.184	<.001
PE	PE	0.9254	0.0453	0.83662	1.01411	1.0000	20.436	<.001
EE	EE	0.7945	0.0528	0.69109	0.89795	1.0000	15.056	<.001
SI	SI	0.6397	0.0574	0.52720	0.75225	1.0000	11.143	<.001
FC	FC	0.7458	0.0885	0.57239	0.91918	1.0000	8.430	<.001
BI	BI	-0.0737	0.0615	-0.19418	0.04679	-0.1027	-1.199	0.231
TA	PE	0.9535	0.0321	0.89055	1.01643	0.9309	29.692	<.001
TA	EE	0.8648	0.0351	0.79607	0.93359	0.9112	24.652	<.001
TA	SI	0.8340	0.0307	0.77376	0.89424	0.9792	27.134	<.001
TA	FC	0.9067	0.0412	0.82596	0.98737	0.9860	22.019	<.001
PE	EE	0.7465	0.0336	0.68052	0.81238	0.8705	22.190	<.001
PE	SI	0.7570	0.0303	0.69755	0.81640	0.9838	24.967	<.001
PE	FC	0.8187	0.0419	0.73645	0.90086	0.9855	19.519	<.001
EE	SI	0.6759	0.0346	0.60807	0.74376	0.9481	19.527	<.001
EE	FC	0.7781	0.0517	0.67674	0.87942	1.0108	15.048	<.001
SI	FC	0.6823	0.0397	0.60447	0.76021	0.9879	17.174	<.001

Intercepts

			95% Confidence Intervals			
Variable	Intercept	SE	Lower	Upper	z	p
TA3	0.000	0.000	0.000	0.000		
TA5	0.000	0.000	0.000	0.000		
TA4	0.000	0.000	0.000	0.000		
TA2	0.000	0.000	0.000	0.000		
TA1	0.000	0.000	0.000	0.000		
PE4	0.000	0.000	0.000	0.000		
PE7	0.000	0.000	0.000	0.000		
PE6	0.000	0.000	0.000	0.000		
PE5	0.000	0.000	0.000	0.000		
PE3	0.000	0.000	0.000	0.000		
PE2	0.000	0.000	0.000	0.000		
PE1	0.000	0.000	0.000	0.000		
EE1	0.000	0.000	0.000	0.000		
EE4	0.000	0.000	0.000	0.000		
EE3	0.000	0.000	0.000	0.000		
EE2	0.000	0.000	0.000	0.000		
SI2	0.000	0.000	0.000	0.000		
SI3	0.000	0.000	0.000	0.000		
SI1	0.000	0.000	0.000	0.000		
FC1	0.000	0.000	0.000	0.000		
FC3	0.000	0.000	0.000	0.000		
FC2	0.000	0.000	0.000	0.000		
BI1	0.000	0.000	0.000	0.000		
BI5	0.000	0.000	0.000	0.000		
BI4	0.000	0.000	0.000	0.000		
BI3	0.000	0.000	0.000	0.000		
BI2	0.000	0.000	0.000	0.000		
TA	0.000	0.000	0.000	0.000		
PE	0.000	0.000	0.000	0.000		
EE	0.000	0.000	0.000	0.000		
SI	0.000	0.000	0.000	0.000		
FC	0.000	0.000	0.000	0.000		
BI	0.000	0.000	0.000	0.000		

Thresholds

Variable	Step	Thresholds	SE	95% Confidence Intervals Lower	Upper	z	p
TA3	t1	-0.155	0.111	-0.372	0.062	-1.397	0.162
TA5	t1	-0.957	0.131	-1.214	-0.701	-7.316	<.001
TA5	t2	0.214	0.111	-0.004	0.432	1.921	0.055
TA4	t1	-1.482	0.168	-1.811	-1.153	-8.825	<.001
TA4	t2	0.155	0.111	-0.062	0.372	1.397	0.162
TA2	t1	-1.282	0.151	-1.577	-0.987	-8.515	<.001
TA2	t2	0.174	0.111	-0.043	0.392	1.572	0.116
TA1	t1	-2.160	0.280	-2.709	-1.611	-7.715	<.001
TA1	t2	-0.019	0.110	-0.236	0.197	-0.175	0.861
PE4	t1	-0.194	0.111	-0.412	0.024	-1.746	0.081
PE4	t2	1.482	0.168	1.153	1.811	8.825	<.001
PE7	t1	-1.482	0.168	-1.811	-1.153	-8.825	<.001
PE7	t2	-0.155	0.111	-0.372	0.062	-1.397	0.162
PE7	t3	1.327	0.154	1.025	1.629	8.614	<.001
PE6	t1	-1.870	0.219	-2.298	-1.441	-8.544	<.001
PE6	t2	-0.097	0.111	-0.313	0.120	-0.874	0.382
PE6	t3	1.327	0.154	1.025	1.629	8.614	<.001
PE5	t1	-1.482	0.168	-1.811	-1.153	-8.825	<.001
PE5	t2	0.097	0.111	-0.120	0.313	0.874	0.382
PE5	t3	1.542	0.174	1.201	1.883	8.855	<.001
PE3	t1	-1.994	0.242	-2.468	-1.520	-8.242	<.001
PE3	t2	-0.314	0.112	-0.534	-0.093	-2.791	0.005
PE3	t3	1.087	0.138	0.817	1.357	7.898	<.001
PE2	t1	-1.769	0.203	-2.166	-1.371	-8.720	<.001
PE2	t2	0.000	0.110	-0.216	0.216	0.000	1.000
PE2	t3	1.375	0.158	1.065	1.684	8.700	<.001
PE1	t1	-2.423	0.363	-3.135	-1.711	-6.671	<.001
PE1	t2	-0.214	0.111	-0.432	0.004	-1.921	0.055
PE1	t3	1.053	0.136	0.787	1.319	7.758	<.001
EE1	t1	-2.423	0.363	-3.135	-1.711	-6.671	<.001
EE1	t2	-0.194	0.111	-0.412	0.024	-1.746	0.081
EE1	t3	1.482	0.168	1.153	1.811	8.825	<.001
EE4	t1	-1.087	0.138	-1.357	-0.817	-7.898	<.001
EE4	t2	0.273	0.112	0.054	0.493	2.443	0.015
EE4	t3	1.375	0.158	1.065	1.684	8.700	<.001
EE3	t1	-2.423	0.363	-3.135	-1.711	-6.671	<.001
EE3	t2	-0.174	0.111	-0.392	0.043	-1.572	0.116
EE3	t3	1.994	0.242	1.520	2.468	8.242	<.001
EE2	t1	-1.542	0.174	-1.883	-1.201	-8.855	<.001
EE2	t2	0.000	0.110	-0.216	0.216	0.000	1.000
EE2	t3	2.160	0.280	1.611	2.709	7.715	<.001
SI2	t1	-1.123	0.140	-1.397	-0.849	-8.034	<.001
SI2	t2	0.334	0.113	0.113	0.555	2.965	0.003
SI3	t1	-1.870	0.219	-2.298	-1.441	-8.544	<.001

Thresholds

SI3	t2	-0.174	0.111	-0.392	0.043	-1.572	0.116
SI3	t3	1.123	0.140	0.849	1.397	8.034	<.001
SI1	t1	-1.087	0.138	-1.357	-0.817	-7.898	<.001
SI1	t2	0.354	0.113	0.133	0.576	3.139	0.002
SI1	t3	2.160	0.280	1.611	2.709	7.715	<.001
FC1	t1	-2.423	0.363	-3.135	-1.711	-6.671	<.001
FC1	t2	-0.135	0.111	-0.352	0.082	-1.223	0.221
FC1	t3	1.769	0.203	1.371	2.166	8.720	<.001
FC3	t1	-0.762	0.123	-1.003	-0.521	-6.203	<.001
FC3	t2	0.687	0.120	0.451	0.923	5.706	<.001
FC3	t3	2.160	0.280	1.611	2.709	7.715	<.001
FC2	t1	-0.334	0.113	-0.555	-0.113	-2.965	0.003
FC2	t2	1.020	0.134	0.757	1.283	7.614	<.001
BI1	t1	-1.994	0.242	-2.468	-1.520	-8.242	<.001
BI1	t2	-0.253	0.112	-0.472	-0.035	-2.269	0.023
BI1	t3	1.087	0.138	0.817	1.357	7.898	<.001
BI5	t1	-0.524	0.116	-0.752	-0.297	-4.519	<.001
BI5	t2	0.662	0.120	0.428	0.897	5.538	<.001
BI5	t3	2.423	0.363	1.711	3.135	6.671	<.001
BI4	t1	-1.769	0.203	-2.166	-1.371	-8.720	<.001
BI4	t2	-0.097	0.111	-0.313	0.120	-0.874	0.382
BI4	t3	1.542	0.174	1.201	1.883	8.855	<.001
BI3	t1	-0.375	0.113	-0.597	-0.153	-3.312	<.001
BI3	t2	0.927	0.129	0.673	1.181	7.163	<.001
BI3	t3	2.423	0.363	1.711	3.135	6.671	<.001
BI2	t1	-0.417	0.114	-0.640	-0.193	-3.658	<.001
BI2	t2	1.282	0.151	0.987	1.577	8.515	<.001

Modifcation indices

Modification indices

			Modif. index	EPC	sEPC (LV)	sEPC (all)	sEPC (nox)
FC	=~	PE4	544.41	-17.199	-14.853	-14.853	-14.853
SI	=~	PE4	441.70	-13.973	-11.176	-11.176	-11.176
BI	=~	PE4	189.93	-4.895	-4.146	-4.146	-4.146
TA	=~	PE4	176.13	-4.138	-4.407	-4.407	-4.407
FC	=~	TA5	150.91	-8.907	-7.692	-7.692	-7.692
SI	=~	TA5	119.09	-7.737	-6.188	-6.188	-6.188
EE	=~	PE4	106.13	-2.501	-2.230	-2.230	-2.230
BI	=~	TA5	63.14	-3.688	-3.124	-3.124	-3.124
SI	=~	TA3	60.45	-5.552	-4.441	-4.441	-4.441
PE	=~	TA5	55.35	-2.534	-2.438	-2.438	-2.438
FC	=~	TA3	42.52	-4.234	-3.656	-3.656	-3.656
FC	=~	TA1	39.39	3.734	3.224	3.224	3.224
SI	=~	TA1	36.54	3.829	3.063	3.063	3.063
FC	=~	PE6	33.27	3.959	3.419	3.419	3.419
SI	=~	PE6	30.25	3.294	2.634	2.634	2.634
EE	=~	TA3	28.46	-1.547	-1.379	-1.379	-1.379
BI	=~	TA1	23.74	1.974	1.672	1.672	1.672
FC2	~~	BI1	22.53	-0.531	-0.531	-1.595	-1.595
EE	=~	TA5	15.39	-1.325	-1.181	-1.181	-1.181
FC	=~	PE1	14.01	2.282	1.971	1.971	1.971
BI	=~	TA3	13.40	-1.528	-1.294	-1.294	-1.294
FC	=~	PE5	12.41	2.476	2.139	2.139	2.139
FC	=~	PE2	9.97	2.086	1.801	1.801	1.801
TA	=~	PE2	9.57	0.865	0.921	0.921	0.921
SI	=~	PE1	9.56	1.616	1.292	1.292	1.292
PE	=~	TA1	9.34	0.849	0.817	0.817	0.817
SI	=~	PE2	9.14	1.642	1.313	1.313	1.313
EE	=~	TA4	8.15	1.458	1.300	1.300	1.300
BI	=~	PE6	7.58	0.961	0.814	0.814	0.814
EE	=~	PE2	6.86	0.513	0.457	0.457	0.457
EE	=~	TA1	6.85	0.711	0.634	0.634	0.634
EE	=~	PE6	6.62	0.569	0.507	0.507	0.507
BI	=~	PE2	6.59	0.816	0.691	0.691	0.691

Note. lavaan->lav_start_check_cov(): starting values imply a correlation larger than 1; variables involved are: PE4 EE2

Note. lavaan->lav_start_check_cov(): starting values imply a correlation larger than 1; variables involved are: TA5 PE4

Note. NaNs produced

Note. lavaan->lav_start_check_cov(): starting values imply NaN for a correlation value; variables involved are: TA3 BI5

Note. lavaan->lav_start_check_cov(): starting values imply a correlation larger than 1; variables involved are: PE4 PE6

Note. Additional warnings are present.

