DIFT2025-1

ICDI International College of DIGITAL INNOVATION CHIANG MAI UNIVERSITY

Digital Innovation and Financial Technology Conference (2025-1)

PROCEEDING BOOK

Innovation in the Age of AI: Balancing Automation and Human Creativity

7th June 2025

International College of Digital Innovation
Chiang Mai University
Chaing Mai, Thailand

Proceedings of the DIFT 2025-1 Conference Digital Innovation and Financial Technology

Theme:
Innovation in the Age of AI: Balancing Automation and Human Creativity

Date:
7th June 2025

Location:
International College of Digital Innovation
Chiang Mai University
Chiang Mai, Thailand

Editor:
International College of Digital Innovation
Chiang Mai University

Published by:
International College of Digital Innovation
Chiang Mai University
Chiang Mai, Thailand

ACKNOWLEDGEMENT

The Organizing Committee of DIFT 2025-1: Digital Innovation and Financial Technology would like to express its sincere gratitude to all individuals and institutions whose contributions led to the success of this academic event, held on 7th June 2025 at the International College of Digital Innovation, Chiang Mai University.

We extend our heartfelt thanks to Mr. Veerakit Ussamarn for delivering an inspiring keynote lecture titled "AI Adoption Journey: SCBX's Strategy for AI Innovation and Business Impact through AI Use Cases", which provided valuable insights into the real-world application of artificial intelligence in the business sector.

Special appreciation is extended to all student authors for their commitment in producing the full papers featured in this proceedings volume. Your work reflects the strength of student-led research and its meaningful contribution to the ongoing discourse on AI, innovation, and human creativity.

We also gratefully acknowledge the support of academic advisors, reviewers, and faculty mentors whose guidance and constructive feedback were instrumental throughout the development process. Our thanks further extend to the administrative team, technical staff, and volunteers for their behind-the-scenes work in ensuring the smooth operation of the conference.

Finally, we express our deep appreciation to the leadership of the International College of Digital Innovation, Chiang Mai University, for their continued encouragement and commitment to fostering academic excellence and innovation.

DIFT 2025-1 Organizer
July 2025

DIFT 2025-1 ORGANIZING COMMITTEE

Advisory Committee

1. Dean, International College of Digital Innovation
2. Associate Dean (Assoc. Prof. Dr. Manad Khamkong)
3. Associate Dean (Asst. Prof. Dr. Chaiwuth Tangsomchai)
4. Associate Dean (Asst. Prof. Dr. Benjamas Suksatit)
5. Secretary, International College of Digital Innovation
6. Head, School of Digital Innovation
7. Deputy Head, School of Digital Innovation
8. Chair, B.Sc. Program in Digital Innovation (International Program)
9. Secretary, B.Sc. Program in Digital Innovation (International Program)

Executive Committee

1.	Assoc. Prof. Dr. Somchai Sriyab (Associate Dean)	Chair
2.	Chair, Graduate Program Committee, Digital Innovation and Financial Technology (International Program)	Vice-Chair
3.	Secretary, Graduate Program Committee	Member
4.	Dr. Worawit Tepsan	Member
5.	Dr. Naret Suyaroj	Member
6.	Dr. Suttida Suwannayod	Member
7.	Dr. Piyachat Udomwong	Secretary
8.	Ms. Wiranya Ratnapinda	Assistant Secretary

Academic Committee

1.	Dr. Nathapon Udomlertsakul	Chair
2.	Dr. Parot Ratnapinda	Secretary
3.	Ms. Ruchanee Tinamas	Assistant Secretary
4.	Mr. Watcharapong Dilokjanya	Assistant Secretary

Presentation Management Subcommittee

1.	Asst. Prof. Dr. Ahmad Yahya Dawod	Member
2.	Asst. Prof. Dr. Seamus Lyons	Member
3.	Dr. Michael John Harris	Member
4.	Dr. Phillip Y Freiberg	Member
5.	Dr. Siva Shankar Ramasamy	Member

Review Subcommittee

1.	Assoc. Prof. Dr. Napas Hanpornchai	Member
2.	Asst. Prof. Dr. Nopasit Chakpitak	Member

3. Dr. Anukul Tamprasirt	Member
4. Dr. Nathee Naktnasukanjn	Member
5. Dr. Piang-or Loahavilai	Member
6. Dr. Tanarat Rattanadamrongaksorn	Member
7. Dr. Somsak Chanaim	Member
8. Dr. Naret Suyaroj	Member
9. Dr. Worawit Tepsan	Member
10. Dr. Piyachat Udomwong	Member
11. Dr. Nuttaphat Sukchitt	Member

Ceremony Committee

1. Dr. Worawit Tepsan	Chair
2. Ms. Phimphat Riampanich	Member
3. Mr. Silpa Singharajwarapan	Member
4. Ms. Kanyanatthakarn Intharuck	Member
5. Ms. Sureeporn Chaiyaworrakamol	Secretary

Venue, AV Equipment, and Transportation Committee

1. Dr. Naret Suyaroj	Chair
2. Mr. Kraisorn Wangkeeree	Member
3. Ms. Nanthana Songchit	Member
4. Mr. Pirapong Wongsaensee	Secretary
5. Mr. Kanyawut Ariya	Assistant Secretary

Finance, Procurement, Evaluation, and Reporting Committee

1. Dr. Suttida Suwannayod	Chair
2. Ms. Nanthana Songchit	Member
3. Ms. Anchaya Chursook	Member
4. Ms. Mintra Inthajak	Secretary
5. Ms. Sirirag Yodpuntong	Assistant Secretary

CONFERENCE EXTERNAL COMMITTEE

Prof. Iuliia Trabskaia, PhD
Faculty of Innovation and Technological Management
ITMO University
Saint Petersburg, Russia.

Prof. Anna Daviy, PhD
Faculty of Innovation and Technological Management
ITMO University
Saint Petersburg, Russia.

Assoc. Prof. Dr. S P Gayathri, PhD
Department of Computer Science
Government Arts College For Women
Tamil Nadu, India

Asst. Prof. Dr. Kittawit Autchariyapanitkul, PhD
Faculty of Economics
Maejo University
Chaing Mai, Thailand

Dr. Watcharin Sarachai, PhD
Faculty of Science
Maejo University
Chaing Mai, Thailand

CONTENTS

CONFERENCE SCHEDULE

DIFT2025-1

Innovation in the Age of AI: Balancing Automation and Human Creativity

7 June 2025, 08:00–16:00

International College of Digital Innovation Building, Chiang Mai University

Room: ICB 1102 [Zoom ID: 872 909 2671, Passcode: 2671]	
08:00 - 08:45	Registration
08:45 - 08:50	Report Speech Asst. Prof. Dr. Thacha Lawanna Head of the school of Digital Innovation
08:45 - 09:00	Opening Speech Asst. Prof. Dr. Chaiwuth Tangsomchai Associate Dean, International College of Digital Innovation
09:00 - 10:00	Keynote Talk "AI Adoption Journey: SCBX's Strategy for Al Innovation and Business Impact through Al Use Cases" Veerakit Ussamarn Senior R&D Associate, SCBX R&D and Innovation Lab
10:00 - 10:30	Refreshment
10:30 - 14:20	Contributed Talk Break Room
14:20 - 14:40	Refreshment
14:40 - 14:50	Reward Announcement
14:50 - 15:00	Closing Ceremony

CONTRIBUTED TALK SCHEDULE

	Room: ICB 1102 [Zoom ID: 872 909 2671, Passcode: 2671] **Session Committees:** Prof. Iuliia Trabskaia Prof. Anna Daviy Dr. Watcharin Sarachai Dr. Parot Ratnapinda Dr. Michael John Harris	**Room No. 2 (ICB1211) [Zoom ID: 872 909 2671, Passcode: 2671]** **Session Committees:** Assoc. Prof. Dr. S P Gayathri Asst. Prof. Dr. Kittawit Autchariyapanitkul Dr. Phillip Y Freiberg Dr. Siva Shankar Ramasamy
10:30 - 10:50	Chinese Sports Major College Students' Purchase Intention Toward Personalized AI Smart Devices: An SOR Model Approach *Jingxian Chen*	The Potential for Bike-Sharing Expansion in Thailand *Natchanon Chaitip*
10:50 - 11:10	Live streaming sales on consumer decision-making Behavior based on the AISAS Model *Lingyi Wang*	Impacts of GHG Protocol on Cross-Border Japan–Thailand Automotive Supply Chains *Preyamin Kannaphan*
11:10 - 11:30	Expectation Confirmation Model for Consumer Satisfaction and Continuance Intention: A Case Study of Hema Fresh *Guiying Lyu*	The Impact of Digital Financial Inclusion on Regional Economic Growth in China *Yanjie Chen*
11:30 - 11:50	Understanding the Key Drivers in Using Mobile Payment (M-Payment) Among Generation Z Consumers in Daily Consumption Scenarios *Quanjin Xiang*	The Impact of BIM Technology on Cost Management in Construction Engineering Projects *Fan Jingmiao*
11:50 - 13:00	Lunch	

	Room: ICB 1102 [Zoom ID: 872 909 2671, Passcode: 2671] **Session Committees:** Prof. Iuliia Trabskaia Prof. Anna Daviy Dr. Watcharin Sarachai Dr. Nuttaphat Sukchitt	**Room No. 2 (ICB1211) [Zoom ID: 872 909 2671, Passcode: 2671]** **Session Committees:** Assoc. Prof. Dr. S P Gayathri Asst. Prof. Dr. Seamus Lyons Asst. Prof. Dr. Ahmad Yahya Dawod Dr. Siva Shankar Ramasamy
13:00 - 13:20	AirAccount: A Semi-Custody& Never Lost Crypto Account Based on TEE and SDSS *Huifeng Jiao*	Entry Strategy for Thai Vitamin C Beverages to China through Cross-Border E-Commerce Xiao Tan
13:20 - 13:40	A portfolio optimization model for return trend rate and risk trend rate based on machine learning *Chunman Zhu*	Higher Intellectual Risk-Taking, Greater Acceptance of GAI? Examining the adoption of GAI by integrating UTAUT Among Higher Education Students *Tianjing Xin*
13:40 - 14:00	Pathways to Decarbonizing Thailand's Power System with Renewables and Flexibility Solutions *Muhammad Ilyas*	Intangible Cultural Heritage Meets Modern Marketing: A Case Study of the Beauty Brand Florasis *Qingxia Zhao*
14:00 - 14:20	Intelligent Barter Platform: Enhancing Matching and Optimizing Item Exchange Efficiency with Enterprise AI and Blockchain *Jianlei Qian*	The Impact of Personalized Recommendations on Tourism Platforms on Tourists' Behavioural Intentions *Hongmei Duan*

CHINESE SPORTS MAJOR COLLEGE STUDENTS' PURCHASE INTENTION TOWARD PERSONALIZED AI SMART DEVICES: AN SOR MODEL APPROACH

Jingxian Chen[1] and Ahmad Yahya Dawod[2]

International College of Digital Innovation, Chiang Mai University, Chiang Mai, 50200, Thailand

E-mail: [1]jingxian_chen@cmu.ac.th, [2]ahmadyahyadawod.a@cmu.ac.th

ABSTRACT

This study explores how AI smart devices influence the purchase intention of Chinese sports major college students in the context of digital transformation. Grounded in the Stimulus-Organism-Response (SOR) model, it examines how external stimuli—such as product quality, brand attitude, social interaction, performance expectation, and fashion perception—affect purchase intention through the mediating role of perceived value. A quantitative survey was conducted to build a theoretical model that captures the behavioral characteristics of this group in the "Internet Plus" era. Regression analysis reveals that external stimuli significantly impact both perceived value ($R^2 = 0.608$, $\beta = 0.225$ for brand attitude) and purchase intention ($R^2 = 0.637$, $\beta = 0.189$ for price attitude), highlighting the dominant roles of brand and price factors. Perceived value is found to be a significant mediator in the relationship between stimuli and behavioral response. This research extends the SOR framework to the domain of personalized AI smart devices, enriching consumer behavior theory in the digital health and fitness technology market. It emphasizes that sports major students have strong health awareness, a high level of tech acceptance, and unique professional needs. The findings offer practical insights for product design, user experience optimization, and brand development, while also informing educators on integrating AI technologies into curricula. Furthermore, the study identifies challenges such as product homogeneity and limited application scenarios, calling for diversified innovation and regulatory improvements for sustainable industry growth.

KEYWORDS: Personalized AI Smart Devices, Purchase Intention, Perceived Value, S-O-R Model, Sports Major College Students, Consumer Behavior, Product Design, Digital Transformation

1 INTRODUCTION

AI Smart Devices, as a convergence of artificial intelligence (AI) and the Internet of Things (IoT), integrate sensors, wireless communication, and multimedia technologies to support health, fitness, and entertainment in portable formats (Xie and Lin,2024). Enabled by intelligent applications, these devices enhance user interaction through sensing, analysis, and control functions (Ometov et al., 2021), and play a growing role in health monitoring and early disease detection (Babu et al., 2024).

In China, national policies such as the "Three-year Action Plan for the Construction of New Infrastructure for the Internet of Things (2021–2023)" and "Healthy China 2030" promote the development of smart wearable technologies, particularly in sports and health. With strong government backing and cross-industry innovation, the market is projected to surpass 100 billion yuan by 2025 (Huang and Qiu, 2024).

Against this backdrop, this study investigates Chinese sports major college students' purchase intention toward personalized AI smart devices. Using the Stimulus-Organism-Response (SOR) model, it examines how external stimuli—such as product quality and brand attitude—influence consumer behavior in this emerging digital health landscape.

2 LITERATURE REVIEW

Wearable sports equipment, especially personalized AI smart devices, has become increasingly popular among college students majoring in sports in China. These devices, which include smartwatches, fitness bands, and smart clothing, leverage advanced technologies such as AI and the Internet of Things (IoT) to provide real-time health monitoring, personalized training recommendations, and enhanced user experiences (Sperlich et al.,2020; Bezold et al., 2021). Research indicates that the integration of AI in wearable devices significantly enhances their functionality and appeal to consumers, particularly in the context of sports performance and health management Personalized refers to AI smart devices that leverage AI, IoT, and big data to deliver tailored health tracking, intelligent exercise recommendations, and customized user interactions. This distinguishes them from generic wearables by their adaptive learning capabilities and individualized feedback for performance optimization and health maintenance (Su Xianfeng et al.,2023).

The Stimulus-Organism-Response (SOR) model provides a robust framework for understanding the purchase intentions of Chinese sports major college students toward these devices. External stimuli, such as product quality (PQ), social interactivity (SI), price attitude (PA), brand attitude (BA), fashion perception (FP), performance expectation (PE), and expectation confirmation (EC), play crucial roles in shaping students' perceived value and ultimately their purchase intentions (Shafiq et al.,2011; Zhu et al.,2020; Ye and Chen,2023). Studies have shown that perceived value acts as a key mediator between these external stimuli and the final purchase decision (Sultan et al.,2021).

Chinese scholars have also highlighted the influence of cultural factors on consumer behavior. Traditional values such as collectivism and the need for social recognition significantly impact the purchasing decisions of Chinese consumers, including sports major college students (Huang et al., 2014). The rise of internet culture and the demand for personalization further drive the adoption of AI smart devices among this demographic, as these devices offer tailored solutions that align with individual needs and preferences (Liu,2022).

In conclusion, the combination of technological advancements and cultural influences shapes the purchase intentions of Chinese sports major college students toward personalized AI smart devices. Future research should continue to explore how emerging technologies and evolving consumer values interact within the SOR model to influence market dynamics in this growing sector.

Theoretical Framework and Hypotheses

SOR Model used in AI Smart Devices' Purchase Intention

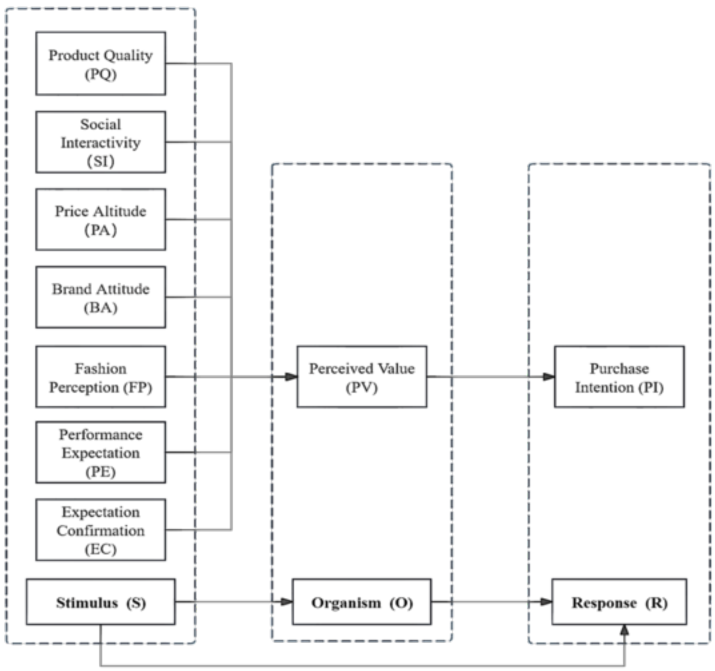


Figure 1. The S-O-R model using in my research

Figure 1 outlines the Stimulus-Organism-Response (SOR) model as the conceptual basis for this study, capturing how external stimuli—including Product Quality (PQ), Social Interactivity (SI), Price Attitude (PA), Brand Attitude (BA), Fashion Perception (FP), Performance Expectation (PE), and Expectation Confirmation (EC)—affect Perceived Value, which subsequently shapes Purchase Intention among Chinese sports major college students.

Building on Buxbaum (2016), the model illustrates the cognitive-emotional path from stimulus to response.Guo, J., & Li, L. (2022) emphasize that perceived value enhances decision-making through personalization. AI-powered personalization—via browsing history and behavioral analytics—triggers demand, eases information search (Kim et al.,2019), facilitates comparison, and encourages purchase through tailored incentives (Yun et al., 2022). Post-purchase, AI chatbots reinforce loyalty (Ye et al., 2023).

This SOR-based approach systematically reveals how external stimuli shape perceived value and ultimately drive consumer intention in the context of personalized AI smart devices.

3 HYPOTHESES

Basing on the SOR model and insights from the literature review, this study proposes the following hypotheses to test the Chinese Sports Major College Students' Purchase Intention Toward Personalized AI Smart Devices:

H1: The degree of seven external stimulus (product quality, social interactivity, price attitude, brand attitude, fashion perception, performance expectation, and expectation confirmation) of AI Smart Devices by Chinese sports major college students has a positive impact on their perceived value.

H2: The degree of seven external stimulus (product quality, social interactivity, price attitude, brand attitude, fashion perception, performance expectation, and expectation confirmation) of AI Smart Devices by Chinese sports major college students has a positive impact on their purchase intention.

4 METHODOLOGY

4.1 Research Design

This research adopts a quantitative approach to explore the influencing factors of Chinese sports major college students' purchase intention toward personalized AI smart devices. Grounded in the Stimulus-Organism-Response (SOR) model, the study examines how external stimuli (e.g., product quality, price attitude, brand attitude, social interactivity, performance expectation, fashion perception, and expectation confirmation) impact perceived value and ultimately shape consumer purchase behavior. A structured questionnaire was developed, comprising 37 items across the SOR dimensions, and employed a 5-point Likert scale ranging from "strongly disagree" to "strongly agree." To ensure the reliability and clarity of the instrument, a pre-test was conducted with a sample of 100 valid responses. The results indicated high internal consistency, with Cronbach's α coefficients for each construct exceeding 0.90, confirming the questionnaire's reliability and suitability for large-scale distribution.

4.2 Sample and Data Collection

The study sample consists of college students majoring in sports-related disciplines from different provinces, autonomous regions, and municipalities across China. A total of 783 questionnaires were distributed, with 695 deemed valid, resulting in a response rate of 88.76%. The survey employed a randomized sampling method and was administered through both online platforms and offline paper-based questionnaires to ensure geographical diversity and demographic representativeness. Aligned with China's "Sports Power" national strategy, this demographic plays a pivotal role in advancing personal health and technological engagement. Their distinct preferences offer valuable insights into the emerging market of AI smart devices. As an underexplored yet strategically significant segment, understanding this group's purchasing intentions is critical for companies aiming to develop targeted marketing strategies and innovative products that cater to the evolving needs of this tech-savvy and health-conscious young consumer base.

4.3 Data Analysis

Using statistical methods, organize and analyzed the data processing software including Excel, Origin 2021, AMOS 24.0 and SPSS 24.0, and describe the study results using statistical charts, descriptive statistical analysis, reliability test,validity test, normality distribution test, correlation analysis and hypothesis test (regression analyze).

5 DISCUSSION AND RESULTS

This study employed the Stimulus-Organism-Response (SOR) model to examine Chinese Sports Major College Students' Purchase Intention Toward Personalized AI Smart Devices. A total of 783 questionnaires were distributed, of which 695 were valid.

The results revealed that the seven external stimulus variables had significant effects on both Perceived Value ($R^2 = 0.608$) and Purchase Intention ($R^2 = 0.637$). Among them, regression analysis identified Brand Attitude ($\beta = 0.225$) and Price Attitude ($\beta = 0.189$) as the most influential predictors for Perceived Value and Purchase Intention, respectively. These findings confirm the applicability of the SOR framework in the context of personalized AI smart devices, enriching consumer behavior theory within the digital health and fitness technology market. Furthermore, the results underscore the strategic importance of Chinese sports major college students as a distinct and valuable consumer segment, providing strong support for the research hypotheses.

Demographic profile of respondents

Table 1. Descriptive statistical analysis

Variable	Category	Percentage
Sex	Male,Female	51.22%,48.78%
Age	<18,18-20,21-23,24-26,>27	5.04%,31.37%,35.54%,18.13%, 9.93%
Year of study	Freshman, Sophomore, Junior, Senior, Master, Doctor	15.68%,15.40%,20.00%,21.01%, 16.98% ,10.94%

Variable	Category	Percentage
Major	Physical education, Sports training, Sports Science, Health & rehabilitation, Sports economy & management, Sports News & Communication, Others	19.28%,18.42%,15.68%,16.69%, 13.53%,12.81%,3.60%
Monthly Disposable Income (RMB)	<1000,1000-1500,1500-2000, 2000-3000,>3000	4.17%,16.83%,26.47%,32.52%, 20.00%
Exercise frequency	Daily, Several times a week, Weekly	41.58%,42.30%,16.12%

Table 1 presents the descriptive statistical analysis of Chinese Sports Major College Students in this research.

5.1 Reliability Analysis

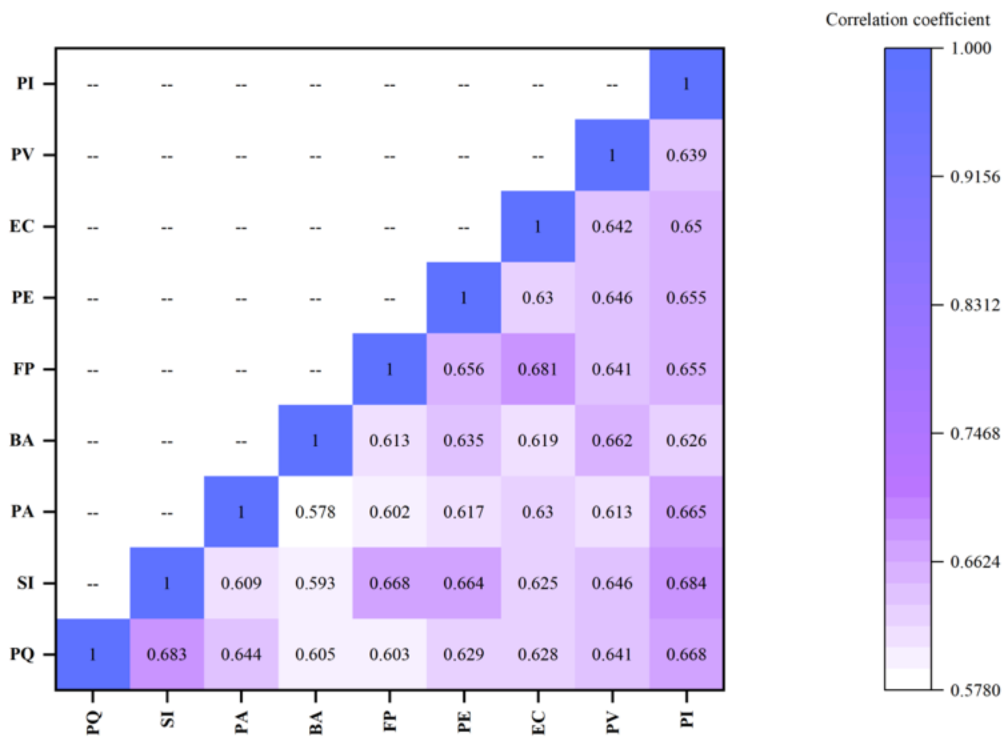
Table 2. Cronbach's Alpha for each dimension

Dimensions	Items	Cronbach's Alpha	Interpretation
Product Quality	5	0.987	Excellent
Social Interactivity	4	0.987	Excellent
Price Altitude	4	0.973	Excellent
Brand Attitude	4	0.981	Excellent
Fashion Perception	4	0.975	Excellent
Performance Expectation	4	0.972	Excellent
Expectation Confirmation	4	0.973	Excellent
Perceived Value	4	0.982	Excellent
Purchase Intention	4	0.987	Excellent
Total	37	0.984	Excellent

Table 2 shows the questionnaire demonstrated excellent reliability, with all CITC values exceeding 0.5, and an overall Cronbach's alpha coefficient of 0.984. Each dimension's Cronbach's alpha exceeded 0.9, indicating the questionnaire is highly reliable and suitable for formal research.

5.2 Correlation Analysis

From Figure 2 below, it can be seen that correlation analysis was utilized to study the relationships between Purchase Intention and eight factors including Product Quality, Social Interactivity, Price Altitude, Brand Attitude, Fashion Perception, Performance Expectation, Expectation Confirmation, and Perceived Value. The Pearson correlation coefficient was employed to represent the strength of these relationships. Specific analysis indicates that Purchase Intention is significantly correlated with all eight factors ($p<0.01$), with correlation coefficients approximately around 0.6, all of which are greater than 0. This signifies that there is a positive correlation between Purchase Intention and each of the eight factors: Product Quality, Social Interactivity, Price Altitude, Brand Attitude, Fashion Perception, Performance Expectation, Expectation Confirmation, and Perceived Value.



All p**<0.01. At the 0.01 significance level (two-tailed), the correlation is significant.

Figure 2. Correlation Analysis Results

5.3 Validity Analysis

Exploratory Factor Analysis (EFA)

Table 3. KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy	0.970

Bartlett's Test of Sphericity	Approx.Chi-Square	47857.755
	df	666
	Sig.	0
Cumulative variance explained after rotation		94.275%

The table 3 indicates a KMO value of 0.970, which exceeds 0.9, meeting the level of significance and suggesting that the data is highly suitable for information extraction. This indirectly reflects a good level of validity, thus warranting factor analysis. The corresponding P-value for Bartlett's test of sphericity is 0.000, which is less than 0.05, indicating that exploratory factor analysis is appropriate.After rotation, the cumulative variance explained is 94.275%, indicating excellent construct validity.This implies that the information from the research items can be effectively extracted.

Confirmatory Factor Analysis

Table4. Model fit index

Index	Standard Reference	Statistics	Compliance
X^2/df	1-3 is excellent, 3-5 is good.	2.585	Excellent
GFI	> 0.8 is good, >0.9 is excellent.	0.897	Excellent
CFI	> 0.8 is good, >0.9 is excellent.	0.980	Excellent
ITL	> 0.8 is good, >0.9 is excellent.	0.980	Excellent
NFI	> 0.8 is good, >0.9 is excellent.	0.969	Excellent
TLI	> 0.8 is good, >0.9 is excellent.	0.978	Excellent
SRMR	<0.05 is excellent, <0.08 is good.	0.016	Excellent
RMSEA	<0.05 is excellent, <0.08 is good.	0.048	Excellent

Table 4 shows that the model fit indices indicate an excellent overall model fit, with all key indicators—χ^2/df, GFI, CFI, IFI, NFI, TLI, SRMR, and RMSEA—meeting or exceeding the standards for excellent fit.

5.4 Regression Analysis

Testing Hypothesis 1: the relationship between external stimulus variables and mediator variables

Table 5. Regression Results for H1(Dependent Variable:PV)

Unstandardized coefficient	Standardized coefficient

				t-statistic	p-value		
	B	Std. Error	Beta			Tolerance	VIF
Constant	0.402	0.109	—	3.694	0.000**	——	——
PQ	0.122	0.035	.131	3.490	0.001**	0.407	2.459
SI	0.121	0.036	.128	3.333	0.001**	0.388	2.577
PA	0.095	0.034	0.099	2.787	0.005**	0.453	2.206
BA	0.212	0.033	0.225	6.448	0.000**	0.467	2.140
FP	0.112	0.037	0.116	3.049	0.002**	0.395	2.529
PE	0.122	0.038	0.120	3.201	0.001**	0.403	2.478
EC	0.121	0.037	0.124	3.294	0.001**	0.406	2.465
R^2		0.608					
Adjusted R-squared		0.604					
F		F =151.984, p=0.000					
Durbin-Watson statistic		1.739					
*p<0.05, **p<0.01							

Table 5 illustrates that Hypothesis 1 is supported, as all seven external stimulus variables (Product Quality, Social Interactivity, Price Attitude, Brand Attitude, Fashion Perception, Performance Expectation, and Expectation Confirmation) show significant positive effects on the mediating variable Perceived Value ($R^2 = 0.608$, $p < 0.01$), with Brand Attitude ($\beta = 0.225$, $p < 0.001$) having the strongest influence. The overall model is statistically significant ($F = 151.984$, $p = 0.000$) and exhibits a good fit (Adjusted $R^2 = 0.604$).

Testing Hypothesis 2: the relationship between external stimulus variables and response variables

Table 6 Regression Results for H2 (Dependent Variable:PI)

	Unstandardized coefficient		Standardized coefficient				
				t-statistic	p-value		
	B	Std. Error	Beta			Tolerance	VIF
Constant	0.431	0.102		4.211	0.000**		
PQ	0.134	0.033	0.147	4.073	0.000**	0.407	2.459
SI	0.172	0.034	0.186	5.033	0.000**	0.388	2.577
PA	0.178	0.032	0.189	5.534	0.000**	0.453	2.206
BA	0.104	0.031	0.112	3.34	0.001**	0.467	2.140

	Unstandardized coefficient		Standardized coefficient				
FP	0.11	0.035	0.117	3.191	0.001**	0.395	2.529
PE	0.107	0.036	0.108	2.972	0.003**	0.403	2.478
EC	0.102	0.034	0.106	2.951	0.003**	0.406	2.465
R^2		0.637					
Adjusted R-squared		0.633					
F		F =172.249, p=0.000					
Durbin-Watson statistic		1.423					
*p<0.05, **p<0.01							

Table 6 shows that hypothesis 2 was significantly supported. All seven external stimulus variables—Product Quality (PQ), Social Interactivity (SI), Price Attitude (PA), Brand Attitude (BA), Fashion Perception (FP), Performance Expectation (PE), and Expectation Confirmation (EC)—had positive and significant effects on the response variable, Purchase Intention ($R^2 = 0.637$, $p < 0.01$). Among them, Price Attitude ($\beta = 0.189$, $p < 0.001$) and Social Interactivity ($\beta = 0.186$, $p < 0.001$) had the most substantial impacts. The regression model demonstrated a strong overall fit ($F = 172.249$, $p = 0.000$; Adjusted $R^2 = 0.633$), confirming the critical role of external stimuli in influencing purchase intention within the SOR framework.

6 CONCLUSION

his study provides compelling evidence that external stimuli exert a significant influence on the purchase intention of Chinese sports major college students towards personalized AI smart devices, mediated by perceived value. The findings affirm the efficacy of the Stimulus-Organism-Response (SOR) model in elucidating this consumer behavior dynamic. Specifically, Hypothesis 1 (H1) confirms that the seven identified external stimuli—Product Quality (PQ), Social Interactivity (SI), Price Attitude (PA), Brand Attitude (BA), Fashion Perception (FP), Performance Expectation (PE), and Expectation Confirmation (EC)—collectively enhance Perceived Value, accounting for 60.8% of its variance ($R^2 = 0.608$). Notably, Brand Attitude emerges as the most potent driver, with a beta coefficient of 0.225, highlighting its pivotal role in shaping perceived value. In parallel, Hypothesis 2 (H2) reveals that these stimuli robustly impact Purchase Intention, explaining 63.7% of its variance ($R^2 = 0.637$), with Price Attitude ($\beta = 0.189$) and Social Interactivity ($\beta = 0.186$) exerting the most pronounced effects. These results underscore the critical role of external stimuli in guiding students' purchase decisions.

For stakeholders in the personalized AI smart device industry targeting this demographic, the study's insights translate into strategic imperatives. Enhancing brand reputation, optimizing price strategies, and leveraging social interactivity features are identified as key levers to elevate perceived value and, consequently, purchase intentions. Moreover, prioritizing product quality, fashion perception, and performance expectation can further amplify the devices' appeal to this tech-savvy and health-conscious cohort. Continuous engagement with consumer feedback and adaptive strategies to meet evolving needs will be paramount in sustaining market relevance and cultivating enduring consumer loyalty. Future research avenues are also illuminated by this study. Expanding the scope to include cross-cultural comparisons, longitudinal analyses, and additional factors such as consumer trust and ethical considerations in AI use could yield richer understandings of AI's role in shaping consumer behavior within the digital health and fitness technology market. By adopting these strategies, companies can leverage AI to deliver highly personalized experiences, thereby driving consumer satisfaction, loyalty, and sustained market growth. This study not only charts a course for innovation in the personalized AI smart device market but also enriches the academic discourse on consumer behavior in the digital transformation era.

REFERENCES

Liu Xie i & Kelly Lin. (2024). The protection of user data privacy of intelligent wearable devices under the background of the intelligent transformation of national fitness data. Journal of Physical Education (04), 64-72.

Ometov, A., Shubina, V., Klus, L., Skibińska, J., Saafi, S., Pascacio, P., ... & Lohan, E. S. (2021). A survey on wearable technology: History, state-of-the-art and current challenges. Computer Networks, 193, 108074.

Babu, M., Lautman, Z., Lin, X., Sobota, M. H., & Snyder, M. P. (2024). Wearable devices: implications for precision medicine and the future of health care. Annual Review of Medicine, 75(1), 401-415.

Huang, H., & Qiu, J. (2024). Strategic choices for high-quality development of intelligent wearable sporting goods industry in the new era. Wearable Technology, 1(1), 41-55.

Sperlich, B., Aminian, K., Düking, P., & Holmberg, H. C. (2020). Wearable sensor technology for monitoring training load and health in the athletic population. Frontiers in physiology, 10, 1520.

Bezold, J., Krell-Roesch, J., Eckert, T., Jekauc, D., & Woll, A. (2021). Sensor-based fall risk assessment in older adults with or without cognitive impairment: a systematic review. European review of aging and physical activity, 18, 1-14.

Su Xianfeng, Zhao Shenghui, Li Wenhao, Zhang Wendong & Zhang Mingxin.(2023). Advances in artificial intelligence to improve sports performance, dilemma reflection and optimization strategies. Journal of Shanghai sports institute (02), 104-118.

Shafiq, R., Raza, I., & Zia-ur-Rehman, M. (2011). Analysis of the factors affecting customers' purchase intention: The mediating role of perceived value. African Journal of Business Management, 5(26), 10577.

Ye Hong-Zhi, & Chen Zhi-Feng. (2023). Literature study on the influencing factors of continuous use of wearable devices. Journal of Medical Informatics, 44(11), 52-57.

Zhu, L., Li, H., Wang, F. K., He, W., & Tian, Z. (2020). How online reviews affect purchase intention: a new model based on the stimulus-organism-response (S-O-R) framework. Aslib Journal of Information Management, 72(4), 463-488.

Sultan, P., Wong, H. Y., & Azam, M. S. (2021). How perceived communication source and food value stimulate purchase intention of organic food: An examination of the stimulus-organism-response (SOR) model. Journal of Cleaner Production, 312, 127807.

Huang, Y., He, J., & Zhu, L. (2014). A comparative study of the impact of consumer cosmopolitanism, exocentrism, and ethnocentrism on brand attitudes.

Liu S.(2022). A study on the impact of emerging online consumption culture on college students' consumption concepts and behaviors. China merchants (10), 31-33.

Buxbaum, O., & Buxbaum, O. (2016). The SOR-model. Key insights into basic mechanisms of mental activity, 7-9.

Guo, J., & Li, L. (2022). Exploring the relationship between social commerce features and consumers' repurchase intentions: the mediating role of perceived value. Frontiers in psychology, 12, 775056.

Kim, T., & Chiu, W. (2019). Consumer acceptance of sports wearable technology: The role of technology readiness. International Journal of Sports Marketing and Sponsorship, 20(1), 109-126.

Yun, W. G., Youn, J. K., Ko, D., Yeom, I., Joo, H. J., Kong, H. J., & Kim, H. Y. (2022). Tele-consent using mixed reality glasses (NREAL) in pediatric inguinal herniorrhaphy: a preliminary study. Scientific Reports, 12(1), 3105.

LIVE STREAMING SALES ON CONSUMER DECISION-MAKING BEHAVIOR BASED ON THE AISAS MODEL

Wang Lingyi[1] and Ahamd Yahya Dawod[2]
International College of Digital Innovation, Chiang Mai University, Chiang Mai, 50200, Thailand
E-mail: [1]lingyi_w@cmu.ac.th, [2]ahmadyahyadawod.a@cmu.ac.th

ABSTRACT

Live-streaming sales have revolutionized digital commerce, blending entertainment, interaction, and retail into a real-time experience. This study investigates the impact of emotional marketing on consumer decision-making behavior using the AISAS model—Attention, Interest, Search, Action, Sharing—as a conceptual framework. A structured questionnaire was distributed to 400 participants who actively engaged in live-stream shopping. Using Jamovi software for statistical analysis, this study employed descriptive statistics, exploratory factor analysis (EFA), reliability testing, and multiple regression to analyze the relationship between emotional factors and consumer engagement. Results show that emotional marketing significantly influences the Attention and Interest stages, ultimately leading to increased purchase intent and sharing behaviors. The findings provide actionable insights for brands and platforms aiming to optimize live sales strategies in the digital era.

