PROCEEDING BOOK

DIFT 2026-1

Digital Innovation and Financial Technology Conference (2026-1)

Regulating the Revolution: Digital Asset Business 2026

6th June 2026

INFORMATION

International College of DIGITAL INNOVATION
CHIANG MAI UNIVERSITY

CONTACT US: 053945711-12 icdi@cmu.ac.th www.icdi.cmu.ac.th CMU International College of Digital Innovation

Proceedings of the DIFT 2026-1 Conference
Digital Innovation and Financial Technology

Theme:
Regulating the Revolution: Digital Asset Business 2026

Date:
6^{th} June 2026

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 2026-1: 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 6th June 2026 at the International College of Digital Innovation, Chiang Mai University. We extend our heartfelt thanks to Mr. Thitiwat Wasarath for delivering an inspiring keynote lecture titled "Digital Assets Business Under Thai Laws", which provided profoundly valuable insights into the legal landscapes, compliance mechanisms, and strategic opportunities shaping the digital asset economy in Thailand.

Special recognition is due to all student researchers for their rigorous commitment to developing the comprehensive full papers compiled in these proceedings. Your dedication beautifully reflects the potential of next-generation academic inquiry and its significant impact on the contemporary discourse surrounding financial technology and digital ecosystem evolution. Furthermore, we express our profound gratitude to the academic advisors, peer reviewers, and faculty mentors whose intellectual guidance and critical feedback elevated the academic standard of this volume. We also extend our gratitude to the dedicated administrative coordinators, technical support staff, and student volunteers, whose tireless behind-the-scenes contributions were vital to the operational success of the event.

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 2026-1 Organizer
15 June 2026

DIFT 2026-1 ORGANIZING COMMITTEE

1. Advisory Committee

1.1 Dean, International College of Digital Innovation
1.2 Associate Dean (Assoc. Prof. Dr. Manad Khamkong)
1.3 Associate Dean (Asst. Prof. Dr. Chaiwuth Tangsomchai)
1.4 Associate Dean (Asst. Prof. Dr. Benjamas Suksatit)
1.5 Head, School of Digital Innovation
1.6 Chair, B.Sc. Program in Digital Innovation (International Program)

2. Executive Committee

2.1 Assoc. Prof. Dr. Somchai Sriyab (Associate Dean)	Chair
2.2 Chair, Graduate Program Committee, Digital Innovation	Vice-Chair
2.3 Secretary, Graduate Program Committee and Financial Technology (International Program)	Member
2.4 Asst. Prof. Dr. Aniwat Phaphuangwittayakul	Member
2.5 Dr. Nathapon Udomlertsakul	Member
2.6 Dr. Suttida Suwannayod	Member
2.7 Asst. Prof. Dr. Somsak Chanaim	Secretary
2.8 Mrs. Wiranya Ratnapinda	Assistant Secretary

3. Academic Committee

3.1 Asst. Prof. Dr. Somsak Chanaim	Chair
Presentation Management Subcommittee	
3.2 Asst. Prof. Dr. Ahmad Yahya Dawod	Member
3.3 Dr. Kanyarat Thitiwatthanakan	Member
3.4 Dr. Michael John Harris	Member
3.5 Dr. Phillip Y Freiberg	Member
3.6 Dr. Siva Shankar Ramasamy	Member
3.7 Dr. Parot Ratnapinda	Member
Review Subcommittee	
3.8 Dr. Chakkrapong Kuensaen	Member
3.9 Assoc. Prof. Dr. Thacha Lawanna	Member
3.10 Asst. Prof. Dr. Nopasit Chakpitak	Member
3.11 Asst. Prof. Dr. Piyachat Udomwong	Member
3.12 Asst. Prof. Dr. Tanarat Rattanadamrongaksorn	Member