Modification indices

PE	=~	**TA3**	6.46	-0.785	-0.755	-0.755	-0.755
TA	=~	**PE6**	6.38	0.740	0.788	0.788	0.788
BI	=~	**PE1**	6.04	0.817	0.692	0.692	0.692
EE4	~~	**FC2**	5.51	-0.156	-0.156	-0.431	-0.431
TA4	~~	**PE4**	5.09	-0.114	-0.114	-0.705	-0.705
PE5	~~	**BI1**	4.87	-0.112	-0.112	-0.405	-0.405
TA2	~~	**PE5**	4.75	0.158	0.158	0.500	0.500
EE3	~~	**FC2**	4.74	-0.122	-0.122	-0.369	-0.369
TA4	~~	**EE4**	4.63	0.185	0.185	0.539	0.539
TA5	~~	**PE3**	4.57	-0.129	-0.129	-0.405	-0.405
PE3	~~	**EE2**	4.51	-0.106	-0.106	-0.381	-0.381
TA1	~~	**EE4**	4.37	-0.128	-0.128	-0.573	-0.573
TA5	~~	**SI3**	4.26	-0.132	-0.132	-0.363	-0.363
PE1	~~	**EE4**	4.03	-0.117	-0.117	-0.369	-0.369
PE6	~~	**FC3**	3.88	-0.137	-0.137	-0.313	-0.313
TA	=~	**PE5**	3.83	0.571	0.608	0.608	0.608
BI	=~	**PE5**	3.66	0.610	0.517	0.517	0.517
TA1	~~	**PE3**	3.61	0.094	0.094	0.456	0.456
SI	=~	**PE5**	3.56	1.155	0.924	0.924	0.924
TA4	~~	**BI1**	3.48	0.109	0.109	0.345	0.345
TA3	~~	**EE2**	3.47	-0.093	-0.093	-0.177	-0.177
PE6	~~	**EE3**	3.44	0.104	0.104	0.329	0.329
TA3	~~	**EE3**	3.41	-0.094	-0.094	-0.178	-0.178
PE2	~~	**SI3**	3.39	-0.119	-0.119	-0.372	-0.372
TA5	~~	**BI1**	3.38	0.112	0.112	0.349	0.349
TA3	~~	**BI3**	3.37	-0.118	-0.118	-0.164	-0.164
PE4	~~	**EE4**	3.26	0.136	0.136	0.860	0.860
PE6	~~	**BI1**	3.19	0.098	0.098	0.307	0.307
TA5	~~	**EE2**	3.13	-0.129	-0.129	-0.408	-0.408
PE6	~~	**FC2**	2.92	-0.087	-0.087	-0.232	-0.232
PE2	~~	**PE1**	2.91	-0.079	-0.079	-0.271	-0.271
SI	=~	**TA4**	2.87	1.156	0.925	0.925	0.925
TA2	~~	**EE4**	2.87	0.156	0.156	0.447	0.447
SI3	~~	**BI4**	2.86	0.117	0.117	0.281	0.281
PE2	~~	**EE3**	2.81	0.085	0.085	0.304	0.304

Note. lavaan->lav_start_check_cov(): starting values imply a correlation larger than 1; variables involved are: PE4 EE2

Note. lavaan->lav_start_check_cov(): starting values imply a correlation larger than 1; variables involved are: TA5 PE4

Note. NaNs produced

Note. lavaan->lav_start_check_cov(): starting values imply NaN for a correlation value; variables involved are: TA3 BI5

Note. lavaan->lav_start_check_cov(): starting values imply a correlation larger than 1; variables involved are: PE4 PE6

Note. Additional warnings are present.

Modification indices

PE5	~~	**EE4**	2.79	-0.117	-0.117	-0.389	-0.389
EE1	~~	**FC2**	2.68	-0.119	-0.119	-0.420	-0.420
TA5	~~	**TA1**	2.68	0.086	0.086	0.370	0.370
TA2	~~	**EE1**	2.66	-0.081	-0.081	-0.296	-0.296
SI2	~~	**BI1**	2.65	-0.089	-0.089	-0.279	-0.279
PE4	~~	**EE1**	2.62	-0.091	-0.091	-0.733	-0.733
TA2	~~	**EE3**	2.62	0.092	0.092	0.287	0.287
TA5	~~	**EE4**	2.60	0.149	0.149	0.428	0.428
TA4	~~	**FC2**	2.56	0.131	0.131	0.353	0.353
TA4	~~	**PE2**	2.48	0.134	0.134	0.426	0.426
TA	=~	**SI3**	2.48	-0.939	-1.000	-1.000	-1.000
PE3	~~	**EE3**	2.41	0.067	0.067	0.240	0.240
EE3	~~	**FC3**	2.38	-0.103	-0.103	-0.265	-0.265
TA1	~~	**EE2**	2.34	0.066	0.066	0.326	0.326
TA1	~~	**PE1**	2.33	-0.067	-0.067	-0.316	-0.316
TA2	~~	**SI1**	2.31	0.104	0.104	0.243	0.243
TA2	~~	**FC2**	2.27	0.114	0.114	0.302	0.302
TA	=~	**PE1**	2.26	0.394	0.419	0.419	0.419
TA5	~~	**PE5**	2.26	0.115	0.115	0.365	0.365
TA5	~~	**BI3**	2.19	-0.113	-0.113	-0.261	-0.261
TA3	~~	**EE1**	2.12	0.069	0.069	0.152	0.152
PE6	~~	**SI2**	2.11	0.097	0.097	0.270	0.270

Note. lavaan->lav_start_check_cov(): starting values imply a correlation larger than 1; variables involved are: PE4 EE2

Note. lavaan->lav_start_check_cov(): starting values imply a correlation larger than 1; variables involved are: TA5 PE4

Note. NaNs produced

Note. lavaan->lav_start_check_cov(): starting values imply NaN for a correlation value; variables involved are: TA3 BI5

Note. lavaan->lav_start_check_cov(): starting values imply a correlation larger than 1; variables involved are: PE4 PE6

Note. Additional warnings are present.

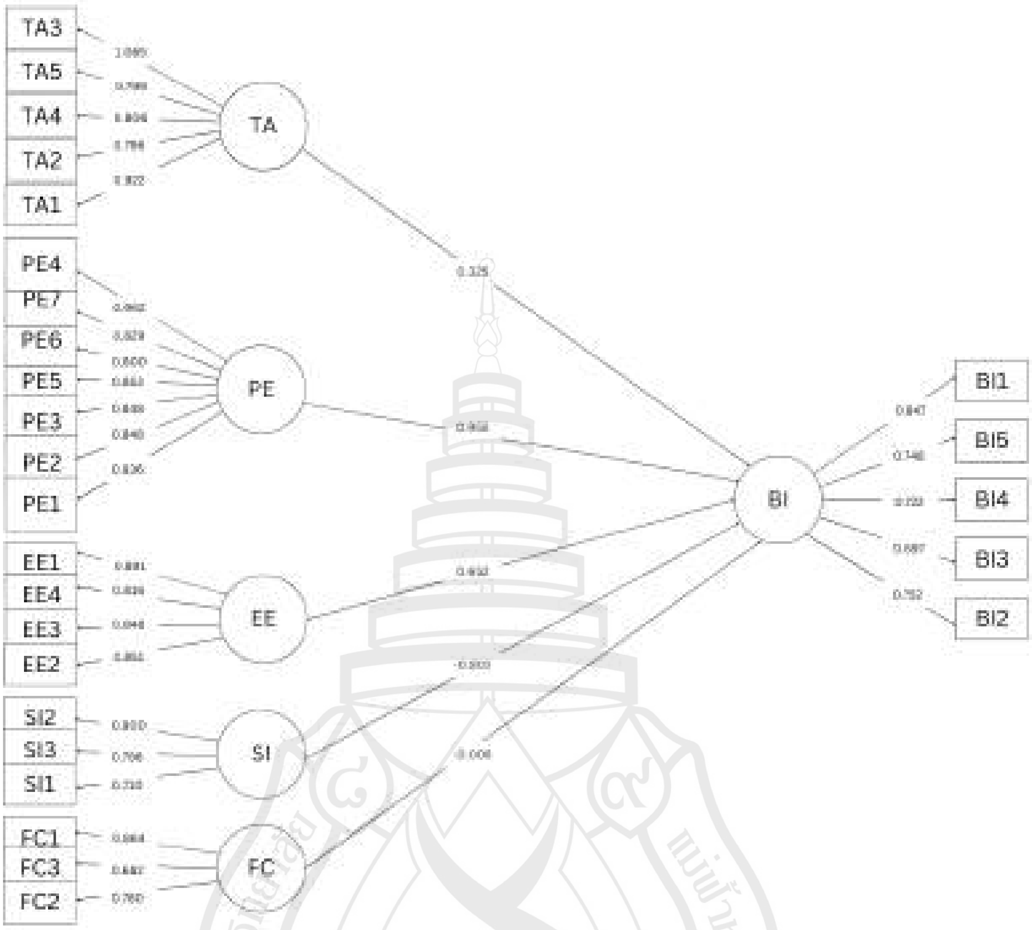
References

[1] The jamovi project (2024). *jamovi*. (Version 2.6) [Computer Software]. Retrieved from https://www.jamovi.org.

[2] R Core Team (2024). *R: A Language and environment for statistical computing*. (Version 4.4) [Computer software]. Retrieved from https://cran.r-project.org. (R packages retrieved from CRAN snapshot 2024-08-07).

[3] Gallucci, M., Jentschke, S. (2021). *SEMLj: jamovi SEM Analysis*. [jamovi module]. For help please visit https://semlj.github.io/.

[4] Rosseel, Y. (2019). lavaan: An R Package for Structural Equation Modeling. *Journal of Statistical Software, 48(2), 1-36*. link.


TA3
TA5
TA4
TA2
TA1
TA
PE4
PE7
PE6
PE5
PE3
PE2
PE1
PE
EE1
EE4
EE3
EE2
EE
SI2
SI3
SI1
SI
FC1
FC3
FC2
FC
BI
BI1
BI5
BI4
BI3
BI2

APPENDIX F

PATH ANALYSIS OF EACH FACTOR FROM PROPOSED UTAUT MODEL ANALYSIS

Path Analysis of PE to BI

Results

Structural Equation Models

Models Info

Estimation Method	DWLS
Optimization Method	NLMINB
Number of observations	130
Free parameters	54
Standard errors	Robust
Scaled test	Mean adjusted scaled and shifted
Converged	TRUE
Iterations	37
Model	PE=~PE1+PE7+PE6+PE5+PE4+PE3+PE2
	BI=~BI2+BI5+BI4+BI3+BI1
	BI~PE
	PE5~~BI1
	PE6~~BI4
	PE6~~BI5
	PE4~~BI1
	PE4~~PE1
	PE1~~BI2
	PE7~~BI1

Note. Variable (PE1,PE7,PE6,PE5,PE4,PE3,PE2,BI2,BI5,BI4,BI3,BI1) has been coerced to ordered type.

Note. lavaan->lav_model_vcov(): The variance-covariance matrix of the estimated parameters (vcov) does not appear to be positive definite! The smallest eigenvalue (= -4.301937e-17) is smaller than zero. This may be a symptom that the model is not identified.

[3] [4]

Overall Tests

Model tests

Label	X^2	df	p
User Model	59.9	46	0.083
Baseline Model	11124.8	66	<.001
Scaled User	75.3	46	0.004
Scaled Baseline	5922.2	66	<.001

Fit indices

Type	SRMR	RMSEA	95% Confidence Intervals		RMSEA p
			Lower	Upper	
Classical	0.049	0.048	0.000	0.080	0.506
Robust	0.041				
Scaled	0.041	0.070	0.040	0.098	0.123

User model versus baseline model

	Model	Scaled
Comparative Fit Index (CFI)	0.999	0.995
Tucker-Lewis Index (TLI)	0.998	0.993
Bentler-Bonett Non-normed Fit Index (NNFI)	0.998	0.993
Relative Noncentrality Index (RNI)	0.999	0.995
Bentler-Bonett Normed Fit Index (NFI)	0.995	0.987
Bollen's Relative Fit Index (RFI)	0.992	0.982
Bollen's Incremental Fit Index (IFI)	0.999	0.995
Parsimony Normed Fit Index (PNFI)	0.693	0.688

Estimates

Parameters estimates

Dep	Pred	Estimate	SE	95% Confidence Intervals		β	z	p
				Lower	Upper			
BI	PE	0.912	0.0475	0.819	1.01	0.956	19.2	<.001

Measurement model

Latent	Observed	Estimate	SE	95% Confidence Intervals Lower	Upper	β	z	p
PE	PE1	1.000	0.0000	1.000	1.000	0.913		
	PE7	0.866	0.0502	0.767	0.964	0.790	17.2	<.001
	PE6	0.860	0.0558	0.750	0.969	0.785	15.4	<.001
	PE5	0.878	0.0527	0.774	0.981	0.801	16.6	<.001
	PE4	0.968	0.0482	0.874	1.063	0.884	20.1	<.001
	PE3	0.932	0.0466	0.841	1.024	0.851	20.0	<.001
	PE2	0.966	0.0523	0.864	1.069	0.882	18.5	<.001
BI	BI2	1.000	0.0000	1.000	1.000	0.872		
	BI5	0.998	0.0431	0.913	1.082	0.870	23.1	<.001
	BI4	0.873	0.0515	0.772	0.974	0.761	16.9	<.001
	BI3	0.957	0.0407	0.877	1.036	0.834	23.5	<.001
	BI1	0.918	0.0454	0.829	1.007	0.800	20.2	<.001

Variances and Covariances

Variable 1	Variable 2	Estimate	SE	95% Confidence Intervals Lower	Upper	β	z	p
PE5	BI1	0.2238	0.0426	0.1403	0.3073	0.6240	5.25	<.001
PE6	BI4	0.1937	0.0518	0.0922	0.2951	0.4815	3.74	<.001
PE6	BI5	0.1700	0.0496	0.0728	0.2671	0.5557	3.43	<.001
PE4	BI1	0.1157	0.0391	0.0392	0.1923	0.4127	2.96	0.003
PE1	PE4	-0.1651	0.0361	-0.2359	-0.0943	-0.8645	-4.57	<.001
PE1	BI2	-0.1609	0.0403	-0.2398	-0.0820	-0.8042	-4.00	<.001
PE7	BI1	0.1549	0.0537	0.0496	0.2603	0.4219	2.88	0.004
PE1	PE1	0.1666	0.0000	0.1666	0.1666	0.1666		
PE7	PE7	0.3754	0.0000	0.3754	0.3754	0.3754		
PE6	PE6	0.3840	0.0000	0.3840	0.3840	0.3840		
PE5	PE5	0.3580	0.0000	0.3580	0.3580	0.3580		
PE4	PE4	0.2189	0.0000	0.2189	0.2189	0.2189		
PE3	PE3	0.2756	0.0000	0.2756	0.2756	0.2756		
PE2	PE2	0.2217	0.0000	0.2217	0.2217	0.2217		
BI2	BI2	0.2403	0.0000	0.2403	0.2403	0.2403		
BI5	BI5	0.2437	0.0000	0.2437	0.2437	0.2437		
BI4	BI4	0.4213	0.0000	0.4213	0.4213	0.4213		
BI3	BI3	0.3050	0.0000	0.3050	0.3050	0.3050		
BI1	BI1	0.3592	0.0000	0.3592	0.3592	0.3592		
PE	PE	0.8334	0.0594	0.7169	0.9499	1.0000	14.02	<.001
BI	BI	0.0660	0.0263	0.0144	0.1175	0.0868	2.51	0.012