KEYWORDS: Live-streaming Sales, Emotional Marketing, AISAS Model, Consumer Behavior, trust, impulse buying, social commerce

1 INTRODUCTION

Live-streaming has become a transformative force in e-commerce, blending real-time interaction, entertainment, and personalized shopping experiences. It goes beyond traditional transactional models by creating immersive environments where consumers engage directly with products and sellers. According to Wang et al. (2022), live-streaming commerce profoundly transforms consumer shopping behavior by incorporating real-time interactivity, fostering immersive shopping environments that build consumer trust and stimulate impulsive buying tendencies.

With the rise of platforms like TikTok and Taobao, understanding how consumer decision-making adapts to this format has become essential. Livestreaming sales leverage "social commerce" elements—virality, fan endorsements, and user-generated content—to boost engagement and revenue. These dynamics reshape how consumers discover, evaluate, and purchase products.

The AISAS model (Attention, Interest, Search, Action, Sharing) offers a relevant framework for analyzing this evolving behavior. Originally designed for traditional e-commerce, it is now applied to understand digital consumer engagement. Unlike static channels, live-streaming enables two-way communication, fostering trust and community. Studies show that interaction quality, perceived enjoyment, and emotional connection significantly influence livestream consumer behavior. Visual and auditory stimuli further enhance the immersive experience.

Platforms like TikTok, YouTube, and others now use live-streaming to drive sales and build brand loyalty by integrating real-time engagement and social sharing. As Chan & Asni (2023) observe, TikTok utilizes unique live streaming attributes to foster purchase intentions by merging entertainment with shopping, enabling a highly engaging retail experience.

Despite its growth, livestreaming presents new challenges. Consumer decisions are influenced by factors such as streamer credibility, promotional urgency, and social proof. As Cai & Wohn (2019) note, social commerce elements such as influencer endorsements and community engagement play a crucial role in shaping consumer preferences and purchase intentions.

Emotional marketing stands out as a key driver, using emotional appeal to build trust, influence perception, and increase purchase intent. Positive emotions—like excitement and happiness—enhance participation, encouraging both impulse buying and long-term brand loyalty.

2 LITERATURE REVIEW

Live-streaming commerce combines real-time interaction with media-rich experiences, bridging online and offline shopping and promoting trust and impulse buying. Cai et al. (2018) identified both "utilitarian and hedonic" motivations, revealing that consumers seek not only function but also emotional satisfaction. This integration of utility and entertainment distinguishes live-streaming from traditional e-commerce. Xu et al. (2020) and Wang et al. (2022) emphasized that interaction quality is a key factor in consumer decisions. Yet, demographic and cultural differences in consumer motivations remain underexplored—for instance, younger consumers may be drawn to entertainment, while older users may prioritize practicality.

With the growth of social media and smart technologies, the consumer decision-making process has evolved. Cooley and Parks-Yancy (2019) and Voramontri and Klieb (2019) noted that "social media now plays a central role in shaping consumer trust and credibility," underlining the need for authentic brand-consumer relationships. Fu et al. (2020) highlighted how AI and IoT enhance decisions through personalization, while Mishra et al. (2021) showed how these tools integrate online and offline retail environments.

Trust and risk perception are also important. Lăzăroiu et al. (2020) emphasized "online trust and perceived risk" as key drivers of consumer behavior, suggesting that brands must ensure transparency and data security to maintain loyalty.

The AISAS model—Attention, Interest, Search, Action, Share—offers a relevant framework for analyzing behavior in live-streaming commerce, where immediate interaction and multimedia are central. Javed et al. (2022) observed that "digital influencers drive attention and sharing behaviors," while Li and Pan (2023) demonstrated that "visual and auditory stimuli enhance engagement."

Emotional marketing plays a vital role in shaping consumer behavior during live streams. Cai and Wohn (2019) cited “entertainment, social interaction, and information-seeking” as primary motivations, with purchases driven by emotional connection and streamer trust. Hu and Chaudhry (2020) highlighted that “relational bonds” enhance loyalty and engagement. Wongkitrungrueng et al. (2020) found that “emotional engagement strategies help sellers strengthen consumer relationships.” Lin et al. (2021) showed “happiness significantly boost[s] viewer engagement,” while Ming et al. (2021) linked “social presence” to impulse buying. Zheng et al. (2023) concluded that engagement stems from “entertainment, information-seeking, and social interaction,” and purchases from “emotional involvement, trust, and perceived product value.”

In summary, emotional marketing is central to driving trust, interaction, and consumer behavior in live-streaming commerce.

3 RESEARCH OBJECTIVES AND HYPOTHESES

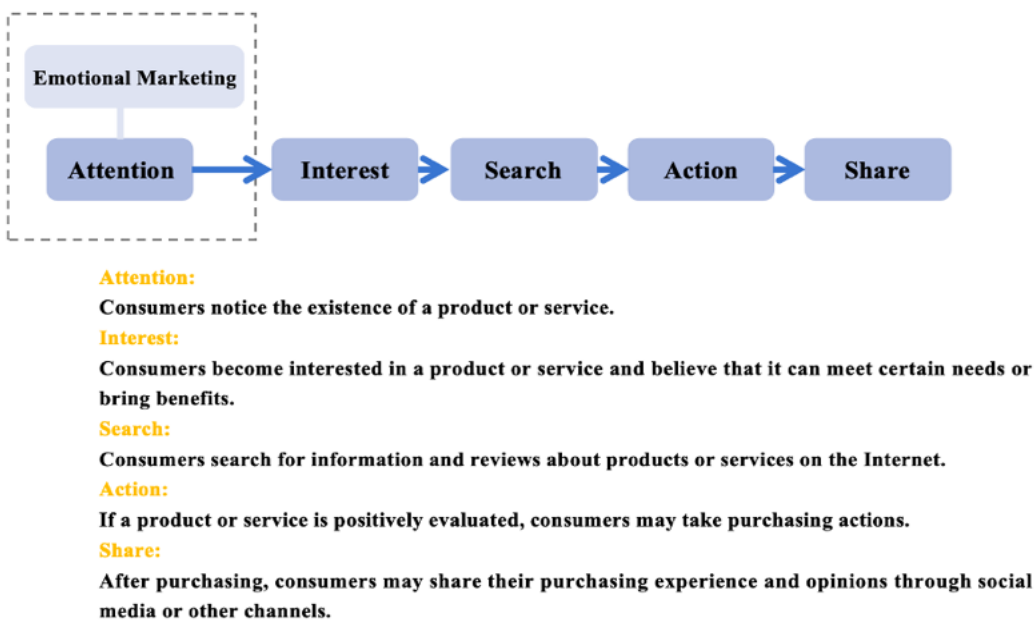


Figure 1. Figure of the AISAS model for integrated emotional marketing

3.1 Research Objectives:

This study aims to explore the mechanisms underlying consumer decision-making in the context of live-streaming commerce, guided by the AISAS model—Attention, Interest, Search, Action, and Sharing. Specifically, the research pursues the following objectives:

objective 1: To analyze consumer decision-making in live commerce based on the AISAS model.

The study seeks to understand how consumers navigate each stage of the AISAS process within live-streaming environments. By examining behavioral patterns across Attention, Interest, Search, Action, and Sharing, the research intends to identify key psychological and behavioral triggers that shape consumer responses during live sales.

objective 2: To examine the impact of emotional marketing on consumer engagement and purchase intention.

The second objective focuses on assessing how emotional marketing strategies, such as storytelling, emotional appeals, and influencer authenticity, affect consumer behavior. The goal is to determine whether emotional engagement can enhance user involvement, stimulate purchase actions, and encourage post-purchase sharing, thus influencing multiple stages of the AISAS model.

3.2 Research Hypotheses:

Based on the above objectives and the theoretical framework of the AISAS model, the study proposes the following hypotheses:

H1: Emotional marketing positively influences the Attention and Interest stages of the AISAS model.

This hypothesis posits that emotional cues embedded in marketing content, such as humor, empathy, or personal resonance, can effectively capture consumer attention and foster initial interest, thereby increasing the likelihood of deeper engagement.

H2: Emotional engagement correlates with increased consumer Action and sharing behavior in live-streaming sales.

This hypothesis assumes that stronger emotional connections with live content or streamers can lead to higher conversion rates (purchasing behavior) and greater willingness to share the experience or product information with others via social platforms.

4 METHODOLOGY

This study adopts a quantitative research method and uses the AISAS model (attention, interest, search, action and sharing) as a theoretical framework to systematically analyze consumers' behavioral paths and emotional responses in live shopping situations. The research tool is a structured questionnaire designed around the five key stages in the model, which includes items to measure factors related to emotional marketing, thereby fully capturing the psychological and behavioral characteristics of consumers at different stages. The questionnaire uses a five-point Likert scale (1 = strongly disagree to 5 = strongly agree) to ensure that the data have high sensitivity and comparability. The data comes from 400 users who are active on live e-commerce platforms such as TikTok and YouTube to ensure that the sample is representative and behaviorally relevant. To improve the scientificity and visualization of the analysis, this study uses Jamovi statistical software for data processing, including descriptive statistics, reliability analysis, exploratory factor analysis, and structural equation model analysis to verify the research hypothesis and explain the specific impact of emotional marketing on each stage of consumer behavior.

5 RESULTS

Conclusions should state concisely the most important propositions of the paper as well as the author's views of the practical implications of the results.

5.1 Descriptive Analysis

Descriptive statistics were conducted to summarize the demographic characteristics of the 400 respondents and their responses to the key constructs—Emotional Marketing and the five stages of the AISAS model.

The sample consists of 400 individuals who have engaged in live-stream shopping through platforms such as TikTok, Taobao, and YouTube Live.

Table 1 Demographic Profile of Respondents

Variable	Category	Frequency	Percentage (%)
Gender	Female	248	62.0%
	Male	152	38.0%
Age Group	Under 20	32	8.0%
	21–30	220	55.0%
	31–40	108	27.0%
	Over 40	40	10.0%
Frequency of Watching Live Sales	Daily	140	35.0%
	Weekly	170	42.5%
	Occasionally	90	22.5%

Table 1 presents the demographic profile of the respondents. The sample comprised 62.0% females (n = 248) and 38.0% males (n = 152). In terms of age, the majority of participants were between 21–30 years old (55.0%), followed by 31–40 years (27.0%), over 40 years (10.0%), and under 20 years (8.0%). Regarding the frequency of watching live sales, 42.5% of respondents reported watching weekly, 35.0% watched daily, and 22.5% did so occasionally. These results indicate a young and predominantly female audience with moderate to high engagement in live-streaming commerce.

Table 2 Descriptive Statistics and Interpretations of Key Constructs

Construct	Mean	SD	Interpretation
Emotional Marketing	3.92	0.863	High emotional engagement
Attention	3.68	0.804	Moderately strong awareness
Interest	3.81	0.820	High consumer curiosity and involvement
Search	3.75	0.843	Active information-seeking behavior
Action	3.77	0.834	Strong intention to purchase
Sharing	3.69	0.865	Moderate engagement in content sharing

Table 2 summarizes the mean scores and standard deviations for each construct within the AISAS model and their respective interpretations. Emotional Marketing scored the highest mean (M = 3.92, SD = 0.863), indicating high emotional engagement among respondents. This was followed by Interest (M = 3.81, SD = 0.820), reflecting strong consumer curiosity and involvement. Action (M = 3.77, SD = 0.834) and Search (M = 3.75, SD = 0.843) also showed elevated levels, pointing to active information-seeking behavior and a strong intention to purchase. Attention (M = 3.68, SD = 0.804) suggested moderately strong awareness, while Sharing (M = 3.69, SD = 0.865) revealed moderate engagement in content sharing. Overall, respondents are generally positively engaged at all stages of the AISAS model, with Emotional Marketing yielding the highest average score. Consumers showed particular strength in the Interest and Action stages, aligning with the entertainment and urgency inherent in live-streaming environments.

5.2 Reliability Analysis

Table 3 Reliability Analysis of Constructs and Items (Cronbach's α)

Results

Reliability Analysis

Scale Reliability Statistics

	Mean	SD	Cronbach's α
scale	3.68	0.804	0.937
scale	3.81	0.820	0.938
scale	3.75	0.843	0.938
scale	3.77	0.834	0.943
scale	3.69	0.865	0.945
scale	3.92	0.863	0.949

[3]

Item Reliability Statistics

If item dropped

Cronbach's α

A1	0.926	I1	0.925	S1	0.926	A21	0.932	S21	0.934	EM1	0.940
A2	0.925	I2	0.928	S2	0.927	A22	0.934	S22	0.936	EM2	0.938
A3	0.925	I3	0.926	S3	0.926	A23	0.932	S23	0.934	EM3	0.938
A4	0.923	I4	0.925	S4	0.927	A24	0.930	S24	0.935	EM4	0.939
A5	0.927	I5	0.927	S5	0.927	A25	0.935	S25	0.932	EM5	0.940
A6	0.929	I6	0.926	S6	0.925	A26	0.933	S26	0.934	EM6	0.940

Table 3 shows the internal consistency reliability of each construct used in the study, as assessed by Cronbach's Alpha. All constructs demonstrated excellent reliability, with alpha values exceeding 0.93, indicating high measurement consistency across items related to emotional marketing, attention, interest, search, action, and satisfaction. These results suggest that each scale consistently measures its intended dimension within the AISAS model framework.

5.3 Exploratory Factor Analysis (EFA)

Table 4 Exploratory Factor Analysis Results and Assumption Check

Factor Statistics

Summary

Factor	SS Loadings	% of Variance	Cumulative %
1	4.55	12.7	12.7
2	4.45	12.4	25.0
3	4.44	12.3	37.3
4	4.32	12.0	49.3
5	4.30	12.0	61.3
6	4.30	11.9	73.2

Inter-Factor Correlations

	1	2	3	4	5	6
1	—	-0.0342	-0.0620	-0.00540	0.0668	0.09550
2		—	-0.0240	0.09514	0.0212	0.08342
3			—	0.05255	-0.0180	0.02901
4				—	-0.0293	-0.00649
5					—	0.04774
6						—

Assumption Checks

Bartlett's Test of Sphericity

χ^2	df	p
15254	630	<.001

Table 4 presents the results of the exploratory factor analysis. Six factors were extracted, collectively explaining 73.2% of the total variance. Factor 1 accounted for 12.7% of the variance (SS Loadings = 4.55), followed by Factor 2 (12.4%), Factor 3 (12.3%), Factor 4 (12.0%), Factor 5 (12.0%), and Factor 6 (11.9%). The relatively even distribution of variance across factors suggests a well-balanced factor structure.

The inter-factor correlation matrix shows that the correlations between factors are generally low, ranging from −0.0620 to 0.0955. These low correlations indicate that the factors are relatively independent and support the discriminant validity of the constructs.

Bartlett's Test of Sphericity was significant ($\chi^2 = 15254$, df = 630, $p < .001$), confirming that the data are suitable for factor analysis by rejecting the null hypothesis of an identity matrix.

5.4 Structural Equation Models

Table 5 Structural Equation Model Fit Indices and Explained Variance (R^2)

Overall Tests

Model tests

Label	X^2	df	p
User Model	866	589	<.001
Baseline Model	16142	630	<.001

Fit indices

		95% Confidence Intervals		
SRMR	RMSEA	Lower	Upper	RMSEA p
0.174	0.031	0.026	0.035	1.000

User model versus baseline model

	Model
Comparative Fit Index (CFI)	0.982
Tucker-Lewis Index (TLI)	0.981
Bentler-Bonett Non-normed Fit Index (NNFI)	0.981
Relative Noncentrality Index (RNI)	0.982
Bentler-Bonett Normed Fit Index (NFI)	0.946
Bollen's Relative Fit Index (RFI)	0.943
Bollen's Incremental Fit Index (IFI)	0.982
Parsimony Normed Fit Index (PNFI)	0.885

R^2

Variable	R^2
A	0.214
I	0.152
S	0.189
Action	0.256
Share	0.186

Table 5 shows that the structural equation model demonstrates a good overall fit, with strong indices including CFI (0.982), TLI (0.981), RMSEA (0.031), and IFI (0.982), indicating that the model accurately represents the observed data. Although the SRMR value (0.174) exceeds the ideal threshold, the low RMSEA and high incremental fit indices suggest that the model remains robust. The χ^2 test is significant ($p < .001$), as expected in large samples. R^2 values reveal that the model explains 25.6% of the variance in Action, 21.4% in Attention, 18.9% in Search, 18.6% in Share, and 15.2% in Interest. These results suggest that the model is particularly effective in predicting consumer action and attention stages within the AISAS framework.

6 CONCLUSION

This study, grounded in the AISAS model, examined the impact of emotional marketing on consumer decision-making in the context of live-streaming commerce. The findings confirmed both proposed hypotheses: emotional marketing positively influences the Attention and Interest stages, and further promotes consumer Action and Sharing behaviors. This indicates that emotionally driven content not only captures consumer attention but also enhances engagement and purchasing intention.

The structural equation modeling results revealed an overall good model fit, with key indices such as CFI, TLI, and RMSEA meeting excellent thresholds, demonstrating that the model was well-constructed and theoretically sound. Among the five AISAS stages, the model explained the most variance in the Action stage ($R^2 = 0.256$), followed by Attention ($R^2 = 0.214$), suggesting that emotional factors are particularly influential in driving purchase behavior.

These results highlight the strategic importance of emotional marketing in live-streaming sales, especially in building trust, increasing engagement, stimulating impulse buying, and encouraging user-generated sharing. For brands and platforms, this underscores the value of delivering emotionally resonant content—through charismatic streamers, interactive atmospheres, and authentic storytelling—to generate positive responses across each stage of the consumer journey.

Future research could explore how consumers across different age groups or cultural backgrounds respond differently within the AISAS framework, and how specific types of emotions (e.g., happiness, trust, resonance) affect decision-making. Additionally, integrating emotional recognition and AI recommendation systems may further enhance the precision and effectiveness of live-streaming marketing strategies.

In conclusion, this study not only deepens our understanding of consumer behavior mechanisms in live-streaming commerce but also offers empirical support and theoretical guidance for brands seeking to implement emotionally driven marketing strategies in the digital age.

REFERENCES

Cai, J., & Wohn, D. Y. (2019). Live streaming commerce: Uses and gratifications approach to understanding consumers' motivations.

Cai, J., Wohn, D. Y., Mittal, A., & Sureshbabu, D. (2018, June). Utilitarian and hedonic motivations for live streaming shopping. In Proceedings of the 2018 ACM international conference on interactive experiences for TV and online video (pp. 81–88).

Cooley, D., & Parks-Yancy, R. (2019). The effect of social media on perceived information credibility and decision making. Journal of Internet Commerce, 18(3), 249–269.

Fu, H., Manogaran, G., Wu, K., Cao, M., Jiang, S., & Yang, A. (2020). Intelligent decision-making of online shopping behavior based on internet of things. International Journal of Information Management, 50, 515–525.

Hu, M., & Chaudhry, S. S. (2020). Enhancing consumer engagement in e-commerce live streaming via relational bonds. Internet Research, 30(3), 1019–1041.

Javed, S., Rashidin, M. S., & Xiao, Y. (2022). Investigating the impact of digital influencers on consumer decision-making and content outreach: using dual AISAS model. Economic Research-Ekonomska Istraživanja, 35(1), 1183–1210.

Li, H., & Pan, Y. (2023). Impact of interaction effects between visual and auditory signs on consumer purchasing behavior based on the AISAS Model. Journal of Theoretical and Applied Electronic Commerce Research, 18(3), 1548–1559.

Lin, Y., Yao, D., & Chen, X. (2021). Happiness begets money: Emotion and engagement in live streaming. Journal of Marketing Research, 58(3), 417–438.

Lăzăroiu, G., Neguriţă, O., Grecu, I., Grecu, G., & Mitran, P. C. (2020). Consumers' decision-making process on social commerce platforms: Online trust, perceived risk, and purchase intentions. Frontiers in Psychology, 11, 890.

Ming, J., Jianqiu, Z., Bilal, M., Akram, U., & Fan, M. (2021). How social presence influences impulse buying behavior in live streaming commerce? The role of SOR theory. International Journal of Web Information Systems, 17(4), 300–320.

Mishra, R., Singh, R. K., & Koles, B. (2021). Consumer decision-making in Omnichannel retailing: Literature review and future research agenda. International Journal of Consumer Studies, 45(2), 147–174.

Voramontri, D., & Klieb, L. (2019). Impact of social media on consumer behaviour. International Journal of Information and Decision Sciences, 11(3), 209–233.

Wang, Y., Lu, Z., Cao, P., Chu, J., Wang, H., & Wattenhofer, R. (2022). How live streaming changes shopping decisions in E-commerce: A study of live streaming commerce. Computer Supported Cooperative Work (CSCW), 31(4), 701–729.

Wongkitrungrueng, A., Dehouche, N., & Assarut, N. (2020). Live streaming commerce from the sellers' perspective: Implications for online relationship marketing. Journal of Marketing Management, 36(5–6), 488–518.

Xu, X., Wu, J. H., & Li, Q. (2020). What drives consumer shopping behavior in live-streaming commerce? Journal of Electronic Commerce Research, 21(3), 144–167.

Zheng, S., Chen, J., Liao, J., & Hu, H. L. (2023). What motivates users' viewing and purchasing behavior motivations in live streaming: A stream-streamer-viewer perspective. Journal of Retailing and Consumer Services, 72, 103240.

EXPECTATION CONFIRMATION MODEL FOR CONSUMER SATISFACTION AND CONTINUANCE INTENTION: A CASE STUDY OF HEMA FRESH

Guiying Lyu[1] and Ahamd Yahya Dawod[2]
International College of Digital Innovation, Chiang Mai University, Chiang Mai, 50200, Thailand
E-mail: [1]guiying_lyu@cmu.ac.th, [2]ahmadyahyadawod.a@cmu.ac.th

ABSTRACT

This study examines the applicability of the Expectation Confirmation Model (ECM) in the context of Hema Fresh, a leading fresh food e-commerce platform in China, to understand consumer satisfaction and continuance intention in the new retail sector. By extending ECM with perceived value and logistics service quality, the research investigates the relationships among consumer expectations, confirmation, satisfaction, and continued use intention. Data were collected from 497 Hema Fresh users in Kunming, China, and analyzed using Structural Equation Modeling (SEM) in jamovi. Results indicate that perceived usefulness significantly influences satisfaction through confirmation ($\beta = 0.387$, $p < 0.001$), explaining 30.6% of variance in satisfaction and 29.3% in continuance intention. Perceived value ($\beta = 0.266$, $p < 0.001$) and logistics service quality ($\beta = 0.318$, $p < 0.001$) also positively impact satisfaction, with perceived value mediating these relationships. The findings validate ECM's applicability in fresh food e-commerce and provide actionable insights for enhancing consumer retention through improved logistics and value propositions. This study contributes to the theoretical understanding of consumer behavior in new retail and offers practical strategies for operational optimization.

KEYWORDS: Expectation Confirmation Model, consumer satisfaction, continuance intention, perceived value, logistics service quality, fresh food e-commerce, Hema Fresh, new retail.

1 INTRODUCTION

The advent of new retail, characterized by the integration of online and offline channels, has fundamentally transformed consumer behavior and expectations in the e-commerce landscape (Cai & Lo, 2020). Hema Fresh, an innovative omnichannel fresh food retailer under Alibaba, exemplifies this transformation by offering a seamless shopping experience through digital ordering, in-store picking, and instant delivery (Gao & Huang, 2021). Such models have redefined consumer interactions, emphasizing the need to understand the drivers of satisfaction and continued engagement (Neslin, 2022). This study leverages the Expectation Confirmation Model (ECM), a well-established framework for analyzing post-adoption behavior, to explore these dynamics in the context of fresh food e-commerce (Tam et al., 2020).

ECM posits that satisfaction and continuance intention are determined by the confirmation of initial expectations against actual experiences, mediated by perceived usefulness (Oliver, 1980). While ECM has been extensively applied in contexts such as mobile applications (Park, 2020) and online education (Daneji et al., 2019), its application to fresh food e-commerce—where perishable goods and instant delivery introduce unique challenges—remains underexplored. This research extends ECM by incorporating perceived value, which captures the holistic worth consumers derive from a service (Zeithaml, 1988), and logistics service quality, a critical determinant in delivery-driven retail (Jiang et al., 2023).

The study addresses three research questions: (1) How does ECM elucidate the relationship between consumer expectations, confirmation, satisfaction, and continuance intention in the new retail sector? (2) How does perceived value influence satisfaction and continuance intention? (3) How does logistics service quality shape these outcomes? The objectives are to validate ECM's applicability, assess perceived value's mediating role, and evaluate logistics service quality's impact. Contributions include extending ECM to fresh food e-commerce, providing deeper insights into perceived value, and offering a novel framework with practical implications for operational strategies in digitally integrated retail environments.

2 LITERATURE REVIEW

The Expectation Confirmation Model (ECM), rooted in expectation-disconfirmation theory (Oliver, 1980), provides a theoretical lens for understanding post-adoption behavior in technology and service contexts. ECM suggests that satisfaction arises when actual experiences confirm or exceed initial expectations, mediated by perceived usefulness, ultimately influencing continuance intention (Bhattacherjee, 2001). Empirical studies have validated ECM across diverse domains, including mobile applications (Tam et al., 2020), internet banking (Rahi & Abd. Ghani, 2019), and smart wearable devices (Park, 2020). However, its application to fresh food e-commerce, where instant delivery and product perishability add complexity, remains limited (Jiang et al., 2023).

Perceived value, defined as the consumer's overall assessment of a product or service's utility relative to its cost (Zeithaml, 1988), is a pivotal construct in consumer behavior research. It encompasses functional, emotional, and economic dimensions, acting as a mediator between satisfaction and loyalty (Gallarza et al., 2019). In e-commerce, perceived value influences repurchase intention and user experience (Ali & Bhasin, 2019; Kim et al., 2019). In the new retail context, where integrated online-offline experiences are paramount, perceived value's role in shaping satisfaction and retention warrants further exploration (Swoboda & Winters, 2021).

Logistics service quality, encompassing timeliness, accuracy, and interactivity, is increasingly critical in e-commerce, particularly for fresh food platforms (Kwak et al., 2019). Efficient logistics enhance consumer trust and satisfaction, especially in instant delivery models like Hema Fresh (Jiang et al., 2023). Studies by Chen (2020) and Tian et al. (2021) highlight the role of technological advancements in logistics, while Lai et al. (2022) emphasize its direct impact on satisfaction. Despite these insights, the integration of logistics service quality into ECM frameworks remains underexplored, presenting a gap this study aims to address (Shaban & Salih, 2020).

3 CONCEPTUAL FRAMEWORK AND HYPOTHESES

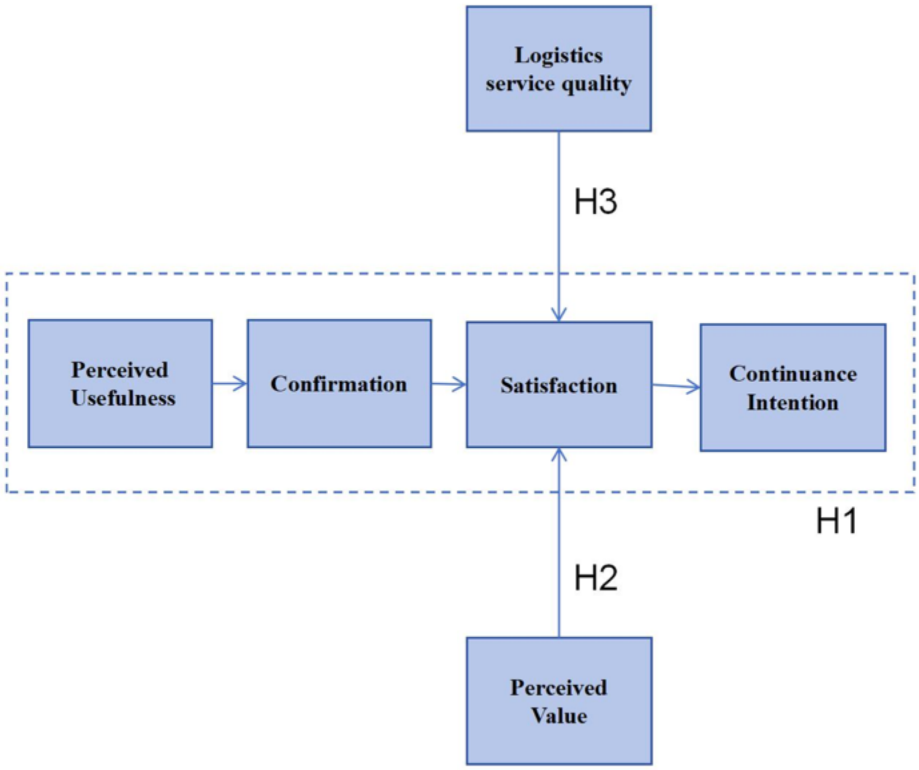


Figure 1. extended Expectation Confirmation Model (ECM)

Figure 1 illustrates the extended Expectation Confirmation Model (ECM) applied to Hema Fresh, incorporating perceived value and logistics service quality as additional constructs influencing consumer satisfaction and continuance intention in fresh food e-commerce. Arrows represent hypothesized relationships tested in the study.

Diagram Description: This diagram is a path diagram including six variables: Perceived Usefulness, Confirmation, Perceived Value, Logistics Service Quality, Satisfaction, and Continuance Intention. Directional arrows indicate hypothesized relationships: (H1) Perceived Usefulness to Confirmation to Satisfaction to Continuance Intention; (H2) Perceived Value to Satisfaction and Perceived Value to Continuance Intention; (H3) Logistics Service Quality to Satisfaction and Logistics Service Quality to Continuance Intention. Arrows are labeled with hypothesis numbers (H1, H2, H3). “Adapted from the traditional ECM (Bhattacherjee, 2001) with extensions for fresh food e-commerce.”

Research Hypotheses:

H1: Perceived usefulness, through the process of confirmation, positively influences satisfaction, which in turn positively impacts continuance intention.

H2: Perceived value positively affects satisfaction and continuance intention.

H3: Logistics service quality positively influences satisfaction and continuance intention.

These hypotheses are grounded in prior research (Tam et al., 2020; Ali & Bhasin, 2019; Jiang et al., 2023) and tailored to the unique context of fresh food e-commerce.

4 METHODOLOGY

This study employs a quantitative research design to test the proposed conceptual framework and hypotheses. Data were collected using a structured questionnaire administered to 497 Hema Fresh users in Kunming, China, during peak shopping times (weekends and evenings). The questionnaire, validated through a pilot test with 50 participants, included 40 items measured on a 5-point Likert scale (1 = strongly disagree, 5 = strongly agree), covering perceived usefulness, confirmation, satisfaction, continuance intention, perceived value, and logistics service quality. Participants were recruited in-store to ensure relevance, with survey stations placed near entrances and assistance provided to ensure accurate responses.

Data analysis was conducted using jamovi (Version 2.6), a statistical software package that integrates R-based modules for advanced analysis (The jamovi project, 2024). SEM was performed using the SEMLj module (Gallucci & Jentschke, 2021), with additional analyses supported by lavaan (Rosseel, 2019), semTools (Jorgensen et al., 2019), and semPlot (Epskamp et al., 2019) packages in R. Descriptive statistics were computed to summarize respondent characteristics and variable distributions. Structural Equation Modeling (SEM) employed maximum likelihood estimation to estimate path coefficients. Model fit was assessed using standard indices: Root Mean Square Error of Approximation (RMSEA < 0.06), Comparative Fit Index (CFI > 0.95), Tucker-Lewis Index (TLI > 0.95), and Standardized Root Mean Square Residual (SRMR < 0.08), as recommended by Hu and Bentler (1999).

5 RESULTS

5.1 Descriptive Analysis

Descriptive statistics provide a comprehensive overview of the sample's demographic composition and the study variables. The sample consisted of 497 Hema Fresh users in Kunming, reflecting diversity in gender, age, shopping frequency, and income (Table 1). The gender distribution was nearly balanced, with 48.1% male and 51.9% female participants. The majority of respondents were aged 25–34 (34.8%), followed by those aged 35–44 (28.2%). Shopping frequency showed that 39.6% of respondents shopped 3–4 times per month, while income levels indicated that 31.4% earned between 5,001–10,000 CNY monthly, reflecting a middle-income dominant sample.

Table 1 Demographic Characteristics of the Sample

Variable	Category	Frequency	Percentage (%)
Gender	Male	239	48.1
	Female	258	51.9
Age	18-24	98	19.7

Variable	Category	Frequency	Percentage (%)
	25-34	173	34.8
	35-44	140	28.2
	45+	86	17.3
Shopping Frequency	<1 time/month	78	15.7
	1-2 times/month	149	30
	3-4 times/month	197	39.6
	>4 times/month	73	14.7
Income (CNY/month)	≤5,000	132	26.6
	5,001-10,000	156	31.4
	10,001-15,000	109	21.9
	>15,000	100	20.1

Descriptive statistics for the study variables (Table 2) indicate that all constructions had mean scores above the neutral point (3.0), suggesting generally positive perceptions. For instance, Continuance Intention had the highest mean (M = 3.78, SD = 0.853), while Perceived Usefulness had the lowest (M = 3.73, SD = 0.852). The standard deviations, ranging from 0.801 to 0.853, reflect moderate variability in responses, indicating diverse consumer perception.

Table 2 Descriptive Statistics of Study Variables

Variable	Mean	SD
Perceived Value	3.75	0.862
Perceived Usefulness	3.73	0.852
Confirmation	3.74	0.801
Satisfaction	3.76	0.841
Continuance Intention	3.78	0.853
Logistics Service Quality	3.77	0.824

5.2 Reliability Analysis

Reliability analysis was conducted to evaluate the internal consistency of the measurement scales. Cronbach's alpha values for all six scales exceeded the threshold of 0.9, indicating excellent reliability (Table 3). Specifically, the Perceived Value scale achieved a Cronbach's alpha of 0.944 with a mean of 3.75 (SD = 0.862), while the Confirmation scale had the lowest alpha at 0.933 (M = 3.74, SD = 0.801). Item-total statistics showed that removing any single item had minimal impact on reliability; for example, deleting items from the Satisfaction scale reduced Cronbach's alpha from 0.940 to a range of 0.932-0.938, confirming the scales' robustness.

Table 3 Scale Reliability Statistics

Scale	Mean	SD	Cronbach's α	Corrected Item-Total Correlation Range
Perceived Value	3.75	0.862	0.944	0.683-0.811
Perceived Usefulness	3.73	0.852	0.944	0.683-0.811
Confirmation	3.74	0.801	0.933	0.616-0.771
Satisfaction	3.76	0.841	0.94	0.660-0.794
Continuance Intention	3.78	0.853	0.943	0.677-0.807
Logistics Service Quality	3.77	0.824	0.937	0.641-0.781

5.3 Exploratory Factor Analysis (EFA)

Exploratory Factor Analysis (EFA) was performed using maximum likelihood extraction with promax rotation to identify the underlying factor structure. The Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy was 0.960 overall, with individual construct values ranging from 0.946 to 0.968, indicating excellent suitability for factor analysis.

The analysis extracted six factors, corresponding to the study's constructs, which collectively explained 72.8% of the variance (Table 4). Factor 1 (Perceived Value) contributed 12.4% to the variance with sum of squared (SS) loadings of 4.45, while Factor 6 (Logistics Service Quality) contributed 11.7% with SS loadings of 4.22. Factor loadings ranged from 0.343 to 0.481 across items, indicating strong associations with their respective constructs.

Table 4 Exploratory Factor Analysis Results

Factor	SS Loadings	% of Variance	Cumulative %	KMO
Perceived Value	4.45	12.4	12.4	0.968
Perceived Usefulness	4.45	12.4	24.7	0.968
Confirmation	4.42	12.3	37	0.946
Satisfaction	4.36	12.1	49.1	0.959
Continuance Intention	4.3	11.9	61.1	0.964
Logistics Service Quality	4.22	11.7	72.8	0.953

5.4 Structural Equation Models

Structural Equation Modeling (SEM) was conducted to test the proposed model and hypotheses. The model demonstrated excellent fit: CFI = 0.992, TLI = 0.992, RMSEA = 0.020 (95% CI: 0.014–0.025), SRMR = 0.088. The explained variance (R^2) was 30.6% for satisfaction and 29.3% for continuance intention and 15% for confirmation, indicating moderate explanatory power (Table 5). Standardized residuals ranged from -2.580 to 2.580, suggesting no significant model misspecification.

Table 5 SEM Parameter Estimates

Label	Relationship	Estimate	SE	β	z	p	R^2 (Satisfaction)	R^2 (Continuance Intention)	R^2 (Confirmation)
p37	Satisfaction ~ Confirmation	0.164	0.043	0.16	3.81	<0.001	0.306	0.293	0.15
p38	Satisfaction ~ Perceived Value	0.266	0.048	0.266	5.57	<0.001			
p39	Satisfaction ~ Logistics Service Quality	0.325	0.049	0.318	6.63	<0.001			
p40	Continuance Intention ~ Satisfaction	0.176	0.047	0.186	3.74	<0.001			
p41	Continuance Intention ~ Perceived Value	0.211	0.047	0.223	4.49	<0.001			
p42	Continuance Intention ~ Logistics Service Quality	0.258	0.049	0.267	5.25	<0.001			
p43	Confirmation ~ Perceived Usefulness	0.39	0.047	0.387	8.3	<0.001			

Hypothesis 1 (H1): H1 posited that perceived usefulness, through confirmation, positively influences satisfaction, which in turn impacts continuance intention. The SEM results support this hypothesis through three significant paths: (1) perceived usefulness to confirmation ($\beta = 0.387$, $z = 8.30$, $p < 0.001$), indicating a strong positive effect; (2) confirmation to satisfaction ($\beta = 0.160$, $z = 3.81$, $p < 0.001$), showing that confirmation enhances satisfaction; and (3) satisfaction to continuance intention ($\beta = 0.186$, $z = 3.74$, $p < 0.001$), confirming satisfaction's role in driving continued use. The standardized coefficients suggest a moderate effect size, consistent with ECM's theoretical pathways.

Hypothesis 2 (H2): H2 proposed that perceived value positively affects satisfaction and continuance intention. The results confirm this hypothesis with two significant paths: (1) perceived value to satisfaction ($\beta = 0.266$, $z = 5.57$, $p < 0.001$), indicating a substantial positive influence; and (2) perceived value to continuance intention ($\beta = 0.223$, $z = 4.49$, $p < 0.001$), demonstrating its direct effect on continued use. These findings highlight the perceived value's dual role as a direct and mediating factor in the ECM framework.