3.13 Dr. Nathapon Udomlertsakul	Member
3.14 Dr. Wasut Pornpatcharapong	Member
3.15 Dr. Saronsad Sokantika	Member
3.16 Dr. Nuttaphat Sukchitt	Member & Secretary
3.17 Mrs. Ruchanee Tinamas	Assistant Secretary
3.18 Mr. Watcharapong Dilokjanya	Assistant Secretary

4 Ceremony Committee

4.1 Mr. Silpa Singharajwarapan	Chair
4.2 Dr. Nattharikran Kaewnil	Member
4.3 Dr. Kanyarat Thitiwatthanakan	Member
4.4 Ms. Kanyanatthakarn Intharuck	Member
4.5 Ms. Sureeporn Chaiyaworrakamol	Secretary

5 Venue, AV Equipment, and Transportation Committee

5.1 Asst. Prof. Dr. Aniwat Phaphuangwittayakul	Chair
5.2 Dr. Saronsad Sokantika	Member
5.3 Mr. Kraisorn Wangkeeree	Member
5.4 Ms. Nanthana Songchit	Member
5.5 Mr. Pirapong Wongsaensee	Member & Secretary
5.6 Mr. Kanyawut Ariya	Secretary Assistant

6 Finance, Procurement, Evaluation, and Reporting Committee

6.1 Dr. Suttida Suwannayod	Chair
6.2 Ms. Nanthana Songchit	Member
6.3 Ms. Anchaya Chursook	Member
6.4 Ms. Mintra Inthajak	Secretary
6.5 Ms. Sirirag Yodpuntong	Assistant Secretary

CONFERENCE EXTERNAL COMMITTEE

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

DIFT2026-1
Regulating the Revolution: Digital Asset Business 2026
6 June 2026, 08:00-15:00
International College of Digital Innovation Building, Chiang Mai University

Chairman: Asst. Prof. Dr. Autchariyapanitkul, Kittawit
Co-chair 1: Asst. Prof. Dr. Ahmad Yahya Dawod (All-day session)
Co-chair 2: Asst. Prof. Dr. Piyachat Udomwong (Morning session)
Co-chair 2: Asst. Prof. Dr. Seamus Lyons (Afternoon session)

Room: ICB 1102 [Zoom ID: 872909 2671, Passcode: 2671]	
08:00-08:45	Registration
08:45-09:00	Report Speech Report Speech by Asst. Prof. Dr. Rujira Ouncharoen Dean of International College of Digital Innovation
09:00-10:00	Keynote Talk "Digital Assets Business Under Thai Laws" Thitiwat Wasarath Chief Legal Compliance and Risk Officer, Gulf Binance Co., Ltd.
10.30-10.50	The Evolution of Governance Discourse in Uniswap DAO By Using BERTopic (Miao Peng)
10.50-11.10	Automated Transaction Risk Scoring in Cryptocurrency Exchanges with a KYT Model for FATF Compliance (Xuan He)
11.10-11.30	Leakage-Controlled and Stability-Aware Motif-Derived Structural Features for Blockchain Transaction Graph Anomaly Detection (Tong Yang)
11.30-11.50	Digital Transformation for Sustainable Development: Examining the Effects of ICT Infrastructure on Socioeconomic Outcomes in Thailand (Phatteera Phengphit)
11.50-13.00	Lunch Break
13.00-13.20	Bitcoin-to-U.S.-Sector Volatility Spillovers: A TVP-VAR Connectedness Framework with Endogenous ChangePoint Detection (Waewwan La-ongsri)
13.20-13.40	Beyond Lexical Analysis: The Meme Receptance Model for Understanding Visual Rhetoric and Social Utility (Linhai Zhang)
13.40-14.00	A Hybrid Imputation Neural Network for Electric Vehicle Time Series Data with Climate-Aging Conditioning and Its Application to Energy Consumption Prediction (Jie Niu)

Chairman: Dr. Watcharin Sarachai
Co-chair 1: Dr. Parot Ratnapinda (All-day session)
Co-chair 2: Assoc. Prof. Dr. Thacha Lawanna (Morning session)
Co-chair 2: Dr. Michael John Harris (Afternoon session)