Intercepts

Variable	Intercept	SE	95% Confidence Intervals Lower	Upper	z	p
PE1	0.000	0.000	0.000	0.000		
PE7	0.000	0.000	0.000	0.000		
PE6	0.000	0.000	0.000	0.000		
PE5	0.000	0.000	0.000	0.000		
PE4	0.000	0.000	0.000	0.000		
PE3	0.000	0.000	0.000	0.000		
PE2	0.000	0.000	0.000	0.000		
BI2	0.000	0.000	0.000	0.000		
BI5	0.000	0.000	0.000	0.000		
BI4	0.000	0.000	0.000	0.000		
BI3	0.000	0.000	0.000	0.000		
BI1	0.000	0.000	0.000	0.000		
PE	0.000	0.000	0.000	0.000		
BI	0.000	0.000	0.000	0.000		

Thresholds

Variable	Step	Thresholds	SE	95% Confidence Intervals Lower	Upper	z	p
PE1	t1	-2.423	0.363	-3.135	-1.711	-6.671	<.001
PE1	t2	-0.214	0.111	-0.432	0.004	-1.921	0.055
PE1	t3	1.053	0.136	0.787	1.319	7.758	<.001
PE7	t1	-1.482	0.168	-1.811	-1.153	-8.825	<.001
PE7	t2	-0.155	0.111	-0.372	0.062	-1.397	0.162
PE7	t3	1.327	0.154	1.025	1.629	8.614	<.001
PE6	t1	-1.870	0.219	-2.298	-1.441	-8.544	<.001
PE6	t2	-0.097	0.111	-0.313	0.120	-0.874	0.382
PE6	t3	1.327	0.154	1.025	1.629	8.614	<.001
PE5	t1	-1.482	0.168	-1.811	-1.153	-8.825	<.001
PE5	t2	0.097	0.111	-0.120	0.313	0.874	0.382
PE5	t3	1.542	0.174	1.201	1.883	8.855	<.001
PE4	t1	-0.194	0.111	-0.412	0.024	-1.746	0.081
PE4	t2	1.482	0.168	1.153	1.811	8.825	<.001
PE3	t1	-1.994	0.242	-2.468	-1.520	-8.242	<.001
PE3	t2	-0.314	0.112	-0.534	-0.093	-2.791	0.005
PE3	t3	1.087	0.138	0.817	1.357	7.898	<.001
PE2	t1	-1.769	0.203	-2.166	-1.371	-8.720	<.001
PE2	t2	0.000	0.110	-0.216	0.216	0.000	1.000
PE2	t3	1.375	0.158	1.065	1.684	8.700	<.001
BI2	t1	-0.417	0.114	-0.640	-0.193	-3.658	<.001
BI2	t2	1.282	0.151	0.987	1.577	8.515	<.001
BI5	t1	-0.524	0.116	-0.752	-0.297	-4.519	<.001
BI5	t2	0.662	0.120	0.428	0.897	5.538	<.001
BI5	t3	2.423	0.363	1.711	3.135	6.671	<.001
BI4	t1	-1.769	0.203	-2.166	-1.371	-8.720	<.001
BI4	t2	-0.097	0.111	-0.313	0.120	-0.874	0.382
BI4	t3	1.542	0.174	1.201	1.883	8.855	<.001
BI3	t1	-0.375	0.113	-0.597	-0.153	-3.312	<.001
BI3	t2	0.927	0.129	0.673	1.181	7.163	<.001
BI3	t3	2.423	0.363	1.711	3.135	6.671	<.001
BI1	t1	-1.994	0.242	-2.468	-1.520	-8.242	<.001
BI1	t2	-0.253	0.112	-0.472	-0.035	-2.269	0.023
BI1	t3	1.087	0.138	0.817	1.357	7.898	<.001

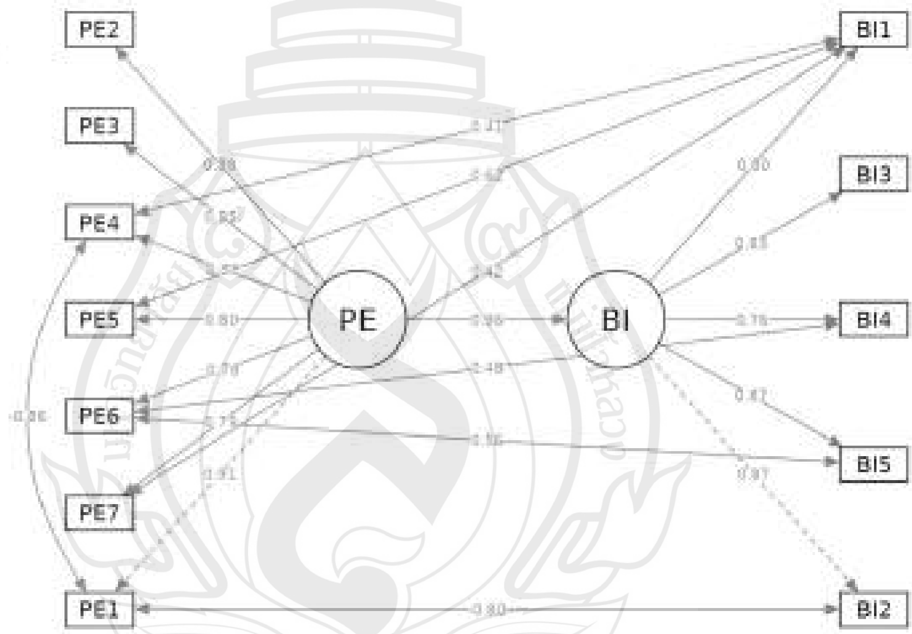
Modifcation indices

Modification indices

			Modif. index	EPC	sEPC (LV)	sEPC (all)	sEPC (nox)
BI	**=~**	**PE1**	10.07	-1.948	-1.698	-1.698	-1.698
PE	**=~**	**BI1**	8.92	-1.837	-1.677	-1.677	-1.677
PE1	**~~**	**PE3**	6.66	0.156	0.156	0.727	0.727
PE6	**~~**	**PE4**	5.10	0.135	0.135	0.466	0.466
BI5	**~~**	**BI3**	4.71	-0.131	-0.131	-0.479	-0.479
PE5	**~~**	**BI4**	4.64	-0.126	-0.126	-0.325	-0.325

Path Model

Path diagrams



[5]

Structural Equation Models

Path Analysis of FC to BI

Models Info

Estimation Method	**DWLS**
Optimization Method	**NLMINB**
Number of observations	**130**
Free parameters	**33**
Standard errors	**Robust**
Scaled test	**Mean adjusted scaled and shifted**
Converged	**TRUE**
Iterations	**27**
Model	**FC=~FC2+FC3+FC1**
	BI=~BI2+BI5+BI4 +BI3+BI1
	BI~FC
	FC1~~BI1
	FC2~~BI1

Note. Variable (FC2,FC3,FC1,BI2,BI5,BI4,BI3,BI1) has been coerced to ordered type.

Note. lavaan->lav_model_vcov(): The variance-covariance matrix of the estimated parameters (vcov) does not appear to be positive definite! The smallest eigenvalue (= 4.166047e-17) is close to zero. This may be a symptom that the model is not identified.

[3] [4]

Overall Tests

Model tests

Label	X^2	df	p
User Model	21.7	17	0.195
Baseline Model	4176.7	28	< .001
Scaled User	32.3	17	0.014
Scaled Baseline	2876.0	28	< .001

Fit indices

			95% Confidence Intervals		
Type	SRMR	RMSEA	Lower	Upper	RMSEA p
Classical	0.046	0.046	0.000	0.098	0.497
Robust	0.036	0.126	0.000	0.237	0.172
Scaled	0.036	0.084	0.037	0.127	0.102

User model versus baseline model

	Model	Scaled	Robust
Comparative Fit Index (CFI)	0.999	0.995	0.964
Tucker-Lewis Index (TLI)	0.998	0.991	0.941
Bentler-Bonett Non-normed Fit Index (NNFI)	0.998	0.991	0.941
Relative Noncentrality Index (RNI)	0.999	0.995	0.964
Bentler-Bonett Normed Fit Index (NFI)	0.995	0.989	
Bollen's Relative Fit Index (RFI)	0.991	0.981	
Bollen's Incremental Fit Index (IFI)	0.999	0.995	
Parsimony Normed Fit Index (PNFI)	0.604	0.600	

Estimates

Parameters estimates

				95% Confidence Intervals				
Dep	**Pred**	**Estimate**	**SE**	**Lower**	**Upper**	**β**	**z**	**p**
BI	FC	1.07	0.0898	0.890	1.24	0.974	11.9	<.001

Measurement model

				95% Confidence Intervals				
Latent	**Observed**	**Estimate**	**SE**	**Lower**	**Upper**	**β**	**z**	**p**
FC	**FC2**	1.000	0.0000	1.000	1.000	0.801		
	FC3	0.983	0.0738	0.838	1.127	0.787	13.3	<.001
	FC1	0.974	0.0868	0.804	1.144	0.781	11.2	<.001
BI	**BI2**	1.000	0.0000	1.000	1.000	0.877		
	BI5	0.994	0.0421	0.912	1.077	0.872	23.6	<.001
	BI4	0.906	0.0570	0.795	1.018	0.795	15.9	<.001
	BI3	0.982	0.0442	0.895	1.069	0.861	22.2	<.001
	BI1	0.834	0.0551	0.726	0.942	0.732	15.1	<.001

Variances and Covariances

Variable 1	Variable 2	Estimate	SE	95% Confidence Intervals Lower	Upper	β	z	p
FC1	BI1	0.2894	0.0557	0.1804	0.399	0.6793	5.201	<.001
FC2	BI1	0.2451	0.0665	0.1148	0.375	0.6011	3.685	<.001
FC2	FC2	0.3579	0.0000	0.3579	0.358	0.3579		
FC3	FC3	0.3800	0.0000	0.3800	0.380	0.3800		
FC1	FC1	0.3908	0.0000	0.3908	0.391	0.3908		
BI2	BI2	0.2310	0.0000	0.2310	0.231	0.2310		
BI5	BI5	0.2397	0.0000	0.2397	0.240	0.2397		
BI4	BI4	0.3682	0.0000	0.3682	0.368	0.3682		
BI3	BI3	0.2582	0.0000	0.2582	0.258	0.2582		
BI1	BI1	0.4645	0.0000	0.4645	0.465	0.4645		
FC	FC	0.6421	0.0751	0.4949	0.789	1.0000	8.550	<.001
BI	BI	0.0388	0.0492	-0.0577	0.135	0.0505	0.788	0.430

Intercepts

Variable	Intercept	SE	95% Confidence Intervals Lower	Upper	z	p
FC2	0.000	0.000	0.000	0.000		
FC3	0.000	0.000	0.000	0.000		
FC1	0.000	0.000	0.000	0.000		
BI2	0.000	0.000	0.000	0.000		
BI5	0.000	0.000	0.000	0.000		
BI4	0.000	0.000	0.000	0.000		
BI3	0.000	0.000	0.000	0.000		
BI1	0.000	0.000	0.000	0.000		
FC	0.000	0.000	0.000	0.000		
BI	0.000	0.000	0.000	0.000		

Thresholds

				95% Confidence Intervals			
Variable	**Step**	**Thresholds**	**SE**	**Lower**	**Upper**	**z**	**p**
FC2	t1	-0.334	0.113	-0.555	-0.113	-2.965	0.003
FC2	t2	1.020	0.134	0.757	1.283	7.614	<.001
FC3	t1	-0.762	0.123	-1.003	-0.521	-6.203	<.001
FC3	t2	0.687	0.120	0.451	0.923	5.706	<.001
FC3	t3	2.160	0.280	1.611	2.709	7.715	<.001
FC1	t1	-2.423	0.363	-3.135	-1.711	-6.671	<.001
FC1	t2	-0.135	0.111	-0.352	0.082	-1.223	0.221
FC1	t3	1.769	0.203	1.371	2.166	8.720	<.001
BI2	t1	-0.417	0.114	-0.640	-0.193	-3.658	<.001
BI2	t2	1.282	0.151	0.987	1.577	8.515	<.001
BI5	t1	-0.524	0.116	-0.752	-0.297	-4.519	<.001
BI5	t2	0.662	0.120	0.428	0.897	5.538	<.001
BI5	t3	2.423	0.363	1.711	3.135	6.671	<.001
BI4	t1	-1.769	0.203	-2.166	-1.371	-8.720	<.001
BI4	t2	-0.097	0.111	-0.313	0.120	-0.874	0.382
BI4	t3	1.542	0.174	1.201	1.883	8.855	<.001
BI3	t1	-0.375	0.113	-0.597	-0.153	-3.312	<.001
BI3	t2	0.927	0.129	0.673	1.181	7.163	<.001
BI3	t3	2.423	0.363	1.711	3.135	6.671	<.001
BI1	t1	-1.994	0.242	-2.468	-1.520	-8.242	<.001
BI1	t2	-0.253	0.112	-0.472	-0.035	-2.269	0.023
BI1	t3	1.087	0.138	0.817	1.357	7.898	<.001