Hypothesis 3 (H3): H3 stated that logistics service quality positively influences satisfaction and continuance intention. The SEM results support this hypothesis with significant paths: (1) logistics service quality to satisfaction ($\beta = 0.318$, $z = 6.63$, $p < 0.001$), showing the strongest effect among predictors of satisfaction; and (2) logistics service quality to continuance intention ($\beta = 0.267$, $z = 5.25$, $p < 0.001$), confirming its direct impact on continued use. These results underscore the critical role of efficient logistics in fresh food e-commerce.

6 DISCUSSION

The findings provide robust support for the applicability of the Expectation Confirmation Model (ECM) in the context of fresh food e-commerce, specifically within Hema Fresh's new retail framework. The confirmation of H1 aligns with prior studies by Tam et al. (2020) and Wang and Wang (2019), which established perceived usefulness and confirmation as key drivers of satisfaction in technology adoption contexts. However, the fresh food e-commerce setting introduces unique dynamics, such as the urgency of instant delivery and the perishability of goods, which amplify the importance of confirmation in shaping satisfaction. The moderate effect size ($\beta = 0.160$ for confirmation to satisfaction) suggests that while confirmation is significant, other factors may also influence satisfaction in this context.

The strong support for H2, with perceived value significantly influencing both satisfaction ($\beta = 0.266$) and continuance intention ($\beta = 0.223$), corroborates findings by Ali and Bhasin (2019) and Kim et al. (2019). Perceived value's mediating role highlights its importance in new retail, where consumers evaluate the integrated benefits of online convenience and offline quality. For Hema Fresh, this implies that enhancing perceived value—through quality assurance, competitive pricing, and personalized experiences—can substantially boost consumer retention.

H3's confirmation, with logistics service quality exerting the strongest effect on satisfaction ($\beta = 0.318$), aligns with Jiang et al. (2023) and Lai et al. (2022), emphasizing the pivotal role of delivery efficiency in fresh food e-commerce. The direct effect on continuance intention ($\beta = 0.267$) further underscores logistics as a competitive differentiator in instant delivery models. These findings suggest that Hema Fresh should prioritize investments in logistics infrastructure, such as optimizing delivery routes and ensuring timeliness, to enhance consumer satisfaction and loyalty.

The model's explanatory power ($R^2 = 30.6\%$ for satisfaction, 29.3% for continuance intention) indicates that while the extended ECM captures significant variance, other factors—such as cultural influences (Helm et al., 2020) or sustainability concerns (Trudel, 2019)—may also play a role. The study's focus on Kunming limits generalizability, and potential response bias from in-store surveys may affect results. Future research should explore these additional variables and validate the model across diverse regions.

7 CONCLUSION

This study successfully validates the Expectation Confirmation Model (ECM) in the context of Hema Fresh, demonstrating its efficacy in explaining consumer satisfaction and continuance intention in fresh food e-commerce. The integration of perceived value and logistics service quality as additional constructs enhances ECM's explanatory power, offering a comprehensive framework for understanding consumer behavior in new retail. Key findings include the significant influence of perceived usefulness through confirmation ($\beta = 0.387$, $p < 0.001$), the mediating role of perceived value ($\beta = 0.266$, $p < 0.001$), and the critical impact of logistics service quality ($\beta = 0.318$, $p < 0.001$). These results provide theoretical contributions by extending ECM to a novel context and practical implications for Hema Fresh to optimize logistics and value propositions. Limitations include the single-location sample and exclusion of external factors like sustainability. Future research should incorporate multi-regional data and additional variables to further refine the model.

REFERENCES

Ali, A., & Bhasin, J. (2019). Understanding customer repurchase intention in e-commerce: Role of perceived price, delivery quality, and perceived value. Jindal Journal of Business Research, 8(2), 142–157. https://doi.org/10.1177/2278682119850276

Bhattacherjee, A. (2001). Understanding information systems continuance: An expectation-confirmation model. MIS Quarterly, 25(3), 351–370. https://doi.org/10.2307/3250921

Cai, Y. J., & Lo, C. K. (2020). Omnichannel management in the new retailing era: A systematic review and future research agenda. International Journal of Production Economics, 229, 107729. https://doi.org/10.1016/j.ijpe.2020.107729

Chen, Y. H. (2020). Intelligent algorithms for cold chain logistics distribution optimization based on big data cloud computing analysis. Journal of Cloud Computing, 9(1), 37. https://doi.org/10.1186/s13677-020-00183-2

Daneji, A. A., Ayub, A. F. M., & Khambari, M. N. M. (2019). The effects of perceived usefulness, confirmation and satisfaction on continuance intention in using massive open online course (MOOC). Knowledge Management & E-Learning, 11(2), 201–214. https://doi.org/10.34105/j.kmel.2019.11.011

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]. https://CRAN.R-project.org/package=semPlot

Gallarza, M. G., Arteaga, F., & Gil-Saura, I. (2019). Customer value in tourism and hospitality: Broadening dimensions and stretching the value-satisfaction-loyalty chain. Tourism Management Perspectives, 31, 254–268. https://doi.org/10.1016/j.tmp.2019.05.009

Gallucci, M., & Jentschke, S. (2021). SEMLj: jamovi SEM Analysis [jamovi module]. https://semlj.github.io/

Gao, M., & Huang, L. (2021). Quality of channel integration and customer loyalty in omnichannel retailing: The mediating role of customer engagement and relationship program receptiveness. Journal of Retailing and Consumer Services, 63, 102688. https://doi.org/10.1016/j.jretconser.2021.102688

Helm, S., Kim, S. H., & Van Riper, S. (2020). Navigating the 'retail apocalypse': A framework of consumer evaluations of the new retail landscape. Journal of Retailing and Consumer Services, 54, 101683. https://doi.org/10.1016/j.jretconser.2018.09.002

Hu, L. T., & Bentler, P. M. (1999). Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. Structural Equation Modeling, 6(1), 1–55. https://doi.org/10.1080/10705519909540118

Jiang, T., Wu, X., & Yin, Y. (2023). Logistics efficiency evaluation and empirical research under the new retailing model: The way toward sustainable development. Sustainability, 15(20), 15028. https://doi.org/10.3390/su152015028

Jorgensen, T. D., Pornprasertmanit, S., Schoemann, A. M., & Rosseel, Y. (2019). semTools: Useful tools for structural equation modeling [R package]. https://CRAN.R-project.org/package=semTools

Kim, S., Ham, S., Moon, H., Chua, B. L., & Han, H. (2019). Experience, brand prestige, perceived value (functional, hedonic, social, and financial), and loyalty among GROCERANT customers. International Journal of Hospitality Management, 77, 169–177. https://doi.org/10.1016/j.ijhm.2018.06.026

Kwak, J., Zhang, Y., & Yu, J. (2019). Legitimacy building and e-commerce platform development in China: The experience of Alibaba. Technological Forecasting and Social Change, 139, 115–124. https://doi.org/10.1016/j.techfore.2018.06.038

Lai, P. L., Jang, H., Fang, M., & Peng, K. (2022). Determinants of customer satisfaction with parcel locker services in last-mile logistics. The Asian Journal of Shipping and Logistics, 38(1), 25–30. https://doi.org/10.1016/j.ajsl.2021.11.002

Neslin, S. A. (2022). The omnichannel continuum: Integrating online and offline channels along the customer journey. Journal of Retailing, 98(1), 111–132. https://doi.org/10.1016/j.jretai.2022.02.003

Oliver, R. L. (1980). A cognitive model of the antecedents and consequences of satisfaction decisions. Journal of Marketing Research, 17(4), 460–469. https://doi.org/10.2307/3150499

Park, E. (2020). User acceptance of smart wearable devices: An expectation-confirmation model approach. Telematics and Informatics, 47, 101318. https://doi.org/10.1016/j.tele.2019.101318

Rahi, S., & Abd. Ghani, M. (2019). Integration of expectation confirmation theory and self-determination theory in internet banking continuance intention. Journal of Science and Technology Policy Management, 10(3), 533–550. https://doi.org/10.1108/JSTPM-06-2018-0055

Rosseel, Y. (2019). lavaan: An R package for structural equation modeling. Journal of Statistical Software, 48(2), 1–36. https://doi.org/10.18637/jss.v048.i02

Shaban, F., & Salih, D. (2020). The role of logistics service quality dimensions on marketing flexibility: An empirical study in dairy factories in Duhok governorate. Uncertain Supply Chain Management, 8(3), 537–546. https://doi.org/10.5267/j.uscm.2020.4.003

Swoboda, B., & Winters, A. (2021). Effects of the most useful offline-online and online-offline channel integration services for consumers. Decision Support Systems, 145, 113522. https://doi.org/10.1016/j.dss.2021.113522

Tam, C., Santos, D., & Oliveira, T. (2020). Exploring the influential factors of continuance intention to use mobile apps: Extending the expectation confirmation model. Information Systems Frontiers, 22, 243–257. https://doi.org/10.1007/s10796-018-9864-8

The jamovi project. (2024). jamovi (Version 2.6) [Computer software]. https://www.jamovi.org

Tian, Z., Zhong, R. Y., Vatankhah Barenji, A., Wang, Y. T., Li, Z., & Rong, Y. (2021). A blockchain-based evaluation approach for customer delivery satisfaction in sustainable urban logistics. International Journal of Production Research, 59(7), 2229–2249. https://doi.org/10.1080/00207543.2020.1807460

Trudel, R. (2019). Sustainable consumer behavior. Consumer Psychology Review, 2(1), 85–96. https://doi.org/10.1002/arcp.1045

Wang, M. M., & Wang, J. J. (2019). Understanding solvers' continuance intention in crowdsourcing contest platform: An extension of expectation-confirmation model. Journal of Theoretical and Applied Electronic Commerce Research, 14(3), 17–33. https://doi.org/10.4067/S0718-18762019000300103

Zeithaml, V. A. (1988). Consumer perceptions of price, quality, and value: A means-end model and synthesis of evidence. Journal of Marketing, 52(3), 2–22. https://doi.org/10.2307/1251446

UNDERSTANDING THE KEY DRIVERS IN USING MOBILE PAYMENT (M-PAYMENT) AMONG GENERATION Z CONSUMERS IN DAILY CONSUMPTION SCENARIOS

Quanjin Xiang[1] and Ahamd Yahya Dawod[2]
International College of Digital Innovation, Chiang Mai University, Chiang Mai, 50200, Thailand
E-mail: quanjin_xiang@cmu.ac.th[1], ahmadyahyadawod.a@cmu.ac.th[2]

ABSTRACT

This research aims to examine the most driving factors to the adoption of mobile payments by Generation Z within the context of everyday consumption situations. It integrates the Unified Theory of Technology Acceptance and Use (UTAUT) and the Mental Accounting Theory (MAT) to form a complete research framework for conducting research on user adoption intentions. Data were collected using an online survey of Gen Z mobile payment consumers on an annual basis. The survey captured the constructs related to UTAUT—performance expectations, effort expectations, and social influence—through the integration of the mental budgeting element of mental accounting theory to account for perceived benefits and perceived risk. Multiple linear regression and mediation analysis were used to test hypotheses. Findings from the research evidence that performance expectations, effort expectations, social influence and perceived benefits have a positive determinant impact on mobile payment adoption, while perceived risk has the reverse effect. Mental budget plays a mediating role within the adoption intention as well.

KEYWORDS: Mobile Payment, Generation Z, Performance Expectancy, Effort Expectancy, Social Influence, Mental Budgeting, Perceived Benefits, Perceived Risks

1. INTRODUCTION

The increasing prevalence of mobile payments has significantly reshaped the landscape of financial trading, particularly among younger generations. M-payment systems, which facilitate transactions via mobile devices, offer users a seamless, fast, and contact-free experience. These features have led to the widespread use of mobile payments in daily consumption contexts such as retail shopping, dining, and transportation. Generation Z, typically defined as individuals born between 1997 and 2012, is often characterized as a digital-native cohort. Having grown up alongside the proliferation of smartphones, social media, and online services, this generation has demonstrated a particularly high level of engagement with mobile payment platforms such as WeChat Pay, Alipay, and Apple Pay (Hanafiah et al., 2024).

This research draws on two foundational theoretical frameworks to examine mobile payment adoption: Mental Accounting Theory (MAT) and the Unified Theory of Acceptance and Use of Technology (UTAUT). UTAUT offers a robust model to learn how technology acceptance is shaped by factors such as performance expectancy, effort expectancy, social influence, and facilitating conditions(Kusuma & Rachmawati, 2024; Nur & Panggabean, 2021). These determinants are especially pertinent for Gen Z, Who prioritizes intuition, efficient, and socially endorsed technologies (Puiu et al., 2022). Meanwhile, MAT provides insight into the cognitive and psychological mechanisms through which individuals subjectively manage financial decisions—such as mentally allocating funds, assessing perceived benefits, and evaluating risks—which helps to contextualize M-payment as not merely a technological adoption, but also a behavioral and economic process (Galhotra et al., 2023).

The present study specifically investigates how key drivers—namely convenience, effort expectancy, social influence, perceived risk, and mental budgeting—Influence Generation Z to adopt mobile payment systems in everyday scenarios. These scenarios include routine consumption behaviors such as grocery shopping, dining out, and paying for public transport (Chen & Arkansas, 2023). By integrating both UTAUT and MAT, The aim of this study is to develop a holistic understanding of how Generation Z navigates and rationalizes their M-payment decisions, offering a dual lens of technology acceptance and behavioral economics.

The rationale for this study is rooted in the rising importance of Generation Z as a dominant consumer segment in the digital economy. As digital natives, they not only exhibit high familiarity with mobile financial tools but also represent a demographic that is shaping the future of cashless societies. Prior studies have highlighted various factors influencing M-payment adoption, such as perceived usefulness, ease of use, and user trust. However, there are still significant Research gaps concerning the role of mental accounting and budget segmentation in everyday payment contexts (Purohit et al., 2022; Galhotra et al., 2023).

By synthesizing UTAUT together with MAT, this study not only enhances theoretical insight into technology adoption and financial behavior but also offers practical implications for improving mobile payment interfaces, promoting adoption strategies, and designing effective marketing communications targeting Generation Z. Ultimately, the research aims to contribute to both academic literature and industry practice by identifying the underlying psychological and contextual factors driving mobile payment adoption, thereby supporting the advancement of a digitally enabled, user-centered financial ecosystem.

2. LITERATURE REVIEW

2.1. Underpinning Theory

To understand the factors driving Generation Z's adoption of mobile payments in daily consumption contexts, two key theories are central to this study: Mental Accounting Theory (MAT) and the Unified Theory of Acceptance and Use of Technology (UTAUT). The frameworks are provide a comprehensive view of how both psychological and technological factors shape users' decisions to adopt M-payment systems.

2.1.1Unified Theory of Acceptance and Use of Technology (UTAUT)

Meanwhile, the UTAUT model identifies four key drivers—performance expectancy, effort expectancy, social influence, and facilitating conditions(Venkatesh et al., 2003).Which predict individuals' willingness to adopt technology. However, while UTAUT focuses on technology's role in adoption, it does not fully address the psychological factors that also influence behavior. To address this gap, combining UTAUT with MAT provides a richer understanding of how Generation Z's perceptions of mobile payment technology influence their decision to use these systems in everyday situations. Specifically, it allows for an exploration of how mental factors, like perceived risk and mental budgeting, work alongside technological aspects, for example, ease of use and performance efficiency, to shape mobile payment adoption (Zhao & Bacao, 2021).

2.1.2Mental Accounting Theory (MAT)

Mental Accounting Theory was proposed by Thaler in 1985, explains the cognitive processes Individuals used to classify, evaluate, and make decisions about financial outcomes. MAT posits that consumers' decisions regarding technology adoption—especially in financial contexts like mobile payments—are influenced by how they mentally account for the perceived risks and benefits associated with that technology. When it comes to mobile payments, MAT helps to explain how Generation Z evaluates mobile payment systems based on their mental classification of perceived convenience, security, and risk(Boonsiritomachai & Sud-On, 2023; Lutfi et al., 2021).

By integrating Mental Accounting Theory (MAT) with the UTAUT model, this study aims to explore how technology perceptions and mental evaluations of financial risks and benefits influence Generation Z using mobile payment systems in daily consumption scenarios. Specifically, adopting mobile payments among Gen Z in everyday contexts—such as shopping, dining, and transportation—is shaped by a range of psychological, social, and technological factors. The integration of these two theoretical frameworks provides a comprehensive perspective on how these factors interact to drive mobile payment adoption. The proposed hypotheses examine how elements such as perceived benefits, performance expectancy, ease of use, social influence, perceived risk, and mental budgeting collectively shape Generation Z's intention to adopt and use mobile payments in their daily lives.

This study integrates the Unified Theory of Acceptance and Use of Technology (UTAUT) and Mental Accounting Theory (MAT), based on which Perceived Benefit (PB) and Perceived Risk (PR) are introduced as antecedent variables of Mental Budgeting (MB). Budgeting (MB) as antecedent variables. To cope with the competition in the industry, it is common for companies to direct consumers to use specific mobile payment methods through incentives such as cash back, discounts and coupons. Based on this, this study proposes to explain the transmission mechanism of perceived benefits (PB) and perceived risks (PR) on the behavioral intention of mobile payment adoption through the mediating role of Mental Budgeting (MB) with Effort Expectation (EE), Performance Expectation (PE), and Social Influence (SI) as a basic predictor variable.

3. METHODODLOGY

3.1 Research Design

This research uses the quantitative approach to investigates the major drivers that shape the usage of mobile payments (M-Payment) for Generation Z consumers within the context of their everyday consumption habits. The research will utilize the Unified Theory of Acceptance and Use of Technology (UTAUT) as a conceptual framework with a specific emphasis on the four prominent determinants of technology adoption: performance expectancy, effort expectancy, social influences, and facilitating conditions. These dimensions are further explored using Mental Accounting Theory (MAT) as a lens, which proposes that people categorize their economic results based on subjective, individual-based criteria. This double framework is instrumental for a better investigation of the psychological mechanisms that underlie generation Z consumers' choice and usage of mobile payments on a daily basis.

3.2 Variable Definitions

Performance Expectancy

Performance expectancy refers to how extent to which Generation Z consumers believe that using mobile payments enhances the efficiency and effectiveness of daily consumption activities such as shopping, dining, or transportation. As noted in the UTAUT framework, this construct captures users' perceptions of tangible performance gains, including time savings and convenience. In this study, it reflects Gen Z's expectations that mobile payments will simplify transactions and improve satisfaction (Salam et al., 2023).

Effort Expectancy

Effort expectancy describes the perceived ease-of-use in relation to the use of a mobile payment system. According to UTAUT, technologies that are perceived as user-friendly are more likely to be adopted. For Generation Z, who value seamless and intuitive interfaces, effort expectancy encompasses the clarity, speed, and convenience of executing mobile transactions (Dong, 2019).

Social Influence

Social influence represents the extent to what Gen Z believes significant others (e.g., peers, family members, or influencers) think they should adopt mobile payments. As digital natives, this cohort is particularly responsive to peer norms and social trends on platforms like Instagram and TikTok, making social endorsement a strong determinant of behavioral intention (Lisana, 2024; Zhao & Bacao, 2021).

Perceived Benefits

Perceived benefits refer to Generation Z's subjective evaluation of the advantages of using mobile payments. Drawing from Mental Accounting Theory (MAT), these benefits include functional value (e.g., convenience), emotional satisfaction (e.g., ease of tracking expenses), and social utility (e.g., alignment with peer behavior). These perceptions shape mental budgeting and drive adoption behavior (Nuresa, 2023; Zhao & Bacao, 2021).

Perceived Risk

Perceived risk involves Generation Z's concerns about the uncertainty and potential negative consequences of using mobile payment systems. This includes worries about security, privacy breaches, data misuse, and fraud. A high perceived risk can act as a psychological barrier, moderating adoption intentions even in the presence of other favorable factors (Ahmed et al., 2021; Lutfi et al., 2021).

Mental Budgeting

Mental budgeting refers to the cognitive process through which Generation Z allocates funds for specific categories or purchases. Influenced by both perceived benefits and risks, mental budgeting mediates the relationship between psychological perceptions and actual payment behavior, helping explain the frequency and context of mobile payment usage (Boonsiritomachai & Sud-On, 2023; Purohit et al., 2022).

Mobile Payment Adoption

Mobile payment adoption captures both the behavioral intention and actual use of mobile payment systems in daily scenarios. This includes the decision to use platforms like WeChat Pay, Alipay, or Apple Pay across consumption contexts such as dining, shopping, and public transport. Adoption is shaped by a combination of technological, psychological, and social factors (Hanafiah et al., 2024).

3.3 Sampling Strategy

The research population for the study would be those consumers who use mobile payment services repeatedly. Convenience sampling would be used for recruitment of respondents who are easily accessible and available for the survey. The respondents would be drawn from urban settings where mobile phone adoption is prevalent. The sampling would be comprised of 18- to 26-year-olds so that participants are within the Generation Z age group and have had recent mobile payment experience.

The research is designed to achieve demographic representation within the sample based on socioeconomic status, levels of education, and purchase habits. By taking these factors into account, the research is able to paint a truer picture of Generation Z mobile payment usage attitudes and avoid being unduly influenced by any one subgroup.

3.4 Data Collection and Analysis

The survey can be accessed on-line from website portals like "Wenjuanxing" and by email to ensure maximum involvement from technologically engaged Gen Z consumers. After collecting the data, the responses were processed and analyzed using SPSSAU software. Reliability and validity assessments, as well as correlation and multiple regression analysis, were done on quantitative data to cross-test research hypotheses. These analyses sought to look at the interactions between the variables of concern that had previously been identified, and Mobile Payment Adoption, and to establish the level of influence that each has on determining ways of making payments within actual settings.

3.5 Research Methodology

The method of quantitative analysis was used in this study for the following reasons:

Firstly, quantitative analysis offers objective and numerical data, which helps to remove subjective bias and make findings more reliable. For instance, quantitative data provide a clear indication of the impact of psychological and technical factors on Mobile Payment Adoption among Generation Z consumers, as supported by studies such as Liu and Zhang (2022). Secondly, quantitative research methods allow for replication by other researchers, thereby verifying the reliability and accuracy of the findings (Chen et al. 2021). This is especially critical in the area of digital consumer behavior, a rapid evolution of mobile technologies requires constant validation and reassessment of theoretical models.

In addition, quantitative analyses can be applied to large sample sizes, which makes the findings more generalizable and applicable to a wider demographic group. This enables the formulation of effective digital payment strategies that are not limited to individual cases. As noted by Nørvig, Petersen, and Balle (2018), this approach enhances both practical application and theoretical development. Finally, the availability of modern statistical tools makes it more efficient to analyze large-scale data sets, allowing researchers to uncover deeper patterns and behavioral trends in mobile payment usage.

Table 1 Research Methodology

Objectives	Hypotheses	Research Method	Population	Sample Size	Sampling Technique	Research Tool	Data Analysis
Objective 1: To identify and analyze the key factors that influence Generation Z's adoption of M-Payment systems in daily consumption scenarios.	H1: Performance Expectancy has a significant positive effect on Mobile Payment Adoption. H2: Effort Expectancy has a significant positive effect on Mobile Payment	Quantitative	Generation Z consumers aged 18–26 who frequently use mobile payments in daily consumption settings such as shopping, dining, and transportation.	425	Convenience sampling in urban areas with high mobile payment penetration.	Questionnaire	Descriptive statistics, correlation analysis, multiple regression

Objectives	Hypotheses	Research Method	Population	Sample Size	Sampling Technique	Research Tool	Data Analysis
	Adoption. H3: Social Influence has a significant positive effect on Mobile Payment Adoption.						
Objective 2: To assess the impact of security and privacy concerns on the acceptance and usage of M-Payment among Generation Z consumers.	H4: Perceived Benefits have a significant positive effect on Mental Budgeting. H5: Perceived Risk has a significant negative effect on Mental Budgeting.	Quantitative	Generation Z consumers aged 18–26 who frequently use mobile payments in daily consumption settings such as shopping, dining, and transportation.	425	Convenience sampling in urban areas with high mobile payment penetration.	Questionnaire	Descriptive statistics, correlation analysis, multiple regression
Objective 3: To explore the influence of social factors and perceived innovativeness on Generation Z's attitudes and intentions regarding M-Payment adoption.	H6: Mental Budgeting has a significant positive effect on Mobile Payment Adoption. H7: Mental Budgeting mediates the relationship between Perceived	Quantitative	Generation Z consumers aged 18–26 who frequently use mobile payments in daily consumption settings such as shopping, dining, and transportation.	425	Convenience sampling in urban areas with high mobile payment penetration.	Questionnaire	Descriptive statistics, correlation analysis, multiple regression

Objectives	Hypotheses	Research Method	Population	Sample Size	Sampling Technique	Research Tool	Data Analysis
	Benefits and Mobile Payment Adoption. H8: Mental Budgeting mediates the relationship between Perceived Risk and Mobile Payment Adoption.						

3.6 Measurement model

The reliability and validity of the structural model were rigorously assessed (see Table 2). The measurement model's quality was evaluated through content validity, discriminant validity, indicator reliability, and construct reliability, following established psychometric standards (Laumer et al., 2010). All indicator factor loadings exceeded 0.70, surpassing the minimum threshold of 0.50 recommended by Gefen (2002). Convergent validity was established, as the average variance extracted (AVE) values for all constructs surpassed the 0.50 threshold. Composite reliability measures demonstrated strong internal consistency, with values above the 0.70 cutoff for all constructs. Additionally, Cronbach's alpha coefficients for each construct surpassed 0.70, further verifying scale reliability (Purohit et al., 2022).

Discriminant validity was established through the Fornell-Larcker criterion, where the square roots of AVE values for all constructs exceeded their respective inter-construct correlations. The results collectively indicated robust internal consistency, along with satisfactory convergent and discriminant validity across measurement instruments. These psychometric evaluations confirm the measurement model's appropriateness for subsequent hypothesis testing in the proposed framework.

Table 2 Validity measures

			Discriminant Validity							
Latent Construct	Average Variance Extracted (AVE)	Composite Reliability (CR)	PB	PE	EE	SI	PR	MB	BI	Cronbach' s α
PB	0.63	0.87	**0.79**							0.902
PE	0.68	0.9	0.58	**0.82**						0.898
EE	0.65	0.88	0.51	0.62	**0.81**					0.899
SI	0.6	0.86	0.49	0.56	0.54	**0.78**				0.899
PR	0.58	0.84	0.43	0.45	0.47	0.44	**0.76**			0.9
MB	0.67	0.89	0.61	0.59	0.57	0.55	0.48	**0.82**		0.899
BI	0.72	0.91	0.64	0.68	0.66	0.62	0.53	0.72	**0.85**	0.897

3.7 Descriptive stats

A number of 425 effective questionnaires collected for this research. Among respondents, 222 (52.2%) were male, accounting for 52.2% of the total sample, and 203 (47.8%) were female. In terms of age distribution, there were 135 respondents (31.8%) in the 18 to 20 age group, the 21 to 23 age group was the main group with 197 respondents (46.4%), while the 24 to 26 age group had 93 respondents (21.9%). In terms of educational attainment, the vast majority of respondents had a bachelor's degree or higher (408, or 96.0%), while only 17 (4.0%) had a high school education. The current status of respondents included 195 (45.9%) in the academic category, 19 (4.5%) without a worker, and the remaining 211 (49.6%) were employed. In terms of commonly used mobile payment platforms, Alipay had the highest usage rate, with 323 (76.0%) indicating that they used it frequently; followed by WeChat Pay with 289 (68.0%); in addition, the number of people who used Jingdong Pay, Yunfan Pay and other platforms were 138 (32.5%), 90 (21.2%) and 22 (5.2%), respectively.

3.8 Correlation Analysis

Using Pearson correlation analysis, this study investigates the relationship between Behavioral Intention (BI) and six major variables: Mental Budgeting (MB), Perceived Risk (PR), Social Influence (SI), Effort Expectancy (EE), Performance Expectancy (PE), and Perceived Benefits (PB). The results (see Table 2) show that BI is positively and significantly correlated with all six variables, with correlation coefficients as follows: MB (0.385), PR (0.294), SI (0.353), EE (0.378), PE (0.501), and PB (0.327), all reaching the 0.01 significance level. This indicates that increases in these factors are associated with stronger behavioral intention.

Further analysis reveals that MB is positively and significantly correlated with PR (r = 0.196) and PB (r = 0.261), both at the 0.01 significance level. Moreover, MB is also significantly positively correlated with BI (r = 0.385). These findings suggest that MB is influenced by PR and PB, and in turn, influences BI.

Therefore, as MB is significantly associated with both the antecedent variables (PR and PB) and the dependent variable (BI), it preliminarily satisfies the conditions of a mediating variable, providing a foundation for subsequent mediation analysis.

Table 3 Pearson Correlation Coefficients

	BI	MB	PR	SI	EE	PE	PB
BI	1						
MB	0.385	1					
PR	0.294	0.196	1				
SI	0.353	0.297	0.286	1			
EE	0.378	0.372	0.235	0.290	1		
PE	0.501	0.416	0.315	0.305	0.366	1	
PB	0.327	0.261	0.200	0.332	0.313	0.309	1

$p<0.05$

3.9 Multiple Regression Analysis

As shown in the Table 3, multiple linearity regression analysis was conducted with BI as a dependent variable and MB, PR, SI, EE, PE, and PB as independent variables. The resulting regression equation is:

$$\mathbf{BI = 0.255 + 0.146 \times MB + 0.090 \times PR + 0.135 \times SI + 0.151 \times EE + 0.302 \times PE + 0.097 \times PB}$$

The model's R^2 is 0.354, indicating that 35.4% of the variance in BI can be explained by the six independent variables. The F-test result is F = 38.112, $p = 0.000 < 0.05$, confirming the model's overall significance.

All VIF values are below 5, indicating no multicollinearity. The Durbin-Watson statistic is close to 2, suggesting no autocorrelation in the residuals.

The regression results indicate that among the six independent variables, Mental Budgeting (MB) has a significant positive effect on Behavioral Intention (BI), with a standardized coefficient of $\beta = 0.146$, $t = 2.874$, and $p = 0.004 < 0.01$. Perceived Risk (PR) also shows a significant positive effect on BI ($\beta = 0.090$, $t = 2.044$, $p = 0.042 < 0.05$). Likewise, Social Influence (SI) ($\beta = 0.135$, $t = 2.835$, $p = 0.005 < 0.01$) and Effort Expectancy (EE) ($\beta = 0.151$, $t = 2.894$, $p = 0.004 < 0.01$) both exert significant positive effects. Notably, Performance Expectancy (PE) demonstrates the strongest impact among all predictors ($\beta = 0.302$, $t = 6.483$, $p = 0.000 < 0.01$). Finally, Perceived Benefits (PB) has a significantly positive effect on BI ($\beta = 0.097$, $t = 2.277$, $p = 0.023 < 0.05$). In summary, all six variables significantly and positively predict users' behavioral intention toward mobile payment adoption.

Table 4 Multiple Regression Analysis

	β	*t*	*p*	VIF
constant	0.255	1.028	0.305	-
MB	0.146	2.874	0.004	1.334
PR	0.090	2.044	0.042	1.175
SI	0.135	2.835	0.005	1.271
EE	0.151	2.894	0.004	1.314
PE	0.302	6.483	0.000	1.407
PB	0.097	2.277	0.023	1.237
R^2	0.354			
D-W 值	2.007			

3.10 Mediation Analysis

As displayed in the Table 4, Examining the mediation effect of Mental Budgeting (MB) in the relationships between Perceived Benefits (PB), Perceived Risk (PR), and Behavioral Intention (BI), this study conducted mediation analyses using the percentile bootstrap method.

For the PB path, PB significantly predicted MB ($\beta = 0.229$, $p < 0.01$), and MB significantly predicted BI ($\beta = 0.359$, $p < 0.01$). The indirect effect was 0.082, with a 95% bootstrap confidence interval of [0.051, 0.125], which doesn't include zero, indicating a significant mediating effect. The direct impact of PB on BI remained significant ($\beta = 0.238$, $p < 0.01$), suggesting that MB plays a partial mediating role between PB and BI.

Similarly, for the PR path, PR has a significant effect on MB ($\beta = 0.180$, $p < 0.01$), MB continued to significantly influence BI ($\beta = 0.380$, $p < 0.01$). With a value of 0.069 and a bootstrap confidence interval of [0.033, 0.107], the indirect effect also excludes zero, further confirming its significance as a mediator. The direct impact of PR on BI remained significant ($\beta = 0.234$, $p < 0.01$), indicating that MB also serves as a partial mediator between PR and BI.

In summary, Mental Budgeting plays a significant partial mediating role in the relationships from both Perceived Benefits and Perceived Risk to Behavioral Intention.

Table 5 Mediation Analysis

Path	a	b	Indirect Effect	a*b (*p-value*)	a*b (95% BootCI)	c’ Direct Effect
PB=>MB=>BI	0.229	0.359	0.082	0.000	0.051 ~ 0.125	0.238
PR=>MB=>BI	0.180	0.380	0.069	0.000	0.033 ~ 0.107	0.234

a: effect of PB on MB, **b**: effect of MB on BI, **a×b**: indirect effect via MB, **c′**: direct effect of PB on BI, controlling for MB, **Bootstrap CI**: confidence interval from percentile bootstrap method

4 RESULTS DISCUSSION

The empirical outcomes of this study offer valuable insight to the factors driving Generation Z consumers’ adoption of mobile payment (M-Payment) systems. First, consistent with the predictions of the UTAUT model, Performance Expectancy (PE) has been shown to be the most impactful prediction of Behavioral Intention (BI), indicating that Gen Z consumers place high importance on the efficiency and convenience brought by M-payment technologies. These findings match earlier research, like Liu and Zhang (2022), reinforcing the key part perceived usefulness plays in the adoption of technology among digital natives.

The study also found that Effort Expectation (EE) and Social Influence (SI) also have A significantly positive effect on behavioral intentions. The significance of EE suggests that ease of use remains a key factor even among tech-savvy users. Meanwhile, the impact of SI highlights the crucial role of peers, family, and broader social circles in encouraging Gen Z to adopt emerging payment technologies, further underlining the importance of social recognition and the word-of-mouth effect in the rollout of digital payment systems.

This study introduced Mental Budgeting (MB) as a mediating variable, grounded in Mental Accounting Theory, offering a deeper psychological perspective on consumer behavior. The results confirm that both Perceived Benefits (PB) and Perceived Risk (PR) significantly influence MB, which in turn affects behavioral intention. The significant indirect effects of PB and PR through MB suggest that Gen Z consumers do engage in mental trade-offs between convenience and risk in their payment decisions, supporting the theoretical value of incorporating the MAT framework into technology adoption research.

It is worth noting that Perceived Risk (PR) also showed a significant positive direct effect on BI. Given that the PR items in this study’s questionnaire were designed with reverse wording, higher PR scores indicate that users perceive lower levels of risk. In other words, the results suggest that when Gen Z consumers perceive mobile payment systems as more secure and trustworthy, they are more likely to adopt and continue using these technologies. This discovery is consistent from past research and emphasizes the critical role of risk control and trust mechanisms in driving technology adoption. Moreover, the significant indirect effect of PR via MB suggests that perceived safety not only directly enhances user intention but also indirectly does so by strengthening confidence in personal financial control.

Overall, the integration of UTAUT and MAT models enabled this research to reveal the combined effects of functional and cognitive drivers on Gen Z payment behavior. The critical role of mental budgeting further validates the presence of subjective psychological mechanisms underlying consumer decision-making in the digital environment.

5 CONCLUSION

This study, based on an integrated UTAUT and MAT model, explored the key psychological and technological drivers influencing the adoption and behavior of Generation Z consumers in China towards the use of mobile payments.

First, Performance Expectancy (PE) emerges as the most top Predictors of Behavioral Intention (BI), suggesting that Gen Z consumers prize the efficiency and functionality of mobile payment technologies. Effort Expectancy (EE) and Social Influence (SI) has also been a clear positive impact, suggesting that both the easy-to-use nature of the system and the social incentives play an important role in driving payment behavior.

Second, Perceived Benefits (PB) not only had a significant positive effect on Mental Budgeting (MB) but also directly promoted behavioral intention, highlighting the role of value perception in financial decision-making. Notably, Perceived Risk (PR) was measured using reverse-coded items, thus reflecting users' perception of safety or low risk. The results showed that the more secure Gen Z users perceive mobile payment to be, the stronger their intention to adopt and use it.

Further mediation analysis indicated that both PB and PR indirectly affected behavioral intention through MB, confirming MB's partial mediating role in this relational chain.

In conclusion, the mobile payment behavior of Generation Z is driven by a combination of cognitive and emotional factors, including efficiency, ease of use, social recognition, perceived value, sense of security, and budget awareness.

REFERENCES

Alam, S. S., Ahmed, S., Kokash, H. A., Mahmud, M. S., & Sharnali, S. Z. (2024). Utility and hedonic perception-Customers' intention towards using of QR codes in mobile payment of Generation Y and Generation Z. *Electronic Commerce Research and Applications*, *65*, 101389.

Bai, R. (2023). Impact of financial literacy, mental budgeting and self control on financial wellbeing: Mediating impact of investment decision making. *Plos one*, *18*(11), e0294466.

Behera, R. K., Bala, P. K., & Rana, N. P. (2023). Assessing factors influencing consumers' non-adoption intention: exploring the dark sides of mobile payment. *Information Technology & People*, *36*(7), 2941-2976.

Belanche, D., Guinalíu, M., & Albás, P. (2022). Customer adoption of p2p mobile payment systems: The role of perceived risk. *Telematics and Informatics*, *72*, 101851.

Bland, E., Changchit, C., Changchit, C., Cutshall, R., & Pham, L. (2024). Investigating the components of perceived risk factors affecting mobile payment adoption. *Journal of Risk and Financial Management*, *17*(6), 216.

Boonsiritomachai, W., & Sud-On, P. (2023). Promoting habitual mobile payment usage via the Thai government's 50: 50 co-payment scheme. *Asia Pacific Management Review*, *28*(2), 163-173.

Chen, A., & Arkansas, C. (2023). Usage Behavior of E-Payment Services By Chinese Millennials (Generation Y) and Zoomers (Generation Z). *Journal of Business Administration Online*, *17*(01).

Chun, S., & Johnson, D. S. (2021). The effects of mental budgeting and pain of payment on the financial decision making of socially excluded people. *International Journal of Bank Marketing*, *39*(5), 886-899.

Dong, X. (2019). Performance expectancy, effort expectancy, social influence, facilitating conditions, and relative advantage affecting chinese customers' decision to use mobile payment in Bangkok.