Room: ICB 1210 [Zoom ID: 872909 2671, Passcode: 2671]	
10.30-10.50	Teacher Shortages and improving Education Quality in the ASEAN Using Digital Education Platforms (Hong Fang Jiang)
10.50-11.10	Traceability in the Tea Supply Chain Based on Blockchain Technology (Su Jue Jiao)
11.10-11.30	An Exploratory Study of Factors Influencing Consumer Purchasing Behavior Toward IoT Smart-Home Devices in China (Chen Guosheng)
11.30-11.50	Multi-Objective Optimisation for Substation Asset Replacement Planning: An NSGA-III-Based ISO 55000 Cost–Performance–Risk Framework (Jianbo Han)
11.50-13.00	Lunch Break
13.00-13.20	AI-Driven Optimization Models for Enhancing Furniture Upcycling Lifecycle Sustainability (Yalan Dan)
13.20-13.40	Do Filter Bubbles Exist on TikTok? Empirical Findings from 669 Chinese University Students (Lin He)

Chairman: Assoc. Prof. Dr. S P Gayathri
Co-chair 1: Dr. Siva Shankar Ramasamy (All-day session)
Co-chair 2: Asst. Prof. Dr. Somsak Chanaim (Morning session)
Co-chair 2: Dr. Suttida Suwannayod (Afternoon session)

Room: ICB 1211 [Zoom ID: 872909 2671, Passcode: 2671]	
10.30-10.50	The Impact of Customized Logistics Under the Influence of IoT Applied in Cross-Border E-Commerce (Shiyu Li)
10.50-11.10	AI-Driven Personalized Recommendations in Digital Banking: Examining Privacy, Trust, and Loyalty from a FinTech Perspective (Haiting Liu)
11.10-11.30	Digital Twin-Based Multi-Source Fusion for Real-Time Health Management and Remaining Useful Life Prediction of Industrial Equipment (Peiyan Guo)
11.30-11.50	Leveraging Artificial Intelligence for Digital Innovation: A Data-Driven Study on Perceived Authenticity and Consumer Trust in Smart Tourism (Weiqi He)
11.50-13.00	Lunch Break
13.00-13.20	Social Influence and Dual-Dimensional Trust on XR Technology Acceptance: Empirical Evidence from Employees of Chinese Telecom Enterprises (Zhu Hui)
13.20-13.40	The Effect of AI-Driven Digital Capabilities on Innovation Adoption among Smallholder Sugarcane Farmers in China (Wen Liao)

Addressing Post-Pandemic International School Teacher Shortages and Improving Education Quality in the ASEAN Region Using Digital Education Platforms

Hong Fang Jiang[1*] and Siva Shankar Ramasamy[2]

[1,2]International College of Digital Innovation, Chiang Mai University, Chiang Mai, 50200, Thailand
E-mail: hongfang_jiang@cmu.ac.th, sivashankar.r@cmu.ac.th
(*corresponding author)

Abstract

The global education sector has undergone major transformation after the COVID-19 pandemic, forcing institutions to adopt alternative approaches to maintain educational continuity. One of the major post-pandemic challenges is the shortage of qualified teachers in international schools, especially across the ASEAN region. This situation has created opportunities for innovation through digital education platforms that can support teaching and learning processes. This study examines the feasibility, advantages, and limitations of recruiting international schoolteachers while integrating digital platforms to reduce the gap between teachers and students. The research evaluates teacher recruitment, training, support systems, and quality assessment by reviewing existing studies and collecting feedback from stakeholders, including students, teachers, and school administrators. In addition, sentiment analysis is applied to support decision-making related to digital education platforms and teacher performance evaluation. The findings contribute to the growing discussion on innovative educational solutions that can address post-pandemic challenges and improve access to quality education in the ASEAN region.

KEYWORDS: Post-pandemic, International school, Teacher shortages, ASEAN region, Digital education platform, Quality Education.