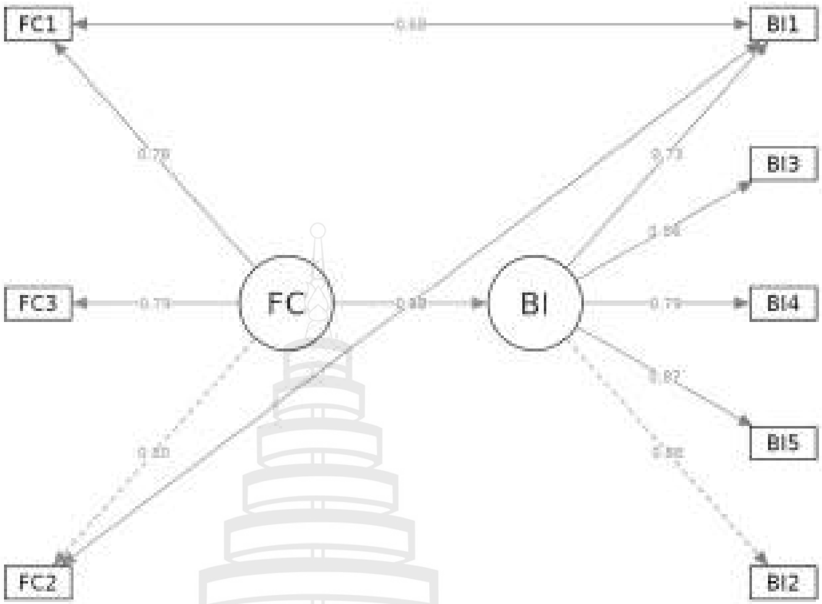
Modifcation indices

Modification indices

	Modif. index	EPC	sEPC (LV)	sEPC (all)	sEPC (nox)

Path Model

Path diagrams



[5]

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Path Analysis of EE to BI

Models Info

Estimation Method	**DWLS**
Optimization Method	**NLMINB**
Number of observations	**130**
Free parameters	**48**
Standard errors	**Robust**
Scaled test	**Mean adjusted scaled and shifted**
Converged	**TRUE**
Iterations	**36**
Model	**EE=~EE3+EE4+EE2+EE1**
	BI=~BI5+BI4+BI3+BI2+BI1
	BI~EE
	EE4~~BI4
	EE2~~EE1
	EE2~~BI1
	EE3~~EE2
	EE3~~EE1
	EE1~~BI1
	EE1~~BI4
	EE3~~BI1
	EE4~~BI1
	BI4~~BI1
	BI4~~BI3
	BI5~~BI4

Note. Variable (EE3,EE4,EE2,EE1,BI5,BI4,BI3,BI2,BI1) has been coerced to ordered type.

Note. lavaan->lav_model_vcov(): The variance-covariance matrix of the estimated parameters (vcov) does not appear to be positive definite! The smallest eigenvalue (= -1.626303e-19) is smaller than zero. This may be a symptom that the model is not identified.

Note. lavaan->lav_object_post_check(): some estimated lv variances are negative

Models Info

Estimation Method	**DWLS**
Optimization Method	**NLMINB**
Number of observations	**130**
Free parameters	**48**
Standard errors	**Robust**
Scaled test	**Mean adjusted scaled and shifted**
Converged	**TRUE**
Iterations	**36**
Model	**EE=~EE3+EE4+EE2+EE1**
	BI=~BI5+BI4+BI3+BI2+BI1
	BI~EE
	EE4~~BI4
	EE2~~EE1
	EE2~~BI1
	EE3~~EE2
	EE3~~EE1
	EE1~~BI1
	EE1~~BI4
	EE3~~BI1
	EE4~~BI1
	BI4~~BI1
	BI4~~BI3
	BI5~~BI4

Note. Variable (EE3,EE4,EE2,EE1,BI5,BI4,BI3,BI2,BI1) has been coerced to ordered type.

Note. lavaan->lav_model_vcov(): The variance-covariance matrix of the estimated parameters (vcov) does not appear to be positive definite! The smallest eigenvalue (= -1.626303e-19) is smaller than zero. This may be a symptom that the model is not identified.

Note. lavaan->lav_object_post_check(): some estimated lv variances are negative

Overall Tests

Model tests

Label	X²	df	p
User Model	2.50	14	1.000
Baseline Model	6618.59	36	<.001
Scaled User	5.77	14	0.972
Scaled Baseline	4071.44	36	<.001

Note. lavaan->lav_object_post_check(): some estimated lv variances are negativelavaan->lav_object_post_check(): some estimated lv variances are negative

Fit indices

			95% Confidence Intervals		
Type	SRMR	RMSEA	Lower	Upper	RMSEA p
Classical	0.014	0.000	0.000	0.000	1.000
Robust	0.011	0.000	0.000	0.000	0.981
Scaled	0.011	0.000	0.000	0.000	0.994

User model versus baseline model

	Model	Scaled	Robust
Comparative Fit Index (CFI)	1.000	1.000	1.000
Tucker-Lewis Index (TLI)	1.004	1.005	1.155
Bentler-Bonett Non-normed Fit Index (NNFI)	1.004	1.005	1.155
Relative Noncentrality Index (RNI)	1.002	1.002	1.060
Bentler-Bonett Normed Fit Index (NFI)	1.000	0.999	
Bollen's Relative Fit Index (RFI)	0.999	0.996	
Bollen's Incremental Fit Index (IFI)	1.002	1.002	
Parsimony Normed Fit Index (PNFI)	0.389	0.388	

Estimates

Parameters estimates

Dep	Pred	Estimate	SE	95% Confidence Intervals Lower	Upper	β	z	p
BI	EE	1.16	0.0907	0.982	1.34	1.06	12.8	<.001

Measurement model

Latent	Observed	Estimate	SE	95% Confidence Intervals Lower	Upper	β	z	p
EE	**EE3**	1.000	0.0000	1.000	1.000	0.827		
	EE4	0.945	0.0461	0.854	1.035	0.781	20.48	<.001
	EE2	0.722	0.0749	0.575	0.869	0.597	9.64	<.001
	EE1	0.796	0.0643	0.669	0.922	0.658	12.37	<.001
BI	**BI5**	1.000	0.0000	1.000	1.000	0.907		
	BI4	0.843	0.0478	0.750	0.937	0.765	17.63	<.001
	BI3	0.985	0.0305	0.925	1.045	0.894	32.29	<.001
	BI2	0.989	0.0367	0.917	1.061	0.898	26.92	<.001
	BI1	0.763	0.0634	0.639	0.888	0.693	12.04	<.001

Variances and Covariances

Variable 1	Variable 2	Estimate	SE	95% Confidence Intervals Lower	Upper	β	z	p
EE4	BI4	0.1659	0.0576	0.0530	0.2789	0.413	2.88	0.004
EE2	EE1	0.3527	0.0536	0.2476	0.4577	0.584	6.58	<.001
EE2	BI1	0.2909	0.0555	0.1822	0.3997	0.503	5.24	<.001
EE3	EE2	0.2598	0.0530	0.1559	0.3638	0.576	4.90	<.001
EE3	EE1	0.2272	0.0571	0.1153	0.3390	0.536	3.98	<.001

Variances and Covariances

				95% Confidence Intervals				
Variable 1	Variable 2	Estimate	SE	Lower	Upper	β	z	p
EE1	BI1	0.2986	0.0652	0.1709	0.4264	0.550	4.58	<.001
EE1	BI4	0.1419	0.0468	0.0502	0.2336	0.293	3.03	0.002
EE3	BI1	0.1586	0.0495	0.0615	0.2557	0.391	3.20	0.001
EE4	BI1	0.1356	0.0483	0.0410	0.2302	0.301	2.81	0.005
BI4	BI1	0.0807	0.0501	-0.0174	0.1788	0.174	1.61	0.107
BI4	BI3	-0.0878	0.0538	-0.1932	0.0177	-0.304	-1.63	0.103
BI5	BI4	-0.0743	0.0554	-0.1830	0.0343	-0.275	-1.34	0.180
EE3	EE3	0.3165	0.0000	0.3165	0.3165	0.316		
EE4	EE4	0.3900	0.0000	0.3900	0.3900	0.390		
EE2	EE2	0.6436	0.0000	0.6436	0.6436	0.644		
EE1	EE1	0.5674	0.0000	0.5674	0.5674	0.567		
BI5	BI5	0.1765	0.0000	0.1765	0.1765	0.176		
BI4	BI4	0.4143	0.0000	0.4143	0.4143	0.414		
BI3	BI3	0.2013	0.0000	0.2013	0.2013	0.201		
BI2	BI2	0.1943	0.0000	0.1943	0.1943	0.194		
BI1	BI1	0.5202	0.0000	0.5202	0.5202	0.520		
EE	EE	0.6835	0.0643	0.5576	0.8095	1.000	10.64	<.001
BI	BI	-0.0964	0.0757	-0.2449	0.0520	-0.117	-1.27	0.203

Intercepts

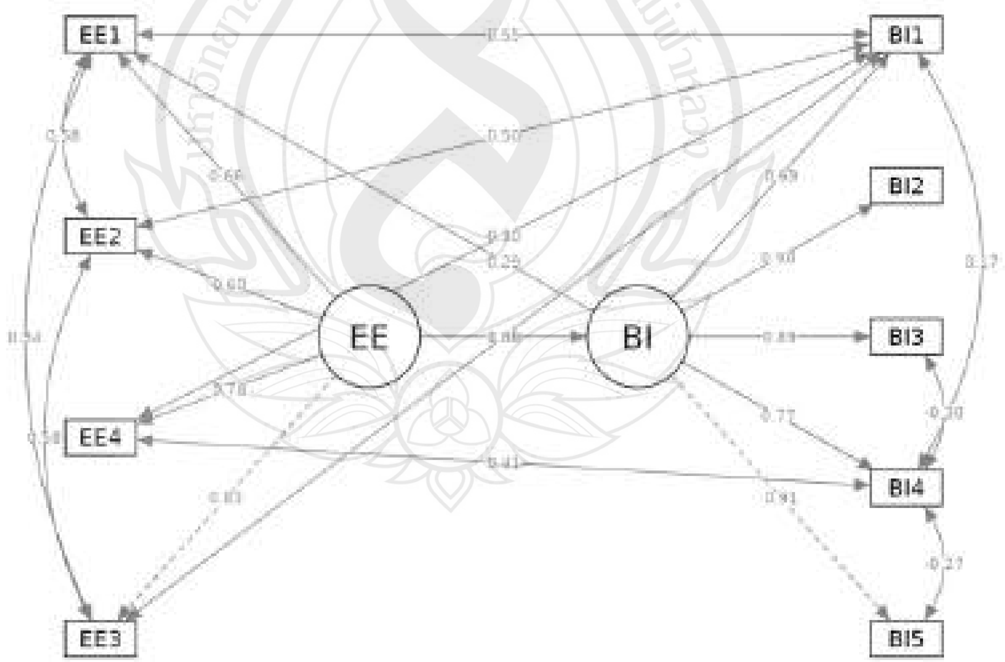
			95% Confidence Intervals			
Variable	Intercept	SE	Lower	Upper	z	p
EE3	0.000	0.000	0.000	0.000		
EE4	0.000	0.000	0.000	0.000		
EE2	0.000	0.000	0.000	0.000		
EE1	0.000	0.000	0.000	0.000		
BI5	0.000	0.000	0.000	0.000		
BI4	0.000	0.000	0.000	0.000		
BI3	0.000	0.000	0.000	0.000		
BI2	0.000	0.000	0.000	0.000		
BI1	0.000	0.000	0.000	0.000		
EE	0.000	0.000	0.000	0.000		
BI	0.000	0.000	0.000	0.000		

Thresholds

				95% Confidence Intervals			
Variable	Step	Thresholds	SE	Lower	Upper	z	p
EE3	t1	-2.423	0.363	-3.135	-1.711	-6.671	<.001
EE3	t2	-0.174	0.111	-0.392	0.043	-1.572	0.116
EE3	t3	1.994	0.242	1.520	2.468	8.242	<.001
EE4	t1	-1.087	0.138	-1.357	-0.817	-7.898	<.001
EE4	t2	0.273	0.112	0.054	0.493	2.443	0.015
EE4	t3	1.375	0.158	1.065	1.684	8.700	<.001
EE2	t1	-1.542	0.174	-1.883	-1.201	-8.855	<.001
EE2	t2	0.000	0.110	-0.216	0.216	0.000	1.000
EE2	t3	2.160	0.280	1.611	2.709	7.715	<.001
EE1	t1	-2.423	0.363	-3.135	-1.711	-6.671	<.001
EE1	t2	-0.194	0.111	-0.412	0.024	-1.746	0.081
EE1	t3	1.482	0.168	1.153	1.811	8.825	<.001
BI5	t1	-0.524	0.116	-0.752	-0.297	-4.519	<.001
BI5	t2	0.662	0.120	0.428	0.897	5.538	<.001
BI5	t3	2.423	0.363	1.711	3.135	6.671	<.001

Thresholds

				95% Confidence Intervals			
Variable	Step	Thresholds	SE	Lower	Upper	z	p
BI4	t1	-1.769	0.203	-2.166	-1.371	-8.720	<.001
BI4	t2	-0.097	0.111	-0.313	0.120	-0.874	0.382
BI4	t3	1.542	0.174	1.201	1.883	8.855	<.001
BI3	t1	-0.375	0.113	-0.597	-0.153	-3.312	<.001
BI3	t2	0.927	0.129	0.673	1.181	7.163	<.001
BI3	t3	2.423	0.363	1.711	3.135	6.671	<.001
BI2	t1	-0.417	0.114	-0.640	-0.193	-3.658	<.001
BI2	t2	1.282	0.151	0.987	1.577	8.515	<.001
BI1	t1	-1.994	0.242	-2.468	-1.520	-8.242	<.001
BI1	t2	-0.253	0.112	-0.472	-0.035	-2.269	0.023
BI1	t3	1.087	0.138	0.817	1.357	7.898	<.001



Path Analysis of SI to BI

Models Info

Estimation Method	DWLS
Optimization Method	NLMINB
Number of observations	130
Free parameters	36
Standard errors	Robust
Scaled test	Mean adjusted scaled and shifted
Converged	TRUE
Iterations	30
Model	SI=~SI1+SI3+SI2
	BI=~BI5+BI4+BI3+BI2+BI1
	BI~SI
	SI2~~BI1
	SI3~~BI1
	SI2~~BI4
	BI4~~BI1
	SI1~~BI3

Note. Variable (SI1,SI3,SI2,BI5,BI4,BI3,BI2,BI1) has been coerced to ordered type.