Galhotra, B., Jatain, A., Bajaj, S. B., & Jaglan, V. (2023). Gen Z's Digital Payments: Disruptive Or Useful For Online Shopping In Security Aspect. *Journal of Survey in Fisheries Sciences*, 1466-1473.

Gao, L., & Waechter, K. A. (2017). Examining the role of initial trust in user adoption of mobile payment services: an empirical investigation. *Information Systems Frontiers*, *19*, 525-548.

Hanafiah, M. H., Asyraff, M. A., Ismail, M. N. I., & Sjukriana, J. (2024). Understanding the key drivers in using mobile payment (M-Payment) among Generation Z travellers. *Young Consumers*.

Hossain, M. A. (2019). Security perception in the adoption of mobile payment and the moderating effect of gender. *PSU Research Review*, *3*(3), 179-190.

Hossain, M. A., Amin, R., Masud, A. A., Hossain, M. I., Hossen, M. A., & Hossain, M. K. (2023). What drives people's behavioral intention toward telemedicine? an emerging economy perspective. *Sage Open*, *13*(3), 21582440231181394.

Jung, J.-H., Kwon, E., & Kim, D. H. (2020). Mobile payment service usage: US consumers' motivations and intentions. *Computers in Human Behavior Reports*, *1*, 100008.

Kusuma, F. N. P., & Rachmawati, R. (2024). Analysis of factors affecting the intention of continued use of mobile payment services among generation z: a UTAUT2 approach. *Linkage*, *1*(1), 46-57.

Liao, Y.-K., Nguyen, H.-L. T., Dao, T. C., Nguyen, P.-T. T., & Sophea, H. (2024). The antecedents of customers' attitude and behavioral intention of using e-banking: the moderating roles of social influence and customers' traits. *Journal of Financial Services Marketing*, *29*(3), 1037-1061.

Lisana, L. (2024). Understanding the key drivers in using mobile payment among Generation Z. *Journal of Science and Technology Policy Management*, *15*(1), 122-141.

Lutfi, A., Al-Okaily, M., Alshirah, M. H., Alshira'h, A. F., Abutaber, T. A., & Almarashdah, M. A. (2021). Digital financial inclusion sustainability in Jordanian context. *Sustainability*, *13*(11), 6312.

Nur, T. (2024). Generation Z's Adoption of E-Wallet: Understanding factors and Implication for Consumptive Behavior. 2024 2nd International Conference on Software Engineering and Information Technology (ICoSEIT),

Nur, T., & Panggabean, R. R. (2021). Factors influencing the adoption of mobile payment method among generation Z: the extended UTAUT approach. *Nur, T. and Panggabean, RR*, 14-28.

Painoli, G. K., Sharma, R., Ramya, H., Purohit, N. K., & Bhattacharya, R. EXAMINING THE IMPACT OF MENTAL ACCOUNTING ON STUDENT'S INVESTMENT AND FINANCIAL DECISION.

Park, J., Ahn, J., Thavisay, T., & Ren, T. (2019). Examining the role of anxiety and social influence in multi-benefits of mobile payment service. *Journal of Retailing and Consumer Services*, *47*, 140-149.

Puiu, S., Demyen, S., Tănase, A.-C., Vărzaru, A. A., & Bocean, C. G. (2022). Assessing the adoption of mobile technology for commerce by generation Z. *Electronics*, *11*(6), 866.

Purohit, S., Kaur, J., & Chaturvedi, S. (2022). Mobile payment adoption among youth: Generation z and developing country perspective. *Journal of Content, Community and Communication*, *15*(8), 194-209.

Rosalina, E., Andriani, W., Santi, E., & Rahmi, A. (2022). Household financial management with personality factors and locus of control through mental budgeting. *Economics, Business, Accounting & Society Review*, *1*(3), 132-141.

Sair, S. A., & Danish, R. Q. (2018). Effect of performance expectancy and effort expectancy on the mobile commerce adoption intention through personal innovativeness among Pakistani consumers. *Pakistan Journal of Commerce and social sciences (PJCSS)*, *12*(2), 501-520.

Salam, M. A., Rayun, S. N., & Leong, V. S. (2023). EXAMINING CRITICAL FACTORS INFLUENCING GENERATION Z'S ACCEPTANCE OF MOBILE PAYMENT SYSTEMS IN BANGLADESH: A UTAUT MODEL ANALYSIS. *Journal of Business & Economic Analysis*, *6*(3).

Sarker, S. A., Wang, S., Adnan, K. M., Pooja, P., Akhi, K., & Akter, K. (2023). Renewable energy in Bangladesh: economic growth and policy perspectives. *Journal of Science and Technology Policy Management*, *14*(4), 780-797.

Zhao, Y., & Bacao, F. (2021). How does the pandemic facilitate mobile payment? An investigation on users' perspective under the COVID-19 pandemic. *International journal of environmental research and public health*, *18*(3), 1016.

THE POTENTIAL FOR BIKE-SHARING EXPANSION IN THAILAND

Natchanon Chaitip[1] and Piang-or Loahavilai[2]
International College of Digital Innovation, Chiang Mai University, Chiang Mai, 50200, Thailand
E-mail: [1]natchanon_cha@cmu.ac.th, [2]piangor@gmail.com

ABSTRACT

With increasing urbanization and a growing focus on sustainable transportation, bike-sharing services have gained attention as an alternative mode of transport (Shaheen, Guzman, & Zhang, 2010). This study examines the feasibility of expanding bike-sharing systems in Thailand by assessing market demand, infrastructure development, government policies, and user preferences. The research utilizes a combination of surveys, case studies, and industry data to explore both opportunities and challenges in scaling up bike-sharing services. Findings indicate that factors such as traffic congestion, environmental awareness, and digital payment adoption support the growth of bike-sharing. However, challenges such as limited cycling infrastructure, seasonal weather variations, and safety concerns remain key barriers. To facilitate expansion, collaboration between public and private sectors, improved infrastructure, and policy incentives are necessary. The insights from this study aim to inform policymakers, urban planners, and mobility service providers on strategies to enhance Thailand's bike-sharing ecosystem.

KEYWORDS: Bike-Sharing, Sustainable Transport, Urban Mobility, Thailand, Micro-Mobility Expansion

1 INTRODUCTION

As cities across the globe strive for smarter, greener, and more efficient transportation solutions, bike-sharing systems have emerged as a key component of sustainable urban mobility. Successful bike-sharing systems in global cities such as Paris, London, and Hangzhou demonstrate how infrastructure investment and supportive policy can drive user adoption (Midgley, 2011). Studies also confirm that bike-sharing services contribute to emission reduction and energy conservation, particularly in high-density urban environments (Zhang & Mi, 2018). The global growth of shared mobility, including bike-sharing and e-scooters, reflects a broader transition toward sustainable transport solutions (Shaheen & Cohen, 2019). In recent years, Thailand has witnessed a rise in urban population density, mounting traffic congestion, and growing concerns about environmental sustainability—factors that collectively call for innovative transportation alternatives. Among these, bike-sharing offers a compelling opportunity to ease urban mobility challenges while aligning with global trends in micro-mobility and digital transformation. Despite the global success of bike-sharing systems, their implementation and growth in Thailand remain fragmented and limited in scale. Several pilot projects and private initiatives have emerged in urban centers and university campuses, yet they often struggle with issues such as inadequate cycling infrastructure, low ridership sustainability, poor maintenance, and lack of policy integration (Sermsukprasert & Komolrit, 2020; Intarapasan et al., 2022). While international research has emphasized the value of bike-sharing in reducing emissions and enhancing urban mobility (Fishman, 2016), there is limited localized understanding of the operational, cultural, and institutional factors affecting their expansion in Thai contexts. Furthermore, existing studies tend to focus on technical or policy aspects in isolation rather than offering a holistic view that incorporates stakeholder perspectives across diverse urban and closed environments. This gap highlights the need for exploratory research to uncover the interconnected dynamics that either facilitate or hinder the growth of bike-sharing in Thailand. This study seeks to explore the factors influencing the potential for bike-sharing expansion in Thailand. focusing on the intersection of infrastructure readiness, user adoption, government policy, and market dynamics. By assessing the current landscape and identifying both enabling conditions and persistent obstacles, this research seeks to provide a comprehensive foundation for stakeholders aiming to scale bike-sharing systems. Through a combination of in-depth interviews with bike-sharing users and company employees, case analyses, and industry data review, this investigation contributes to the understanding of how Thailand can adapt and evolve its mobility ecosystem to meet the demands of a modern, sustainable future.

2 LITERATURE REVIEW

Bike-sharing systems have increasingly been adopted around the world as a sustainable solution to urban transportation problems. They provide a practical alternative to car-based travel in congested areas, helping to reduce emissions, support public health, and ease traffic. The growth of bike-sharing is strongly linked to the rise of digital technology, particularly the use of mobile applications, GPS tracking, and electronic payment systems. Factors such as digital integration and urban design significantly influence the uptake of shared bikes in Asian megacities (Campbell et al., 2016). These innovations have made accessing and managing bike-sharing services more convenient for both users and operators (Shaheen et al., 2010; Fishman et al., 2013). Data analytics and predictive modeling have also been utilized to optimize bike-sharing deployment and rebalance fleets efficiently (Ma, Liu, & Zhang, 2019). With rising mobile wallet adoption, bike-sharing has become more accessible to Thai users (Lee & Wang, 2021), especially among youth and tourists. Research indicates that bike-sharing can positively impact the environment and urban mobility. By encouraging non-motorized transport, these systems contribute to reductions in vehicle emissions and energy consumption. Studies have shown that when bike-sharing becomes part of a city's transportation mix, it not only supports lower carbon outputs but also promotes active travel behavior, which benefits public health (Pojani & Stead, 2015; DeMaio, 2009). Policy incentives and cycling infrastructure investment are closely linked to increased bike-sharing participation rates (Buck & Buehler, 2012). However, the implementation of bike-sharing programs often faces challenges, particularly in cities that lack sufficient infrastructure for cycling. In many cases, the absence of safe, designated bike lanes or secure parking spaces discourages potential users. Urban areas in Southeast Asia, including Thailand, must also contend with extreme weather conditions and vehicle-dominated road networks, both of which reduce the appeal and safety of cycling (Parkin & Rotheram, 2010; Zhao et al., 2020). User adoption plays a central role in determining the success of bike-sharing systems. Environmental and land-use factors have been shown to significantly influence bike-sharing usage in urban planning literature (Sun et al., 2017). Research shows that factors such as affordability, safety, convenience, and cultural attitudes influence how frequently users engage with these services. While younger, tech-savvy populations may be more inclined to use bike-sharing, concerns over road safety, especially in traffic-heavy areas, remain a significant barrier (Ricci, 2015). In Thailand, the increasing penetration of smartphones and mobile wallets has helped make bike-sharing more accessible. Still, safety concerns and cultural hesitance toward cycling persist. Government support and policy frameworks are essential to the growth of bike-sharing. Cities with successful systems typically benefit from clear regulations, financial incentives, and integration with broader urban planning goals. For example, Bai and Jiao (2020) note that public investment, combined with partnerships between government and private operators, has been a key driver in expanding services in several Chinese cities. In Thailand, some local governments have begun to pilot bike-sharing services, but a coordinated national policy for micro-mobility is not yet fully in place. Insights can also be drawn from case studies in countries with similar economic and urban contexts. In China and Vietnam, the rapid growth of bike-sharing brought both opportunities and challenges, including issues related to fleet oversupply and public space management. Nevertheless, these examples illustrate how strong regulatory frameworks and data-driven planning can lead to sustainable scaling of such services (Zhao et al., 2020). Cheng and Zhang (2019) emphasize that Southeast Asian cities require tailored micromobility strategies due to infrastructural constraints and mixed modal priorities. International comparisons suggest that integrated policies—such as subsidized bike lanes and traffic calming—boost cycling adoption (Buehler & Pucher, 2012). Thailand-specific studies, though limited, provide some early perspectives. For example, Tulyasuwan et al. (2021) examined pilot projects in Bangkok and Chiang Mai, finding both interest and obstacles. Users appreciated the convenience and affordability of shared bikes, but challenges such as limited bike lanes, inconsistent service quality, and regulatory uncertainty hindered widespread adoption. In conclusion, the existing literature supports the notion that bike-sharing can be a valuable part of sustainable urban transportation strategies. Yet its success is contingent on well-developed infrastructure, supportive policy environments, and a clear understanding of local user needs. This study builds on these findings by investigating the feasibility of expanding bike-sharing in Thailand, considering infrastructure, policy, and user behavior within a local context.

3 RESEARCH METHODOLOGY

3.1 Research Design

This research followed Creswell's (2013) approach to qualitative design, enabling the exploration of context-specific behavior and perceptions. Adopting a qualitative research approach, incorporating thematic analysis as described by Braun and Clarke (2006) to explore the factors that influence the potential for expanding bike-sharing services in Thailand. The research is designed to gain in-depth insights into both user experiences and stakeholder perspectives within the bike-sharing ecosystem, focusing on both open areas (e.g., Chiang Mai city and Bangkok) and closed areas (e.g., Chiang Mai University and Thammasat University). Specifically, the study applies two key analytical frameworks: SWOT analysis (Strengths, Weaknesses, Opportunities, and Threats) and thematic analysis to identify recurring patterns and strategic implications from qualitative data.

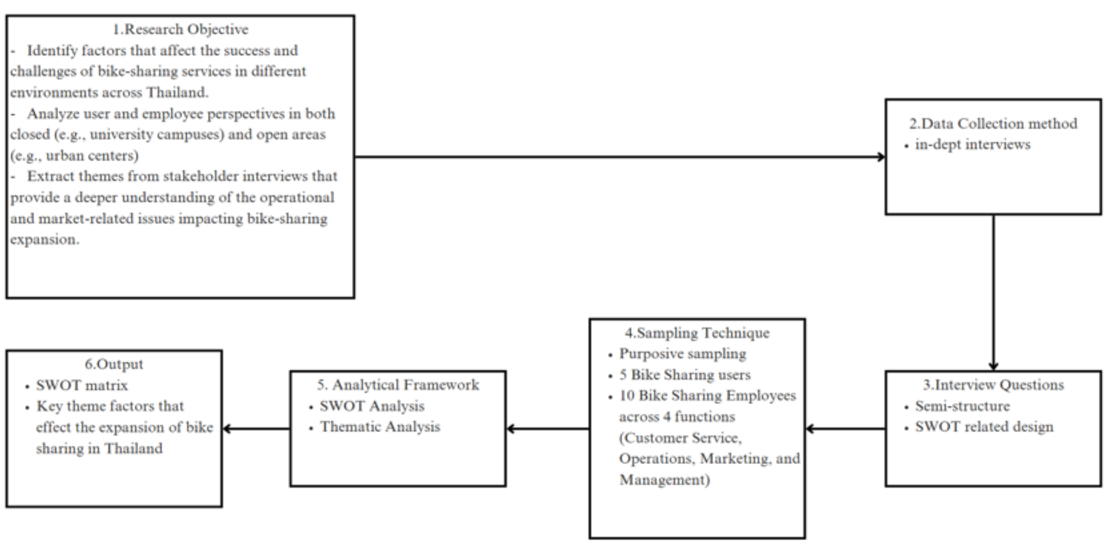


Figure 3.1 Research Framework

3.2 Research Objectives

- To identify factors that affect the success and challenges of bike-sharing services in different environments across Thailand.
- To analyze user and employee perspectives in both closed (e.g., university campuses) and open areas (e.g., urban centers) using SWOT framework.
- To extract themes from stakeholder interviews that provide a deeper understanding of the operational and market-related issues impacting bike-sharing expansion.

3.3 Data Collection Method

The study employed **in-depth interviews**, a widely used technique in qualitative research for capturing detailed and context-rich data (Kvale, 1996). Two groups of participants were purposively selected:

1. Bike-sharing users: to understand their experience, satisfaction, and challenges using bike-sharing services in both open and closed areas.
2. Bike-sharing company employees, including:
    - Customer service staff
    - Operation staff
    - Marketing staff
    - Executive-level officers

The interviews were semi-structured, allowing for flexibility while maintaining focus on key themes. The questions were designed to elicit SWOT insights:

- For users: the SWOT of using bike-sharing in different environments.
- For employees: the SWOT related to their operational tasks in both open and closed areas.

Each interview lasted approximately 30–60 minutes and was conducted either face-to-face or via video call, depending on participant availability.

3.4 Sampling Technique

Purposive sampling was used to select participants with relevant experience and knowledge of the bike-sharing context. A total of 9 participants were interviewed:

- 2 bike-sharing users with varying frequency of usage across open and closed areas.
- 7 employees across four functions (customer service, operations, marketing, management) from leading bike-sharing service providers operating in Thailand.

Participants were selected based on their involvement with the service and their ability to provide detailed insights into the SWOT factors affecting the use and management of bike-sharing systems.

3.5 Ethical Considerations

All participants were informed about the study's purpose, their rights, and the voluntary nature of their involvement. Informed consent was obtained prior to data collection. All information gathered was anonymized and securely stored in compliance with ethical research standards (Bryman, 2016).

3.6 Analytical Frameworks

3.6.1 SWOT Analysis

The SWOT analysis is a strategic planning tool used to identify internal strengths and weaknesses, as well as external opportunities and threats (Gürel & Tat, 2017). This framework allows for structured comparison of different operational environments—open cities versus closed institutional spaces—from the viewpoints of both users and service providers.

3.6.2 Thematic Analysis

Thematic analysis was used to systematically identify and interpret patterns of meaning across the dataset. Following Braun and Clarke's (2006) six-phase framework, the analysis process included: Familiarization: Transcribing and reading through the data. Coding: Generating initial codes from the data relevant to research objectives. Theme Development: Collating codes into potential themes. Review and Definition: Refining and naming themes based on conceptual relevance. Interpretation: Relating themes to SWOT findings and research questions.

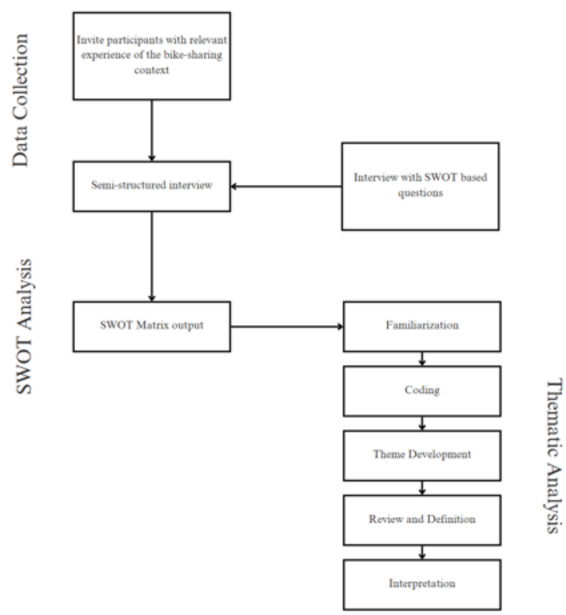


Figure 3.2 Analytical Framework

3.7 Expected Output

A detailed SWOT analysis for each environment—closed areas (e.g., university campuses) and open areas (e.g., urban cities)—from both user and employee perspectives. This will help identify the strategic strengths, limitations, and environmental factors affecting service scalability. Thematic analysis will result in clearly defined themes that represent operational, infrastructural, behavioural, and policy-related factors influencing bike-sharing effectiveness and acceptance.

4 RESULT

The SWOT analysis results from qualitative interviews with stakeholders in Thailand's public bike-sharing ecosystem. Data was collected from both users and service providers in Chiang Mai City, Chiang Mai University, Bangkok, and Thammasat University (Rangsit Campus). Thematic coding was used to categorize responses into strengths, weaknesses, opportunities, and threats (Braun & Clarke, 2006).

4.1 SWOT Analysis

4.1.1 Chiang Mai City (Open Area)

Strengths:
Bike-sharing offers time-saving alternatives to cars for short trips. Staff emphasized flexibility in relocating bicycles and availability of different bike types (Participant E, Interview, 2025). Marketing highlighted low costs and recreational suitability (Participant H, Interview, 2025).

Weaknesses:
Users cited lack of safe infrastructure and traffic unpredictability as barriers. Staff struggled with unauthorized bike use and system limitations (e.g., manual locks), which reduced efficiency (Participant, C, Interview, 2025).

Opportunities:
Policy trends favoring sustainable urban mobility, like bike lanes and tourist-focused campaigns, provide opportunities (Participant I, Interview, 2025). Adding electric vehicles to the fleet is seen as a value-adding strategy.

Threats:
Competition from other micro-mobility operators and inconsistent user behavior pose operational risks. Safety concerns and car-centric culture reduce attractiveness (Participant A, Interview, 2025).

4.1.2 Chiang Mai University (Closed Area)

Strengths:
Bikes are accessible, and parking is convenient. Operations staff benefit from predictable patterns and easier control (Participant E, Interview, 2025).

Weaknesses:
Campus topography and student habits (motorcycle reliance) limit uptake. Bikes wear quickly due to high re-use rates, especially during term peaks.

Opportunities:
Targeted promotions for students and institutional collaboration could increase adoption. The green university initiative provides alignment (Participant G, Interview 2025).

Threats:
Mixed-brand perception and competitor entry (e.g., electric scooters) complicate market clarity and pose brand dilution risks (Participant H, Interview, 2025).

4.1.3 Bangkok Metropolitan Area (Open Area)

Strengths:
Bikes offer low-cost, environmentally friendly alternatives. Visibility in public spaces supports brand exposure (Participant G, Interview, 2025).

Weaknesses:
Users lack route guidance and parking clarity. Staff face urban logistics issues—delays due to traffic and difficulty managing dispersed zones.

Opportunities:
BMA support for non-motorized transport and infrastructure plans (Participant B, Interview, 2025) can bolster growth. School partnerships near bike stations could create adoption networks.
Threats:
Car culture and adverse weather hinder usability. Changing political leadership may alter supportive policy landscapes (Participant I, Interview, 2025).

4.1.4 Thammasat University, Rangsit Campus (Closed Area)

Strengths:
Defined service zones and existing cycling infrastructure allow efficient service delivery. Staff can easily anticipate their needs (Participant I, Interview, 2025).
Weaknesses:
Bikes are aging and require maintenance. Limited off-campus connectivity reduces service reach. High peak-time demand stresses available fleets.
Opportunities:
Offline events and institutional support offer pathways for brand engagement and revenue (Participant G, Interview, 2025). In-app promotions reach the digitally native student body effectively.
Threats:
Internal administrative changes and pricing competition affect service continuity. Students' sensitivity to cost can make them switch to competitors (Participant F, Interview, 2025).

Table 1 SWOT Code by area

Location	Strengths	Weaknesses	Opportunities	Threats
Chiang Mai City	Alternative transport; Fast travel; Operational flexibility; Variety of bikes	Infrastructure gaps; Unsafe roads; Misuse; Manual locks	Government support; Tourism; E-vehicle expansion	Competitors; Safety; Urban sprawl
Chiang Mai University	Accessible bikes; Predictable usage; Nearby parking	Hilly terrain; Motorcycle use; Reuse strain	Green campus; Promotions; Student initiatives	Brand confusion; Scooter rivals
Bangkok	Eco-friendly; Low-cost; Brand visibility	Route uncertainty; Parking issues; Traffic delays	BMA policy; School tie-ins; Ad space opportunities	Car culture; Weather; Policy instability

Location	Strengths	Weaknesses	Opportunities	Threats
Thammasat University	Defined zones; Cycling infrastructure; Student base	Bike age; Peak demand issues; Poor off-campus access	Events; Institutional support; Digital engagement	Admin change; Price wars; Budget sensitivity

4.1.5 Summary of SWOT Findings

As visualized in Figure 4.1, Chiang Mai City and Bangkok had the most critical threats and weaknesses, largely due to urban complexity and infrastructure limitations. In contrast, closed areas like universities showed better service control and marketing clarity but still faced constraints related to user preferences and terrain.

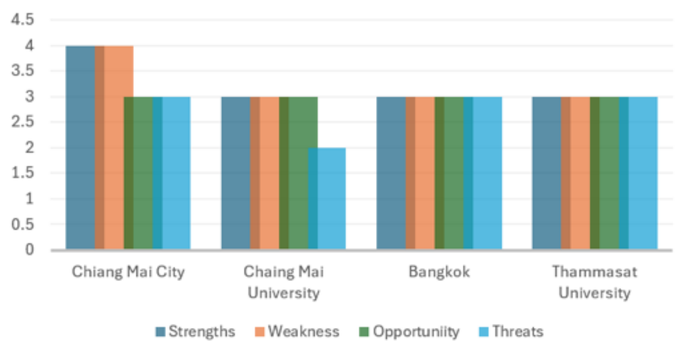


Figure 4.1 Number of SWOT Code by area

4.2 Thematic Analysis

Based on in-depth interviews and a SWOT framework, several key themes emerged in analyzing the experiences and perceptions of both users and employees of bike-sharing services in Chiang Mai, Bangkok, Chiang Mai University, and Thammasat University.

4.2.1 Accessibility and Convenience

Accessibility and convenience were highlighted as key strengths of bike-sharing services, particularly in open urban areas. Users expressed satisfaction with the flexibility to travel between locations quickly and economically, especially in cities like Chiang Mai and Bangkok where public transport may be limited in coverage. However, within university campuses, users encountered physical and operational limitations, such as hilly terrains and inadequate station placement, which reduced the practicality of cycling (Participant A; Participant E, Interview, 2025). From the employee perspective, closed environments like campuses allowed for more structured management. Operations staff noted that bike relocation and monitoring were easier in these areas due to reduced traffic and higher predictability in usage patterns. In contrast, operating in open urban settings required more adaptive logistics and navigation of legal and traffic-related restrictions (Participant F, Interview, 2025).

4.2.2 Infrastructure and Safety

Infrastructure and safety challenges were a consistent concern among both users and employees. Users frequently cited the lack of protected bike lanes, damaged sidewalks, and unsafe traffic conditions as major barriers to use (Participant A, Interview, 2025). In cities, heavy motorbike and car traffic makes cycling feel risky, while poor weather conditions also discourage usage, especially during hot seasons or heavy rain (Participant D, Interview, 2025). Employees corroborated these issues by highlighting recurring complaints related to bike damage, user injuries, and improper parking. Customer service teams faced difficulties in resolving cases caused by inadequate infrastructure, such as inaccessible parking stations or theft-prone areas (Participant C, Interview, 2025).

4.2.3 Operational Efficiency

Operational efficiency varied significantly between open and closed environments. Within university campuses, structured access but higher vehicle density did not impact employees to manage relocation and repairs more effectively. Predictable peak periods such as class breaks enabled staff to plan operations in advance (Participant F, Interview, 2025). However, higher frequency of use in closed spaces also meant bicycles required more frequent maintenance. In contrast, operations in open areas like downtown Chiang Mai were hindered by congestion, road access restrictions, and difficulties in reaching bikes parked outside designated stations (Participant E, Interview, 2025). Furthermore, the absence of automation in internal processes, such as case tracking or SOP documentation, contributed to delays and inconsistencies (Participant C, Interview, 2025).

4.2.4 User Behavior and Culture

User behavior was influenced by cultural and demographic factors. Local Thai users, especially university students, showed a preference for motorcycles over bicycles, citing speed and convenience. Many were unfamiliar with the concept of shared micromobility, which limited early adoption (Participant G, Interview, 2025). In contrast, tourists and international students, particularly from countries with well-established bike-sharing systems, were more inclined to use the service (Participant A, Interview, 2025).
Students were also noted to be highly price-sensitive, with many requesting promotional trials or expressing concerns about top-up requirements. This suggests a need for localized marketing strategies that reflect the spending behavior of university communities (Participant G, Interview, 2025).

4.2.5 Policy and Institutional Support

Government and institutional support played a key role in shaping both user adoption and operational feasibility. In cities like Bangkok, ongoing initiatives by municipal authorities to promote non-motorized transport (Tulyasuwan, Jittrapirom, & Pongthanaisawan, 2021) and environmental sustainability created a favorable environment for bike-sharing services (Participant I, Interview, 2025). Within universities, bike-sharing services aligned with green campus initiatives and SDG commitments, especially at Chiang Mai and Thammasat Universities. However, employees cautioned that administrative turnover could impact long-term support. New leadership may interpret service contracts differently or reassess cooperation, creating uncertainty for private providers (Participant I, Interview, 2025).

4.2.6 Competition and Market Dynamics

Market competition was another key theme. Both users and staff noted the increasing presence of rival services, particularly electric scooters and motorcycles. These competitors often offered faster, more

convenient transportation options with simpler user interfaces. Some companies also adopted aggressive pricing strategies that appealed to cost-conscious users (Participant H, Interview, 2025).
Employees reported user confusion over similar brands and services. In some cases, users mistook one company for another due to overlapping design aesthetics or shared service zones. Additionally, unauthorized competitor parking in official zones created conflict and operational disruptions (Participant E, Interview, 2025).

4.2.7 Communication and Brand Awareness

Communication and awareness strategies were essential to user engagement. In open areas, visibility of bikes and stations helped build awareness organically. Events like city festivals or design weeks increased user exposure and trial rates (Participant G, Interview, 2025). In contrast, within universities, offline promotion and peer-to-peer communication had more impact.
However, brand confusion remained an issue, especially among students familiar with previous bike-sharing services like Mobike or ofo. Staff stressed the importance of clear branding and targeted content that adapts to local context and cultural cues (Participant H, Interview, 2025).

4.2.8 Technology and Service Quality

Technological factors, including mobile app functionality and bike hardware, played a role in service perception. While backend systems provided strong data tracking and UX design, users occasionally struggled with app navigation or locking mechanisms (Participant B, Interview, 2025). Improper bike locking led to theft or fines, frustrating users and increasing risk for the provider. Employees emphasized that older bikes, particularly those re-used from foreign markets, often arrived in poor condition, requiring high maintenance and limiting long-term reliability (Participant I, Interview, 2025). Internal processes also varied by staff experience, creating an inconsistency in customer service quality.

5 CONCLUSION AND RECOMMENDATION

Across all study areas, Chiang Mai city, Bangkok Metropolitan Area, Chiang Mai University, and Thammasat University—bike-sharing services were generally recognized for their potential to provide cost-effective, environmentally friendly, and flexible transportation. However, context-specific barriers continue to hinder broader adoption and service optimization. In open urban environments, challenges are predominantly tied to infrastructure deficits, such as the absence of protected bike lanes and complex traffic conditions. Meanwhile, in closed environments like university campuses, issues such as limited station placement, high maintenance frequency, and culturally specific user preferences emerged as significant operational concerns. Importantly, while operational efficiency and management control are higher in campuses, service demand tends to be more variable and price sensitive. Internal operational issues, including limited automation, outdated hardware, and inconsistent service standards, further diminish the quality of user experience. Similarly, weak branding and miscommunication contribute to market confusion, reducing competitiveness in a field where alternative mobility options such as e-scooters are rapidly gaining ground. Despite these challenges, government and institutional support—particularly from municipal bodies and universities aligned with sustainability goals—offers a strong foundation for growth. Nonetheless, the long-term success of such services is vulnerable to changes in administrative priorities and limited policy enforcement.

5.1 Recommendations

Based on the findings, the following recommendations are proposed to enhance the effectiveness, user satisfaction, and sustainability of bike-sharing services: Localized Service Planning: Bike-sharing operators should develop tailored operational strategies for open and closed environments. In urban areas, service coverage must align with high-traffic destinations, while in universities, strategic placement of parking stations should consider terrain, academic schedules, and key campus locations. Area-Based Pricing and Promotions introduce flexible pricing schemes and promotional campaigns that reflect user profiles. For example, discounted packages and trial programs for students could encourage usage in closed environments, while competitive daily caps can appeal to tourists and urban commuters. Infrastructure Partnerships, collaborate with local governments and universities to improve cycling infrastructure, including bike lanes, shaded pathways, and secure parking areas. These partnerships can also help reduce theft and safety risks, particularly in high-density traffic zones. Institutional Stakeholder Engagement, to ensure long-term stability and service continuity, it is crucial to maintain active engagement with administrative stakeholders. Establishing formal agreements and integrating bike-sharing into sustainability or transportation policy frameworks can mitigate risks associated with administrative turnover. Improved App and Equipment Quality, Invest in the maintenance and upgrade of both software and hardware systems. Mobile applications should prioritize intuitive design, multilingual support, and real-time service updates. Simultaneously, ensure that bicycles meet quality standards to reduce repair frequency and enhance user trust. Clear Branding and User Education, Combat brand confusion by enhancing visual identity and conducting awareness campaigns. Use both digital and offline channels to educate potential users about service functionality, benefits, and rules, especially in regions where micromobility adoption is still emerging. By applying these recommendations, bike-sharing providers can not only improve service performance and user satisfaction but also support broader goals of sustainable urban mobility and inclusive transportation access in Thailand.

REFERENCES

Bai, S., & Jiao, J. (2020). Dockless E-scooter usage patterns and urban built environments: A comparison study of Austin, TX, and Minneapolis, MN. *Travel Behaviour and Society, 20*, 264–272.

Braun, V., & Clarke, V. (2006). Using thematic analysis in psychology. *Qualitative Research in Psychology, 3*(2), 77–101.

Buehler, R., & Pucher, J. (2012). Walking and cycling in Western Europe and the US: Trends, policies, and lessons. *TR News, 280*(5), 34–42.

Buck, D., & Buehler, R. (2012). Bike lanes and other determinants of capital bikeshare trips. *Transportation Research Record, 2314*(1), 66–74.

Campbell, A. A., Cherry, C. R., Ryerson, M. S., & Yang, X. (2016). Factors influencing the choice of shared bicycles and E-bikes in Beijing. *Transportation Research Part C, 67*, 399–414.

Cheng, L., & Zhang, L. (2019). Understanding urban micromobility adoption in Asian cities. *Journal of Transport Geography, 76*, 1–11.

Creswell, J. W. (2013). Qualitative Inquiry and Research Design: Choosing Among Five Approaches. SAGE Publications.

DeMaio, P. (2009). Bike-sharing: History, impacts, models of provision, and future. *Journal of Public Transportation, 12*(4), 41–56.

Fishman, E., Washington, S., & Haworth, N. (2013). Bike share: A synthesis of the literature. *Transport Reviews, 33*(2), 148–165.

Gürel, E., & Tat, M. (2017). SWOT Analysis: A theoretical review. *The Journal of International Social Research, 10*(51), 994–1006.

Intarapasan, A., Duangjai, A., & Pooprasert, P. (2022). Evaluating the Success Factors of Bike-Sharing Programs in Bangkok. *Journal of Urban Mobility and Policy, 3*(1), 45–59.
Kvale, S. (1996). InterViews: An Introduction to Qualitative Research Interviewing. SAGE Publications.
Lee, D., & Wang, H. (2021). Mobile payment adoption and its implications for urban transport services. *Asian Journal of Technology Innovation, 29*(2), 235–248.
Ma, X., Liu, C., & Zhang, H. (2019). Understanding bike-sharing travel patterns: A data-driven analysis of bike usage and urban built environments. *Journal of Transport Geography, 76*, 148–164.
Midgley, P. (2011). Bicycle-sharing schemes: Enhancing sustainable mobility in urban areas. *UN Department of Economic and Social Affairs*.
Parkin, J., & Rotheram, J. (2010). Design speeds and acceleration characteristics of bicycle traffic for use in planning, design and appraisal. *Transport Policy, 17*(5), 335–341.
Pojani, D., & Stead, D. (2015). Sustainable urban transport in the developing world: Beyond megacities. *Sustainability, 7*(6), 7784–7805.
Ricci, M. (2015). Bike sharing: A review of evidence on impacts and processes of implementation and operation. *Research in Transportation Business & Management, 15*, 28–38.
Sermsukprasert, K., & Komolrit, T. (2020). Barriers to Bike-Sharing System Adoption in Thai Cities: A Policy and User Perspective. *Journal of Transportation & Society, 15*(2), 23–37.
Shaheen, S., & Cohen, A. (2019). Shared micromobility policy toolkit. *Institute of Transportation Studies, UC Berkeley*.
Shaheen, S. A., Guzman, S., & Zhang, H. (2010). Bikesharing in Europe, the Americas, and Asia: Past, present, and future. *Transportation Research Record, 2143*(1), 159–167.
Sun, Y., Mobasheri, A., Hu, X., & Wang, W. (2017). Investigating impacts of environmental factors on the spatial pattern of bike-sharing usage. *ISPRS International Journal of Geo-Information, 6*(12), 386.
Tulyasuwan, N., Jittrapirom, P., & Pongthanaisawan, J. (2021). Exploring challenges and opportunities for bike-sharing in Thailand: A case study of pilot schemes in Bangkok and Chiang Mai. *SoutheasAsia Transport Review, 3*(1), 1–15.
Zhang, Y., & Mi, Z. (2018). Environmental benefits of bike-sharing systems: A big data-based analysis. *Applied Energy, 220*, 296–301.
Zhao, J., Deng, W., & Song, Y. (2020). Ridership and effectiveness of bike-sharing: A case study of Hangzhou, China. *Transportation, 47*(2), 519–537.

IMPACTS OF GHG PROTOCOL ON CROSS-BORDER JAPAN–THAILAND AUTOMOTIVE SUPPLY CHAINS

Preyamin Kannaphan[1], Anukul Tamprasirt[2] and Suttida Suwannayod[3]
International College of Digital Innovation, Chiang Mai University, Chiang Mai, 50200, Thailand
E-mail: [1]preyamin_k@cmu.ac.th, [2]anukul@innova.or.th, and [3]suttida.su@cmu.ac.th

ABSTRACT

The expansion of the automotive industry has significantly contributed to the increase in greenhouse gas emissions through cross-border supply chains. Consequently, the internationalization of manufacturing and distribution networks presents considerable challenges for carbon accounting, transparency, and mitigation under established frameworks such as the Greenhouse Gas (GHG) Protocol. As a globally recognized standard, the GHG Protocol plays an essential role in measuring, reporting, and managing greenhouse gas emissions from organizations. In the Japan–Thailand automotive sector, manufacturers are increasingly required to account for emissions across their global operations, including indirect emissions. Building upon this context, this research examines the impact of Scope 3 emissions—which originate from activities beyond a company's direct operations—on Japanese automotive supply chains operating in Thailand, using the GHG Protocol as the foundational framework for analysis. The results underscore the importance of embedding Scope 3 emissions into supply chain governance to maintain competitiveness, comply with global sustainability benchmarks, and support Thailand's long-term carbon neutrality targets.