1 Introduction

The COVID-19 pandemic created unprecedented disruptions across the global education sector, affecting both developed and developing countries. International schools in the ASEAN region were among the institutions that experienced severe operational difficulties during and after the pandemic period. One of the most critical challenges was the shortage of qualified international schoolteachers. Travel restrictions, border closures, quarantine policies, and health concerns limited the mobility of foreign educators, making it difficult for schools to recruit and retain experienced teachers from different countries. As a result, many international schools struggled to maintain consistent academic quality and provide effective learning experiences for students from diverse cultural and educational backgrounds. The post-pandemic environment has encouraged educational institutions to search for alternative and sustainable approaches to overcome these challenges. In this context, online education platforms have gained significant attention as an innovative solution for reducing the impact of teacher shortages. These digital platforms support remote teaching, virtual collaboration, flexible scheduling, and cross-border educational engagement. Through technological integration, schools can access a broader pool of qualified educators from various parts of the world without depending entirely on physical relocation. Such platforms also enable schools to continue academic activities during uncertain situations while supporting continuity in teaching and learning processes.

This study investigates the role of online education platforms in addressing teacher shortages faced by international schools in the ASEAN region after the pandemic. The research focuses on evaluating how digital education systems can support teacher recruitment, instructional delivery, and student learning outcomes. In addition, the study examines the ability of these platforms to create interactive and student-centered learning environments that encourage participation, communication, and academic engagement. Attention is also given to the effectiveness of digital teaching tools in maintaining educational standards within international school systems. The paper further discusses the present condition of teacher shortages in ASEAN countries and identifies the major difficulties experienced by international schools. It explains the concept of online education platforms by highlighting their major features, technological advantages, and educational applications. The study also analyzes both the strengths and limitations of these platforms in the ASEAN context, considering issues such as cultural diversity, language differences, internet accessibility, digital literacy, and technological infrastructure. Furthermore, this research reviews successful practices and implementation models from other regions that have effectively used online education platforms to support teacher recruitment and digital learning. The study explores strategies used to attract qualified educators, improve teaching effectiveness, and establish inclusive learning environments for students.

Overall, this research aims to provide practical insights and recommendations for international schools, educational policymakers, and other stakeholders in the ASEAN region. By adopting innovative digital education approaches, schools can minimize the impact of post-pandemic teacher shortages and continue delivering quality education in an increasingly digital academic environment.

2 Literature Review

Educational institutions across the world continue to face multiple challenges that demand innovative strategies to improve teaching effectiveness and student learning experiences. This literature review examines several studies that introduce practical and technology-supported approaches for addressing educational issues in different academic environments. The reviewed works focus on areas such as practical science education in secondary schools, teaching practice modules, communication enhancement within schools, accessibility in computing education, and innovative STEAM education models in China. These studies collectively provide valuable insights into sustainable educational practices, institutional improvements, communication support systems, accessibility considerations, and interdisciplinary teaching methods.

Eco-friendly Micro-scale Chemistry Experimental Kits:

The use of microscale practical activities through eco-friendly chemistry experimental kits in secondary education has been widely discussed in the literature [1]. The study discusses modifications to chemistry laboratory activities by incorporating affordable, reusable, and locally available materials for classroom demonstrations. According to the findings, the microscale kits developed under the RSC-YHIC program effectively support practical sessions, strengthen laboratory skills, and improve the confidence and teaching capabilities of secondary school science teachers in India.

Teaching Practice Modules:

An internal evaluation of teaching practice modules implemented within the VU system was conducted to identify limitations in course structures, procedures, and quality control mechanisms [2]. The purpose of the review is to identify limitations in course structures, procedures, and quality control mechanisms. The study highlights the importance of continuous improvement in teaching practice modules to ensure better preparation, training, and professional development for student teachers.

Communication Improvement:

Communication support requirements among school leaders and teacher leaders were investigated using mixed research methods, including survey-based analysis [4]. The study focuses on improving interaction among staff members and students to maintain a stable and productive educational environment. The findings emphasize that effective communication strategies can positively influence collaboration, understanding, and institutional stability.