Note. lavaan->lav_model_vcov(): The variance-covariance matrix of the estimated parameters (vcov) does not appear to be positive definite! The smallest eigenvalue (= -4.942608e-17) is smaller than zero. This may be a symptom that the model is not identified.

Overall Tests

Model tests

Label	X^2	df	p
User Model	4.46	14	0.992
Baseline Model	4154.26	28	<.001
Scaled User	8.23	14	0.877

Model tests

Label	X^2	df	p
Scaled Baseline	3003.10	28	<.001

Fit indices

			95% Confidence Intervals		
Type	SRMR	RMSEA	Lower	Upper	RMSEA p
Classical	0.022	0.000	0.000	0.000	0.998
Robust	0.017	0.000	0.000	0.000	0.987
Scaled	0.017	0.000	0.000	0.043	0.964

User model versus baseline model

	Model	Scaled	Robust
Comparative Fit Index (CFI)	1.000	1.000	1.000
Tucker-Lewis Index (TLI)	1.005	1.004	1.114
Bentler-Bonett Non-normed Fit Index (NNFI)	1.005	1.004	1.114
Relative Noncentrality Index (RNI)	1.002	1.002	1.057
Bentler-Bonett Normed Fit Index (NFI)	0.999	0.997	
Bollen's Relative Fit Index (RFI)	0.998	0.995	
Bollen's Incremental Fit Index (IFI)	1.002	1.002	
Parsimony Normed Fit Index (PNFI)	0.499	0.499	

Estimates

Parameters estimates

				95% Confidence Intervals				
Dep	Pred	Estimate	SE	Lower	Upper	β	z	p
BI	SI	1.04	0.0949	0.852	1.22	0.994	10.9	<.001

Measurement model

				95% Confidence Intervals				
Latent	**Observed**	**Estimate**	**SE**	**Lower**	**Upper**	**β**	**z**	**p**
SI	**SI1**	1.000	0.0000	1.000	1.000	0.884		
	SI3	0.832	0.0743	0.687	0.978	0.736	11.2	< .001
	SI2	0.790	0.0772	0.638	0.941	0.698	10.2	< .001
BI	**BI5**	1.000	0.0000	1.000	1.000	0.923		
	BI4	0.775	0.0471	0.683	0.867	0.715	16.5	< .001
	BI3	0.943	0.0422	0.861	1.026	0.871	22.3	< .001
	BI2	0.983	0.0440	0.897	1.069	0.907	22.3	< .001
	BI1	0.744	0.0573	0.632	0.856	0.687	13.0	< .001

Variances and Covariances

				95% Confidence Intervals				
Variable 1	**Variable 2**	**Estimate**	**SE**	**Lower**	**Upper**	**β**	**z**	**p**
SI2	BI1	0.30657	0.0663	0.17666	0.436	0.5890	4.625	< .001
SI3	BI1	0.19800	0.0841	0.03325	0.363	0.4023	2.356	0.018
SI2	BI4	0.13896	0.0593	0.02277	0.255	0.2776	2.344	0.019
BI4	BI1	0.11962	0.0496	0.02249	0.217	0.2355	2.414	0.016
SI1	BI3	0.09573	0.0512	-0.00455	0.196	0.4160	1.871	0.061
SI1	SI1	0.21884	0.0000	0.21884	0.219	0.2188		
SI3	SI3	0.45868	0.0000	0.45868	0.459	0.4587		
SI2	SI2	0.51292	0.0000	0.51292	0.513	0.5129		
BI5	BI5	0.14812	0.0000	0.14812	0.148	0.1481		

Variances and Covariances

Variable 1	Variable 2	Estimate	SE	95% Confidence Intervals Lower	Upper	β	z	p
BI4	BI4	0.48857	0.0000	0.48857	0.489	0.4886		
BI3	BI3	0.24197	0.0000	0.24197	0.242	0.2420		
BI2	BI2	0.17705	0.0000	0.17705	0.177	0.1771		
BI1	BI1	0.52815	0.0000	0.52815	0.528	0.5282		
SI	SI	0.78116	0.0886	0.60754	0.955	1.0000	8.818	<.001
BI	BI	0.00979	0.0797	-0.14643	0.166	0.0115	0.123	0.902

Intercepts

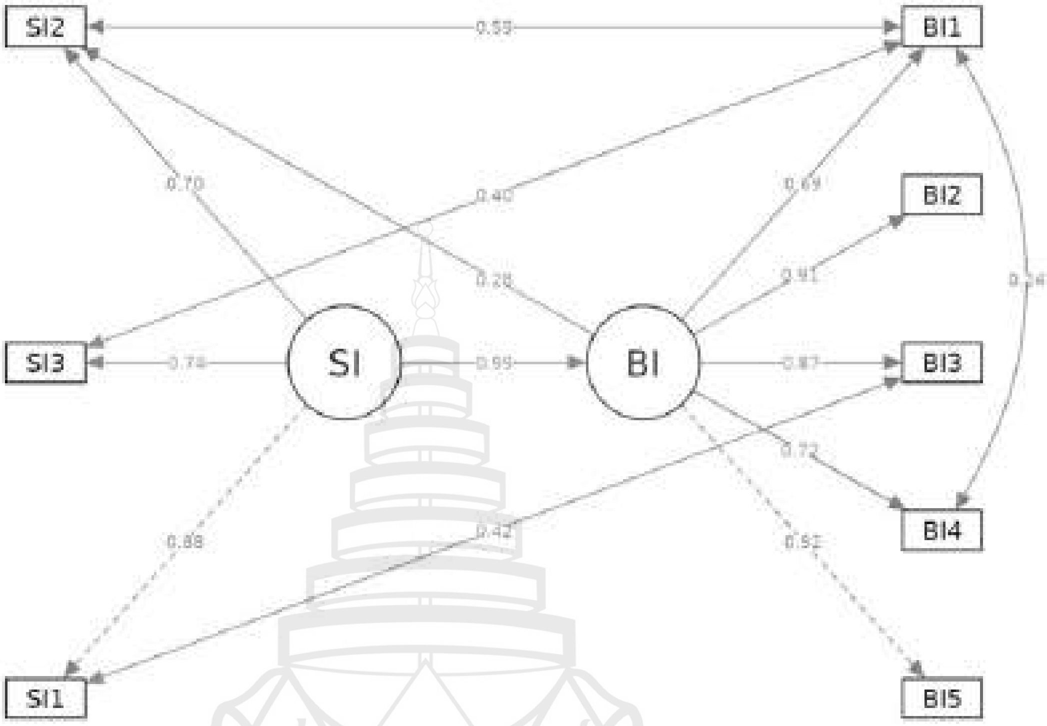
Variable	Intercept	SE	95% Confidence Intervals Lower	Upper	z	p
SI1	0.000	0.000	0.000	0.000		
SI3	0.000	0.000	0.000	0.000		
SI2	0.000	0.000	0.000	0.000		
BI5	0.000	0.000	0.000	0.000		
BI4	0.000	0.000	0.000	0.000		
BI3	0.000	0.000	0.000	0.000		
BI2	0.000	0.000	0.000	0.000		
BI1	0.000	0.000	0.000	0.000		
SI	0.000	0.000	0.000	0.000		
BI	0.000	0.000	0.000	0.000		

Thresholds

				95% Confidence Intervals			
Variable	Step	Thresholds	SE	Lower	Upper	z	p
SI1	t1	-1.087	0.138	-1.357	-0.817	-7.898	<.001
SI1	t2	0.354	0.113	0.133	0.576	3.139	0.002
SI1	t3	2.160	0.280	1.611	2.709	7.715	<.001
SI3	t1	-1.870	0.219	-2.298	-1.441	-8.544	<.001
SI3	t2	-0.174	0.111	-0.392	0.043	-1.572	0.116
SI3	t3	1.123	0.140	0.849	1.397	8.034	<.001
SI2	t1	-1.123	0.140	-1.397	-0.849	-8.034	<.001
SI2	t2	0.334	0.113	0.113	0.555	2.965	0.003
BI5	t1	-0.524	0.116	-0.752	-0.297	-4.519	<.001
BI5	t2	0.662	0.120	0.428	0.897	5.538	<.001
BI5	t3	2.423	0.363	1.711	3.135	6.671	<.001
BI4	t1	-1.769	0.203	-2.166	-1.371	-8.720	<.001
BI4	t2	-0.097	0.111	-0.313	0.120	-0.874	0.382
BI4	t3	1.542	0.174	1.201	1.883	8.855	<.001
BI3	t1	-0.375	0.113	-0.597	-0.153	-3.312	<.001
BI3	t2	0.927	0.129	0.673	1.181	7.163	<.001
BI3	t3	2.423	0.363	1.711	3.135	6.671	<.001
BI2	t1	-0.417	0.114	-0.640	-0.193	-3.658	<.001
BI2	t2	1.282	0.151	0.987	1.577	8.515	<.001
BI1	t1	-1.994	0.242	-2.468	-1.520	-8.242	<.001
BI1	t2	-0.253	0.112	-0.472	-0.035	-2.269	0.023
BI1	t3	1.087	0.138	0.817	1.357	7.898	<.001

Path Model

Path diagrams


SI2
BI1
BI2
SI3
SI
BI
BI3
BI4
SI1
BI5
0.70
0.40
0.69
0.28
0.91
0.78
0.87
0.72
0.88
0.42

Path Analysis of TA to BI

Results

Structural Equation Models

Models Info

Estimation Method	**DWLS**
Optimization Method	**NLMINB**
Number of observations	**130**
Free parameters	**38**
Standard errors	**Robust**
Scaled test	**Mean adjusted scaled and shifted**
Converged	**TRUE**
Iterations	**38**
Model	**TA=~TA3+TA5+TA4 +TA2+TA1**
	BI=~BI2+BI5+BI4 +BI3+BI1
	BI~TA
	TA4~~TA2
	TA3~~TA1
	TA5~~TA1
	BI5~~BI3

Note. Variable (TA3,TA5,TA4,TA2,TA1,BI2,BI5,BI4,BI3,BI1) has been coerced to ordered type.

Note. lavaan->lav_samplestats_step2(): correlation between variables BI2 and TA1 is (nearly) 1.0

Note. lavaan->lav_model_vcov(): The variance-covariance matrix of the estimated parameters (vcov) does not appear to be positive definite! The smallest eigenvalue (= -1.896999e-17) is smaller than zero. This may be a symptom that the model is not identified.