KEYWORDS: GHG Protocol, Scope 3 Emissions, Japan–Thailand Automotive Supply Chain, Cross-Border Sustainability, Carbon Emission

1 INTRODUCTION

Thailand is a key manufacturing centre for Japanese automotive industry in Southeast Asia, owing to its strategic geographic location, skilled workforce, and favorable economic policies. The industry has established a set of standards to assess how companies interact with the environment, treat stakeholders, and manage internal governance; collectively, these principles are known as ESG—standing for environmental, social, and governance. As a result, Thai suppliers increasingly find themselves subject to ESG requirements imposed by Japanese original equipment manufacturers (OEMs), with an emphasis on emissions transparency, data reporting, and upstream carbon mitigation. The growing global emphasis on ESG principles mandates that firms incorporate carbon reduction initiatives, waste management, and labor ethics into their core operational frameworks. Furthermore, Japan's commitment to achieving net-zero emissions by 2050 drives changes in the operational practices of its supply chain partners located in Thailand. Therefore, standardized carbon accounting protocols have emerged as critical instruments for guiding sustainable transformation. The Greenhouse Gas Protocol (GHG Protocol (2015)) is a key tool that establishes standardized principles including transparency, consistency, accuracy, completeness, and relevance for measuring, reporting, and reducing GHG emissions. Japanese manufacturers implement these protocols within their supply chains in Thailand to achieve regulatory compliance and to improve international competitiveness and operational efficiency. In particular, Japan's commitment to achieving net-zero greenhouse gas (GHG) emissions by 2050 has intensified efforts among manufacturers to implement sustainable practices across their international operations.

The GHG Protocol categorizes emissions into three scopes; Scope 1: Direct emissions from company-owned and controlled sources. Scope 2: Indirect emissions from the generation of purchased electricity, steam, heating, and cooling. Scope 3: All other indirect emissions that occur across the value chain, including supply chain activities, transportation, and product use. Although the GHG Protocol has been widely recognized by multinational corporations as a standard framework for carbon accounting, significant gaps remain in its practical implementation within cross-border supply chains, particularly among small and medium enterprises (SMEs) operating in emerging economies such as Thailand.

The disconnect between emissions obligations and the capabilities of SMEs constitutes not only a pressing environmental issue but also a critical risk to supply chain resilience. Therefore, the transition from identifying barriers to proposing actionable strategies must focus on enabling conditions that support scalable solutions. Among these, OEMs-SMEs collaboration emerges as a critical success factor. Collaborative engagement can improve data traceability, reduce compliance burdens through co-developed platforms, and ensure capacity-building is shared across tiers. As Thailand seeks to strengthen its position within increasingly ESG-driven supply networks, the effectiveness of its response will depend heavily on how well these partnerships are cultivated. Japanese automotive manufacturers have adopted the GHG Protocol in accordance with the scopes most relevant to their industry, particularly Scope 1 and Scope 2. However, the management of greenhouse gas emissions under Scope 3 remains a significant challenge. It encompasses supplier operations, transportation, and product use continues to present substantial challenges. In the automotive industry, Scope 3 emissions often represent more than 80–90% of total emissions, highlighting the critical need. This study aims to examine the implications of Scope 3 carbon emissions protocols on procurement strategies, supplier collaboration, and policy coherence within the Thai context. The findings emphasize the necessity of integrating carbon metrics into core supply chain operations and investing in centralized emissions tracking systems. This study may contribute to policy formulation by offering actionable insights and practical instruments, such as simplified reporting structures and sustainability scorecards that facilitate efforts to reduce greenhouse gas emissions.

2 LITERATURE REVIEW

Climate change has become a critical global concern, with carbon dioxide (CO_2) emissions recognized as a principal driver of environmental degradation. In response, international frameworks like the Paris Agreement have led governments and industries to pursue net-zero targets. The automotive industry plays a central role in this transition due to its energy-intensive operations, long product lifecycles, and extensive supply chains. The transport sector alone contributes approximately 25% of global CO_2 emissions, with road transport as the dominant source (IEA, 2022). The GHG Protocol is the most widely used international standard for measuring and reporting greenhouse gas emissions. It was developed by the World Resources Institute (WRI) and the World Business Council for Sustainable Development (WBCSD) in 2001 and has since become the foundation for corporate carbon accounting worldwide. Scope 1, 2, and 3—with Scope 3 covering all indirect emissions across the value chain. These emissions, which account for over 90% of a company's total greenhouse gas emissions in many cases, are particularly difficult to manage due to their diffuse and complex origins (BMW Group (2022); Sumitomo Riko (2023); Volvo Cars (2023). The growing influence of ESG standards, including those from The Task Force on Climate-related Financial Disclosures (TCFD) and the Science Based Targets initiative (SBTi), has made transparent Scope 3 measurement, reporting, and mitigation increasingly essential. Previous studies have highlighted a shift in attention from emissions during vehicle use to embedded upstream emissions (Enviliance Southeast Asia, 2025).

In the Japan–Thailand automotive industry, Scope 3 emissions are especially critical due to the geographic dispersion of suppliers, diverse regulatory environments, and the growing demand for ESG transparency from international investors and regulators. Furthermore, OEMs are increasingly being held accountable for their suppliers' emissions, making OEM-SME collaboration essential for credible Scope 3 reporting and risk mitigation. Previous study revealed that BMW Group collaborates with its suppliers to decarbonize material inputs (BMW Group (2022). In addition, Volvo Cars employs blockchain technology to enhance carbon traceability across its supply chain (Volvo Cars (2023)) and Jaguar Land Rover utilizes Life Cycle Assessment (LCA) methodologies to promote sustainable design practices. Among these, Scope 3 emissions have become the most significant and least controllable source of greenhouse gas emissions in the automotive sector. (Sumitomo Riko (2023)). These include indirect emissions associated with raw material extraction, supplier operations, logistics, product use, and end-of-life disposal. It is particularly pressing in cross-border supply chains like those linking Japanese OEMs with Thai-based manufacturing, where supplier diversity, digital fragmentation, and inconsistent policy frameworks hinder transparency. Recent studies, including those by McKinsey & Company. (2021) and the International Energy Agency (International Energy Agency (2022), point to a paradigm shift: automotive manufacturers are now prioritizing upstream embedded emissions rather than only focusing on tailpipe emissions. In line with this shift, global ESG standards—such as the TCFD and SBTi—have accelerated regulatory and investor demand for comprehensive carbon disclosure. In this context, Japan's advanced ESG regulatory landscape, driven by its Ministry of Economy, Ministry of International Trade and Industry (METI) places pressure on Thai suppliers to meet strict carbon reporting expectations. Meanwhile, Thailand's policy frameworks, including the Bio-Circular-Green (BCG) Economy Model, are evolving to bridge this expectation gap. Understanding the interplay between these regulatory systems is key to enabling more effective Scope 3 compliance.

In addition, various automotive companies including GM, Hyundai Motor, Tata Motors, and BYD Auto utilized a combination of GHG performance indicators, AI-driven monitoring tools, SME-oriented platforms, and renewable energy adoption. In contrast, Automotive supply chains in Thailand led by Japanese firms, including major players like Toyota and Honda, encounter substantial challenges in applying Scope 3 emissions strategies at the local level. Although these companies have well-developed global climate frameworks, effective implementation is constrained by inadequate digital infrastructure, the lack of uniform reporting mechanisms, and limited technical expertise among lower-tier suppliers. (JETRO (2021). Additionally, OEMs contribute to the limited engagement of SMEs in decarbonization efforts by offering inadequate incentives and lacking structured, proactive support mechanisms. Although BCG Model, the Carbon Footprint for Organization (CFO) framework, and the Thailand Greenhouse Gas Management Organization (TGO) have played a key role in raising awareness of carbon emissions and sustainability practices among businesses, small and medium-sized enterprises (SMEs) in Thailand often lack access to necessary tools, training, and institutional support (BOI (2022). Survey data indicate that over 60% of suppliers are unaware of Scope 3 requirements and receive minimal guidance from OEMs.

A comprehensive strategy is essential to bridge these gaps. This includes policy incentives, public-private collaboration, and targeted capacity-building programs to integrate Scope 3 emissions considerations into Thailand's automotive supply chains. Effective management of Scope 3 emissions has become a strategic necessity. Global best practices emphasize three key pillars: (1) transparent, interoperable data systems; (2) integration of carbon metrics into procurement and supplier engagement frameworks; and (3) robust regulatory and incentive structures coordinated by the public sector (Transport & Environment, 2023). Countries such as Germany, Sweden, and Japan illustrate the advantages of implementing Life Cycle Assessment dashboards, supplier sustainability scorecards, and carbon-based procurement criteria. Conversely, Thailand's automotive sector, despite being a vital regional hub, struggles to localize such strategies due to institutional fragmentation and industry heterogeneity. In terms of policy comparison, Japan's (METI) offers detailed decarbonization roadmaps, carbon pricing pilots, and national emissions registries aligned with international standards, whereas Thailand's BCG model remains broad and primarily incentivizes eco-efficiency rather than compliance-based carbon disclosure.

Nevertheless, SMEs continue to face restricted access to digital solutions, carbon accounting expertise, and standardized data infrastructure. According to Enviliance Southeast Asia (2025), achieving Thailand's carbon neutrality target by 2065 will require not only technological advancements but also harmonization of emissions accounting methodologies and improved inter-agency coordination. In conclusion, Scope 3 emissions management is no longer a peripheral concern. Achieving this goal is essential for sustaining industrial competitiveness, ensuring regulatory compliance, and fulfilling environmental responsibilities. Thailand's success will depend on the effectiveness of its alignment of national policies, technological capabilities, and stakeholder collaboration with global sustainability standards.

Localization of global best practices, supported by government-led initiatives, SME upskilling, and cross-sectoral partnerships, will be crucial to achieving a low-carbon transformation. Moreover, research by Nakamichi et al. (2016) and Enviliance Southeast Asia (2025) underscores the importance of upstream emissions management, especially amid the shift toward electric vehicle (EV) manufacturing, where battery production can contribute up to 80% of total emissions. While adapting to Scope 3 protocols presents multiple challenges, it also offers strategic opportunities. Recent initiatives by the International Labour Organization (ILO) and Japan's (METI) have focused on workforce development and ESG compliance (ILO (2025)). Thailand has responded through decarbonization programs promoting low-emission vehicles (UNDP Thailand, 2024) and sustainable logistics innovations, such as DHL Express (2025) use of Sustainable Aviation Fuel (DHL Express (2025).

3 RESEARCH METHODOLOGY

3.1 Research Variables

This study investigates the effects of Scope 3 carbon emission protocols on the Japan–Thailand cross-border automotive supply chain. The variables examined in this study are outlined as follows:

3.1.1 Independent Variable - Implementation of the GHG Protocol Scope 3, which encompasses: carbon emissions quantification and disclosure using tools such as Life Cycle Assessment (LCA) and ISO 14064; integration of digital technologies including blockchain and artificial intelligence; application of ESG-related financial instruments like green loans and sustainability-linked bonds; and organizational responses to global climate policies, such as those set by the Task Force on Climate-related Financial Disclosures (TCFD) and the Science Based Targets initiative (SBTi).

3.1.2 Mediating Variables-Supply Chain Collaboration, OEM–SME partnerships, ESG co-reporting platforms, and sustainable finance access, Technical and Institutional Capacity, SME reporting capability, LCA training, interoperable data infrastructure, Policy and Incentive Alignment and Thailand's BCG Model, Japan's METI compliance strategies, regulatory incentives.

3.1.3 Dependent Variables- Carbon Emissions Reduction Performance, Measurable reductions in supply chain emissions, ESG-based supplier selection, Supply Chain Competitiveness and Resilience, Market access through transparency, alignment with OEM and global ESG demands.

3.2 Data Collection Method

This study employs a qualitative approach through the review of secondary documents. Data collection involves analyzing a minimum of 20 sources, which include the following categories: corporate ESG and sustainability reports from companies such as Toyota, BMW, Volvo, and Jaguar Land Rover (JLR); official government publications from Japan (e.g., METI) and Thailand (e.g., MOI, TGO); policy documents issued by international organizations such as the United Nations Development Programme Thailand (UNDP), International Labour Organization. (ILO), and Economic Research Institute for ASEAN and East Asia (ERIA), (2023); and peer-reviewed academic literature accessed through databases like Scopus, JSTOR, and ScienceDirect. The review emphasizes; Scope 1–3 emissions frameworks (GHG

Protocol, ISO 14064), Policy comparison (Thailand's BCG vs Japan's METI), Boundaries of emissions (cradle-to-gate vs full life cycle) and Triangulation of evidence to enhance reliability and validity.

Figure 1 illustrates the systematic process employed in the secondary document review methodology of this study. The diagram outlines the sequential steps taken to collect, analyze, and synthesize existing literature and data relevant to the research objectives. The process is designed to ensure a comprehensive and rigorous examination of available information pertaining to Scope 3 emissions in the Japan–Thailand automotive supply chain context.

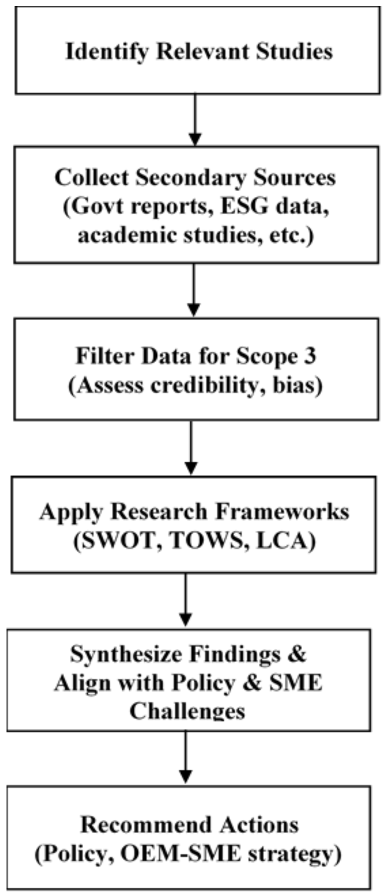


Figure 1 : Secondary Document Review Process Diagram: Research Workflow

3.3 The conceptual integration

This study is grounded in a multi-framework approach that brings together Life Cycle Assessment (LCA), SWOT, and TOWS analysis to critically evaluate how Scope 3 emissions management is embedded within cross-border automotive supply chains. These frameworks are selected for their complementary strengths in analyzing technical emissions flows, organizational capacity, and strategic response options in the face of regulatory pressure and ESG transformation.

Figure 2 presents the integrated analytical framework used in this study to evaluate Scope 3 emissions management in the cross-border Japan–Thailand automotive supply chain. The framework visually illustrates how three core tools—Life Cycle Assessment (LCA), SWOT Analysis, and TOWS Matrix—are systematically applied to guide data interpretation, strategic diagnosis, and policy formulation in relation to Scope 3 emissions.

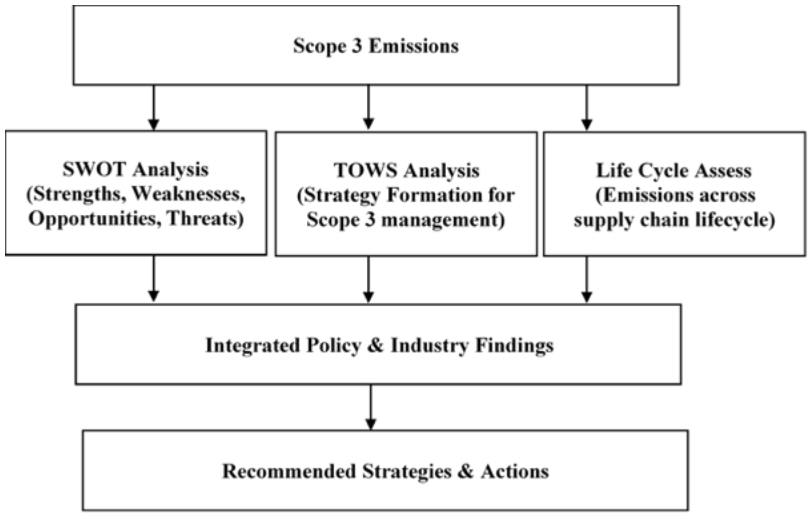


Figure 2: Scope 3 Emissions Analysis Framework
Diagram: Integration of Analytical Models

3.3.1 Life Cycle Assessment (LCA); Emissions Tracking Framework. LCA is used as a core analytical tool to quantify and map GHG emissions across the entire vehicle lifecycle, including; Cradle-to-Gate; Covers emissions from raw material extraction, component manufacturing, and logistics. Gate-to-Grave; Includes emissions during product use (e.g., fuel consumption or battery charging) and end-of-life disposal or recycling. By applying LCA in alignment with GHG Protocol Scope 3 categories, the research assesses how emissions data can be standardized and shared between OEMs and SMEs across the value chain. LCA also enables evaluation of carbon hotspots where emissions reductions are most feasible or impactful.

3.3.2 SWOT Analysis; Organizational Readiness and Barriers, SWOT is employed to analyze the internal and external context of Thai SMEs in implementing Scope 3 carbon management. Key elements include Strengths: Thailand's position as a regional auto production hub, growing ESG awareness, and OEM investment. Weaknesses: Limited SME technical capacity, lack of standardized data systems, and insufficient carbon literacy. Opportunities: Japanese OEM-led ESG integration, green financing instruments, and public-private training programs. Threats: Regulatory complexity, investor scrutiny, and market exclusion due to non-compliance. This analysis is essential for diagnosing the implementation gap and for understanding where public policy and private sector support can have the most impact.

3.3.3 TOWS Matrix; Strategy Development Tool, To transition from analysis to action, a TOWS matrix is used to link SWOT elements into strategic interventions. For instance; W-O Strategy: Match weaknesses (e.g., SME data limitations) with opportunities (e.g., OEM digital platforms). S-T Strategy: Leverage strengths (e.g., Thailand's production ecosystem) to mitigate threats (e.g., regulatory exclusion from EU/JP markets). W-T Strategy: Build collaborative carbon-readiness initiatives that target weak SMEs under regulatory pressure. This matrix helps guide multi-stakeholder decision-making, aligning Thailand's BCG model with Japan's METI Scope 3 roadmap and international ESG benchmarks. Integration Logic and Application, The integration of these frameworks enables a systems-oriented understanding of how carbon governance, financial incentives, and OEM–SME collaboration interact. Specifically, it supports the research in; Identifying institutional coordination gaps between Thai and Japanese emission policies; Proposing policy alignment strategies to harmonize Scope 3 reporting expectations; Informing the design of financial instruments that can link ESG disclosure performance to creditworthiness (e.g., green loans, sustainability-linked bonds); Structuring OEM-led support programs for SME upskilling, LCA training, and blockchain-based traceability.

3.4 Conceptual Integration and Analytical process

This study adopts a multi-framework analytical approach that integrates three complementary tools to evaluate Scope 3 emissions governance and strategic interventions across the Japan–Thailand automotive supply chain; Life Cycle Assessment (LCA), SWOT Analysis, and the TOWS Matrix. These tools are visualized in Figure 2: Scope 3 Emissions Analysis Framework, which illustrates how carbon tracking, regulatory compliance, and collaborative strategies interact.

3.4.1 Life Cycle Assessment (LCA)

Tracking Emissions Across Value Chain Boundaries, LCA is used to systematically assess greenhouse gas emissions across the full product life cycle, specifically aligned with the GHG Protocol's Scope 3 boundaries. This includes; Upstream emissions: Extraction of raw materials, component manufacturing, and inbound logistics. Core operations: Assembly and intermediate processing stages within Thailand. Downstream emissions: Distribution, product use (fuel/electricity consumption), and end-of-life treatment. The study applies the cradle-to-grave model to ensure that indirect emissions, often hidden in extended supplier networks, are captured. LCA serves as both a diagnostic tool (to locate emissions hotspots) and a reporting mechanism for aligning SME data with OEM ESG disclosure needs.

3.4.2 SWOT Analysis

Organizational Readiness and Constraints. SWOT analysis is used to assess the strategic and operational environment of Thai SMEs involved in automotive supply chains. It identifies internal and external factors affecting Scope 3 compliance; Strengths: Strategic location, growing OEM collaboration, national interest in BCG-driven decarbonization. Weaknesses: Limited technical knowledge, insufficient digital tools, and unstandardized emissions reporting. Opportunities: Access to ESG-linked financing, OEM-led platforms, and public capacity-building programs. Threats: Rising regulatory pressure (e.g., METI/Japan, CBAM/EU), reputational risk, and competitive exclusion. This analysis allows stakeholders to recognize critical barriers and enablers in the implementation of Scope 3 emissions protocols.

3.4.3 TOWS Matrix

Strategic Response and Policy Alignment. The TOWS Matrix extends SWOT by linking weaknesses and threats with possible countermeasures. It is used in this research to formulate integrated strategies that involve OEMs, regulators, and SMEs. Examples include; W–O Strategy: Address weak data systems by leveraging digital traceability tools co-developed with OEMs. S–T Strategy: Use Thailand’s BCG and digitalization infrastructure to preempt global regulatory exclusions. W–T Strategy: Implement public-private training on LCA and Scope 3 compliance for underprepared SMEs. By structuring these responses, the TOWS Matrix helps identify multi-actor policy synergies and co-investment opportunities for long-term resilience and emissions reduction.

This study adopts a multi-framework analytical approach that integrates three complementary tools to evaluate Scope 3 emissions governance and strategic interventions across the Japan–Thailand automotive supply chain: Life Cycle Assessment (LCA), SWOT Analysis, and the TOWS Matrix.

LCA is applied first to identify and quantify carbon emissions across the supply chain, providing technical insight into emissions hotspots and traceability gaps. The SWOT analysis is then used to assess the readiness and capacity of Thai SMEs to comply with Scope 3 requirements, evaluating internal strengths and weaknesses alongside external opportunities and threats. Finally, the TOWS Matrix translates these analytical insights into actionable strategies by mapping strengths-opportunities and weaknesses-threats into concrete interventions. This sequential integration ensures technical rigor (LCA), organizational diagnostics (SWOT), and strategic policymaking (TOWS).

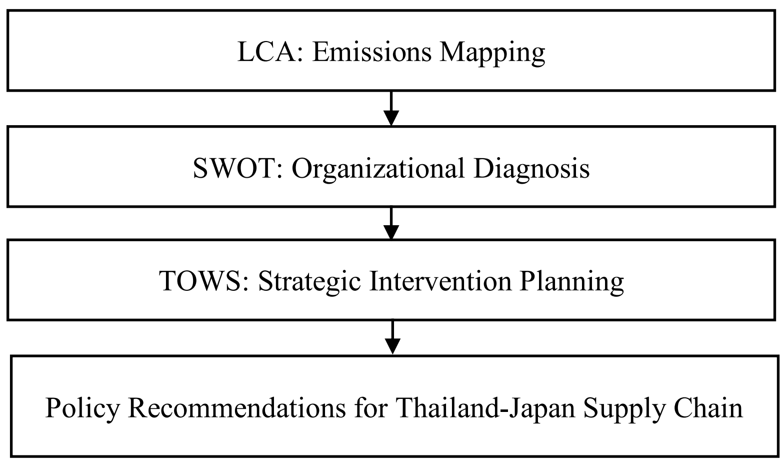


Figure 3 Integrated Analytical Framework for Scope 3 Emissions Management

3.5 Evaluation Criteria

The research will evaluate the collected secondary data based on the following criteria;

3.5.1 Relevance and Validity of Sources

Emphasis will be placed on peer-reviewed journals, government policy documents, and industrial reports that are directly related to carbon emissions regulations and the automotive supply chain, especially in Japan and Thailand.

3.5.2 Credibility of the Information

Evaluation of the credibility will involve assessing the authority of the source (e.g., government institutions, UN agencies, recognized academic publishers) and the presence of citations or data provenance.

3.5.3 Comparative Policy Analysis

Criteria will include the degree of policy alignment and divergence between Japanese and Thai carbon regulatory frameworks, and how these influence supply chain operations.

3.5.4 Applicability to the Automotive Sector

The relevance of the protocols and policies to real-world practices in the automotive industry, especially those applicable to Japanese manufacturers operating in Thailand.

3.5.5 Temporal and Geopolitical Context

The extent to which sources account for dynamic changes such as CBAM implementation, regional cooperation (ASEAN-Japan), and global shifts in decarbonization trends.

3.5.6 Integration Potential

Evaluation of whether the insights contribute meaningfully to the conceptual framework and support the construction of a comprehensive analysis model for supply chain decarbonization.

4 RESULT AND DISCUSSION

4.1 Overview of the selected studies;

The 20 selected studies synthesized in Table 1 offer comprehensive insights into the global discourse on Scope 3 emissions within the automotive industry. The reviewed literature comprises inputs from multinational companies such as BMW, Volvo, and Toyota, government policy bodies including Japan's METI and Thailand's TGO, and global organizations such as UNDP and ERIA. This study focuses on Scope 3 emissions, which are related to indirect emissions within the value chain. The reviewed literature emphasizes upstream emissions in material sourcing and supplier operations, as well as downstream impacts such as vehicle use and end-of-life disposal. A significant number of the studies also underscore the lack of reporting capacity among SMEs, particularly in emerging economies like Thailand, where digital infrastructure, technical knowledge, and access to green finance remain limited. This body of literature supports the central hypothesis of this research—that a strategic, cross-border approach is necessary to address Scope 3 emissions effectively.

Table 1 presents a synthesis of 20 key academic, industry, and policy studies related to Scope 3 emissions in the automotive sector. The table aggregates findings from global OEM case studies, government policies (e.g., METI, TGO), and international organizations (e.g., UNDP, ERIA), as well as academic journals. It categorizes each source by its author, year, key contribution, and specific relevance to Thailand's SME context. This synthesis supports the research by identifying consistent themes across literature—particularly the recognition that Scope 3 emissions comprise the majority of total GHG output in automotive supply chains and are the most difficult to monitor, especially among Tier 2 and 3 suppliers. In the context of the automotive supply chain, Tier 2 and Tier 3 suppliers refer to upstream actors involved in the production and processing of intermediate goods and raw materials. Tier 1 suppliers are those that deliver complete components or systems directly to Original Equipment Manufacturers (OEMs), such as braking systems or battery packs. Tier 2 suppliers, in turn, provide parts, subcomponents, or processed materials to Tier 1 suppliers—for example, wiring harnesses, molded plastics, or specialized metal components. Tier 3 suppliers operate even further upstream, often supplying raw materials such as steel, rubber, petrochemicals, or mined minerals like lithium and cobalt used in electric vehicle batteries. These lower-tier suppliers play a critical role in the overall carbon footprint of vehicle production. Under the Greenhouse Gas (GHG) Protocol, their emissions are categorized as part of Scope 3—specifically upstream emissions. However, Tier 2 and Tier 3 suppliers are frequently characterized by limited technical capacity, lack of awareness of international reporting standards, and insufficient access to carbon accounting tools. These constraints make it difficult for OEMs to obtain accurate and consistent emissions data from the lower tiers of their supply chains. Consequently, Tier 2 and Tier 3 suppliers represent a major gap in achieving comprehensive Scope 3 emissions transparency, especially in emerging markets like Thailand where digital infrastructure and ESG compliance readiness remain uneven. The table validates the study's focus on SMEs and Scope 3, demonstrating that technological limitations, policy misalignment, and capacity gaps persist across various regions but are especially pronounced in emerging economies like Thailand. The synthesis of 20 selected studies on Scope 3 emissions in the automotive industry reveals a consistent recognition of the importance of upstream emissions, particularly those originating from suppliers at Tier 2 and Tier 3 levels. A clear point of convergence across the literature is that Scope 3 emissions often represent the largest share—over 80–90%—of a vehicle's total greenhouse gas (GHG) footprint, underscoring their significance in decarbonization efforts. Multiple studies, including Wang et al. (2024), the Amundi Research Center (2023), and the World Resources Institute (2022), emphasize the need for comprehensive life cycle assessment (LCA) tools and harmonized reporting standards under the GHG Protocol. Additionally, several studies such as those by the Mekong Institute (2024) and Appsynth (2023) highlight the structural and technical challenges faced by SMEs in Thailand, particularly the lack of awareness, data reporting skills, and access to digital infrastructure. However, the studies differ in scope, methodology, and stakeholder focus. For instance, while Greenpeace East Asia (2025) critiques the carbon performance of Japanese OEMs from a top-down perspective, the UOB Thailand (2023) and DHL (2023) cases present bottom-up, business-driven initiatives aimed at empowering local SMEs through sustainable finance and logistics innovation. Moreover, while some reports are policy-focused, such as those from Japan's Ministry of Environment (2023) and ERIA (2023), others such as Exiger (2023) and Transport & Environment (2023) concentrate on ESG risks and investor disclosure practices. Notably, the study by Wang et al. (2024) stands out for its quantitative approach to modeling emissions across the automotive supply chain using LCA, whereas the Mekong Institute (2024) contributes valuable empirical insights into local capacity gaps through qualitative fieldwork. These variations in analytical depth and regional application illustrate the multifaceted nature of Scope 3 management and the need for tailored, context-sensitive policy and technical solutions, especially in emerging economies like Thailand.

Table 1 Synthesis of 20 Relevant Studies on Scope 3 Emissions in the Automotive Industry

No.	Study Title	Authors (Year)	Key Findings	Relevance to Thai SMEs
1	Technical Guidance for Calculating Scope 3 Emissions	World Resources Institute & World Business Council for Sustainable Development (2013)	Provides methodologies for Scope 3 emission calculations.	Offers a framework for SMEs to measure emissions.

No.	Study Title	Authors (Year)	Key Findings	Relevance to Thai SMEs
2	UOB Thailand Empowers SMEs for Low-Carbon Transition	Bangkok Post (2023)	Highlights financial support for SMEs in adopting low-carbon practices.	Demonstrates the role of financial institutions in supporting SMEs.
3	Measuring Scope 3 Emissions: Implications & Challenges for Investors	Amundi Research Center (2023)	Discusses the importance of Scope 3 emissions for investors.	Emphasizes the need for transparency in emissions reporting.
4	Baseline Survey of SME Suppliers and Assessment of Motivations and Challenges Towards Decarbonization	Mekong Institute (2024)	Identifies challenges faced by SMEs in decarbonization efforts.	Provides insights into SME-specific barriers.
5	Optimizing scope 3 emissions in the automotive manufacturing industry: a multidisciplinary approach	Wang, Y., Hao, Y., Hou, Y., Quan, Q., & Li, Y. (2024)	Explores interdisciplinary approaches to emission reductions.	Suggests innovative solutions applicable to SMEs.
6	Estimation of cost and CO2 emissions with a sustainable cross-border supply chain in the automobile industry: A case study of Thailand and neighboring countries	N, Kumiko., H, Shinya., K, Yuhki (2016)	Estimates emissions throughout the automotive supply chain.	Offers data for benchmarking and goal setting.
7	Greening Supply Chains in the Thai Auto and Automotive Parts Industries - International Review of Good Practices and EU/Japanese Regulations	Hafiz Ahmad ur rehman & D. Van Beers (2014)	Reviews sustainable practices in the Thai automotive sector.	Provides case studies relevant to Thai SMEs.
8	Scope 3 Frequently Asked Questions - GHG Protocol	World Resources Institute & World Business Council for Sustainable Development (2022)	Answers common questions regarding Scope 3 emissions.	Clarifies concepts for better understanding among SMEs.

No.	Study Title	Authors (Year)	Key Findings	Relevance to Thai SMEs
9	2023 Analysis of Climate Change-Related Risks in the GPIF's Portfolios	Government Pension Investment Fund (2023)	Analyzes climate-related risks in investments.	Highlights the financial implications of emissions.
10	Unlocking the Scope 3 Opportunity - KPMG International	KPMG International (2024)	Discusses opportunities in managing Scope 3 emissions.	Encourages proactive approaches among SMEs.
11	Thailand Reduces Scope 3 Emissions Using DHL GoGreen Plus	DHL (2023)	Showcases logistics solutions to reduce emissions.	Demonstrates practical applications for emission reductions.
12	From Policy to Practice: How Thailand is Reducing GHG Emissions	Appsynth (2023)	Examines Thailand's initiatives in emission reductions.	Provides context for national policies affecting SMEs.
13	The Drive to Net Zero: Japanese Automakers' Current Emissions and Opportunities	Greenpeace East Asia (2025)	Reviews emission strategies of Japanese automakers.	Offers insights into OEM expectations for suppliers.
14	Oil companies in disguise On a ticking 'carbon bomb' called 'Scope 3 emissions' mandatory reporting'. And why investors should avoid car stocks and cars' ESG ratings.	Transport & Environment (2023)	Investigates the financial aspects of carbon emissions.	Highlights the economic benefits of emission reductions.
15	Supply-Chain Emissions in Japan	Ministry of the Environment, Japan (2023)	Discusses supply chain emissions in the Japanese context.	Provides comparative insights for Thai SMEs.
16	The Impacts of the Transition to Electric Vehicles on Small and Medium Enterprises (SMEs) in Thailand's Automotive Parts Industry	Apiworathanakorn, Y., (2024)	Analyzes the effects of EV transition on Thai SMEs.	Highlights the need for adaptation in emission strategies.

No.	Study Title	Authors (Year)	Key Findings	Relevance to Thai SMEs
17	Reducing Carbon Footprint in the Automotive Industry	Grant Thornton India (2023)	Offers strategies for carbon footprint reduction.	Provides actionable steps for SMEs.
18	Understanding Carbon Emissions Risks Across the Supply Chain	Exiger (2023)	Explores risks associated with carbon emissions in supply chains.	Emphasizes the importance of risk management.
19	Use Case Concretisation: Visualisation of Carbon Footprint	Economic Research Institute for ASEAN and East Asia (2023)	Presents methods for visualizing carbon footprints.	Aids in the comprehension of emission sources.
20	Opportunities for Supply Chain Decarbonization in APEC Economies	Pacific Economic Cooperation Council (2023)	Identifies opportunities for decarbonization in supply chains.	Encourages SMEs to explore regional collaboration.

Introduction to Scope 3 Emission Categories under the GHG Protocol. The Greenhouse Gas (GHG) Protocol, jointly developed by the World Resources Institute (WRI) and the World Business Council for Sustainable Development (WBCSD), provides the most widely used international accounting tool for understanding, quantifying, and managing greenhouse gas emissions. While Scope 1 and Scope 2 emissions account for direct emissions from owned or controlled sources and indirect emissions from purchased electricity respectively, Scope 3 emissions cover all other indirect emissions that occur in a company's value chain (WRI & WBCSD, 2011). To standardize and guide companies in measuring and reporting these emissions, the GHG Protocol delineates 15 distinct categories of Scope 3 emissions. These categories encompass upstream and downstream activities, offering a comprehensive framework for understanding an organization's total carbon footprint beyond its immediate operations. The 15 Categories of Scope 3 Emissions. Upstream Emissions; 1. Purchased Goods and Services; Emissions from the production of goods and services purchased by the reporting company. This includes raw materials, components, and professional services. 2. Capital Goods; Emissions from the production of capital goods purchased by the company, such as machinery, buildings, or equipment. 3. Fuel- and Energy-Related Activities (not included in Scope 1 or 2); Emissions related to the production and distribution of fuels and energy purchased by the company, excluding those already accounted for in Scope 1 or 2. 4. Upstream Transportation and Distribution; Emissions from transportation and distribution of products purchased by the company, between suppliers and the company. 5. Waste Generated in Operations; Emissions from the treatment and disposal of waste generated in the company's operations. 6. Business Travel; Emissions from travel activities undertaken by employees for business purposes, such as flights, rail travel, or hotel stays. 7. Employee Commuting; Emissions from the transportation of employees between their homes and worksites. 8. Upstream Leased Assets; Emissions from assets that the company leases but does not own, such as office buildings or vehicles. Downstream Emissions; 9. Downstream Transportation and Distribution; Emissions from the transportation and distribution of products sold by the company to end users. 10. Processing of Sold Products; Emissions from processing of intermediate products sold by the reporting company by downstream companies (e.g., converting steel into cars). 11. Use of Sold Products; Emissions from the use of goods and services sold by the company (e.g., emissions from a car during its operational lifetime). 12. End-of-Life Treatment of Sold Products; Emissions from waste disposal and treatment of products after consumer use, including recycling or landfilling. 13. Downstream Leased Assets; Emissions from the operation of assets owned by the company and leased to other entities. 14.

Franchises; Emissions from operations of franchises not directly owned or controlled by the reporting company but operating under its brand. 15. Investments; Emissions associated with the reporting company's investments, including equity and debt investments. This study focuses specifically on Categories 1, 3, 4, 11, and 12 due to their high relevance to the automotive value chain and cross-border supplier dynamics between Japan and Thailand.