Accessibility in Computing Education:

Accessibility issues in computing education beyond curriculum design and classroom tools have received limited attention in previous studies [7]. The study recommends conducting observations in real programming classrooms to better understand the learning experiences of students with disabilities. The research particularly focuses on identifying barriers associated with programming courses and digital learning environments.

STEAM Education in China:

An innovative STEAM education framework was proposed to address challenges faced by K–12 schools in China, including shortages of qualified teachers, sustainability concerns, and difficulties in integrating multiple disciplines effectively [10]. The proposed model combines cooperative teaching, project-based learning, and collaborative learning approaches to support comprehensive and meaningful STEAM education.

Overall, the reviewed studies demonstrate the importance of innovation in modern education systems. The findings contribute valuable knowledge related to practical science learning, teacher preparation, communication development, accessibility in computing education, and interdisciplinary STEAM learning. These innovative approaches may help educational institutions improve learning outcomes and adapt to changing academic demands. Future studies should continue exploring and refining such approaches to maximize their effectiveness across diverse educational settings.

3 Methodology

The proposed methodology provides a structured framework for evaluating digital education platforms, teacher acceptance, and stakeholder perceptions in international schools across the

ASEAN region. The conceptual framework for addressing educational challenges through innovative approaches offers a theoretical foundation for examining factors that influence educational improvement. This study integrates two established methods: the Technology Acceptance Model (TAM), originally proposed by Davis [16] and further extended by Venkatesh et al. [17], associated with the STEAM-China education platform and Sentiment Analysis for evaluating feedback collected from stakeholders, including students, parents, teachers, and school management. The combined framework supports the analysis of interactions among critical educational components and their influence on learning outcomes. It also guides the research process and intervention strategies by emphasizing the relationship between technology adoption, stakeholder perceptions, and educational effectiveness.

A. Technology Acceptance Model-STEAM (TAM-STEAM)

This research enhances the traditional TAM framework by incorporating the STEAM (Science, Technology, Engineering, Arts, and Mathematics) educational approach to examine the acceptance and usage of digital education platforms among teachers and students, as illustrated in Figure 1.

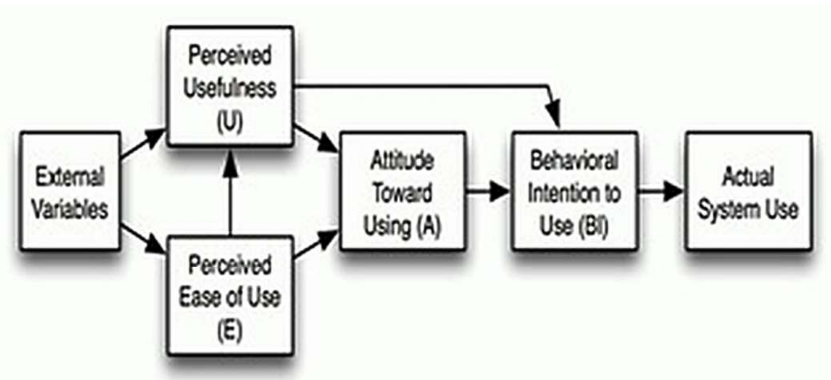

Figure 1: *Technology Acceptance Model [Source: Wiki_File]*

The study investigates teachers' perceptions of digital education platforms by focusing on three important dimensions. Perceived usefulness examines how these platforms improve teaching efficiency and help reduce teacher shortages through their educational functionality and value. Ease of use evaluates teachers' opinions regarding platform simplicity, accessibility, and adaptability within online classroom environments. STEAM fit analyzes the capability of the platforms to support integrated Science, Technology, Engineering, Arts, and Mathematics education, which may encourage greater educator participation.