Note. lavaan->lav_object_post_check(): some estimated ov variances are negative

[3] [4]

Overall Tests

Model tests

Label	X^2	df	p
User Model	30.4	30	0.444
Baseline Model	14569.7	45	<.001
Scaled User	42.3	30	0.068
Scaled Baseline	8818.1	45	<.001

Fit indices

			95% Confidence Intervals		
Type	SRMR	RMSEA	Lower	Upper	RMSEA p
Classical	0.044	0.011	0.000	0.068	0.823
Robust	0.037				
Scaled	0.037	0.056	0.000	0.093	0.369

User model versus baseline model

	Model
Comparative Fit Index (CFI)	1.000
Tucker-Lewis Index (TLI)	1.000
Bentler-Bonett Non-normed Fit Index (NNFI)	1.000
Relative Noncentrality Index (RNI)	1.000
Bentler-Bonett Normed Fit Index (NFI)	0.998
Bollen's Relative Fit Index (RFI)	0.997
Bollen's Incremental Fit Index (IFI)	1.000
Parsimony Normed Fit Index (PNFI)	0.665

Estimates

Parameters estimates

				95% Confidence Intervals				
Dep	Pred	Estimate	SE	Lower	Upper	β	z	p
BI	TA	0.737	0.0320	0.674	0.800	0.950	23.0	<.001

Measurement model

				95% Confidence Intervals				
Latent	Observed	Estimate	SE	Lower	Upper	β	z	p
TA	**TA3**	1.000	0.0000	1.000	1.000	1.146		
	TA5	0.693	0.0452	0.604	0.781	0.794	15.3	<.001
	TA4	0.664	0.0377	0.590	0.738	0.761	17.6	<.001
	TA2	0.625	0.0343	0.558	0.692	0.716	18.2	<.001
	TA1	0.961	0.0333	0.896	1.026	1.101	28.9	<.001
BI	**BI2**	1.000	0.0000	1.000	1.000	0.889		
	BI5	0.917	0.0351	0.849	0.986	0.815	26.1	<.001
	BI4	0.860	0.0396	0.782	0.938	0.764	21.7	<.001
	BI3	0.915	0.0376	0.841	0.989	0.813	24.4	<.001
	BI1	0.900	0.0342	0.833	0.967	0.800	26.3	<.001

Variances and Covariances

Variable 1	Variable 2	Estimate	SE	95% Confidence Intervals Lower	Upper	β	z	p
TA4	TA2	0.3091	0.0430	0.2249	0.393	0.6823	7.19	<.001
TA3	TA1	-0.2877	0.0597	-0.4046	-0.171	-1.1151	-4.82	<.001
TA5	TA1	-0.2113	0.0568	-0.3226	-0.100	-0.7540	-3.72	<.001
BI5	BI3	0.1532	0.0591	0.0375	0.269	0.4550	2.59	0.009
TA3	TA3	-0.3132	0.0000	-0.3132	-0.313	-0.3132		
TA5	TA5	0.3696	0.0000	0.3696	0.370	0.3696		
TA4	TA4	0.4212	0.0000	0.4212	0.421	0.4212		
TA2	TA2	0.4873	0.0000	0.4873	0.487	0.4873		
TA1	TA1	-0.2125	0.0000	-0.2125	-0.213	-0.2125		
BI2	BI2	0.2099	0.0000	0.2099	0.210	0.2099		
BI5	BI5	0.3352	0.0000	0.3352	0.335	0.3352		
BI4	BI4	0.4158	0.0000	0.4158	0.416	0.4158		
BI3	BI3	0.3384	0.0000	0.3384	0.338	0.3384		
BI1	BI1	0.3607	0.0000	0.3607	0.361	0.3607		
TA	TA	1.3132	0.0635	1.1888	1.438	1.0000	20.69	<.001
BI	BI	0.0766	0.0318	0.0143	0.139	0.0970	2.41	0.016

Intercepts

Variable	Intercept	SE	95% Confidence Intervals Lower	Upper	z	p
TA3	0.000	0.000	0.000	0.000		
TA5	0.000	0.000	0.000	0.000		
TA4	0.000	0.000	0.000	0.000		
TA2	0.000	0.000	0.000	0.000		
TA1	0.000	0.000	0.000	0.000		
BI2	0.000	0.000	0.000	0.000		
BI5	0.000	0.000	0.000	0.000		
BI4	0.000	0.000	0.000	0.000		
BI3	0.000	0.000	0.000	0.000		
BI1	0.000	0.000	0.000	0.000		
TA	0.000	0.000	0.000	0.000		
BI	0.000	0.000	0.000	0.000		

Thresholds

				95% Confidence Intervals			
Variable	Step	Thresholds	SE	Lower	Upper	z	p
TA3	t1	-0.155	0.111	-0.372	0.062	-1.397	0.162
TA5	t1	-0.957	0.131	-1.214	-0.701	-7.316	<.001
TA5	t2	0.214	0.111	-0.004	0.432	1.921	0.055
TA4	t1	-1.482	0.168	-1.811	-1.153	-8.825	<.001
TA4	t2	0.155	0.111	-0.062	0.372	1.397	0.162
TA2	t1	-1.282	0.151	-1.577	-0.987	-8.515	<.001
TA2	t2	0.174	0.111	-0.043	0.392	1.572	0.116
TA1	t1	-2.160	0.280	-2.709	-1.611	-7.715	<.001
TA1	t2	-0.019	0.110	-0.236	0.197	-0.175	0.861
BI2	t1	-0.417	0.114	-0.640	-0.193	-3.658	<.001
BI2	t2	1.282	0.151	0.987	1.577	8.515	<.001
BI5	t1	-0.524	0.116	-0.752	-0.297	-4.519	<.001
BI5	t2	0.662	0.120	0.428	0.897	5.538	<.001
BI5	t3	2.423	0.363	1.711	3.135	6.671	<.001
BI4	t1	-1.769	0.203	-2.166	-1.371	-8.720	<.001
BI4	t2	-0.097	0.111	-0.313	0.120	-0.874	0.382
BI4	t3	1.542	0.174	1.201	1.883	8.855	<.001
BI3	t1	-0.375	0.113	-0.597	-0.153	-3.312	<.001
BI3	t2	0.927	0.129	0.673	1.181	7.163	<.001
BI3	t3	2.423	0.363	1.711	3.135	6.671	<.001
BI1	t1	-1.994	0.242	-2.468	-1.520	-8.242	<.001
BI1	t2	-0.253	0.112	-0.472	-0.035	-2.269	0.023
BI1	t3	1.087	0.138	0.817	1.357	7.898	<.001

Modifcation Indices

Modification indices

			Modif. index	EPC	sEPC (LV)	sEPC (all)	sEPC (nox)
BI	=~	**TA1**	33003.99	136.009	120.893	120.893	120.893
BI	=~	**TA3**	16763.75	94.441	83.945	83.945	83.945
BI	=~	**TA5**	3203.93	38.659	34.363	34.363	34.363
TA2	~~	**BI5**	4.77	0.143	0.143	0.354	0.354
BI2	~~	**BI5**	4.75	-0.134	-0.134	-0.505	-0.505
TA	=~	**BI1**	4.39	-0.878	-1.006	-1.006	-1.006
BI2	~~	**BI1**	3.03	0.105	0.105	0.383	0.383

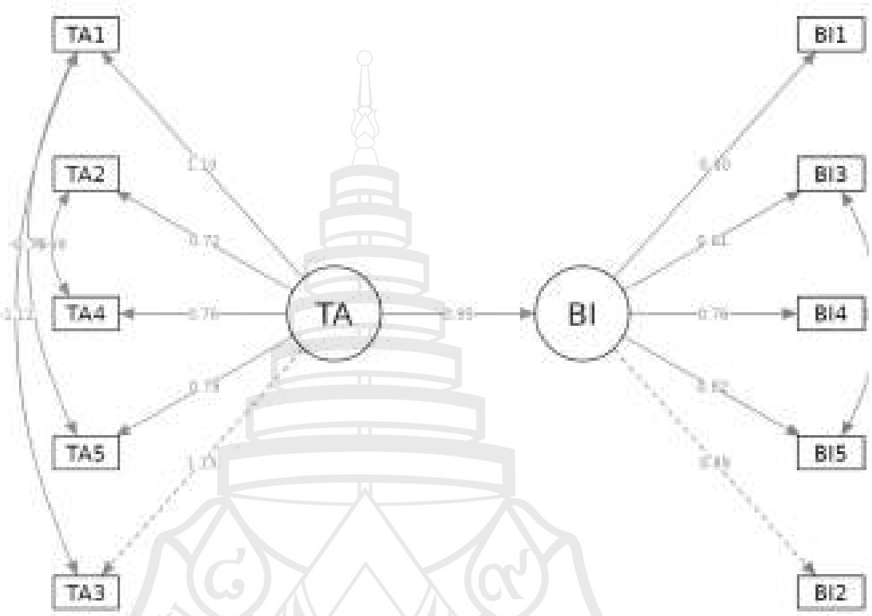
Note. lavaan->lav_start_check_cov(): starting values imply a correlation larger than 1; variables involved are: TA3 TA1

Note. NaNs produced

Note. lavaan->lav_start_check_cov(): starting values imply NaN for a correlation value; variables involved are: TA5 TA1

Path Model

Path diagrams



[5]

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Results

Structural Equation Models

APPENDIX G

RESEARCH PUBLICATION

dusit thani college

BEYOND EDUCATION

DTC.717/2025

30 April 2025

Decision on your manuscript – Dusit Thani College Journal

Dear Ms. Jeeranan Wandee, Damrongpol Kamhangwong, Ph.D. and Samatthachai Yamsa-ard, Ph.D.

Your submitted article entitled "Alternative UTAUT Model Influencing the Adoption of a Blockchain Traceability Platform in the Rubber Industry Supply Chain in Thailand" has now been reviewed and follow the process of peer reviewed at least 3 experts from various institutions. I am pleased to accept your article, which will be published in Dusit Thani College Journal Year 2025 Volume 19 Issue 1 (January – April 2025).

Thank you for your contribution to Dusit Thani College Journal and we look forward to receiving further submissions from you.

Best regards,

Siripong Rugmai, Ph.D.
Editor of Dusit Thani College Journal

Remark: Dusit Thani College Journal ISSN 1906-070X is a certified quality journals in Group 2 (Tier2) of Quality Assessment by Thai-Journal Citation Index (TCI) Centre.
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Bangkok: 1 Soi Kaenthong, Nongbon, Prawet, Bangkok 10250 Thailand **Tel**: +66 (0) 2361 7811-5 **Fax**: +66 (0) 2361 7806
Pattaya: 382/2 Moo 6 Sukhumvit Rd., Banglamung, Chonburi 20150 Thailand **Tel**: +66 (0) 3848 8463-7 **Fax**: +66 (0) 3848 8955
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แบบจำลองทางเลือกของ UTAUT ที่มีอิทธิพลต่อการยอมรับแพลตฟอร์มการตรวจสอบย้อนกลับด้วยบล็อกเชนในห่วงโซ่อุปทานอุตสาหกรรมยางพาราของประเทศไทย

ธีรนันท์ วันดี[1] ธำรงพล คำแหงวงศ์[2] และสมรรถชัย แย้มสอาด[3*]

[1]สำนักวิชาการจัดการ มหาวิทยาลัยแม่ฟ้าหลวง
[2]สำนักวิชาอุตสาหกรรมเกษตร มหาวิทยาลัยแม่ฟ้าหลวง
[3]ศูนย์วิจัยการประเมินวัฏจักรชีวิตเพื่ออุตสาหกรรมเกษตรและธุรกิจ มหาวิทยาลัยแม่ฟ้าหลวง

*Corresponding Author Email: samatthachai.yam@mfu.ac.th

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บทคัดย่อ

การศึกษานี้มีวัตถุประสงค์เพื่อสำรวจปัจจัยที่เกี่ยวข้องกับแพลตฟอร์มบล็อกเชนในการตรวจสอบย้อนกลับภายใต้แบบจำลอง UTAUT ที่ตั้งสมมติฐานไว้ และเพื่อพัฒนาแบบจำลอง UTAUT ทางเลือก ที่มีอิทธิพลต่อการนำแพลตฟอร์มบล็อกเชนในการนำไปใช้ในห่วงโซ่อุปทานอุตสาหกรรมยางพาราของประเทศไทย โดยได้ทดสอบแบบจำลอง UTAUT แบบดั้งเดิมร่วมกับการเพิ่มปัจจัยความวิตกกังวลทางเทคโนโลยี (TA) ซึ่งได้ตั้งสมมติฐานว่ามีอิทธิพลต่อการยอมรับแพลตฟอร์มบล็อกเชนของผู้มีส่วนได้ส่วนเสีย ในการนี้แบบจำลอง UTAUT แบบดั้งเดิมประกอบด้วยปัจจัยอิทธิพลทางสังคม (SI), เงื่อนไขส่งเสริม (FC), การคาดหวังด้านประสิทธิภาพ (PE) และการคาดหวังด้านความพยายาม (EE) ซึ่งปัจจัยดังกล่าวอาจมีอิทธิพลต่อความตั้งใจในการใช้งาน (BI) กลุ่มตัวอย่าง คือ ผู้มีส่วนได้ส่วนเสีย จำนวน 130 ราย เครื่องมือที่ใช้ในการวิจัย คือ แบบสอบถาม วิเคราะห์ผลการทดลองโดยใช้เทคนิค Structural Equation Modeling (SEM) โดยโปรแกรม Excel และโปรแกรม JAMOVI เวอร์ชัน 2.6 เพื่อทดสอบแบบจำลอง UTAUT ที่ตั้งสมมติฐานไว้และแบบจำลอง UTAUT ทางเลือก

ผลการวิจัยพบว่า แบบจำลอง UTAUT ที่ตั้งสมมติฐาน ไม่สอดคล้องกับข้อมูลเชิงประจักษ์ จึงนำเสนอผลการวิเคราะห์แบบจำลอง UTAUT ทางเลือก ซึ่งพบว่าสอดคล้องกับข้อมูลเชิงประจักษ์ โดย BI มีอิทธิพลอย่างชัดเจนต่อการนำมาใช้ในห่วงโซ่อุปทานอุตสาหกรรมยางพารา ซึ่งสรุปได้ว่า ปัจจัย FC มีอิทธิพลโดยตรงต่อ BI ($\beta = 0.996$; $p<0.001$) ซึ่ง FC สามารถส่งเสริมการขับเคลื่อนพฤติกรรมของผู้มีส่วนได้ส่วนเสียในกระบวนการของห่วงโซ่ยางพารา และเน้นความสำคัญของ FC เช่น โครงสร้างพื้นฐานด้านเทคโนโลยีสารสนเทศ การปรับปรุงกฎระเบียบให้ทันสมัย และการฝึกอบรมด้านเทคโนโลยีบล็อกเชนให้แก่ผู้มีส่วนได้ส่วนเสีย อย่างไรก็ตาม ปัจจัย TA, PE, SI และ EE ได้ส่งผลอิทธิพลทางอ้อมต่อ BI ดังนั้น จากผลการศึกษาดังกล่าว จึงได้มีข้อเสนอแนะสำหรับผู้กำหนดนโยบายของประเทศไทย เพื่อพิจารณาสนับสนุนและส่งเสริมการนำแพลตฟอร์มบล็อกเชนสำหรับการตรวจสอบย้อนกลับมาใช้ในห่วงโซ่อุปทานอุตสาหกรรมยางพาราของประเทศไทยต่อไป

คำสำคัญ: แบบจำลอง UTAUT ห่วงโซ่อุปทานยางพารา เทคโนโลยีบล็อกเชน พฤติกรรมการยอมรับ โมเดลทางเลือก

Alternative UTAUT Model Influencing the Adoption of a Blockchain Traceability Platform in the Rubber Industry Supply Chain in Thailand

Jeeranan Wandee[1], Damrongpol Kamhangwong[2] and Samatthachai Yamsa-ard[1*]

[1]School of Management, Mae Fah Luang University

[2]School of Agro-Industry, Mae Fah Luang University

[3]Digital Transformation Research Center for Agro-Industry and Business, Mae Fah Luang University

*Corresponding Author Email: samatthachai.yam@mfu.ac.th

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Abstract

This study aimed to explore factors related to the blockchain traceability platform within the hypothesis of the Unified Theory of Acceptance and Use of Technology (UTAUT) model. and to develop an alternative UTAUT model that influenced the adoption of a blockchain traceability platform in the rubber industry supply chain in Thailand. The study employed the conventional UTAUT model by incorporating the Technological Anxiety (TA) factor, which was hypothesized to influence stakeholders' adoption of the blockchain traceability platform. The conventional UTAUT model included Social Influence (SI), Facilitating Conditions (FC), Performance Expectancy (PE), and Effort Expectancy (EE) factors, all of which were theorized to influence Behavioral Intention (BI). The sample group consisted of 130 stakeholders. The research tool was a questionnaire, and the results were analyzed using Structural Equation Modeling (SEM), utilized Excel and JAMOVI Software (Version 2.6), for statistical analysis, testing both the hypothesis of the UTAUT model and an alternative UTAUT model.