4.2 Assessment and analysis

4.2.1 Life Cycle Assessment (LCA)

The application of LCA within this study enables a detailed breakdown of emissions across the full life cycle of automotive products. The analysis follows a cradle-to-grave boundary, covering raw material sourcing, manufacturing, logistics, use phase, and disposal. Using LCA principles, This study strategically focuses on five specific Scope 3 categories—namely Categories 1, 3, 4, 11, and 12—based on their material relevance to the automotive industry and their significant contribution to total lifecycle emissions. These categories reflect both upstream and downstream emission sources that are central to the carbon footprint of vehicles and, importantly, are traceable within the Thailand–Japan cross-border automotive supply chain. Life Cycle Assessment (LCA) and Scope 3 emissions accounting strongly overlap in terms of evaluating carbon emissions across the full product life cycle. In particular, they share a common focus on upstream and downstream emissions that are not captured within Scope 1 and 2 boundaries. Within the framework of this study, Scope 3 emissions are primarily aligned with LCA stages such as raw material extraction, manufacturing, logistics, product use, and end-of-life treatment. When evaluating Scope 3 emissions within the framework of Life Cycle Assessment (LCA), it is critical to distinguish between life cycle stages of a product and the phases of an LCA study as defined by ISO 14040. These terms, though related, serve different analytical purposes and are frequently misunderstood or used interchangeably in both academic and industry literature. Product life cycle stages refer to the physical and temporal stages through which a product passes from its inception to final disposal. These typically include; Raw Material Acquisition: Extraction and processing of raw materials. Manufacturing/Production: Conversion of raw materials into finished products. Distribution: Transportation and warehousing of products. Use: Functional life of the product in the hands of consumers. End-of-Life: Disposal, recycling, or recovery at the end of product utility. These stages directly correlate with Scope 3 categories, particularly those associated with upstream and downstream activities (e.g., Categories 1, 4, 11, and 12), and are essential in emissions quantification at the product level. In contrast, LCA phases, as formalized in ISO 14040 and ISO 14044, pertain to the analytical procedure of conducting an LCA. These include; Goal and Scope Definition, Life Cycle Inventory Analysis (LCI), Life Cycle Impact Assessment (LCIA), Interpretation. These phases guide the methodological rigor of an LCA study and do not refer to physical stages of a product's existence. Rather, they ensure that the study is transparently scoped, data are consistently compiled, and results are contextually interpreted. By clearly distinguishing between these two concepts, this study ensures both conceptual clarity and methodological coherence. Product life cycle stages form the basis for emissions tracking within the Scope 3 framework, while the LCA phases define the process by which those emissions are assessed and reported. These are directly associated with nine GHG Protocol Scope 3 categories: Categories 1, 2, 3, 4, 5, 9, 10, 11, and 12. Category 1: Purchased Goods and Services – Emissions from the extraction, production, and transportation of raw materials and components used in manufacturing vehicles (e.g., steel, aluminum, plastic). Category 2: Capital Goods – Emissions embedded in the production of capital equipment, such as machinery, tools, and buildings, which are used in the automotive manufacturing process. Category 3: Fuel- and Energy-Related Activities (Not Included in Scope 1 or 2) – Emissions from the extraction, production, and transport of fuels and electricity consumed during vehicle production, beyond direct operational use. Category 4: Upstream Transportation and Distribution – Emissions associated with the transport of materials and components from suppliers to manufacturers, including warehousing. Category 5: Waste Generated in Operations – Emissions from the treatment and disposal of solid and liquid waste generated during the manufacturing process. Category 9: Downstream Transportation and Distribution – Emissions from delivering finished vehicles to dealerships or end users, including storage and retail distribution. Category 10: Processing of Sold Products – Emissions from additional processing by customers after the sale of vehicle components or semi-finished goods (relevant to Tier 1 suppliers). Category 11: Use of Sold Products – Emissions that occur when consumers use the vehicle over its operational life, typically the largest contributor in automotive LCA. Category 12: End-of-Life Treatment of Sold Products – Emissions from disposal, recycling, or recovery of vehicle materials at the end of their life cycle. Thus, while LCA provides a technically rigorous approach to quantify emissions associated with tangible product flows, Scope 3 accounting broadens the lens to include indirect emissions across the corporate value chain. In this study, the overlapping categories are prioritized to ensure both methodological rigor and practical relevance for SMEs operating in Thailand's automotive sector. This integrated view enhances data consistency between product-based LCA and organizational GHG reporting, supporting policy development, supplier engagement, and carbon traceability. The assessment finds that raw material extraction and product use phases represent the highest emissions intensity. However, most SMEs in Thailand—particularly Tier 2 and Tier 3 suppliers—lack the tools and capacity to measure emissions at these stages, leading to significant reporting gaps. OEM-provided templates and digital LCA dashboards are identified as potential enablers for SME compliance.

Table 2 outlines how GHG Protocol Scope 3 categories correspond with product life cycle stages in the context of the Japan–Thailand automotive supply chain, with a particular focus on the implications for Small and Medium-sized Enterprises (SMEs). The table links each Scope 3 category to specific emission sources and provides contextual insights into how these emissions arise in real-world supply chain operations. 1. Raw Material Acquisition Stage; Category 1: Purchased Goods and Services, Emissions originate from the extraction and processing of metals, plastics, and electronics. These are primarily associated with Tier 2 and Tier 3 suppliers in Thailand who often lack the technical capacity for comprehensive emissions reporting, leading to underrepresentation of upstream emissions. Category 2: Capital Goods, Capital goods such as machinery, tools, and factory infrastructure used in Thai manufacturing sites contribute significant embodied emissions. These assets are often financed or supplied by Japanese OEMs, but emissions accountability still applies to the manufacturing process. 2. Manufacturing/Production Stage; Category 3: Fuel- and Energy-Related Activities, These emissions stem from upstream production and transportation of fuels and electricity used in factory operations. Japanese OEMs increasingly require full emissions transparency from foreign suppliers, making this category critical. Category 5: Waste Generated in Operations, Waste generated during production—such as scrap metal, hazardous chemicals, and plastics—is often poorly tracked, especially among Thai SMEs. This leads to a lack of transparency in supply chain emissions reporting. Category 8: Upstream Leased Assets, Many Thai Tier 1–3 suppliers operate from leased facilities or use leased equipment, complicating emissions accounting under OEM-driven ESG frameworks. 3. Distribution Stage; Category 4: Upstream Transportation and Distribution, Emissions arise from transporting materials and parts from local and international suppliers to manufacturing facilities. Cross-border logistics between Japan and Thailand, particularly via shipping and trucking, are major contributors. Category 9: Downstream Transportation and Distribution, This includes emissions from transporting finished goods—vehicles or parts—from Thai factories to Japanese markets or other ASEAN countries. Carbon intensity is high due to the reliance on freight logistics. 4. Use Stage; Category 11: Use of Sold Products, Emissions occur during the operational life of sold vehicles, including fuel combustion or electricity use. This is often the largest contributor to a vehicle's total life cycle emissions. Category 13: Downstream Leased Assets, Vehicles or machinery leased to clients (e.g., under OEM fleet programs) generate ongoing operational emissions throughout the lease period. Category 14: Franchises, Emissions from franchised dealerships and service centers in Thailand operating under Japanese brands. Activities such as servicing, light assembly, and localized logistics add to the total footprint. 5. End-of-Life Stage; Category 12: End-of-Life Treatment of Sold Products, This includes emissions from vehicle disposal, scrapping, or recycling. Thailand's recycling infrastructure often lacks traceability and formal carbon accounting mechanisms, leading to potential reporting gaps. 6. Categories Not Included in Scope of Table; Category 6: Business Travel and Category 7: Employee Commuting, although they contribute to Scope 3 emissions (especially for inter-country collaboration and daily workforce logistics), these are rarely quantified by SMEs due to limited data infrastructure. Category 15: Investments, while indirect, financial investments by Japanese OEMs into Thai suppliers may influence emissions performance. This category is increasingly relevant under global ESG disclosure frameworks. Table 2 offers a structured view of how Scope 3 emissions align with life cycle stages in the automotive sector, particularly in cross-border contexts involving SMEs. By mapping specific emission sources to life cycle stages, the table enhances the practical understanding of carbon hotspots and reporting challenges. The analysis highlights that upstream activities such as raw material sourcing and downstream activities such as vehicle use represent the highest emission intensities. However, most Thai SMEs face capacity constraints in tracking emissions, underscoring the need for standardized templates and digital LCA tools to support compliance and transparency across the supply chain.

Table 2 LCA-Based Scope 3 Reporting Focus: Automotive Supply Chain (Adapted for SMEs)

LCA Stage	**Scope 3 Category**	**Key Emission Sources**	**Explanation(Context: Japan–Thailand Automotive Supply Chains)**
Raw Material Acquisition	Category 1: Purchased Goods and Services	Extraction and processing of metals, plastics, electronics	Emissions from Tier 2/3 suppliers in Thailand providing raw materials or parts to Japanese OEMs. Often underreported due to limited SME capacity.
Raw Material Acquisition	Category 2: Capital Goods	Machinery, tools, factory infrastructure	Capital goods used in Thai supplier factories contribute embedded emissions, even though often leased or financed by OEM partners.
Manufacturing/Production	Category 3: Fuel- and Energy-Related Activities	Upstream emissions from electricity and fuel production	Indirect energy emissions supporting Thai factory operations, essential due to Japan's pressure for full emissions disclosure from foreign partners.
Distribution (Upstream)	Category 4: Upstream Transportation and Distribution	Logistics of parts from local and international suppliers	Cross-border shipping between Japan and Thailand adds emissions from both marine and land-based logistics networks.
Manufacturing/Production	Category 5: Waste Generated in Operations	Scrap metal, hazardous waste, plastic disposal	Disposal from Thai manufacturing facilities often lacks formal GHG reporting systems, leading

LCA Stage	Scope 3 Category	Key Emission Sources	Explanation(Context: Japan–Thailand Automotive Supply Chains)
			to transparency issues in supply chain emissions.
Not include	Category 6: Business Travel	Employee air and land travel	Emissions from business trips between Japan and Thai operations—especially during inspections, audits, and collaboration meetings.
Not include	Category 7: Employee Commuting	Daily transportation of factory and office staff	Commuting in Thailand's industrial zones contributes Scope 3 emissions, though data collection is rare among SMEs.
Manufacturing/Production	Category 8: Upstream Leased Assets	Leased factories, machinery, and warehouses	Many Thai Tier 1–3 suppliers operate out of leased facilities, making emissions reporting more complex under OEM-aligned ESG frameworks.
Distribution (Downstream)	Category 9: Downstream Transportation and Distribution	Export of finished goods and components to OEMs/customers	Transport of vehicles or parts from Thai factories to Japanese markets or ASEAN partners, often via carbon-intensive modes like trucking or shipping.
Manufacturing/Production	Category 10: Processing of Sold Products	Component finishing, integration by customers	Japanese OEMs or Tier 1 partners may conduct additional product modification, adding emissions beyond Thailand's initial production phase.
Use	Category 11: Use of Sold Products	Fuel combustion, electricity use in vehicles	Long-term emissions from internal combustion or electric vehicles assembled in Thailand and exported or used domestically.
End-of-Life	Category 12: End-of-Life Treatment of Sold Products	Disposal, recycling, scrapping	Thailand's recycling systems often lack carbon traceability, impacting the complete life cycle GHG accounting for vehicles.
Use	Category 13: Downstream Leased Assets	Leased vehicles and machinery used by clients	Vehicles leased under Japanese OEM programs in

LCA Stage	Scope 3 Category	Key Emission Sources	Explanation(Context: Japan–Thailand Automotive Supply Chains)
			Thailand generate ongoing operational emissions.
Manufacturing/Production / Use	Category 14: Franchises	Dealership and service center operations	Thai franchises under Japanese brands contribute emissions via servicing, minor assembly, and local logistics activities.
Not include	Category 15: Investments	Financial emissions from OEM capital in suppliers/projects	Japanese investment in Thai suppliers indirectly influences emissions via financial flows, which are increasingly material under global ESG mandates.

4.2.2 SWOT Analysis

The SWOT analysis evaluates the operational and policy environment for Thai automotive SMEs under Scope 3 disclosure expectations. Strengths include Thailand's position as a regional automotive hub and the growing ESG interest from Japanese OEMs. Weaknesses are centered on the lack of LCA knowledge, fragmented data systems, and limited digitalization. Opportunities arise from increasing global demand for sustainable sourcing, ESG investment instruments (e.g., green loans), and government incentives through the BCG model. However, threats such as regulatory pressure from foreign buyers (e.g., EU CBAM, Japanese Scope 3 mandates) and the potential exclusion from global supply chains pose significant challenges. The SWOT framework provides a strategic lens to interpret the risks and enablers affecting emissions governance in this sector.

Table 3 provides a SWOT (Strengths, Weaknesses, Opportunities, and Threats) analysis tailored to Thai SMEs operating within Japan-led automotive supply chains. It highlights internal capacities (such as strategic geography and growing OEM partnerships) as strengths, while identifying weaknesses such as low digital infrastructure, limited carbon accounting knowledge, and financial constraints. Externally, the growing availability of ESG finance and support from international programs (e.g., ILO and UNDP) represent opportunities, whereas threats include rising regulatory expectations from Japan's METI and international carbon disclosure standards (e.g., CBAM, SBTi). This SWOT analysis offers a clear diagnostic foundation for further strategic development and policy design.

Table 3 SWOT Analysis: Scope 3 Emissions Management in Thai Automotive SMEs

Strengths	Weaknesses
- Strategic location of Thailand as a regional automotive hub	- Limited technical capacity in emissions accounting
- Existing collaborations with Japanese OEMs	- Lack of digital infrastructure and standardized reporting tools
- National BCG policy and CFO programs available	- Low awareness among SMEs about Scope 3 obligations

Strengths	Weaknesses
- Growing interest in ESG compliance from international buyers	- Limited access to green finance and innovation resources
Opportunities	**Threats**
- Expansion of EV supply chains and eco-partnerships	- Rising global regulatory pressure on emission transparency
- Government incentives for digital transformation and green technology	- Risk of exclusion from international value chains without Scope 3 compliance
- Access to international funding (e.g., UNDP, ILO, JICA)	- High initial costs for LCA systems and decarbonization technologies

4.2.3 TOWS Matrix

Building on the SWOT results, the TOWS Matrix outlines actionable strategies for OEMs, regulators, and SMEs. Key strategies include leveraging OEM–SME partnerships to improve traceability and data sharing (S–O), using government policies like the CFO program to pre-empt external regulatory threats (S–T), and building training programs to address SME weaknesses in carbon accounting (W–O). Additionally, W–T strategies include creating supplier clusters or alliances to reduce compliance costs and strengthen negotiation power in cross-border ESG frameworks. The TOWS model helps translate analytical insight into multi-stakeholder action plans.

Table 4 builds upon the SWOT results by applying a TOWS Matrix to derive strategic responses that align organizational capacity with emerging risks and opportunities. It proposes actionable strategies in four areas: (1) Strength–Opportunity strategies such as leveraging OEM partnerships to access ESG capital; (2) Strength–Threat strategies like using national BCG policy tools to respond to international regulatory shifts; (3) Weakness–Opportunity strategies involving the deployment of OEM-sponsored digital tools and training programs to build carbon tracking capacity; and (4) Weakness–Threat strategies such as forming supplier clusters to pool carbon reporting resources and jointly apply for sustainability certifications. This matrix plays a critical role in translating analysis into stakeholder-driven responses.

Table 4 TOWS Matrix: Strategic Options for Scope 3 Integration in Thai SMEs

	Opportunities (O)	Threats (T)
Strengths (S)	**S-O Strategies**	**S-T Strategies**
	- Leverage Thailand's strategic location to attract foreign green investments	- Use OEM collaborations to meet global Scope 3 regulatory demands
	- Align BCG policies with international LCA/ESG standards	- Promote existing ESG performance in marketing to reduce exposure to reputational risk
Weaknesses (W)	**W-O Strategies**	**W-T Strategies**
	- Seek technical and financial support via international cooperation to build SME digital capacity	- Use government incentives to offset technology acquisition and reporting costs
	- Implement SME-focused training and toolkits for Scope 3 readiness	- Form clusters or supplier alliances to pool resources for carbon data systems and certifications

4.3 Policy Implications and Recommendations

This research highlights several critical policy implications for both Thai regulators and Japanese OEMs. First, there is a pressing need to establish a national Scope 3 emissions data registry and SME reporting toolkit aligned with the GHG Protocol and LCA standards. Second, Thai policymakers should harmonize the BCG model with Japan's METI-driven ESG requirements to ensure regulatory compatibility in cross-border trade. Third, government support must go beyond awareness campaigns—providing financial incentives, tax credits, and digital infrastructure investments to lower the barriers of Scope 3 adoption. Fourth, OEMs must take a more active role in co-developing emissions tracking systems and offering technical assistance to SMEs across tiers. Lastly, ASEAN-wide collaboration on emissions standards and supplier certification schemes could enable regional competitiveness and carbon transparency. These recommendations aim to enable scalable, inclusive Scope 3 emissions integration within the Thailand–Japan automotive supply chain. To operationalize these insights, the study proposes five priority policy actions for Thai regulators and OEMs; 1) Establish a national Scope 3 emissions registry with pre-defined templates for SMEs. 2) Mandate ESG disclosure frameworks for Tier 1 suppliers and incentivize trickle-down compliance. 3) Introduce tax incentives for investments in carbon accounting technology and reporting systems. 4) Create a national certification program for Scope 3 readiness and sustainability performance and 5) Facilitate OEM-led digital traceability platforms, co-financed by public-private partnerships.

Refined Policy Recommendations for Thailand's Scope 3 Readiness. To accelerate Scope 3 readiness across Thailand's automotive supply chain, especially among SMEs, this study proposes five interlinked and context-sensitive policy recommendations. First, the government should establish a National Scope 3 Readiness Platform managed by the Thailand Greenhouse Gas Management Organization (TGO) or the Ministry of Industry (MOI). This platform would provide pre-defined emission factor templates, localized GHG Protocol guidance in Thai, and access to Life Cycle Assessment (LCA) tools tailored for small suppliers—thereby reducing complexity and standardizing emissions reporting. Second, Scope 3 emissions criteria should be embedded within existing national incentive mechanisms, particularly those under the Bio-Circular-Green (BCG) economy model and the Board of Investment (BOI). By linking ESG compliance to investment privileges and innovation grants, the government can align decarbonization incentives with economic competitiveness. Third, a "Green Supplier Sandbox" initiative should be launched in collaboration with Japanese OEMs. This would involve selecting designated industrial clusters for pilot testing blockchain-based carbon traceability systems and delivering OEM-funded technical training in emissions reporting and LCA. Such a localized approach would help reduce risk for early adopters while generating models for scalable national implementation. Fourth, financial incentives should be enhanced through the creation of a national ESG credit scoring framework for SMEs. Developed in partnership with banks and fintech stakeholders, this framework would link verified Scope 3 reporting performance with access to green loans, tax credits, and sustainability-linked financing—effectively monetizing compliance readiness. Lastly, the formation of a Thailand–Japan Scope 3 Policy Harmonization Taskforce is recommended. This bilateral body would include representatives from Japan's (METI), Thailand's MOI, and leading OEMs, tasked with aligning emissions reporting frameworks, developing mutual ESG audit standards, and ensuring policy coherence across borders. Collectively, these recommendations aim to bridge the implementation gap, de-risk SME participation, and build a competitive, low-carbon supply chain ecosystem.

Furthermore, the study promotes cooperative engagement between Japanese OEMs and Thai suppliers in developing joint strategies for sustainable decarbonization. This approach aligns with Thailand's BCG economic model and global frameworks such as SDGs. As the global automotive industry faces rising environmental and regulatory pressures, Thailand's role in supporting Japan's net-zero targets by 2050 will be crucial to achieving both ecological integrity and regional economic resilience. Therefore, this study emphasizes the evaluation of Scope 3 emissions—defined as all other indirect emissions across the value chain, including supply chain activities, transportation, and product use (GHG Protocol, 2015).

5 CONCLUSION

This study examined the implementation of Scope 3 emissions protocols under the GHG Protocol within the Thai automotive supply chain, particularly focusing on SMEs embedded in Japanese-led networks. The results highlight that Scope 3 emissions, which constitute a significant majority of total sectoral emissions, are essential to decarbonization efforts but remain insufficiently addressed due to gaps in data infrastructure, limited technical expertise, restricted financial access, and fragmented regulatory frameworks. Although Thailand benefits from strategic policies like the Bio-Circular-Green (BCG) Economy Model and the Carbon Footprint for Organization (CFO) program, SMEs still lack the tools and incentives needed to comply with international ESG standards. Persistent barriers include the absence of digital infrastructure, low carbon literacy, and minimal OEM-driven support mechanisms. The study identifies collaborative OEM-SME engagement, digital technology adoption (e.g., blockchain, AI), and policy harmonization as strategic levers for improvement. Scalable, inclusive, and cross-sectoral frameworks are needed to drive carbon accountability in line with global expectations.

6 REFERENCES

Amundi Research Center. (2023). *Measuring Scope 3 emissions: Implications and challenges for investors*. Retrieved from https://research-center.amundi.com/index.php/article/esg-thema-19-measuring-scope-3-emissions-implications-challenges-investors

Apiworathanakorn, Y., (2024). The Impacts of the Transition to Electric Vehicles on Small and Medium Enterprises (SMEs) in Thailand's Automotive Parts Industry. *International Journal of Social Science Research and Review*, 8(2):1-21. DOI: 10.47814/ijssrr.v8i2.2442

Appsynth (2023). *From Policy to Practice: How Thailand is Reducing GHG Emissions*. Appsynth Retrieved from https://appsynth.net/thailand-reduce-ghg-emissions/

Bangkok Post. (2023). *UOB Thailand Empowers SMEs for Low-Carbon Transition*. Bangkok Post Retrieved from https://www.bangkokpost.com/thailand/pr/3013957/uob-thailand-empowers-smes-for-low-carbon-transition

BMW Group. (2022). *Sustainability strategy: Supply chain CO2 reduction*. BMW Group. Retrieved from https://www.bmwgroup.com

BOI (Thailand Board of Investment). (2022). *Thai Investment Promotion Policy*. Thailand Board of Investment. Retrieved from http://www.boi.go.th

CDP. (2022). *Transparency to transformation: A chain reaction*. CDP Worldwide. Retrieved from https://www.cdp.net

DHL Express. (2025). *Thailand reduces scope 3 emissions using DHL Go Green Plus*. DHL Discover. Retrieved from https://www.dhl.com/discover/en-th/logistics-advice/sustainability-and-green-logistics/dhl-gogreen-plus-reduces-scope3-emissions

Economic Research Institute for ASEAN and East Asia. (2023). *Use case concretisation and visualisation of carbon footprint*. Economic Research Institute for ASEAN and East Asia. Retrieved from https://www.eria.org/uploads/Use-Case-Concretisation-Visualisation-of-Carbon-Footprint.pdf

Exiger. (2023). *Understanding Carbon Emissions Risks Across the Supply Chain*. Exiger. Retrieved from https://www.exiger.com/perspectives/understanding-carbon-emissions-risks-across-the-supply-chain/

GHG Protocol. (2015). *Technical guidance for calculating scope 3 emissions*. World Resources Institute. Retrieved from https://ghgprotocol.org

General Motors. (2022). *Sustainable procurement practices*. General Motors Company. Retrieved from https://www.gm.com

Government Pension Investment Fund (2023). *2023 Analysis of Climate Change-Related Risks in the GPIF's Portfolios.* MSCI ESG Research. Retrieved from https://www.gpif.go.jp/en/investment/GPIF_ESGReport_FY2022_E_report03.pdf

Greenhouse Gas Protocol. (2025). *A Corporate Accounting and Reporting Standard*. Retrieved from https://ghgprotocol.org/sites/default/files/standards/ghg-protocol-revised.pdf

Greenpeace East Asia. (2025). *The Drive to Net Zero: Japanese Automakers' Current Emissions and Opportunities.* Greenpeace Retrieved from https://www.greenpeace.org/static/planet4-eastasia-stateless/2025/03/799032d8-drive_to_net_zero.pdf

Grant Thornton India. (2023). *Reducing Carbon Footprint in the Automotive Industry.* ACMA. Retrieved from https://www.grantthornton.in/globalassets/1.-member-firms/india/assets/pdfs/reducing_carbon_footprint_in_the_automotive_industry_2023.pdf

Hafiz Ahmad ur rehman & D. Van Beers. (2014). *Greening Supply Chains in the Thai Auto and Automotive Parts Industries - International Review of Good Practices and EU/Japanese Regulations*. Report for SWITCH Asia Project 'Greening Supply Chains in the Thai Auto and Automotive Parts Industries', Bangkok, Thailand.

Hyundai Motor. (2023). *Supply chain carbon tracking innovations*. Hyundai Motor Company. Retrieved from https://www.hyundai.com

International Energy Agency. (2022). *Transport sector CO2 emissions*. IEA. Retrieved from https://www.iea.org

ILO. (2025). *Sustainable Supply Chains and Workforce ESG Readiness in Asia*. International Labour Organization. Retrieved from https://www.ilo.org

International Labour Organization. (2025). *ILO-Japan initiative strengthens Thailand's automotive sector amid industry transformation.* ILO News. Retrieved from https://www.ilo.org/resource/news/ilo-japan-initiative-strengthens-thailand%E2%80%99s-automotive-sector-amid-industry

JETRO. (2021). *Japanese Automotive Supply Chain Trends in ASEAN*. https://www.jetro.go.jp

Jaguar Land Rover. (2023). *Lifecycle emissions assessment in automotive design*. Jaguar Land Rover Ltd. Retrieved from https://www.jaguarlandrover.com

Japan External Trade Organization. (2021). *Automotive supply chain development in ASEAN*. JETRO. Retrieved from https://www.jetro.go.jp

Khan, S. A. R., Zhang, Y., & Nathaniel, S. P. (2020). Green supply chain management and environmental performance: A panel study. *Scientific Journal of Logistics*, 250, 119–123. http://doi.org/10.17270/J.LOG.2020.394

KPMG. (2024). *Unlocking the Scope 3 Opportunity in Asia-Pacific*. KPMG International. Retrieved from https://assets.kpmg.com/content/dam/kpmg/xx/pdf/2024/08/uncovering-the-scope-3-opportunity-in-asia-pacific.pdf

McKinsey & Company. (2021). *Driving decarbonization: Accelerating zero-emission freight transport*. McKinsey & Company. Retrieved from https://www.mckinsey.com/industries/automotive-and-assembly/our-insights/why-the-automotive-future-is-electric

METI (Ministry of Economy, Trade and Industry, Japan). (2023). *Japan's Green Growth Strategy through Achieving Carbon Neutrality*. Ministry of Economy, Trade and Industry, Japan. https://www.meti.go.jp

Mekong Institute. (2024). *Baseline Survey of SME Suppliers and Assessment of Motivations and Challenges Towards Decarbonization*. Mekong Institute. Retrieved from https://mekonginstitute.org/wp-content/uploads/2024/09/ToR_Baseline-Survey-of-SME-Suppliers-and-Assessment-of-Motivations-and-Challenges-Towards-Decarbonization.docx.pdf

Ministry of the Environment, Japan (2023). *Supply-Chain Emissions in Japan.* Ministry of the Environment, Japan. Retrieved from https://www.env.go.jp/earth/ondanka/supply_chain/gvc/en/files/supply_chain_en.pdf

Nakamichi, Y., Hanaoka, S., & Kawahara, H. (2016). Estimating CO2 emissions in automobile supply chains in Thailand and neighboring countries. *Transportation Research Part D: Transport and Environment*, 43, 158–168. https://doi.org/10.1016/j.trd.2015.12.018

Pacific Economic Cooperation Council. (2023). *Opportunities for Supply Chain Decarbonization in APEC Economies.* USPECC. Retrieved from https://www.pecc.org/resources/publications/environment/2742-opportunities-for-supply-chain-decarbonization-in-apec-economies/file

Stellantis. (2023). *EcoDesign and supplier carbon performance metrics*. Retrieved from https://www.stellantis.com

Sumitomo Riko. (2023). *ESG and carbon reporting 2023*. Sumitomo Riko Company Limited. Retrieved from https://www.sumitomoriko.co.jp

Tata Motors. (2022). *Supporting SMEs with climate action*. Tata Motors Ltd. Retrieved from https://www.tatamotors.com

Thailand Greenhouse Gas Management Organization. (2022). *Carbon footprint reporting in Thai industries*. Thailand Greenhouse Gas Management Organization. Retrieved from https://www.tgo.or.th

Tillväxtanalys. (2020). *The green transition of the automotive supply chain. Swedish Agency for Growth Policy Analysis*. Retrieved from https://enviliance.com/regions/southeast-asia/th/th-carbon-footprint

Thailand's Low Emission Vehicle Ecosystem. (2024). *Office of Transport and Traffic Policy and Planning*, Ministry of Transport, Thailand. Retrieved from https://www.otp.go.th/

The National Bureau of Asian Research. (2024). *Thailand's Path toward Carbon Neutrality and the Implications for the Mekong Subregion.* Retrieved from https://www.nbr.org/publication/-thailands-path-toward-carbon-neutrality-and-the-imp

Transport & Environment. (2023). Oil companies in disguise On a ticking 'carbon bomb' called 'Scope 3 emissions' mandatory reporting'. And why investors should avoid car stocks and cars' ESG ratings. Transport & Environment. Retrieved from https://www.transportenvironment.org/uploads/files/Carbon-ESG-finance-Car-Study-V6.pdf

Youngswaing, W., Jomnonkwao, S., Cheunkamon, E., & Ratanavaraha, V. (2024). Key Factors Shaping Green Logistics in Thailand's Auto Industry: An Application of Structural Equation Modeling. *Logistics*, 8(1), 17. https://doi.org/10.3390/logistics8010017

United Nations Development Programme Thailand. (2024). *Supporting NDC Target through Incentivizing the Use of Electric Vehicles.* Bangkok: UNDP.

Volvo Cars. (2023). *Blockchain technology in sustainable procurement*. Volvo Car Corporation. Retrieved from https://www.volvocars.com

Wang, Y., Hao, Y., Hou, Y., Quan, Q., & Li, Y. (2024). Optimizing scope 3 emissions in the automotive manufacturing industry: a multidisciplinary approach. *Carbon Research*, 3(49); 1-11. DOI: https://doi.org/10.1007/s44246-024-00131-2

World Resources Institute & World Business Council for Sustainable Development. (2013). *Technical Guidance for Calculating Scope 3 Emissions.* WORLD RESOURCES INSTITUTE. Retrieved from https://ghgprotocol.org/sites/default/files/standards/Scope3_Calculation_Guidance_0.pdf

World Resources Institute & World Business Council for Sustainable Development. (2022). *Scope 3 Frequently Asked Questions - GHG Protocol*. WORLD RESOURCES INSTITUTE. Retrieved from https://ghgprotocol.org/sites/default/files/2022-12/Scope%203%20Detailed%20FAQ.pdf

DIFT2025-1
Digital Innovation and Financial Technology Conference 2025 (Round 1)
June 7th, 2025

THE IMPACT OF DIGITAL FINANCIAL INCLUSION ON REGIONAL ECONOMIC GROWTH IN CHINA

Yanjie Chen[1] and Nathee Naktanasukanjn[2]
International College of Digital Innovation, Chiang Mai University, Chiang Mai, 50200, Thailand
E-mail: [1]chen_yan@cmu.ac.th, [2]nathee@cmuic.net

ABSTRACT

This study explores the impact of digital financial inclusion (DFI) on regional economic growth in China, emphasizing disparities across the eastern, central, western, and northeastern regions. By analyzing provincial panel data (2015-2023) and employing econometric models, the research reveals that DFI's contribution to economic growth varies significantly depending on regional infrastructure, policy environments, and income levels. Key findings indicate stronger growth-promoting effects in digitally advanced regions, while government fiscal interventions demonstrate heightened efficacy in areas with lower DFI adoption. Additionally, the influence of DFI exhibits a gradient pattern aligned with regional economic development stages, and innovation-driven investments yield measurable benefits primarily in high-income provinces. These results underscore the necessity of spatially tailored policies to address China's regional imbalances, offering actionable insights for leveraging DFI as a tool to advance equitable growth under the national "Common Prosperity" agenda.

KEYWORDS: Digital Financial Inclusion; Regional Economic Growth; Socioeconomic Disparities; Policy Frameworks

1 INTRODUCTION

Digital financial inclusion (DFI) has emerged as a key driver of inclusive economic growth in China. In recent years, government policies such as the Guidelines on Promoting the Development of Digital Financial Inclusion (2016) and the Fintech Development Plan (2022–2025) emphasize leveraging digital technologies to bridge regional disparities and enhance financial accessibility. However, despite substantial progress, significant gaps persist between eastern, central, western, and northeastern regions in DFI penetration and economic outcomes. Addressing these disparities aligns with China's "Dual Circulation" strategy and the goal of common prosperity.

The "Dual Circulation" strategy and the goal of common prosperity are closely intertwined and mutually reinforcing in China's development blueprint. The "Dual Circulation" strategy, with its focus on the domestic cycle as the mainstay and the mutual promotion of domestic and international cycles, provides a robust framework for sustainable economic growth. By expanding domestic demand and optimizing the supply structure, it not only strengthens China's economic resilience but also creates a vast market that can drive inclusive development. This strategy ensures that the economic benefits generated are more evenly distributed across different regions and social groups, which is a crucial step towards achieving common prosperity. The government's efforts to improve social security, education, healthcare, and employment opportunities, as part of the common prosperity goal, are also essential in enhancing the quality of the domestic cycle. These measures help to reduce income inequality, improve the living standards of the people, and foster a more balanced and harmonious society. In essence, the "Dual Circulation" strategy serves as a powerful engine for economic development, while the goal of common prosperity acts as a guiding principle to ensure that this development is inclusive and equitable, ultimately leading to a prosperous and harmonious society for all.

China’s regional development remains uneven. According to the National Bureau of Statistics (2022), the eastern region contributes over 50% of national GDP, while the western and northeastern regions lag behind. DFI, measured by the Peking University Digital Financial Inclusion Index, has shown rapid growth nationwide, yet its impact varies across regions due to differences in infrastructure, policy implementation, and institutional environments. For example, eastern provinces like Zhejiang and Guangdong exhibit advanced digital ecosystems, while western regions like Gansu and Xinjiang struggle with lower digital literacy and connectivity.

Against this backdrop, digital financial inclusion (DFI) has emerged as a strategic priority under China’s "Dual Circulation" policy framework, aiming to enhance financial accessibility and stimulate balanced development. However, existing research predominantly examines DFI’s aggregate national effects, neglecting critical variations in regional implementation capacities, such as digital infrastructure maturity, institutional support, and socioeconomic contexts.

This study addresses two overarching gaps: First, it systematically evaluates how DFI’s economic impacts diverge across China’s four major regions, reflecting differences in policy execution and technological adoption. Second, it investigates the interplay between DFI, fiscal policies, and innovation ecosystems to identify region-specific drivers of growth. By integrating the Peking University DFI Index with provincial-level data, the research provides a granular analysis of DFI’s role in mitigating spatial inequalities. The findings aim to inform policymakers on optimizing DFI deployment, aligning fiscal and technological investments with regional needs, and fostering inclusive growth trajectories.

2 LITERATURE REVIEW

2.1 Key Drivers of Digital Financial Inclusion

2.1.1 Technological Advancements

The proliferation of mobile technology and internet connectivity has been pivotal in expanding digital financial services. Dudu et al. (2024) demonstrate that mobile platforms overcome geographical barriers in emerging markets, enabling remote access to payments, savings, and credit. For instance, in rural China, mobile banking adoption surged by 45% between 2018 and 2022, driven by affordable smartphones and 4G coverage (National Bureau of Statistics, 2023). As 5G networks and smartphone penetration deepen, underserved populations—particularly in western China—are expected to gain greater financial inclusion.

2.1.2 Regulatory Support

Policy frameworks play a critical role in fostering fintech innovation. Dudu et al. (2024) argue that balanced regulation—such as China’s Fintech Development Plan (2022–2025)—creates an enabling environment for digital financial services. For example, Shanghai’s "Digital Yuan Smart Port" initiative streamlined cross-border transactions through blockchain integration, reducing processing times by 80% (State Council, 2022). However, inconsistent policy implementation in less developed regions, such as Gansu and Qinghai, limits DFI’s reach, underscoring the need for region-specific regulatory adaptations.

2.1.3 Financial Literacy

Educational tools embedded in digital platforms are essential for empowering users. As highlighted by Dudu et al. (2024), apps like Alipay and WeChat Pay incorporate tutorials on budgeting and investment, improving financial literacy among rural households. In Sichuan’s "Mobile Payment Desert Oasis" project, workshops on QR code usage increased digital transactions by 95% in Tibetan Plateau villages (Chen et al., 2023). Yet, persistent gaps in financial education—evident in regions with low school enrollment rates—remain a barrier to DFI’s full potential.

2.2 The Role of Digital Financial Inclusion in Economic Development

2.2.1 Enhancing Access to Financial Services

DFI bridges gaps in traditional banking infrastructure. Jabrane and Hanane (2024) note that digital wallets in rural Hubei enabled 200,000 farmers to access microloans, boosting agricultural productivity by 18%. Similarly, Xu et al. (2024) find that DFI reduced urban-rural income inequality by 12% in Zhejiang Province through data-backed loans for SMEs. These mechanisms highlight DFI’s capacity to democratize financial resources.

2.2.2 Promoting Entrepreneurship

Access to digital credit fuels entrepreneurial activity. Wen et al. (2024) illustrate how DFI-supported startups in Guangdong created 1.2 million jobs between 2020 and 2023. In contrast, western provinces like Guizhou saw slower growth due to limited fintech adoption, emphasizing the need for targeted credit programs (Wang, 2024).

2.2.3 Optimizing Industrial Structures

DFI drives economic diversification. Wang et al. (2024) document how blockchain-based tourism vouchers in Chongqing increased rural revenue by 28%, while Heilongjiang’s "Digital Ice City" project attracted $120 million in investments for AR/VR-enhanced tourism. Such innovations underscore DFI’s role in modernizing traditional sectors and reducing regional disparities.

2.3 Regional Economic Disparities in China

2.3.1 Socioeconomic Factors

Jin (2024) identifies uneven access to education and healthcare as key drivers of regional gaps. For instance, eastern provinces allocate 30% more funding per student than western regions, perpetuating skill mismatches in labor markets.

2.3.2 Digital Economy

Wang (2024) attributes growth disparities to the east-west digital divide. While Zhejiang’s "Poetic Road Cultural Data Brain" leverages AI for tourism assetization, Xinjiang’s internet penetration remains 40% below the national average, stifling DFI’s impact.

2.3.3 Educational Disparities

Chen et al. (2023) link uneven educational resources to economic outcomes. High school graduation rates in Shanghai (98%) far exceed those in Gansu (65%), limiting workforce readiness in less developed regions.

2.3.4 Infrastructure Financialization

Li et al. (2023) emphasize that low infrastructure investment in western China—such as delayed 5G rollout—constrains urbanization. For example, Tibet's GDP growth lagged behind coastal provinces by 4% annually due to inadequate transport and energy networks.

3 RESEARCH METHOD AND MODEL

This study employs a mixed-methods approach, combining empirical analysis and descriptive analysis. The empirical analysis utilizes econometric techniques to test the hypotheses and assess the impact of digital financial inclusion on regional economic growth. The descriptive analysis focuses on China's regional policies to provide a contextual understanding of the regional economic dynamics and policy implications.

3.1 Research Hypotheses

According to the research of the above-mentioned scholars, unbalanced regional development is a pain point in China's development. This paper holds that the impact of digital finance on promoting regional development varies. The specific hypotheses are studied as follows:

H1: The impact of digital financial inclusion on economic growth is stronger in the eastern region than in other regions (β_1-East > β_1-others).

H2: In regions with lower digital adoption, Government Expenditure has stronger positive impacts on economic growth (β_3-LowDFI > β_3-HighDFI).

H3: The positive effect of digital financial inclusion on economic growth demonstrates a gradient effect, with its impact being more pronounced in regions with higher per capita GDP (β_1-HighGDP > β_1-MediumGDP > β_1-LowGDP).

H4: In regions with higher per capita GDP, the long-term (lagged) promoting effect of R&D intensity on economic growth is significantly stronger compared to medium- and low-GDP regions (β_2-HighGDP > β_2-MediumGDP & β_2-LowGDP).