The TAM-STEAM framework identifies major factors affecting platform adoption, including user attitudes and technical challenges. The findings support the improvement and optimization of digital education platforms to enhance usability, functionality, teacher engagement, and overall educational effectiveness in addressing teacher shortages.

B. Sentiment Analysis Natural language is the primary medium through which individuals communicate their opinions, emotions, and intentions. However, natural language often contains vague and unstructured expressions, whereas computers process information using numerical and logical representations. This difference creates a communication gap between human language and computer-based systems. Natural Language Processing (NLP) is widely used to reduce this gap by enabling computers to interpret and analyze human language effectively. In this study, the proposed approach mainly focuses on identifying the sentiment and tone expressed in expert feedback and discussions. Experts generally prefer using natural language to describe their experiences, observations, and viewpoints because it allows more flexible and meaningful communication.

To process such textual information, computational techniques capable of understanding natural language are required. Many existing approaches in the literature extract meaningful concepts and patterns from textual data so that computers can manage and interpret the information efficiently. Among various sentiment analysis methods, the bag-of-words approach is one of the most commonly adopted techniques. Before constructing the bags of words, unnecessary information such as articles, symbols, and prepositions must be removed to improve analysis quality. Furthermore, unigrams are simplified to avoid grouping similar words with different prefixes or suffixes separately. The bag-of-words approach is among the most frequently adopted techniques in sentiment classification and opinion mining research [18]. The process of building the bags of words involves several stages.

• Removal of additional information: The first stage removes unnecessary words, symbols, and numerical values that do not contribute significantly to the learning process. Eliminating irrelevant content such as articles and prepositions helps produce clearer and more meaningful comments. This filtering process improves the quality of the bag-of-words generation and enhances sentiment detection performance.

• Finding appropriate information: The second stage focuses on extracting meaningful and relevant information from the processed comments. This step analyzes word roots and identifies unigrams from the filtered data obtained in the previous stage. The procedure further refines and clarifies the bag-of-words structure for improved analysis.

• Separating the comments: In this stage, comments are divided into smaller textual units called n-grams, where $n \in N$. When n = 1, the comments are segmented into individual words known as unigrams. This segmentation process helps identify specific words and language patterns associated with different emotions and sentiments expressed in the comments.

• Building the bags of words: The final stage involves constructing bags of words based on predefined sentiment classes. In this study, four different sentiment categories are defined, and each unigram appears only once within the corresponding bag of words for that specific class. This structured representation supports effective sentiment classification and interpretation of stakeholder feedback.

Employee surveys, social media comments, performance evaluations, and internal organizational analytics are often stored in different data formats. Much of this information exists as unstructured data, requiring real-time processing and extraction techniques for effective analysis. Such data processing methods support organizations in understanding employee sentiment, which can improve productivity, employee engagement, and retention levels. In this research, both quantitative and qualitative analyses are applied. Quantitative analysis focuses mainly on measurable factors such as time and cost-related data. In contrast, qualitative analysis emphasizes communication patterns, opinions, and stakeholder feedback. The proposed scope and research methods provide a structured framework for evaluating digital education platforms, teacher acceptance, and stakeholder perceptions in international schools across the ASEAN region. However, the methodology and research scope may be refined further during