The findings revealed that the hypothesis of the UTAUT model was not consistent with the empirical data. Therefore, an alternative UTAUT model was proposed, which was found to be consistent with the empirical data. In this model, BI had a clear influence on the adoption of blockchain in the rubber supply chain industry. It was concluded that FC had a direct influence on BI (β = 0.996; p < 0.001). FC plays a significant role in driving stakeholder participation in the rubber supply chain process and highlights the importance of facilitating conditions, such as information technology infrastructure, regulatory modernization, and blockchain technology training for stakeholders. However, TA, PE, SI, and EE were found to have an indirect influence on BI. Based on these findings, the study provides specific recommendations for each factor, suggesting that RAOT should support and encourage the adoption of the blockchain traceability platform in Thailand's rubber industry supply chain.

Keywords: UTAUT Model, Rubber Supply Chain, Blockchain Technology, Adoption Behavior, Alternative Model

Introduction

Natural rubber, also known as India rubber, is derived from latex produced by rubber trees. Thailand is the world's leading natural rubber producer, contributing 33% of global production in 2022. In this business line, the Thai government established the Rubber Authority of Thailand (RAOT) in 2015 to support the rubber industry, improve stakeholder livelihoods, and stabilize prices. At the present, RAOT is facing challenges in managing big data related to rubber production and trade, which hinders effective supply chain management and demand forecasting. With the advancement of digital technology, the blockchain technology is considered as a decentralized technology, with its transparency, security, and reliability, offering a potential solution to these challenges by enabling efficient data management and traceability. While the Unified Theory of Acceptance and Use of Technology (UTAUT) framework is interesting for understanding how and why people accept and use technology, it can be useful to solve these challenges of the RAOT in the future (Venkatesh et al., 2003).

Due to abovementioned in term of stakeholders, RAOT's challenges and a potential technological solution as "Blockchain Traceability Platform", it is important for finding what is an essential key success to the implementation of Blockchain in Thai rubber industry. It may be the acceptance of all stakeholders in cooperation with the implementation process. However, it is necessary for the study to find out the factors influencing the way of all stakeholders' acceptance, the UTAUT will be appropriate model to test the acceptance of technology among all stakeholders in rubber supply chain.

Therefore, this study aims to explore the digital technology as the blockchain to overcome challenges by applying the possible Unified Theory of Acceptance and Use of Technology (UTAUT) framework in order to test the factors influencing the adoption of the blockchain technology in the rubber industry supply chain in Thailand.

Research Objectives

1. To explore factors that are related to the blockchain traceability platform within the hypothesis of the Unified Theory of Acceptance and Use of Technology (UTAUT) model.

2. To develop an alternative UTAUT model that influences the adoption of a blockchain traceability platform in the rubber industry supply chain in Thailand.

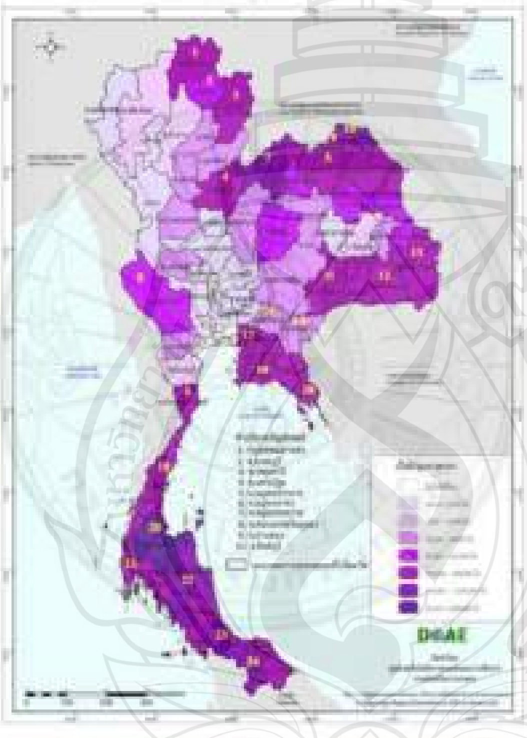
Scope of Study Area

1. The scope of contents: The study of five factors including Social Influence (SI), Facilitating Conditions (FC), Performance Expectancy (PE), Effort Expectancy (EE) and Technological Anxiety (TA) that influence the Behavioral Intention (BI).

2. The scope of population and sample size: This research focused on a total of 130 respondents from five groups of stakeholders (farmers, collectors, exporters, government agencies, and others) in the rubber supply chain in Thailand. Due to the high cost of the technology and limitations of the data server, the study specifically targeted large landowners owning more than 100 rai, as well as the 10 largest businesses registered in the government database, which had a significant impact on the industry.

3. The Scope of Area: Covering five regions and 24 provinces, including the Northern, Central, Northeastern, Eastern, and Southern regions. The sample distribution across these regions is illustrated in Figure 1.

4. The scope of period: November 2023 – April 2024



Regions	Provinces
Northern	1. Chiang Rai
	2. Phayao
	3. Nan
	4. Phitsanulok
Central	5. Kanchanaburi
	6. Prachuap Khiri Khan
Northeastern	7. Loei
	8. Udon Thani
	9. Nong Khai
	10. Bueng Kan
	11. Buri Ram
	12. Si Sa Ket
	13. Ubon Ratchathani
Eastern	14. Prachinburi
	15. Sa Kaeo
	16. Rayong
	17. Chachoengsao
	18. Trat
Southern	19. Chumphon
	20. Surat Thani
	21. Phang Nga
	22. Nakhon Si Thammarat
	23. Songkhla
	24. Yala

Figure 1 The Map of Sample Distribution in Rubber Supply Chain
(Adapted from Department of Agricultural Extension (2022).

Conceptual Framwork

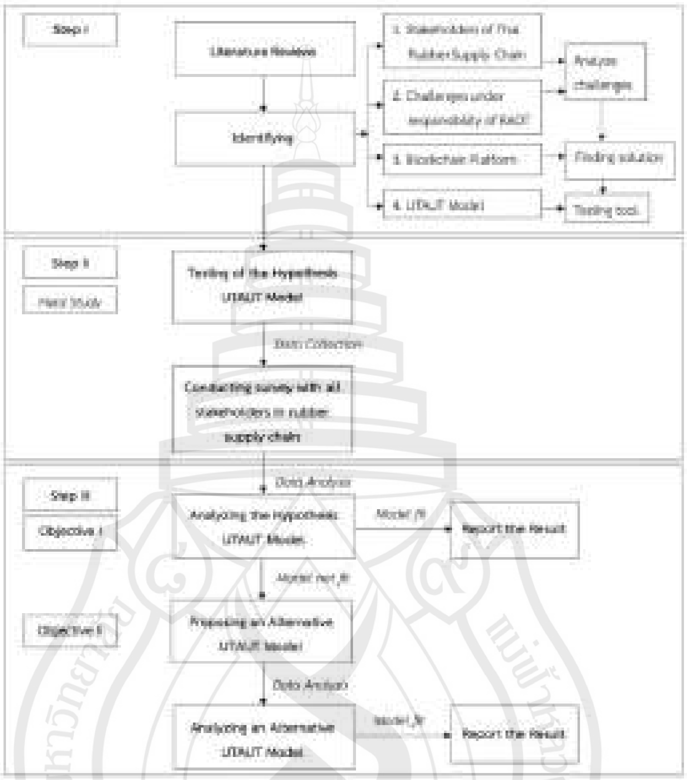


Figure 2 Conceptual Framwork

Literature Reviews

Thailand's rubber industry, governed by the Rubber Control Act (1999) and the Rubber Authority of Thailand Act (2015), operated through a structured three-tier supply chain (upstream, midstream, downstream), maintaining its global leadership. However, the sector faced price volatility as the major challenge due to supply-demand imbalances, economic slowdowns in key markets (China, the US, Japan), and investor speculation in futures markets. Although supply-demand imbalances were considered a minor challenge, they underscored the need for innovative solutions by RAOT, such as the adoption of blockchain technology to enhance transparency and stabilize the market, especially in relation to the Rubber Trading License Policy, which was the root cause of the lack of data on domestic supply and demand. RAOT needed to address data gaps and improve stakeholder collaboration to strengthen supply chain efficiency and maintain competitiveness.

Thailand's rubber sector faced critical data management challenges, with RAOT struggling to integrate rubber production and trade data across government and private stakeholders. This data fragmentation hindered effective supply chain management and accurate demand forecasting. Blockchain technology offered a transformative solution through its decentralized, transparent ledger system since its 2008 introduction (Nakamoto, 2008; Chang & Chen, 2020). Proven successful in agriculture for traceability and verification (Lin et al., 2020), blockchain could enhance supply chain visibility, improve demand-supply balance and reduce price volatility (Wang et al., 2020).

To understand stakeholder acceptance of blockchain technology in Thailand's rubber industry, this study employed the Unified Theory of Acceptance and Use of Technology (UTAUT) as its theoretical framework. Originally developed by Venkatesh et al. (2003), the conventional UTAUT model examines four factors: (1) Performance Expectancy (PE) refers to the extent to which an individual believes that using a new system will enhance job performance, with this relationship moderated by gender and age (Venkatesh et al., 2003), (2) Effort Expectancy (EE) refers to the degree of ease associated with using a new system, with this relationship moderated by gender, age, and experience (Venkatesh et al., 2003), (3) Social Influence (SI) refers to the extent to which an individual perceives that others' beliefs influence their decision to use a new system, with this relationship moderated by gender, age, experience, and voluntariness (Venkatesh et al., 2003), and (4) Facilitating Conditions (FC) refers to the extent to which an individual believes that an organization's system and technical infrastructure support the use of a new system, with this relationship moderated by age and experience (Venkatesh et al., 2003). This research extended the conventional UTAUT model by incorporating Technological Anxiety (TA) is defined based on Bozionelos (2001) study, which investigated computer anxiety related to the use of computers, an additional factor that Bozionelos (2001) did a research. The hypothesis UTAUT model was visually shown in Figure 3 and supported by previous research findings presented in Table 1.

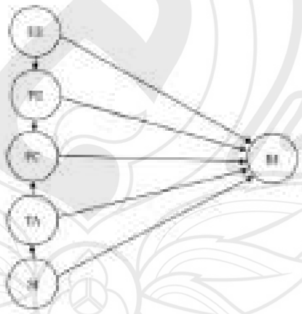


Figure 3 The Hypothesis UTAUT Model with Additional TA Factor

(Adapted from Venkatesh et al., 2003)

Table 1 Previous Studies Related to Various Factors in the UTAUT Model

Author	Category Field	Factors Influenced to BI					FC	PE	TA
		PE	EE	SI	FC	TA	Others		
Budhathoki et al., 2024	ChatGPT	√	√	√	√	√	-	-	-
Popova and Zagulova, 2022	Smart City	√	-	√	-	-	-	FC	-
Smyth et al., 2021	Automated Vehicles	-	-	-	-	-	-	EE	-
Gunasinghe et al., 2019	Education	√	-	-	√	√	-	TA	-

Methodology

1. Data Collection

This study collected data by implementing a constructed questionnaire survey approach. The development process began with focus group meetings involving stakeholders and experts to identify key concerns and challenges related to the study objectives. Insights from these meetings, along with open-ended responses, informed the initial draft of the questionnaire. The draft was reviewed by senior supply chain specialists to ensure alignment with the study's objectives. The final questionnaire designed based on focus group feedback and specialist input (Mazur and Bennett, 2008) included closed-ended questions and a 7-point Likert scale for responses, ranging from 1 (Strongly Disagree) to 7 (Strongly Agree). The scale was chosen to provide greater response variety and better capture stakeholders' perceptions and beliefs (Joshi et al., 2015).

2. Sample Groups

This study determined the sample size for structural equation modeling (SEM) using Analytics Calculators (2024), a widely used tool for calculating sample sizes. The calculation indicated that the recommended minimum sample size was 88 stakeholders from the rubber supply chain industry in Thailand. The research was designed using a multi-stage sampling method, combining stratified random sampling and quota sampling. A total of 150 respondents were selected from five groups of stakeholders in the rubber supply chain across Thailand, covering the northern, northeastern, central, eastern, and southern regions, as shown in Figure 1. The details of the sample groups were as follows.