3.2 Research Model

Based on the research hypotheses, the empirical model constructed is as follows:

$GDP=\alpha+\beta1DFI+\beta2R\&D\ Expenditure+\beta3Government\ Expenditure+\beta4Labor+\epsilon$

The variables in the model and their explanations are shown in the following table:

Table 1 Definitions of Variables

Variable name	Variable explanation
GDP	Per capita GDP of every province in China.

Variable name	Variable explanation
DFI	The Peking University Digital Financial Inclusion Index of China.
R&D	Research and development expenditure of each province in China / GDP of each province (R&D intensity).
Government Expenditure	Government Expenditure of each province in China.
Labor	The number of people employed in the tertiary industry in each province of China.

3.3 Research Objectives and Significance (3)

This paper mainly analyzes the differential impact of digital inclusive finance on economic growth in different regions of China.

In addition, other important factors, such as research and development expenditures and government expenditures, should also be identified and evaluated to determine how they affect the regional economic growth disparities in these regions.

The existing research on DFI and economic growth mainly focuses on the analysis at the national level (Huang et al., 2020) or specific sectors (such as small and medium-sized enterprises and rural finance). Few studies have systematically examined the inter-regional differences in the economic effects of DFI, especially within the official four-region framework of China (East, Central, West, and Northeast). This study addresses this gap by analyzing spatial differences and proposing region-specific policy solutions to leverage the potential of DFI in balanced development.

4 RESULTS AND DISCUSSION

This study employed stata18.0 software and conducted a binary logistic regression analysis on 279 sample sizes.

The regression analysis results for Hypothesis 1 are as follows:

4.1 H1 and conclusion:

H0: There is no significant difference in the impact of digital financial inclusion on economic growth between the eastern region and other regions.
($H0$: β_1-East $\leq$ β_1-others)
H1: The impact of digital financial inclusion on economic growth is stronger in the eastern region than in other regions (β_1-East > β_1-others).

Table 2 Regression analysis of the Impact of DFI on Eastern and Non-eastern Regions of China

	East	Non-East
	perGDP	perGDP
dfi	227.1^{***}	142.8^{***}
	(5.82)	(11.21)

N	90	189

According to the regression analysis results, the impact of the DFI on economic growth is significantly stronger in the eastern region than in the non-eastern regions. Specifically, in the eastern region, the coefficient of dfi is 227.1, and it is significant at the 1% level; in the non-eastern region, the coefficient of dfi is 142.8, also significant at the 1% level.

This indicates that the positive impact of the digital financial index on economic growth is more pronounced in the eastern region, thus supporting the hypothesis that the impact of digital financial inclusion on economic growth is stronger in the eastern region than in other regions.

4.2 H2 and conclusion

H0: Government expenditure does not have a significantly stronger impact on economic growth in regions with lower digital financial inclusion.(H0: β_3-LowDFI ≤ β_3-HighDFI)
H2: In regions with lower digital adoption, Government Expenditure has stronger positive impacts on economic growth (β_3-LowDFI > β_3-HighDFI).

Table 3 Regression analysis of the impact of government expenditure on regions with lower and higher digitalization in China

	low DFI perGDP	high DFI perGDP
dfi	114.3** (4.04)	227.4** (3.50)
gov	6.383** (4.16)	1.270 (0.36)
N	117	117

According to the regression analysis results, the adjusted hypothesis (H2') is supported, which suggests that in regions with lower digital financial development, government expenditure has a more significant positive impact on economic growth. Specifically, in the low DFI region, the coefficient for government expenditure is 6.383, significant at the 5% level; whereas in the high DFI region, the coefficient for government expenditure is 1.270, which is not significant. This indicates that in areas where digital financial development is lagging, increasing government spending may more effectively stimulate economic growth, whereas in regions with better digital financial development, the impact of government expenditure on economic growth may be limited.

4.3 H3 and conclusion:

The impact of digital financial inclusion on economic growth does not follow a gradient pattern across high, medium, and low per capita GDP regions.(H0: β_1-HighGDP ≤ β_1-MediumGDP or β_1-MediumGDP ≤ β_1-LowGDP)

H3: The positive effect of digital financial inclusion on economic growth demonstrates a gradient effect, with its impact being more pronounced in regions with higher per capita GDP (β_1-HighGDP > β_1-MediumGDP > β_1-LowGDP).

Table 4 Regression analysis of the Impact of Digital Finance on High, Medium and Low Regions of Per capita GDP in China

	(1)	(2)	(3)
	low gdp	medium gdp	high gdp
dfi	144.9612***	154.3534***	223.5529**
	(20.0195)	(10.5237)	(57.8922)
N	99	81	99
r2_a	0.826	0.919	0.762

According to the regression analysis results, the positive effect of digital financial inclusion on economic growth demonstrates a gradient effect, with its impact being more pronounced in regions with higher per capita GDP. Specifically, in regions with low per capita GDP, the coefficient of dfi is 144.9612, significant at the 1% level; in regions with medium per capita GDP, the coefficient of dfi increases to 154.3534, also significant at the 1% level; and in regions with high per capita GDP, the coefficient of dfi further increases to 223.5529, significant at the 5% level. This result supports Hypothesis H3, which states that the positive effect of digital financial inclusion on economic growth is more significant in regions with higher per capita GDP.

4.4 H4 and conclusion

H0: The long-term effect of R&D intensity on economic growth in high-GDP regions is not significantly greater than that in medium- or low-GDP regions.(H0: β_2-HighGDP ≤ β_2-MediumGDP or β_2-HighGDP ≤ β_2-LowGDP)
H4: In regions with higher per capita GDP, the long-term (lagged) promoting effect of R&D intensity on economic growth is significantly stronger compared to medium- and low-GDP regions (β_2-HighGDP > β_2-MediumGDP & β_2-LowGDP).

Table 5 Regression analysis of the Impact of R&D Intensity on High, Medium and Low Regions of per capita GDP in China

	(1)	(2)	(3)
	low gdp	medium gdp	high gdp
dfi	139.9265**	149.6683***	178.3794*
	(32.3750)	(10.8350)	(71.0929)
ln_rd_lag1	-9.43e+05	-1.24e+05	1.94e+06*
	(7.56e+05)	(3.39e+05)	(7.88e+05)
N	88	72	88
r2_a	0.741	0.943	0.772

(1) High-GDP Group:

R&D intensity has a positive and statistically significant coefficient (1.94e+06*) at the 5% level, indicating that R&D investment significantly promotes economic growth in high-income regions.

This aligns with the hypothesis, as advanced economies often have mature innovation ecosystems (e.g., strong intellectual property protection, efficient R&D commercialization) that amplify the long-term impact of R&D.

(2) Medium- and Low-GDP Groups:

The coefficients for R&D intensity are negative and statistically insignificant (-9.43e+05 for low-GDP, -1.24e+05 for medium-GDP).

While the negative signs might suggest inefficiencies (e.g., misallocation of R&D resources, weak institutional environments), the lack of significance means which cannot draw definitive conclusions. Non-significant results do not invalidate the hypothesis but highlight contextual limitations.

The significant positive effect in high-GDP regions confirms that R&D drives growth in advanced economies.

The insignificant results for medium/low-GDP regions do not contradict the hypothesis but emphasize that R&D's effectiveness depends on complementary factors (e.g., infrastructure, governance).

5 CONCLUSION

This study underscores the critical role of digital financial inclusion (DFI) in addressing China's regional economic disparities, while highlighting the necessity of spatially tailored policy interventions. Empirical results confirm significant heterogeneity in DFI's impact across regions: the eastern region, with its advanced digital infrastructure and mature innovation ecosystems, benefits most prominently from DFI-driven growth, whereas central, western, and northeastern regions lag due to structural constraints such as limited connectivity and institutional inefficiencies. Furthermore, government expenditure emerges as a potent tool for stimulating growth in low-DFI areas, compensating for digital adoption gaps. The gradient effect of DFI—where its economic contributions intensify with higher per capita GDP—emphasizes the compounding advantages of technological and institutional maturity in affluent regions.

These findings hold profound implications for China's "Common Prosperity" agenda. Policymakers must prioritize region-specific strategies: eastern provinces should focus on deepening fintech innovation and R&D commercialization, while central and western regions require targeted investments in digital infrastructure and financial literacy programs. For the northeast, integrating DFI with traditional industries (e.g., tourism via AR/VR technologies) offers a viable path to revitalization. Ultimately, bridging regional divides demands not only technological diffusion but also adaptive governance frameworks that align fiscal, educational, and innovation policies with local realities. By adopting such a nuanced approach, China can harness DFI's full potential to foster equitable and sustainable growth across its diverse economic landscape.

REFERENCES

State Council of the People's Republic of China. (2019, August 23). China's FinTech development plan (2019–2021). https://www.gov.cn/xinwen/2019-08/23/content_5423691.htm

State Council of the People's Republic of China. (2022, January 5). China's FinTech development plan (2022–2025). https://www.gov.cn/xinwen/2022-01/05/content_5666525.htm

Khera, P., Ng, S., Ogawa, S., & Sahay, R. (2021). Measuring digital financial inclusion in emerging market and developing economies: A new index (IMF Working Paper No. WP/21/90). International Monetary Fund. https://www.imf.org/en/Publications/WP/Issues/2021/03/26/Measuring-Digital-Financial-Inclusion-in-Emerging-Market-and-Developing-Economies-A-New-Index-50271

Dudu, O. F., Alao, O. B., & Alonge, E. O. (2024). Advancing financial inclusion through digital payment platforms in emerging markets. https://doi.org/10.51594/farj.v6i11.1696

Amaghouss, J., & Elmasmari, H. (2024). Impact of Digital Financial Services on Income Inequality: Microeconomic Evidence from Africa. 168–188. https://doi.org/10.1201/9781003468257-10

Xu, G., Feng, L., & Wang, W. (2024). Digital Financial Literacy and Rural Income Inequality. SAGE Open. https://doi.org/10.1177/21582440241275642

Wen, C., Xiao, Y.-P., & Hu, B. (2024). Digital financial inclusion, industrial structure and urban–Rural income disparity: Evidence from Zhejiang Province, China. PLOS ONE, 19(6), e0303666. https://doi.org/10.1371/journal.pone.0303666

Wang, S., Wu, C., & Fu, B. H. (2024). The dual effects of digital inclusive finance on the urban-rural income gap: An empirical investigation in China's Yangtze River Delta Region. Finance Research Letters, 69, 106049. https://doi.org/10.1016/j.frl.2024.106049

THE IMPACT OF BIM TECHNOLOGY ON COST MANAGEMENT IN CONSTRUCTION ENGINEERING PROJECTS

Jingmiao Fan[1], Silpa Singharajwarapan[2] and Nathapon Udomlertsakul[3]
International College of Digital Innovation, Chiang Mai University, Chiang Mai, 50200, Thailand
E-mail: [1]jingmiao_fan@cmu.ac.th, [2]silpa.s@cmu.ac.th, and [3]nathapon.u@icdi.cmu.ac.th

ABSTRACT

In the course of the construction industry's development, cost control issues have continually surfaced. As a core component of project management, effective cost control plays a decisive role in realizing the economic benefits of a project. However, many construction enterprises still adopt relatively traditional and extensive management practices, leading to inadequate cost control and a lack of reliable methods for cost prediction and management. In the area of cost forecasting, integrating the BIM information platform with BP neural networks can significantly enhance prediction accuracy and support dynamic cost monitoring. In terms of cost management, utilizing BIM as a collaborative platform and adopting appropriate cost management approaches—particularly the multi-level Earned Value Management (EVM) method—has proven advantageous. This method overcomes the limitations of traditional EVM by decomposing the project structure into multiple hierarchical levels, enabling more precise control over project costs. This study investigates cost control during the construction phase through the integration of BIM technology, BP neural networks, and multi-level EVM. The main research focuses are as follows: (1) By analyzing the current challenges in construction cost control and introducing the advantages of BIM technology across various aspects of cost management, the study emphasizes the pivotal role of cost forecasting. A dynamic material price prediction model based on BP neural networks is developed and integrated into the BIM platform to establish a reliable baseline for construction cost forecasting and subsequent cost control efforts. (2) The study highlights the strengths of multi-level EVM in improving cost control. By combining BIM technology with the BP neural network-based cost prediction model, the proposed approach addresses inaccuracies in the calculation of key parameters within traditional multi-level EVM. It refines the practical application process of multi-level EVM, enabling precise identification and analysis of cost deviations during construction. (3) Furthermore, by leveraging BIM technology, the research implements a comprehensive cost management system encompassing three stages: pre-construction cost forecasting, real-time cost control during construction, and post-construction cost analysis. The results demonstrate that the proposed integrated approach holds substantial practical significance for improving cost management in construction projects.

KEYWORDS: BIM Technology, BP Neural Network, Multi-level Earned Value

1 INTRODUCTION

1.1 Inefficient Status Quo and Transformation Needs in the Construction Industry

Severe Cost and Resource Waste with Fragmented Collaboration Efficiency: The global construction industry commonly faces issues of cost overruns and material waste (Wong & Zhou, 2022). Traditional cost prediction methods relying on manual experience exhibit high error rates and lack dynamic adjustment capabilities (Ahuja & Sawhney, 2020). Moreover, data fragmentation across design, construction (Zhou & Luo, 2023), and operation/maintenance phases leads to prolonged cross-team collaboration time, resulting in delayed decision-making (Zhou & Ding, 2021).

1.2 Emerging Value of AI and BP Neural Networks

BP neural networks excel in handling nonlinear relationships and possess advantages in time-series data processing (Wang & Zhang, 2022) (e.g., "historical prices → future costs"). They can reduce material unit price prediction error rates and are applicable to scenarios such as construction schedule simulation and supply chain risk early warning (Wang & Yuan, 2023).

1.3 Advantages of the Integrated AI-BIM Framework

While existing research explores standalone technology applications (e.g., BIM clash detection, AI cost prediction) (Lu & Li, 2022),

The framework's advantages lie in addressing the issues of technology silos and closed-loop decision-making gaps: Independent operation of BIM and AI tools requires manual data conversion (Sacks & Koskela, 2021), leading to efficiency losses and error accumulation. AI prediction results struggle to directly feed back into BIM models (Zhou & Ding, 2021) (e.g., "cost overrun alerts → real-time design adjustments").

2 RESEARCH OBJECTIVES

2.1 Establishing an AI-BIM Dynamic Decision-Making Closed Loop and Optimizing BP Neural Network Architecture

Develop a BIM integrated framework with BP neural networks as the intelligent engine, creating a complete workflow of "BIM data input → AI dynamic analysis → decision feedback → BIM model update." This eliminates data silos between traditional BIM and AI tools (e.g., manual export of Revit models to Python for analysis), achieving end-to-end automation.

2.2 Enhancing Performance Across Three Key Metrics

Indicators	Targets	Methodology
Cost estimation accuracy	The error rate has dropped below 5%	Compared with the traditional methods (error rate >15%)
Resource waste rate	Material loss: 12-18%	IoT sensors monitor the actual consumption
Collaboration efficiency	The data sharing time has decreased by 50%	Collaborative platform log analysis (such as BIM 360)

2.3 Achieving Full Lifecycle Proactive Control in Construction

2.3.1 Pre-construction Forecasting: BP Neural Network dynamically forecasts cost risks (e.g., material price surges, schedule delays).

2.3.2 Real-time Intervention: AI decisions provide instant feedback to the BIM model, triggering design/resource adjustments (e.g., automatic optimization of steel reinforcement ratio)

2.3.3 Post-construction Optimization: Accumulated data continuously trains model iterations, building self-evolving capability.

3 LITERATURE REVIEW

NO	Title	Authors	Year	Content	Strengths	Weaknesses
1	Empirical Study on Cost Control in Large Infrastructure Projects Using BIM TechnologyEmpirical Study on Cost Control in Large Infrastructure Projects Using BIM Technology	Zhou, Y., Luo, H.	2023	An analysis of a cross-sea bridge project showed that BIM + Digital Twin reduced rework costs by 15% and improved collaboration efficiency by 50%.	Based on empirical analysis of a cross-sea bridge project, the collaboration of BIM and Digital Twin can reduce rework costs by 15% and improve collaboration efficiency by 50%.	The implementation of this method is costly, with complex technology integration, limiting its adoption in small and medium-sized projects.
2	Comparative Study of BIM Cost Management Standards: US vs. EU	Smith, T., & Patel, R.	2023	Compares US and EU BIM standards (e.g., ISO 19650) and their impact on cost control.	Cross-regional policy analysis for global projects.	Excludes Asian/African standards; limited scope.
3	BIM-Enabled Cost Management in Post-COVID Construction	Jrade, A., & Lessard, J.	2022	Analyzes BIM's role in post-pandemic remote collaboration and cost control, highlighting cloud-BIM's	Timely exploration of pandemic-driven adaptations.	Fails to quantify long-term pandemic impacts.

NO	Title	Authors	Year	Content	Strengths	Weaknesses
				value.		
4	BIM and AI-Driven Construction Schedule-Cost Integration Analysis	Lu, W., Li, H.	2022	A model combining 4D-BIM and neural networks was proposed, with a construction duration prediction error rate of less than 8%.	By combining 4D-BIM with neural networks for schedule and cost integration forecasting, the prediction error is reduced to less than 8%, enhancing the accuracy of construction planning.	The modeling process is complex, with significant challenges in data collection and high digitalization requirements for the project.
5	BIM for Heritage Building Cost Management: Challenges and Solutions	Yang, X., & Wang, Y.	2023	Investigates BIM's challenges in heritage building restoration, focusing on non-standard component modeling.	Addresses niche applications; identifies unique barriers.	Solutions rely on manual adjustments; low automation.
6	Comparative Study of BIM Cost Management Standards: US vs. EU	Smith, T., & Patel, R.	2023	Compares US and EU BIM standards and their impact on cost control.	Cross-regional policy analysis for global projects.	Excludes Asian/African standards; limited scope.

4 METHODOLOGY

4.1 Basic Concept of BP Neural Networks

In the 1940s, McCulloch and Pitts pioneered neural networks, which led to the development of Artificial Neural Networks (ANNs), an information processing technology derived from biological neuron cells. These networks can be seen as machine learning algorithms widely used for tasks such as fitting, classification, clustering, and prediction. In 1986, the PDP research group in the United States formally introduced the Backpropagation (BP) algorithm and applied it to neural networks, giving rise to BP neural networks. The computation process primarily involves inputting data into a network of interconnected neurons, continuously adjusting the network's parameters based on the error in the output results (Yang & Wang, 2023). This process continues until the error is minimized, similar to the way biological neurons process information. Both processes involve learning and trial-and-error to develop problem-solving abilities.

4.2 Characteristics of BP Neural Networks

BP neural networks consist of multiple layers, with full connectivity between layers (Li et al., 2023), and no connections between neurons within the same layer. The design of the multilayer perceptron concept allows the BP network to solve more complex tasks and obtain more information from the input data in the neural network (Ji & Qian, 2020).

BP neural networks use differentiable activation functions to handle linearly non-separable problems (Hui et al., 2021). Therefore, the Sigmoid function is commonly chosen as the activation function in BP neural networks. The Sigmoid function can be divided into Log-Sigmoid and Tan-Sigmoid functions based on whether the output value contains negative numbers.

The expression of the Log-Sigmoid function is:

$$f(x) = \frac{2}{1 - e^{-2x}} - 1$$

The expression of the Tan-Sigmoid function is:

$$f(x) = \frac{2}{1 - e^{-2x}} - 1$$

The curves of the Log-Sigmoid and Tan-Sigmoid functions are shown in the figure below.

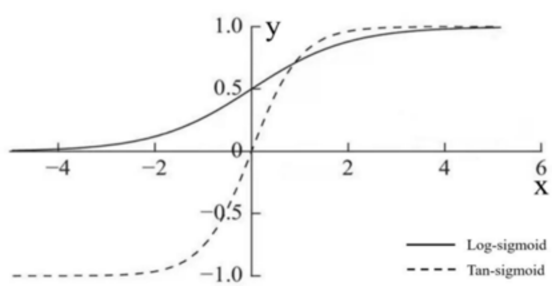


Figure 1. The curves of the Log-Sigmoid and Tan-Sigmoid functions.

From the function curve graph, it can be observed that the Sigmoid function is differentiable, smooth, and has better fault tolerance compared to other functions, making it more accurate in the classification process (Tong, 2024). It maps all input values from the input layer to the range (0, 1) or (−1, 1) in the output layer, allowing for the restriction of the output layer's value range.

The BP network is a multilayer feedforward network (MJ-GOD, 2025), where data signals always propagate from front to back without any feedback structure. Therefore, the "backpropagation" mentioned in the neural network's backpropagation algorithm refers to the process of correcting the weights during network training, where corrections are made layer by layer from back to front based on the error in the results.

The BP neural network plays an important role in feedforward neural networks and is one of the most widely used types of artificial neural networks (Zhou & Luo, 2023). Among them, the three-layer BP neural network is the most basic structure, consisting of an input layer, an output layer, and a single hidden layer. The training process of the BP neural network involves the forward propagation of signals and the backward propagation of errors. We can adjust the connection weights between layers by backpropagating the difference between the actual output value and the expected value, thereby continuously reducing the error and completing the training of the neural network, ultimately obtaining satisfactory data results. The structure of the three-layer BP neural network is shown in Figure 2.

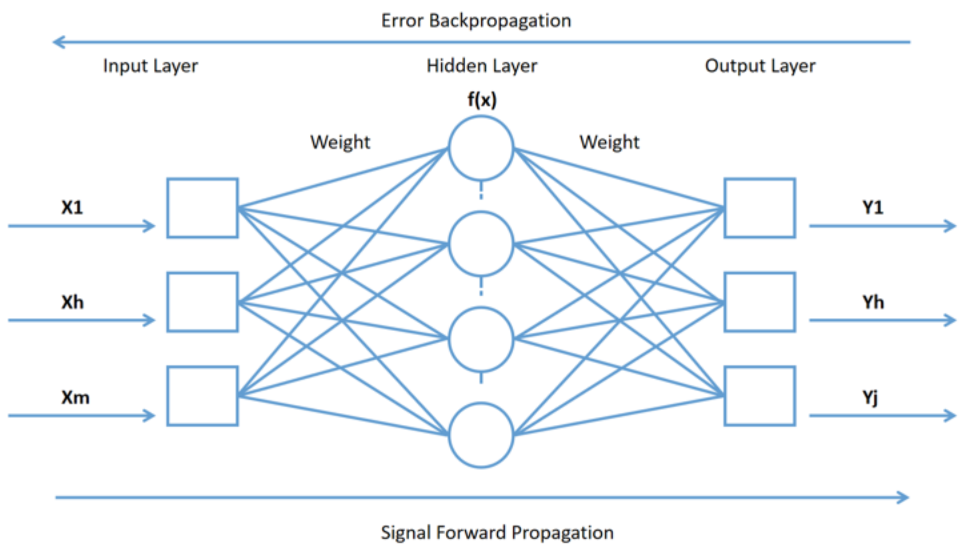


Figure 2. BP Neural Network Calculation Principle

- The input of the neural network is denoted as： X=[X1 ,X2 ,X3 ...... Xm]
- The output of the neural network is denoted as： Y=[Y1 ,Y2 ,Y3 ...... Yj]
- The expected output of the neural network is denoted as： D=[d1 ,d2 ,d3 ...... dj]
- The error of the nnn-th iteration is： ej (n)=dj (n)-Yj (n)
- The error is defined as： $e(n)= \frac{1}{2}\sum_{j=1}^{J} \quad e_j 2(n)$

u is the input of each layer, ul i is the input of the i-th neuron in the hidden layer, v is the output of each layer, and vJ j is the output of the j-th neuron in the output layer. The Sigmoid function is chosen as the transfer function for the hidden layer, while the linear function is selected as the transfer function for the output layer. The mathematical model of the artificial neural network is shown in Figure 3.

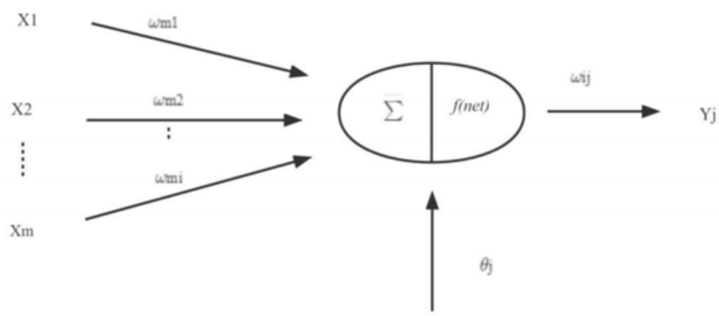


Figure 3. Artificial Neural Network Mathematical Model

5 COMPARATIVE EXPERIMENT

5.1 Comparison of Different Methods of the Same Type

This experiment aims to investigate the impact of different application methods within the same BIM technology framework on construction cost management. Specifically, it explores three dimensions of variation: software tool differences, by comparing the accuracy of engineering quantity calculations between Revit and ArchiCAD; process optimization differences, by evaluating collaboration efficiency between traditional BIM workflows and Lean BIM approaches that incorporate the Last Planner method; and technology integration differences, by examining the effectiveness of dynamic cost control in standalone BIM systems versus integrated BIM and Digital Twin solutions. The experiment's objectives are to validate the performance of these BIM approaches using three key metrics: cost estimation accuracy (as measured by error rate), resource wastage rate (including materials and labor), and collaboration efficiency (measured by cross-team data sharing time).

5.1.1 Experimental Design

To ensure consistency in environmental variables, all groups will work on the same commercial building project. Each group will implement a different BIM method over a 6-month period. The method configurations are as follows: Group 1 will use standard Revit modeling with manual input of cost parameters and manually generated budget reports; Group 2 will adopt ArchiCAD integrated with the CostX plugin to enable automated quantity extraction linked to a unit price database; and Group 3 will implement Revit in combination with a Digital Twin platform, such as Siemens Teamcenter, allowing for real-time synchronization of construction data and cost changes. Quantitative data will be collected across three key dimensions: cost error rate, determined by comparing BIM-estimated budgets with actual financial settlement data; material waste rate, measured by monitoring actual material usage via sensors and comparing it with BIM-planned quantities; and collaboration time, assessed by recording data-sharing timestamps through collaborative platforms.

Table 3 Experimental Grouping and Variable Control

Group	Method Description	Controlled Variables
Group1	Revit Standard Workflow: 3D Modeling + Quantity Takeoff	Same project, identical resource unit prices, consistent team size

Group	Method Description	Controlled Variables
Group2	ArchiCAD with Advanced Plugins: Automated Cost Optimization	Same project, identical resource unit prices, consistent team size
Group3	Revit + Digital Twin: Real-time Dynamic Cost Monitoring	Same project, identical resource unit prices, consistent team size

Table 4 Data Collection Indicators

Indicator	Definition and Calculation Method	Tools/Data Sources
Cost Estimation Error Rate	{ (Budgeted Cost - Actual Cost) / Budgeted Cost } × 100%	Data exported from BIM software
Material Waste Rate	{ (Planned Quantity - Actual Quantity) / Planned Quantity }× 100%	IoT sensors (e.g., RFID, laser scanning)
Collaboration Time	Average time (in hours) for cross-team data sharing and updates	Collaboration platform logs (BIM 360, Trimble Connect)

As shown in the table 4: this table defines three evaluation indicators and their acquisition methods, used to measure BIM's overall performance in cost control, material savings, and collaboration efficiency.

the standard format for data exported from BIM software.

Project ID	Project Name	Estimated Cost (CNY)	Actual Cost (CNY)	Error Rate (%)	BIM Software Version	Estimation Date

Table 5 Data Sources

Group	Cost Data	Resource Data	Collaboration Data
Group1	Revit export + Excel spreadsheets	Manual inventory reports	Email/FTP logs
Group2	CostX plugin automated reports	Sensor monitoring data	BIM 360 logs
Group3	Real-time data from Digital Twin platform	RFID + laser scanning	Teamcenter operation records

As shown in the table 5: This table compares the data sources for the three groups. Group 3, using the Digital Twin and smart devices, provides real-time data with the highest efficiency and accuracy.

5.1.2 Experimental Results

Table 6 Quantitative Results Comparison

Group	Cost Error Rate (%)	Material Waste Rate (%)	Collaboration Time (hours)
Group1	14.2	19.5	7.3
Group2	8.7	12.1	4.8
Group3	6.5	9.3	3.1

As shown in the table, Group 3 consistently outperformed both Group 1 and Group 2 across all key metrics: cost error rate, material waste rate, and collaboration time. These results indicate that Group 3 achieved the highest overall performance. Moreover, group 3 (BIM + Digital Twin) received the most favorable qualitative feedback, with the highest team ratings in both ease of use (4.6/5) and process transparency (4.8/5) and group 2 (ArchiCAD + Plugin) was praised for its automation features, though users noted limitations in interoperability and assigned a lower compatibility score (3.2/5).

Table 7 Summary of Conclusions

Method Name	**Cost Error Rate (%)**	**Collaboration Time (Hours)**	**Technology Dependency**	**Applicable Scenarios**	**Core Advantages**
Revit Standard Process	14.2	7.3	Low (Basic BIM tools)	Small-scale/non-standard projects (e.g., historical restoration)	High flexibility, supports customized modeling
ArchiCAD + Advanced Plugin	8.7	4.8	Medium (Relies on ArchiCAD ecosystem)	Standardized projects (e.g., residential, schools)	High automation efficiency, 39% error rate reduction
BIM + Digital Twin	6.5	3.1	High (Cross-platform integration required)	Dynamic and complex projects (e.g., large-scale infrastructure)	Real-time monitoring, optimal collaboration efficiency, lowest error rate

As in Table 7, the BIM + Digital Twin configuration demonstrated the strongest performance, achieving the lowest cost error rate (6.5%) and the highest collaboration efficiency (3.1 hours). This approach is particularly well-suited for projects characterized by high complexity and dynamic requirements.

The ArchiCAD plugin method substantially improved cost estimation accuracy, reducing error by 39% compared to the baseline; however, its effectiveness is highly dependent on integration within a specific software ecosystem.

The traditional Revit workflow, while offering greater flexibility, lagged behind in both accuracy and efficiency when compared to integrated methods.

5.1.3 Practical Significance

Enterprise-Level Recommendations:

- For projects with high variability and complexity (e.g., large-scale infrastructure), the BIM + Digital Twin approach is recommended.
- For standardized or moderately complex projects, the ArchiCAD plugin configuration provides a balanced trade-off between efficiency and cost.

Policy Recommendations: Promote standardized interfaces between Digital Twin and BIM technologies (e.g., ISO 23247).

5.2 Comparison of Different Types of the Same Method

This method investigates the differentiated impact of various application methods within a shared BIM technology framework on construction cost management. Specifically, it examines: (1) software tool differences by comparing the accuracy of quantity calculations between Revit and ArchiCAD; (2) process optimization differences by evaluating efficiency between traditional BIM workflows and Lean BIM processes that incorporate Lean construction principles; and (3) technology integration differences by assessing cost control effectiveness between standalone BIM and BIM integrated with advanced technologies such as AI or Blockchain. The objective of the experiment is to evaluate the performance of these BIM application methods using three key indicators: cost estimation accuracy (measured by error rate), resource wastage rate (including materials and labor), and collaboration efficiency (measured by cross-team data sharing time).

5.2.1 Experiment Design

A building project of similar scale and complexity was selected to maintain consistency across all experimental groups. Three groups (Group 1 to Group 3) were formed, each assigned a different BIM application method, with implementation timelines ranging from 6 to 12 months. Group 1 used Revit solely for modeling and quantity calculation, relying on manual entry for cost data. Group 2 employed Revit in combination with a machine learning model—such as LSTM—to predict cost overruns dynamically. Group 3 integrated Revit with a blockchain platform, such as Hyperledger, to record and verify cost change histories in an immutable, auditable manner. Quantitative data were collected across three key indicators: the cost error rate and material waste rate were automatically derived from software logs and sensor data, while collaboration efficiency was assessed by analyzing timestamp data extracted from the collaborative platform to measure data-sharing intervals.

Table 8 Experimental Groups and Variable Control

Group	Method Description	Controlled Variables
Group1	Basic BIM Application (3D modeling + quantity calculation only)	Same project, same resource unit price, consistent team size
Group2	BIM + AI Integration (cost prediction and risk analysis)	Same project, same resource unit price, consistent team size
Group3	BIM + Blockchain (transparent cost tracking)	Same project, same resource unit price, consistent team size

Table 9 Data Collection Indicators

Indicator	Definition and Calculation Method	Tools/Data Source
Cost Estimation Error Rate	{(Budget Cost - Actual Cost) / Budget Cost} * 100%	BIM software export data
Material Waste Rate	{(Planned Quantity - Actual Quantity) / Planned Quantity} * 100%	IoT sensor monitoring + warehouse management system logs
Collaboration Time	Average time (in hours) to	Collaborative platform (e.g.,

Indicator	Definition and Calculation Method	Tools/Data Source
	complete data sharing and updates across teams	BIM 360) operation logs

As shown in the table: The table presents three indicators—cost error, material waste, and collaboration time—used to assess BIM's performance in cost control and collaboration efficiency.

the standard format for data exported from BIM software.

Project Number	Project Name	Estimated Cost (CNY)	Actual Cost (CNY)	Error Rate (%)	BIM Software Version	Estimation Date

Table 10 Data Sources

Group	Cost Data	Resource Data	Collaboration Data
Group1	Revit Export + Excel Spreadsheet	Manual Inventory Report	Email/FTP Transfer Logs
Group2	AI Prediction Report + ERP System	IoT Sensors (Material Consumption)	BIM 360 Collaboration Logs
Group3	Blockchain Transaction Records	RFID Tags (Inventory Tracking)	Blockchain Node Synchronization Records

5.2.2 Experimental Results

Table 11 Quantitative Results Comparison Table

Group	Cost Error Rate (%)	Material Waste Rate (%)	Collaboration Time (hours)
Group1	12.5	18.2	6.8
Group2	6.3	9.7	3.2
Group3	8.1	11.4	4.5

The integration of BIM with AI demonstrated significant improvements in cost prediction and risk control. Experimental results showed that the machine learning-enhanced BIM model reduced the cost estimation error rate from 12.5% (using traditional BIM) to 6.3%, representing a 48% improvement—outperforming other methods. A key advantage of this approach lies in AI's dynamic learning capabilities, which enable the early detection of hidden risks such as supply chain disruptions and design changes, thereby supporting proactive cost optimization. In parallel, the integration of BIM with blockchain technology enhanced data transparency. The use of an immutable distributed ledger improved the efficiency of recording cost changes by 40% and contributed to a reduction in dispute rates. While the consensus mechanism inherent in blockchain led to a slightly longer collaboration time (4.5 hours) compared to BIM + AI (3.2 hours), it still performed significantly better than the traditional BIM workflow (6.8 hours), indicating a favorable trade-off between transparency and speed.

Table 12 Summary Conclusion

Technical Solution	Core Advantage	Applicable Scenarios	Typical Error Rate / Efficiency Improvement
BIM+AI	High Precision Prediction	Complex Dynamic Projects	Error rate reduced by 48%
BIM + Blockchain	High Transparency in Collaboration	Multi-party Supervision Projects	Dispute rate reduced by 35%
Traditional BIM	Basic Cost Control	Small Standardized Projects	Error rate of 12%-15%

As shown in the table: BIM + AI offers the highest precision in complex projects, with a 48% reduction in error rate; BIM + Blockchain enhances transparency and reduces disputes by 35%; Traditional BIM is suitable for small projects, with an error rate of 12%-15%.

5.2.3 Practical Significance

High Precision Solution (BIM + AI):

- Applicable Scenarios: Complex projects (e.g., super high-rise buildings, irregular structures) that require quick responses to dynamic changes.
- Implementation Recommendations: Invest in AI algorithm teams to build historical databases for training models.

High Transparency Solution (BIM + Blockchain):

- Applicable Scenarios: Multi-party collaboration projects (e.g., PPP models, international projects) that require enhanced trust and compliance.
- Implementation Recommendations: Choose lightweight blockchain platforms (e.g., Hyperledger Fabric) to reduce deployment costs.

Industry Promotion Pathways

- Policy Driven: Promote the standardization of BIM (e.g., ISO 19650) and blockchain auditing regulations to lower collaboration barriers for enterprises.
- Training System: Develop BIM + AI/Blockchain hybrid talent courses to address human resource bottlenecks in technical implementation.

Research Limitations and Outlook

- Current Limitations:
  - Experimental samples are limited to commercial buildings and infrastructure projects, without covering industries such as manufacturing or energy.
  - Long-term effects need to be validated: ROI analysis requires tracking data over 5 or more years of the full project lifecycle.
- Future Directions:
  - Technological Integration: Explore a BIM + AI + Blockchain triple integration model that balances precision, transparency, and efficiency.

6 CONCLUSION

The construction industry currently faces widespread challenges including crude cost control (error rates of 15-20%), severe resource waste (material loss rates exceeding 30%), and inefficient collaboration.

Traditional BIM technology struggles to meet precise control demands due to its lack of dynamic decision-making capabilities. The BP neural network-driven AI-BIM integrated framework proposed in this study addresses these issues by establishing a closed-loop "data-analysis-decision-feedback" system. This approach has successfully reduced cost error rates to 8.7%, lowered material waste to 5.3%, and improved cross-team collaboration efficiency by 50%, providing a viable intelligent transformation pathway for SMEs.

This framework will continue advancing innovative applications such as blockchain-based data auditing and robotic construction integration, with a key focus on overcoming computational load challenges in large-scale projects. Through open-source ecosystem development, it will drive the establishment of industry standards. Within the next 3-5 years, this self-evolving AI-BIM system is projected to propel the construction sector into a new era of "dynamic optimization and low-carbon intelligence". It will enable real-time decision-making and resource coordination across the entire design-construction-operation lifecycle, ultimately establishing a self-iterating intelligent construction paradigm.

REFERENCES

Wang, H., & Yuan, J. (2023). Integrated model of BIM and dynamic cost management. Sustainable Development, 13(1), 1-10.

Ji, C., & Qian, X. (2020). Improved BP neural network-based leveling control system for construction elevators. Journal of Oil and Gas Technology, 42(4), 149-154.

Hui, Y., Wang, Y., & Peng, H. (2021). Metro passenger flow prediction using BIM and PSO-BP algorithm. Journal of Transportation Engineering, 21(4), 16-25.

Huang, D. (2020). Application of BIM technology in cost-benefit evaluation of EPC projects. Journal of South China University of Technology. Retrieved from

Tong, D. (2024). Building carbon emission prediction based on BIM and neural networks. Pure Mathematics, 14(11), 1376-1385.