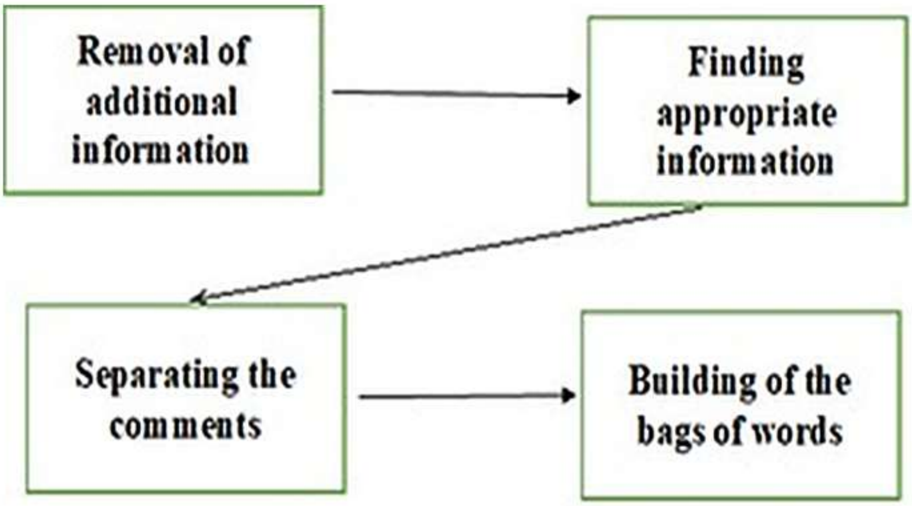

Figure 2: *Sequel of the Sentiment analysis path*

the study based on practical challenges and emerging research findings.

4 Results and Discussion

The primary objective of this study is to identify and evaluate the effectiveness of ASEAN teachers and digital education platforms. The evaluation process is conducted using a unique combination of direct and indirect feedback collected from parents, teachers, students, and school administrators. Primary data collection is carried out through surveys and interviews involving major educational stakeholders, as illustrated in Figure 3. The survey method gathers quantitative information related to user perceptions, experiences, and preferences regarding online education platforms. In addition, interviews provide qualitative insights into the practical implementation, effectiveness, and challenges associated with the use of these digital platforms.

The study also identifies major educational challenges, including limited resources, outdated teaching approaches, shortages of qualified teachers, accessibility issues, communication barriers, curriculum limitations, and sustainability concerns. To address these issues, the research explores innovative approaches such as technological integration, pedagogical improvements, curriculum redesign, teacher training programs, collaborative learning, project-based learning, and interdisciplinary educational practices.

Furthermore, the study recognizes the importance of stakeholders, including students, teachers, administrators, policymakers, parents, and community members, whose perspectives and interactions significantly influence the successful adoption of innovative educational approaches.

Table 1 highlights the importance of continuous feedback, evaluation, and iterative improvement in digital education platforms. Feedback is collected regularly for courses, teachers, and students to understand their perceptions and experiences with the platform. Continuous monitoring and assessment help identify strengths, weaknesses, and areas requiring improvement, thereby supporting the gradual enhancement of educational practices and digital interventions.

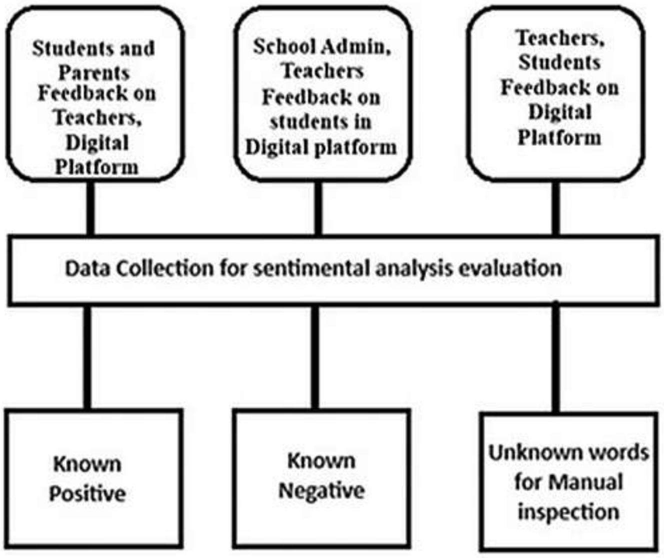

Figure 3: *Feedbacks are used in Sentiment Analysis.*

Table 1: *Exhibits the context which is taken from Feedbacks for Teachers, students and Digital Education platform.*