2.1 Farmers: There were 1,667,095 rubber farming families, most of whom owned areas of 20–50 rai, registered in the government database for growing rubber trees and producing materials such as cup lump, latex, and crepe rubber, which were sold to collectors. This study focused on large landowners, specifically those owning more than 100 rai, who represented 0.01% of the families registered in the government database.

2.2 Collectors: There were around 1,000 middlemen and factories registered in the government database. The middlemen and factory operators purchased natural rubber from farmers, processed it into semi-finished or finished products, and sold it to exporters or other buyers. This study focused on the 10 largest businesses registered in the government database.

2.3 Exporters: There were 38 export companies registered in the government database. They were responsible for exporting semi-finished products (e.g., block rubber, ribbed smoked sheets) and finished products (e.g., tires, medical gloves). This study focused on the 10 largest businesses registered in the government database.

2.4 Government Agencies: The government agencies involved in the Thai rubber supply chain included three key organizations: the Rubber Authority of Thailand (RAOT), the Department of Agriculture (DOA), and the Customs Department. These agencies played important roles in the rubber industry supply chain. This research focused on executives, heads of rubber divisions, and staff responsible for rubber data.

2.5 Others: This group included brokers from the business sector, who facilitated trade within the supply chain, and rubber scholars from government agencies and universities, who contributed academic and technical expertise to the industry.

3. Statistical Data Analysis

Structural Equation Modeling (SEM): SEM was used to analyze the relationships between observed and latent variables, providing a systematic method for testing hypotheses. The proposed modified UTAUT model was evaluated using SEM in five steps, following Schumacker and Lomax's structural thinking framework (Suksawang, 2020), and based on the conceptual framework shown in Figure 2. The study utilized Excel and JAMOVI software (version 2.6) (The jamovi project, 2024) for statistical analysis. JAMOVI is a modern, user-friendly, open-source alternative to proprietary software such as SPSS, and was applied for testing both the hypothesis and the alternative UTAUT model. Licensed under the GNU General Public License (GPL), it is entirely free and is becoming increasingly popular alongside established tools such as LISREL, AMOS, and Mplus. Its accessibility and ease of use made it an effective choice for data analysis in this study.

Research Results

1. Respondent's General Information

The validity of the questionnaire from the focus group comprised 27 statement items as shown in Annex 1. The results of questionnaire survey was distributed to 130 respondents, with demographic analysis revealing the following key characteristics: Gender: 98% male (typically family heads and key contributors to the rubber industry) and 2% female; Experience: Most respondents have over five years of experience, establishing them as industry specialists; Age: Predominantly between 51-65 years; Occupation: Farmers (51%), collectors (12%), government agencies (22%), exporters (12%), and others, including brokers and rubber scholars (1%). These findings are summarized in Table 1.

Table 2 Respondent's General Information

General Information	Items	Number	Percentage (%)
Gender	Male	128	98%
	Female	2	2%
Age range	31-65		
Experience	Over 5 years	130	100%
Stakeholders	Farmers (F)	40	31%
	Collectors (C)	29	22%
	Government Agencies (G)	29	22%
	Exporters (E)	15	12%
	Others (Brokers, Rubber Scholars) (O)	17	13%
Total		**130**	**100%**

2. Path Analysis of the Hypothesis UTAUT Model

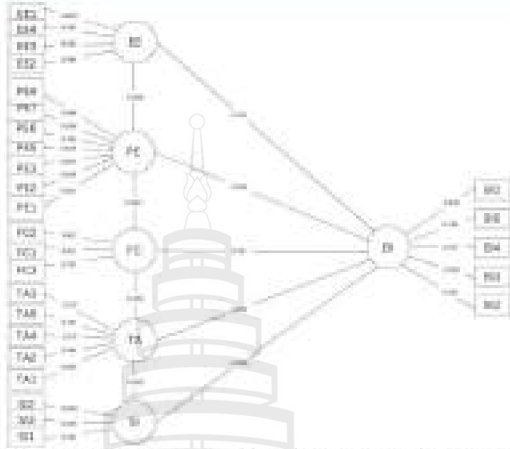
The analysis consider the β ratios, z ratios, and *p*-values. The acceptance criteria require that the values of β do not exceed the threshold of 1 and are in a positive direction, with $z > 1.96$ being significant at 0.05 or $z > 2.58$ being significant at 0.01, as the rule of thumb. These results must align with the criteria for model fit with $N < 250$ and $12 < m < 30$ which require a Relative Chi-Square of less than 2, RMSEA or SRMR values below 0.08, CFI or TLI values above 0.97 (Hair et al., 2019).

The results showed that the hypothesized UTAUT model was not consistent with the empirical data and could not be accepted, as shown in Table 3 and Figure 4. One possible reason was that the factors had an indirect influence on behavioral intention (BI). Therefore, it was necessary for this study to propose an alternative UTAUT model, developed based on information gathered during the focus group discussion, which better fits the adoption of the blockchain traceability platform, as shown in Table 4 and Figure 5.

Table 3 Path Analysis of the Hypothesis Structural Model

Construct path			β	z	p-value	Result
PE	→	B	0.0281	0.153	0.878	Rejected
EE	→	B	0.3850	1.091	0.275	Rejected
SI	→	B	-0.2891	-1.021	0.307	Rejected
FC	→	B	0.3567	1.534	0.125	Rejected
TA	→	B	0.6003	1.980	0.048	Accepted
PE	→	FC	0.3618	2.351	0.019	Accepted
TA	→	FC	0.7201	4.650	<.001	Accepted
EE	→	PE	0.9292	20.346	<.001	Accepted
SI	→	TA	0.9516	28.881	<.001	Accepted

Note: m = number of observed variables; N = applies to a number of observations per group when applying CFA to multiple groups at the same time.



Chi-Square (χ^2)= 328, df = 314, Relative Chi-Square= 1.0 , p-value = 0.977 , RMSEA = 0.011, SRMR = 0.048, CFI = 1.000, TLI = 1.000

Figure 4 The Hypothesis UTAUT Model.

3. Path Analysis of an Alternative UTAUT Model

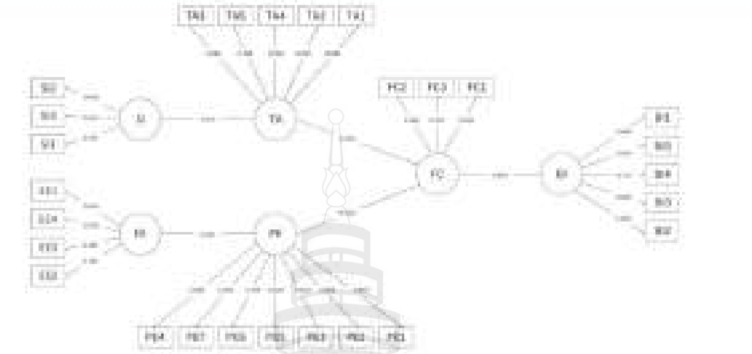
The analysis consider the β ratios, z-ratios, and *p*-values. The acceptance criteria require that the values of β do not exceed the threshold of 1 and are in a positive direction, with $z > 1.96$ being significant at 0.05 or $z > 2.58$ being significant at 0.01, as the rule of thumb. These results must align with the criteria for model fit with $N < 250$ and $12 < m < 30$ which require a Relative Chi-Square of less than 2, RMSEA or SRMR values below 0.08, CFI or TLI values above 0.97 (Hair et al., 2019).

The results showed that the alternative UTAUT model was consistent with the empirical data, indicating that the model was a good fit. Moreover, the alternative model included six factors, with the strongest influencing indicators for each factor listed, as shown in Table 4 and Figure 4.

Table 4 The Path Analysis of an Alternative UTAUT Model

Construct path	β	z	*p*-value	Result
FC → BI	0.996	28.73	<0.001	Accepted
PE → FC	0.900	2.47	0.015	Accepted
TA → FC	0.759	6.05	<0.001	Accepted
EE → PE	0.911	19.75	<0.001	Accepted
SI → TA	0.975	24.57	<0.001	Accepted

Note: m = number of observed variables; N = applied to a number of observations per group when applying CFA to multiple groups at the same time.



Chi-Square (χ2) = [illegible], df = [illegible], Relative Chi-Square= [illegible], p-value <0.001, RMSEA = [illegible], SRMR = [illegible], CFI = [illegible], TLI = [illegible]

Figure 5 An Alternative UTAUT Model

Discussion and Conclusion

Discussion

1. The effect of the hypothesis UTAUT model on the behavior intention (BI) of a blockchain traceability platform.

These results indicate that the hypothesis based on the UTAUT model, which incorporated the addition of "Technological Anxiety (TA)" from Bozionelos (2001) into the model structure. The model had a non-significant influence on the intention to adopt a blockchain traceability platform in Thailand's rubber industry supply chain, and was therefore rejected, as shown in Table 3 and Figure 4. One possible explanation for these results is that TA, PE, EE, SI, and FC may have an indirect rather than a direct influence on Behavioral Intention (BI). The findings show that only TA had a direct influence on BI, while the other constructs did not. Therefore, it was found that PE and TA influence FC, EE influences PE, and SI influences TA.

2. The effect of an alternative UTAUT model on the behavior intention (BI) of a blockchain traceability platform.

on Behavioral Intention (BI), this study aimed to further explore how individual factors influence BI. Therefore, an alternative UTAUT model was developed by integrating SI, TA, EE, PE, and FC, all of which are consistent with BI toward the adoption of a blockchain traceability platform in Thailand's rubber industry supply chain. The path coefficients of the alternative UTAUT model were constructed based on findings from the hypothesis UTAUT model results and 27 statement items gathered from focus group discussions with stakeholders. The results indicate a positive and significant influence of the alternative UTAUT model on the adoption of the blockchain traceability platform. The contributing factors are as follows.

2.1 The factor that directly influences BI is as follows.

2.1.1 FC (β = 0.996; p< 0.001), as reported by Budhathoki et al. (2024) and Gunasinghe et al. (2019). FC refers to the extent to which an individual believes that an organization's systems and technical infrastructure support the use of a new system (Venkatesh et al., 2003).

2.2 The factors indirectly influence BI are as follows.

2.2.1 SI directly influences TA at (β = 0.973; p<0.001), as reported by RAOT (2024). SI refers to the extent to which an individual perceives that others' beliefs influence their decision to use a new system (Venkatesh et al., 2003). In this result, it is indicated that others' beliefs influence TA.

2.2.2 TA directly influences FC (β = 0.739; p<0.001), as reported by RAOT (2024). TA is defined based on the study by Bozionelos (2001), which investigated computer anxiety related to the use of computers. The results indicate that computer anxiety influences FC.

2.2.3 EE directly influences PE at (β = 0.941; p<0.001), as reported by Smyth *et al.*, 2021. Users perceive that the system is not easy to use, as the blockchain traceability platform is an advanced technology that is difficult to understand. This observation is supported by the prior research of Limbas et al. (2022). The results indicate that the the degree of convenience regarding the use of the system influences PE.

2.2.4 PE directly influences FC (β = 0.300; p<0.015), as reported by Popova and Zagulova, 2022. PE refers to the extent to which an individual believes that using a new system will enhance job performance (Venkatesh et al., 2003). The results indicate that the belief in improved job performance through the use of a new system influences FC.

Hence, the development of an alternative UTAUT model was shown to the consistent with the empirical data, confirming that BI strongly strengthens the process of rubber supply chain by driving the adoption of the blockchain traceability platform rubber industry supply chain in Thailand.

Conclusion

In conclusion, regarding the first objective of this research found out that the hypothesis UTAUT model with 4 original factors plus TA factor does not directly influence BI. Then, TA, PE, EE, SI and FC factors may have some influences between each factors, as the results indicate inconsistencies in terms of the empirical data. Therefore, with these results also guiding to the second objective of this study, the design of an alternative UTAUT model is to develop for finding out which factors influence BI in terms of direct and indirect aspects. It is confirmed that FC directly influences BI (β = 0.996; p<0.001), that will strengthen the process of rubber supply chain by the active involvement of all stakeholders. Therefore, it also indicates the importance of facilitating conditions (FC) (e.g. IT infrastructure, updated rules & regulations, capacity building to the blockchain technology for all stakeholders) to be emphasized in order to promote the adoption of the blockchain traceability platform in Thailand rubber industry supply chain. But TA and PE also directly influence FC, both factors also need some support in terms of PDPA (Personal Data Protection Act) compliance, Non-rigid system, clear benefit to stakeholders, one-stop system for all, etc.

The study also recommends to RAOT that the adoption of a blockchain traceability platform is highly possible to implement in the supply chain of the rubber industry in Thailand. To achieve the success of the blockchain traceability platform implementation, it is necessary for the RAOT to play a significant and supportive roles such as to updated IT literacy to all stakeholders, proactive and clear communication of the blockchain benefits, modernized rules & regulation, etc. which will actively strengthen the process of supply chain by the involvement of all stakeholders.

Recommendation

This study is the first in Thailand to apply a blockchain traceability platform to the rubber supply chain, focusing on a major sector of the rubber industry by specifically targeting large landowners owning more than 100 rai, as well as the 10 largest businesses registered in the government database, including farmers, collectors, factories, exporters, government agencies, brokers, and experts, all of whom have a significant impact on the industry. Due to its broad scope, the research faces several challenges and limitations, including the complexity of the rubber supply chain industry and the high cost of technology and data servers. It is recommended that future research focus on smaller-scale operations, particularly rubber farmers (1,667,095 farming families) most of whom own areas of 20–30 rai and are registered in the government database or other stakeholder groups.

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