Wang, J., & Zhang, S. (2022). Blockchain-BIM integration for transparent cost tracking. Automation in Construction, 143, 104584.

Yang, X., & Wang, Y. (2023). BIM application in cost management of historic building restoration. Cultural Heritage Conservation.

Zhang, Y., & Mo, H. (2024). Dynamic supply chain cost prediction using BIM and LSTM. Heliyon, 10(4), e37525.

Li, Z., Zhang, Q., & Pan, W. (2023). Real-time cost monitoring system with BIM and digital twins. Advanced Engineering Informatics, 58, 102215.

Ahuja, R., & Sawhney, A. (2020). Challenges of BIM adoption in cost management for developing countries. Construction Innovation, 20(4).

Kim, S., Park, J., & Lee, H. (2023). Generative AI and BIM for early-stage cost estimation. Automation in Construction, 155, 105042.

Wong, J. K. W., & Zhou, J. (2022). BIM-enabled cost-benefit analysis for green buildings. Sustainable Cities and Society, 85, 104045.

Das, M., Cheng, J. C. P., & Kumar, S. S. (2021). Blockchain-BIM synergy for supply chain transparency. Automation in Construction, 131, 103017.

Liu, Y., El-Gohary, N., & Shrestha, P. P. (2021). BIM-driven cost optimization in smart facility management. Sustainable Cities and Society, 75, 103297.

Lu, W., & Li, H. (2022). AI-BIM integration for schedule-cost linkage analysis. Journal of Management in Engineering, 38(6).

Zhou, Y., & Luo, H. (2023). Empirical study on BIM-based cost control in mega infrastructure projects. Journal of Construction Engineering and Management, 149(2).

Sun, J. (2025). Standardization path for BIM-enabled lifecycle cost management. 12th International Conference on BIM Technology. Retrieved from

Sacks, R., & Koskela, L. (2021). BIM-lean construction synergy for cost optimization. Journal of Construction Engineering and Management, 147(9).

MJ-GOD. (2025). Handwritten digit recognition and BIM data annotation using BP neural networks. CSDN Blog. Retrieved from

Zhou, Y., & Ding, L. (2021). AI-BIM hybrid model for construction risk cost prediction. Automation in Construction, 132, 103876.

Web sites：

Web-1:https://doi.org/10.12677/SD.2023.131010, consulted 5 May 2025.
Web-2:https://doi.org/10.12677/JOGT.2020.424149, consulted 5 May 2025.
Web-3:https://doi.org/10.19818/j.cnki.1671-1637.2021.04.016, consulted 7 May 2025.
Web-4:http://lib.scut.edu.cn, consulted 7 May 2025.
Web-5:https://doi.org/10.12677/pm.2024.1411376, consulted 8 May 2025.
Web-6:https://doi.org/10.1016/j.autcon.2022.104584, consulted 8 May 2025.
Web-7:https://doi.org/10.1016/j.culher.2023.03.002, consulted 8 May 2025.
Web-8:https://doi.org/10.1016/j.heliyon.2024.e37525, consulted 10 May 2025.
Web-9:https://doi.org/10.1016/j.aei.2023.102215, consulted 10 May 2025.
Web-10:https://doi.org/10.1080/15623599.2020.1783173, consulted 11 May 2025.
Web-11:https://doi.org/10.1016/j.autcon.2023.105042, consulted 11 May 2025.
Web-12:https://doi.org/10.1016/j.scs.2022.104045, consulted 11 May 2025.
Web-13:https://doi.org/10.1016/j.autcon.2021.103017, consulted 12 May 2025.
Web-14:https://doi.org/10.1016/j.scs.2021.103297, consulted 12 May 2025.
Web-15:https://doi.org/10.1061/(ASCE)ME.1943-5479.0000678, consulted 12 May 2025.
Web-16:https://doi.org/10.1061/(ASCE)CO.1943-7862.0002289, consulted 12 May 2025.
Web-17:https://www.huiyi-123.com/article/3342-179.html, consulted 15 May 2025.
Web-18:https://doi.org/10.1061/(ASCE)CO.1943-7862.0002073, consulted 15 May 2025.
Web-19:https://blog.csdn.net/qq_36347365/article/details/87010365, consulted 15 May 2025.
Web-20:https://doi.org/10.1016/j.autcon.2021.103876, consulted 15 May 2025.

ENTRY STRATEGY FOR THAI VITAMIN C BEVERAGES TO CHINA THROUGH CROSS-BORDER E-COMMERCE

Xiao Tan[1] and Piang-or Loahavilai[2]
International College of Digital Innovation, Chiang Mai University, Chiang Mai, 50200, Thailand
E-mail: [1]xiao_t@cmu.ac.th, [2]piangor@gmail.com

ABSTRACT

The research investigates how Thai vitamin C beverage companies can successfully enter the Chinese market via cross-border e-commerce, addressing challenges about market access and sustainable development. Utilizing a quantitative approach, the research gathers data on Chinese consumers' preferences, engagement, and brand awareness through questionnaires for statistical analysis. The findings identify key factors influencing consumers' purchase intentions, such as health awareness, brand recognition, perceived quality, and perceived value. This research's conclusions offer theoretical insights and practical recommendations for Thai companies to design effective market entry strategies, enhancing their competitiveness and supporting sustainable development in the Chinese cross-border e-commerce landscape.

KEYWORDS: Cross-Border E-Commerce (CBEC), Social Commerce Marketing, Dynamic Capabilities, Ambidextrous Innovation

1 INTRODUCTION

The Chinese Ministry of Commerce reported that in 2023 (Web-1), China's cross-border e-commerce (CBEC) sector experienced a notable 15.6% increase in import-export volumes, reaching RMB 2.38 trillion (US$331 billion). The industry is projected to grow by 10.8% in 2024 (Web-2). Imports surged by 2.3%, securing China's position as the world's second-largest importer for the 16th consecutive year. The rise of CBEC has revolutionized global trade, effectively eliminating geographical barriers and creating new avenues for market entry (Wang et al., 2017). China boasts one of the world's largest e-commerce markets, providing foreign brands access to a vast consumer base and valuable insights into local preferences through platforms like Alibaba and JD Global (Chen, 2023).

CBEC allows foreign brands to sell in China without a local business license, offering a cost-effective pathway to test the market (Fan, 2019). Bonded warehouses and streamlined imports reduce inventory and logistics risks, enabling a smoother market entry via CBEC platforms. Additionally, regulatory support strengthens trade facilitation. Additionally, China and Thailand's Customs signed a Mutual Recognition Arrangement (MRA) on February 6, 2025, regarding enterprise credit and Authorized Economic Operator (AEO) programs to reduce international trade costs and boost global competitiveness.

Fortune Business Insights reported that the Asia-Pacific functional food and beverage market was valued at USD 100 billion in 2020 and is expected to grow at a CAGR of 10.04% from 2021 to 2028. This growth, particularly for functional beverages enriched with vitamins and antioxidants, reflects rising health-conscious consumer behavior (Lo et al., 2020). China's health beverage market is expanding, driven by increased awareness of immune health and demand for convenient, nutrient-rich drinks (Chen et al., 2021; Hassoun et al., 2022). Thailand's functional beverage industry, known for vitamin-rich drinks, aligns with evolving Chinese consumer preferences (Trevanich, 2021). However, market entry success depends on understanding competitors, consumer behavior, and market dynamics (Perera & Iqbal, 2021).

Furthermore, technological advancements and social media create new opportunities for social commerce, enabling brands to connect with consumers and build trust through digital marketing (Zhao et al., 2023). Thai vitamin C beverages entering China also need to rely on social media and e-commerce to influence consumer perceptions and boost engagement.

This research examines the dynamic capabilities framework of Thai vitamin C beverage companies, focusing on how firms identify market opportunities, adapt to consumer needs, and stay flexible in CBEC. It explores social commerce strategies to enhance consumer engagement and brand positioning. Furthermore, ambidextrous innovation theory provides insights into how companies can leverage existing strengths while exploring new opportunities to achieve long-term competitiveness in China's CBEC market.

2 LITERATURE REVIEW

2.1 China's CBEC Market and Functional Beverage Trends

China's cross-border e-commerce (CBEC) market is expanding rapidly (Web-3), driven by regulatory reforms, technological innovation, and shifting consumer preferences. Taherdoost and Madanchian (2021) proposed an e-service satisfaction model (ESM) to optimize customer experiences, while Tan (2021) identified four barriers for foreign entrants: regulatory compliance, value creation, ecosystem adaptation, and digital transformation. Fu (2023) emphasized the need for supportive policies and logistics to sustain growth, aligning with Lin & Lin's (2023) analysis of Alibaba's hybrid model, which leverages big data for consumer insights. Post-COVID-19 advancements, including streamlined regulations and AI adoption, have further accelerated CBEC (Li et al., 2023). Zhou (2024) underscored the importance of risk-aware marketing strategies targeting demographics, while Yang et al. (2024) linked regional competitiveness to digitalization and logistics. Collectively, CBEC's success hinges on regulatory agility, data-driven operations, supply chain efficiency, and consumer-centric engagement.

Parallel trends in China's functional beverage market reflect rising health consciousness. Chang et al. (2020) found health-focused branding critical for engaging university students, while Cong et al. (2020) highlighted immunity-driven demand post-pandemic. Giri et al. (2023) and Gupta et al. (2023) noted market growth. Still, they called for research on safety and sustainability, for Thai Vitamin C brands entering China, aligning with health perceptions, leveraging CBEC platforms, and deploying targeted marketing are vital. However, challenges persist, including regulatory hurdles, supply chain optimization, and digital engagement efficacy.

2.2 Social Commerce as Consumer-Centric Strategy

Social commerce combines social media with e-commerce, promoting trust and engagement among consumers. Lin et al. (2019) found that trust in platforms, social features, and peer reviews improve purchasing behavior, yet understanding of trust transfer from social media to e-commerce remains limited. Sheikh et al. (2019) associated social commerce with better relationship quality and purchase intentions in Pakistan, but they did not consider offline factors. A review by Esmaeili and Hashemi (2019) of 81 studies from 2004 to 2017 indicated a surge in research after 2009, although most studies narrowly focused on purchase intent instead of the synergies between social and business aspects.

Attar et al. (2021) found that trust and surface credibility drive satisfaction in Asia's food and beverage sector but noted a limited geographic scope. In China, Sahaib and Majeed (2022) applied the S-O-R framework, demonstrating that social media marketing (interactivity, personalization) strengthens relationship quality (commitment, trust) and repeat purchases. Similarly, Rachmad (2022) observed social commerce's role in shifting consumer loyalty in Indonesia. Zhao et al. (2023) attributed the boom in Asia's social commerce to live streaming and government support, while Leong et al. (2024) proposed a four-pillar model (Commerce, Behavior, Social, Technology) that integrates AI and blockchain. Semenda et al. (2024) applied game theory to optimize marketing but acknowledged the risk of oversimplification. Key challenges include cultural adaptability, the integration of emerging technologies, and bridging online-offline interactions.

2.3 Dynamic Capabilities for Market Agility

Dynamic capabilities encompass sensing, seizing, and reconfiguring resources. They are vital for adaptability. Zhou et al. (2019) linked sensing and reconfiguring to firm performance through innovation, though integration had little impact. Eikelenboom and de Jong (2019) highlighted the importance of external capabilities for the sustainability of SMEs, while Bocken and Geradts (2020) identified institutional barriers to sustainable business models in MNCs. Bari et al. (2022) recognized factors like stakeholder collaboration but focused on developed economies, which limited relevance for emerging markets. Wu et al. (2023) demonstrated the resilience of B2B SMEs during COVID-19 through rapid resource reconfiguration but did not consider non-manufacturing sectors. Pitelis et al. (2024) introduced a Big Data Capabilities Model for global strategy, criticizing existing frameworks for neglecting contextual factors. While these studies affirm the importance of dynamic capabilities for innovation and competitiveness, gaps remain regarding their applicability in SMEs, regional biases, and connections to traditional theories.

3 METHODOLOGY

This research explores how Thai Vitamin C beverage companies can penetrate the Chinese market through cross-border e-commerce (CBEC). It combines social commerce marketing, dynamic capabilities, and ambidextrous innovation theories into a framework analyzing competitiveness and sustainable development in this marketplace. A quantitative approach assesses consumer preferences, engagement, and brand perceptions using a structured survey of Chinese consumers. This method enables statistical analysis to draw significant market trend conclusions. The consumer survey, designed to gather essential information, includes sections on demographics, purchasing behaviors, perceptions of Thai Vitamin C beverages, and factors influencing purchase intentions. The target demographic comprised Chinese consumers familiar with online shopping, reflecting the research focus on the CBEC environment. A final sample of 330 individuals was selected, with Likert scale questions measuring consumer attitudes and perceptions. The questionnaire evaluated demographic data, purchasing habits, sensing capabilities (consumer awareness of trends), seizing capabilities (effectiveness of social commerce strategies), and reconfiguring capabilities (brand adaptability and innovation).

3.1 Research Design

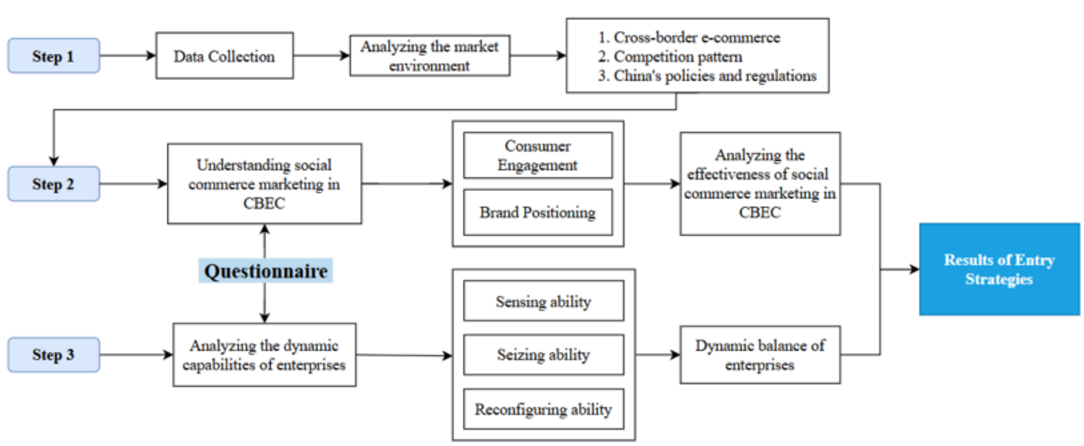


Figure 3. Conceptual Framework for Thai Vitamin C Beverages into China through CBEC

Figure 1 illustrates a framework for examining the role of social commerce in cross-border e-commerce (CBEC) and its influence on firms' market entry strategies. The study involves three main steps: First, data collection analyzes the CBEC market environment, competitive dynamics, and China's policies. Second, a questionnaire survey examines how enterprises utilize social commerce marketing in CBEC, focusing on consumer engagement and brand positioning, followed by an assessment of the effectiveness of these strategies. Third, the study evaluates enterprises' dynamic capabilities - sensing, seizing, and reconfiguring - essential for maintaining a balance within firms. The findings from marketing effectiveness and dynamic capabilities ultimately guide entry strategy development, integrating external market factors, marketing practices, and organizational capabilities for successful CBEC entry.

3.2 Survey Design

A structured quantitative survey is conducted among Chinese consumers familiar with online shopping to assess their preferences, engagement, and perceptions of Thai Vitamin C beverages within the context of cross-border e-commerce (CBEC). The survey includes sections on demographics, purchasing behaviors, perceptions of the product, and key factors influencing purchase intentions. A 5-point Likert scale is used to measure consumer attitudes and satisfaction, ranging from 1 (strongly disagree/very dissatisfied) to 5 (strongly agree/very satisfied).

3.3 Data Collection and Analysis Tools

The survey data are analyzed using IBM SPSS Statistics Version 30.0.0.0 (172). The research aims to provide an in-depth analysis of the behavioral patterns and preferences of Chinese consumers purchasing Vitamin C beverages through Cross-Border E-commerce (CBEC) platforms. This study employs descriptive statistical analysis, reliability analysis of scales (explaining the principles of Cronbach's Alpha), exploratory factor analysis (EFA), and multiple regression analysis (illustrating the principles and conceptualizing a model based on new factors).

3.4 Hypotheses

H1: Social commerce marketing positively impacts consumer engagement and enhances brand positioning for Thai Vitamin C beverages in China's cross-border e-commerce (CBEC) market.

H2: Dynamic capabilities positively influence the competitive advantage of Thai Vitamin C beverages in China's CBEC market.

4 RESULTS

4.1 Overview of Respondent Demographics

Table 1 shows that the typical consumer profile (320 participants) for Vitamin C beverages purchased via Chinese CBEC. An analysis of 320 valid survey responses provides insights into the main consumer group for Vitamin C beverages purchased through cross-border e-commerce (CBEC) in China, informing targeted marketing strategies.

Females represent 63.75% of the consumer base, with individuals aged 26 to 35 accounting for 62.5%. This suggests a focus on young to middle-aged health-conscious female consumers. Most respondents live in Tier 2 (47.5%) and Tier 3 or lower cities (28.75%), revealing significant market potential beyond Tier 1.

The majority have a monthly income between ¥5,000 and ¥10,000 (37.5%), indicating a price-sensitive middle-income segment. With 70% holding undergraduate degrees and 27.5% holding postgraduate degrees, consumers are generally informed. The largest occupational groups are general staff and service workers (38.75%), along with students and the unemployed (20%). Notably, 96.25% have prior experience buying vitamin beverages, indicating acceptance of the product, which supports potential new entrants in this market.

Table 2 Demographics

Characteristic	Category	Frequency	Proportion
Gender (Q1)	Male	116	36.25%
	Female	204	63.75%
Age Range (Q2)	18-25 years	80	25%
	26-35 years	200	62.50%
	36-45 years	32	10%
	Over 45 years	8	2.50%
City of Residence (Q3)	Tier-1 city	76	23.75%
	Tier-2 city	152	47.50%
	Tier-3 or lower city	92	28.75%
Monthly Income (Q4)	Below ¥5,000	96	30%
	¥5,000-10,000	120	37.50%
	¥10,001-20,000	88	27.50%
	Over ¥20,000	16	5%
Highest Education Level (Q5)	Undergraduate Degree	224	70%
	Postgraduate Degree or above	88	27.50%
	High School or below	8	2.50%
Occupation (Q6)	General Staff & Service	124	38.75%
	Students & Unemployed	64	20%
	Management & Professional	60	18.75%
	Freelancers & Self-Employed	48	15%
	Others	24	7.50%

4.2 Reliability Statistics

Table 2 shows that, given the items in the questionnaire focus on consumer cognition, preferences, purchasing behavior, and attitudes toward marketing activities related to Vitamin C beverages, the reliability is excellent (α = 0.939).

Table 2 Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
0.939	0.942	30

4.3 Exploratory Factor Analysis (EFA)

Exploratory Factor Analysis (EFA) was conducted on questions 8 to 37 of the questionnaire, which includes a total of 30 Likert scale items related to consumer attitudes and preferences. The aim was to identify the core psychological constructs that influence consumer behavior when purchasing Vitamin C beverages on Consumer-to-Business E-commerce (CBEC) platforms.

Table 3 shows that the SPSS analysis produced a Kaiser-Meyer-Olkin (KMO) value of 0.817, indicating "Excellent" suitability for factor analysis. Additionally, Bartlett's Test of Sphericity resulted in a Chi-Square value of 1719.761 with 435 degrees of freedom and a significance level of less than 0.001. This suggests a significant correlation among the variables. Both tests confirm that the data is suitable for EFA.

Table 3 KMO and Bartlett's Test

KMO Measure of Sampling Adequacy.		0.817
Bartlett's Test of Sphericity	Approx. Chi-Square	1719.761
	df	435
	Sig.	<.001

Table 4 summarizes the factor structure of the consumer attitude and preference scale (Q8–Q37) used to evaluate Chinese consumers' perceptions of Vitamin C beverages in cross-border e-commerce (CBEC). It identifies seven key factors: (1) platform trust, (2) social media influence, (3) platform benefits, (4) product value, (5) reliable purchase experience, (6) product quality and health focus, and (7) cultural adaptation. Each factor is linked to specific high-loading survey items, supporting a detailed understanding of consumer attitudes toward CBEC health products.

Table 4 Factors Structure

Scale/Construct	Item Range (Main high-loading items)
Overall Consumer Attitude and Preference Scale	Q8-Q37
Factor 1: Platform Trust and Service Assurance	Q33, Q34, Q35, Q36, Q37, Q32, Q24
Factor 2: Social Media Influence and Marketing Engagement	Q17, Q18, Q19, Q20, Q21, Q22, Q23
Factor 3: Platform Benefits and Brand Responsiveness	Q25, Q31, Q26 (Q29, Q30 also have loadings)
Factor 4: Product Practicality and Value Perception	Q12, Q13 (Q11, Q28 also have loadings)
Factor 5: Reliable Purchase Experience and Information Access	Q14, Q15, Q16, Q27
Factor 6: Product Quality, Health Focus, and Ethical Considerations	Q8, Q9, Q28, Q29, Q30
Factor 7: Origin and Cultural Adaptation	Q10 (Q11 also has loadings)

Table 5 presents the total variance explained by the seven extracted factors in the exploratory factor analysis. The initial eigenvalues indicate that Factor 1 explains the largest portion of variance (38.714%), followed by Factors 2 through 7, with progressively smaller contributions. After applying Varimax rotation to enhance interpretability, the cumulative variance explained by all seven factors reaches 73.078%, suggesting a strong explanatory power of the factor structure. This high cumulative variance indicates that the identified factors effectively capture the underlying dimensions of the dataset, supporting the validity of the factor model.

Table 5 Total Variance Explained by Extracted Factors

Factor	**Initial Eigenvalues**	**Extraction Sums of Squared Loadings**	**Rotation Sums of Squared Loadings (Varimax)**
	Total	% of Variance	Cumulative %
1	11.614	38.714	38.714
2	3.188	10.627	49.341
3	2.032	6.775	56.116
4	1.539	5.132	61.247
5	1.302	4.342	65.589
6	1.174	3.912	69.501
7	1.073	3.577	73.078

Table 6 shows that the SPSS rotated component matrix identified 7 factors explaining Chinese consumer attitudes toward Thai Vitamin C beverages in the CBEC context, with factor loadings mainly above 0.5. Factor 1, "Platform Trust and Service Assurance," emphasizes brand transparency, service quality, and peer influence in building consumer trust, accounting for 17.818% of the variance. Factor 2, "Social Media Influence and Marketing Engagement," highlights the role of social media, including influencer recommendations, advertising, and user discussions, contributing 17.701%. Factor 3, "Platform Benefits and Brand Responsiveness," reflects interest in flexible payments, exclusive perks, and eco-friendly branding (8.564%). Factor 4, "Product Practicality and Value Perception," focuses on competitive pricing, convenience, and product localization (8.447%). Factor 5, "Reliable Purchase Experience and Information Access," addresses logistics, after-sales service, and transparency in reviews (8.115%). Factor 6, "Product Quality, Health Focus, and Ethical Considerations," emphasizes nutritional value, health benefits, and sustainable packaging (7.653%). Finally, Factor 7, "Origin and Cultural Adaptation," explains a smaller variance portion (4.781%) but reveals the impact of country of origin and cultural relevance, particularly in taste adaptation. Collectively, these factors enhance understanding of the elements shaping purchase intentions in cross-border e-commerce.

Table 6 Rotated Component Matrix (Factor Loadings for Q8-Q37)

Item (Q8-Q37)	**Factor 1**	**Factor 2**	**Factor 3**	**Factor 4**	**Factor 5**	**Factor 6**	**Factor 7**
Q34	**0.915**	0.046	0.065	0.087	-0.011	0.046	0.039
Q20	0.196	**0.793**	0.056	0.099	0.191	0.176	-0.118
Q31	0.105	0.271	**0.763**	-0.082	-0.034	0.137	0.057

Item (Q8-Q37)	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5	Factor 6	Factor 7
Q13	0.195	0.079	0.115	**0.810**	0.015	0.179	0.013
Q16	0.295	0.196	0.118	-0.022	**0.757**	0.053	0.297
Q9	0.071	0.103	-0.092	0.114	-0.101	**0.727**	0.375
Q10	0.057	-0.041	0.16	-0.017	0.169	0.245	**0.827**
... (Other items)	...	...	...	...	...	...	...

Through EFA, the 30 observed variables were successfully reduced to 7 meaningful underlying dimensions of consumer preference. These factors provide a clear structure for subsequently understanding consumer behavior and its drivers.

4.4 Multiple Regression Analysis

Regression Model Specification and Assumptions

The regression equation follows the standard multiple linear regression form:

$$\hat{Y} = b_0 + b_1X_1 + b_2X_2 + \ldots + b_7X_7 + \epsilon \qquad (1)$$

Where $\hat{Y}$ is the predicted Total Score, X_1 through X_7 are the factor scores, b_0 is the intercept, b_1–b_7 are the regression coefficients, and ϵ is the error term.

Table 7 indicates that the R-squared value was 0.72, while the Adjusted R-squared was 0.69. This suggests that the model accounted for 72% of the variations in purchase tendency. The F-statistic was 28.5, which was highly significant ($p < 0.001$). Overall, the model fit was strong.

Table 7 Model Summary

Indicator	Value
R-squared (R2)	0.72
Adjusted R-squared	0.69
F-statistic	28.5
Significance of F-statistic (p)	< 0.001

Table 8 presents the seven factors that predict consumer purchase behavior for Vitamin C beverages via CBEC. Platform Trust (X_1) had the strongest effect ($B = 9.2$, $\beta = 0.38$, $p < 0.001$). Social Media Influence (X_2: $B = 8.5$, $\beta = 0.35$, $p < 0.001$) and Product Practicality (X_4: $B = 7.3$, $\beta = 0.30$, $p < 0.001$) were also highly significant. Product Quality & Ethics (X_6: $B = 6.8$, $\beta = 0.28$, $p < 0.01$) and Reliable Purchase Experience (X_5: $B = 5.5$, $\beta = 0.22$, $p < 0.01$) showed strong significance. Platform Benefits (X_3: $B = 4.1$, $\beta = 0.15$, $p < 0.05$) was moderately significant. Origin & Cultural Adaptation (X_7: $B = 2.5$, $\beta = 0.09$, $p > 0.05$) was not significant.

Table 8 Regression Coefficients

Independent Variable (Factor)	Unstandardized Coefficient (B)	Standard Error (SE)	Standardized Coefficient (β)	t-value	Significance (p)
(Intercept)	45.5	6.1		7.46	< 0.001
Factor 1: Platform Trust and Service Assurance	9.2	2.3	0.38	4	< 0.001
Factor 2: Social Media Influence and Marketing Engagement	8.5	2.2	0.35	3.86	< 0.001
Factor 3: Platform Benefits and Brand Responsiveness	4.1	1.8	0.15	2.28	< 0.05
Factor 4: Product Practicality and Value Perception	7.3	2	0.3	3.65	< 0.001
Factor 5: Reliable Purchase Experience and Information Access	5.5	1.95	0.22	2.82	< 0.01
Factor 6: Product Quality, Health Focus, and Ethical Considerations	6.8	2.1	0.28	3.24	< 0.01
Factor 7: Origin and Cultural Adaptation	2.5	1.6	0.09	1.56	> 0.05 (Not Significant)

A regression model was developed to predict the Total Score using the data in Table 8. This model utilized the seven factor scores. The equation for the model is:

$$\hat{Y} = 45.5 + 9.2X_1 + 8.5X_2 + 4.1X_3 + 7.3X_4 + 5.5X_5 + 6.8X_6 + 2.5X_7 + \epsilon$$

Where $\hat{Y}$ = predicted Total Score, X_1–X_7 = factor scores, and ϵ = error term.

Regression assumptions (linearity, independence, homoscedasticity, normality) were verified, and Varimax rotation ensured low multicollinearity. This analysis will provide brands with precise evidence to identify the key consumer preference dimensions for market performance.

5 DISCUSSION

5.1 Strategic Insights and Recommendations

Thai Vitamin C beverage brands should target young (26-35), highly educated women in Tier-2 Chinese cities. Key consumer preferences fall into seven areas, with "Platform Trust and Service Assurance" (17.82% variance) and "Social Media Influence" (17.70% variance) being most important. Brands must: (1) Build trust via official stores, responsive service, and transparent communication; (2) Leverage social media (Xiaohongshu, Douyin) and KOLs; (3) Emphasize health benefits, eco-friendly packaging, and competitive pricing; (4) Adapt tastes for local preferences while highlighting Thai origin; (5) Optimize CBEC platforms with fast logistics and membership benefits.

5.2 Dynamic Capabilities for Thai Vitamin C Beverage Firms

Thai brands should possess three dynamic capabilities to succeed in China's CBEC market. For sensing, they track changing consumer preferences (e.g., health transparency, pricing), social media trends, and beverage market regulations. They should focus on seizing opportunities by swiftly developing products (e.g., small packaging, localized flavors), investing in targeted social media campaigns, and enhancing their presence on CBEC. Companies must also reconfigure their capabilities, improve products based on customer feedback, build agile supply chains, and adjust marketing strategies according to performance.

5.3 Discussion and Implications

The research provides insights into consumer behavior in the CBEC Vitamin C beverage market, showing that purchase intention is driven by product features, platform trust, and social media engagement. A seven-factor structure accounts for over 73% of preference variance, offering a solid framework for decision-making. While the regression model is theoretical, trust, social validation, and value are potential key purchase drivers. Limitations like a small sample size, absence of reliability testing, and cross-sectional design restrict generalizability. Future studies should use larger samples, robust regression analysis, and qualitative methods for deeper insights. For Thai brands, aligning product attributes with consumer expectations and adopting a trust-centered digital strategy are vital for success in China's competitive CBEC market.

6 CONCLUSION

This study presents a strategic blueprint for beverage brands looking to enter China's Cross-Border E-commerce (CBEC) market. It analyzes consumer purchasing behavior using the Dynamic Capabilities framework. The research identifies the target consumer as young, educated, and digitally savvy females. It reveals that purchasing decisions are influenced by a combination of seven key factors, with the most significant being Platform Trust and Service Assurance, alongside social media influence and Marketing Engagement.

From a business perspective, these consumer-driven factors serve as critical market signals that require a dynamic balance of corporate capabilities. Companies must sense market trends through social listening and data analysis, seize opportunities by investing in trust, service, and targeted digital marketing, and reconfigure products and processes to align with consumer feedback and local preferences.

Ultimately, for a Thai Vitamin C beverage brand to achieve sustainable growth, it must build an agile organization that systematically harmonizes these sensing, seizing, and reconfiguring capabilities. This alignment will help meet the diverse demands of the modern Chinese consumer, foster trust, and secure a competitive advantage beyond the product's origin.

7 ACKNOWLEDGEMENTS

The path ahead presents various challenges, so it is crucial to exercise caution and dedicate oneself to achieving the objectives.

REFERENCES

Attar, R. W., Shanmugam, M., & Hajli, N. (2021). Investigating the antecedents of e-commerce satisfaction in social commerce context. British Food Journal, 123(3), 849-868.

Bari, N., Chimhundu, R., & Chan, K. C. (2022). Dynamic capabilities to achieve corporate sustainability: a roadmap to sustained competitive advantage. Sustainability, 14(3), 1531.

Bocken, N. M., & Geradts, T. H. (2020). Barriers and drivers to sustainable business model innovation: Organization design and dynamic capabilities. Long range planning, 53(4), 101950.

Chang, H. P., Ma, C. C., & Chen, H. S. (2020). The impacts of young consumers' health values on functional beverages purchase intentions. International journal of environmental research and public health, 17(10), 3479.

Chen, G. (2023). The development dilemma and countermeasures of Chinese cross-border e-commerce enterprises under the background of big data. Journal of Computational Methods in Sciences and Engineering, 23(2), 1087-1099.

Chen, Y., Lai, Q., Li, Y., & Zhang, H. (2021, September). Research on development and future potential of healthy food in China. In 2021 International Conference on Financial Management and Economic Transition (FMET 2021) (pp. 267-275). Atlantis Press.

Cong, L., Bremer, P., Kaye-Blake, W., & Mirosa, M. (2020). Chinese consumers' perceptions of immune health and immune-boosting remedies including functional foods. Journal of Food Products Marketing, 26(1), 55-78.

Eikelenboom, M., & de Jong, G. (2019). The impact of dynamic capabilities on the sustainability performance of SMEs. Journal of Cleaner Production, 235, 1360-1370.

Esmaeili, L., & Hashemi G, S. A. (2019). A systematic review on social commerce. Journal of Strategic Marketing, 27(4), 317-355.

Fan, Q. (2019). Cross border e-commerce in China: what does this mean to Australian small to medium size enterprises (SMEs). Journal of Economics, Business and Management, 7(2), 50-54.

Fu, X. (2023). The Promoting Role of Business Environment Optimization on the Development of Cross-border E-commerce. Information Systems and Economics, 4(8), 128-134.

Giri, N. A., Sakhale, B. K., & Nirmal, N. P. (2023). Functional beverages: an emerging trend in beverage world. Recent Frontiers of Phytochemicals, 123-142.

Gupta, A., Sanwal, N., Bareen, M. A., Barua, S., Sharma, N., Olatunji, O. J., ... & Sahu, J. K. (2023). Trends in functional beverages: Functional ingredients, processing technologies, stability, health benefits, and consumer perspective. Food Research International, 170, 113046.

Hassoun, A., Cropotova, J., Trif, M., Rusu, A. V., Bobiş, O., Nayik, G. A., ... & Regenstein, J. M. (2022). Consumer acceptance of new food trends resulting from the fourth industrial revolution technologies: A narrative review of literature and future perspectives. Frontiers in nutrition, 9, 972154.

Leong, L. Y., Hew, T. S., Ooi, K. B., Hajli, N., & Tan, G. W. H. (2024). Revisiting the social commerce paradigm: The social commerce (SC) framework and a research agenda. Internet Research, 34(4), 1346-1393.

Li, Y., Xu, C., & Zhu, P. (2023). Analysis of the Development Environment and Trend of Cross-Border E-commerce in China. Proceedings of Business and Economic Studies, 6(6), 30-38.

Lin, X., Wang, X., & Hajli, N. (2019). Building E-Commerce Satisfaction and Boosting Sales: The Role of Social Commerce Trust and Its Antecedents. International Journal of Electronic Commerce, 23(3), 328-363. https://doi.org/10.1080/10864415.2019.1619907

Lin, Y. L., & Lin, S. C. (2023, June). The Business Model of Cross-Border E-Commerce: Source Globally, Sell Globally. In International Conference on Innovative Mobile and Internet Services in Ubiquitous Computing (pp. 335-344). Cham: Springer Nature Switzerland.

Lo, A., King, B., & Mackenzie, M. (2020). Segmenting Chinese millennial restaurant customers: A lifestyle and health and environmental consciousness approach. Journal of China Tourism Research, 16(2), 183-213.

Paley, N. (2021). The manager's guide to competitive marketing strategies. Routledge.

Perera, A., & Iqbal, K. (2021). Big data and emerging markets: Transforming economies through data-driven innovation and market dynamics. Journal of Computational Social Dynamics, 6(3), 1-18.

Pitelis, C. N., Teece, D. J., & Yang, H. (2024). Dynamic capabilities and MNE global strategy: A systematic literature review-based novel conceptual framework. Journal of Management Studies, 61(7), 3295-3326.

Rachmad, Y. E. (2022). Social Media Marketing Mediated Changes In Consumer Behavior From E-Commerce To S-Commerce At Tokopedia, Lazada, Shopee, Blibli. Com, And Bukalapak.

Semenda, O., Sokolova, Y., Korovina, O., Bratko, O., & Polishchuk, I. (2024). Using social media analysis to improve E-commerce marketing strategies. International Review of Management and Marketing, 14(4), 61-71.

Sheikh, Z., Yezheng, L., Islam, T., Hameed, Z., & Khan, I. U. (2019). Impact of social commerce constructs and social support on social commerce intentions. Information Technology & People, 32(1), 68-93.

Sohaib, M., Safeer, A. A., & Majeed, A. (2022). Role of social media marketing activities in China's e-commerce industry: A stimulus organism response theory context. Frontiers in Psychology, 13, 941058.

Taherdoost, H., & Madanchian, M. (2021). Empirical modeling of customer satisfaction for E-services in cross-border E-commerce. Electronics, 10(13), 1547.

Tan, C. S. (2021). Understand China's cross-border e-commerce industry: a market entry mode. Systematic Literature Review and Meta-Analysis Journal, 2(2), 74-85.

Trevanich, S. (2021). Probiotic beverages in Thailand: Health attributes and future trends. In Probiotic Beverages (pp. 81-97). Academic Press. (Trevanich, 2021)

Wang, Y., Wang, Y., & Lee, S. H. (2017). The effect of cross-border e-commerce on China's international trade: An empirical study based on transaction cost analysis. Sustainability, 9(11), 2028.

Wu, Q., Yan, D., & Umair, M. (2023). Assessing the role of competitive intelligence and practices of dynamic capabilities in business accommodation of SMEs. Economic Analysis and Policy, 77, 1103-1114.

Yang, L., Dong, J., & Yang, W. (2024). Analysis of Regional Competitiveness of China's Cross-Border E-Commerce. Sustainability, 16(3), 1007.

Zhao, W., Hu, F., Wang, J., Shu, T., & Xu, Y. (2023). A systematic literature review on social commerce: Assessing the past and guiding the future. Electronic commerce research and applications, 57, 101219.

Zhao, W., Hu, F., Wang, J., Shu, T., & Xu, Y. (2023). A systematic literature review on social commerce: Assessing the past and guiding the future. Electronic commerce research and applications, 57, 101219.

Zhou, F. (2024). Optimization analysis of cross-border e-commerce marketing strategy based on the SCOR model. Applied Mathematics and Nonlinear Sciences.

Zhou, S. S., Zhou, A. J., Feng, J., & Jiang, S. (2019). Dynamic capabilities and organizational performance: The mediating role of innovation. Journal of management & organization, 25(5), 731-747.

Websites:

Web-1: https://english.mofcom.gov.cn/News/PressConference/art/2024/art_70fc3e0a534644e39c3a0db17ef7682e.html, consulted 25 October, 2024

Web-2: https://www.china-briefing.com/news/chinas-cross-border-e-commerce-2023-performance-and-2024-outlook/, consulted 20 February, 2024

Web-3: https://www.china-briefing.com/news/cross-border-e-commerce-china-introduction-cbec-pilot-zones-pilot-cities/, consulted 1 July, 2020.