Sl.No	Context in Digital Platform	Quantitative findings
1	Study Hours	Max : 21 hours/week Min : 0 hours/week Standard Deviation: 5.43 hours
2	Overall Satisfaction on Teachers	Max: 10 Min: 0 Standard Deviation: 3.6
3	Attendance:	Regular: 76% Occasional: 23%
4	Course Difficulty:	Easy: 31% Moderate: 30% Difficult: 20% Challenging: 19%
5	Platform accessibility	Maximum: 70% Minimum:0% Standard Deviation: 4.48
6	Storage in Platform	Satisfied: 62% Unsatisfied: 24% Undecisive: 14%

Based on the analysis, the study presents findings regarding the effectiveness of online education platforms in reducing teacher shortages and improving educational quality in international schools. The research also provides recommendations and guidelines for policymakers, school administrators, and educators to support the successful implementation and effective utilization of these platforms. Some teachers actively guide students in using digital education platforms, encouraging greater student engagement and maximizing learning benefits. This approach also assists teachers and schools in monitoring student activities and improving communication with parents.

From the perspective of school administration, the integration of a unified technological platform combined with sentiment analysis can reveal hidden insights and innovative patterns related to teaching and learning performance. Subject-level and teacher-level analyses may support administrative decisions regarding teacher training, skill enhancement, promotions, or performance warnings. Schools aiming to develop future leaders and technical experts can also identify talented students for competitions, scholarships, and academic opportunities. Parents and school administrators play an important observational role and can use digital education platforms to support students in learning under the most suitable teachers and educational environments.

5 Conclusion

This study was conducted during the COVID-19 pandemic when strict lockdowns and educational restrictions prevented direct interaction between teachers and students. In this context, digital education platforms became an essential solution for continuing academic activities. Schools in China adopted digital platforms integrated with the STEAM-China concept to meet pandemic-related educational requirements. Feedback from teachers and students helped school administrators evaluate whether existing platforms should be maintained or replaced with advanced cloud-based systems for future use. The Technology Acceptance Model (TAM) was applied to identify educational challenges and propose suitable solutions for international schools. Sentiment analysis was also used to evaluate stakeholder feedback, supporting schools in identifying, retraining, and retaining qualified teachers while reducing teacher shortages. The findings showed that ASEAN teachers often connected more effectively with students because of cultural similarities and familiar Asian English pronunciation styles. Although native English-speaking teachers demonstrated strong expertise, some cultural and communication challenges were identified with Chinese students. Additionally, ASEAN teachers provided socio-economic advantages related to salary, accommodation, visa processing, and adaptability within China. Overall, digital innovations supported educational evaluation and administrative decision-making.

References

[1] P. S. Kandagal, “Impact of Royal Society of Chemistry–Yusuf Hamied Inspirational Chemistry Programme in the development of innovative and eco-friendly micro-scale experiments for secondary school education in India,” *PEOPLE: International Journal of Social Sciences*, 2019.

[2] N. A. Abdullah and M. S. Mirza, "Evaluating pre-service teaching practice for online and distance education students in Pakistan," *The International Review of Research in Open and Distributed Learning*, vol. 21, no. 2, 2020.

[3] D. Kim, Y. Lee, W. L. Leite, and A. C. Huggins-Manley, "Exploring student and teacher usage patterns associated with student attrition in an open educational resource-supported online learning platform," *Computers & Education*, vol. 156, Art. no. 103961, 2020.

[4] L. Williams, M. Martinasek, K. Carone, and S. Sanders, "High school students' perceptions of traditional and online health and physical education courses," *Journal of School Health*, vol. 90, no. 3, pp. 234–244, 2020.

[5] O. Botezat and R. Mihaila, "Revisiting and reassessing pedagogical and methodological skills after the global pandemic: Online teaching and learning challenges," 2021.

[6] C. Bent-Cunningham and N. Mauzard, "Empowering leaders through the COVID-19 crisis: Implementing a transformative communication model," 2021.

[7] E. W. Huff and J. Brinkley, "A diary study of the teaching and learning experience in a high school programming course," *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, vol. 65, no. 1, pp. 1100–1104, 2021.

[8] A. Hira and E. Anderson, "Motivating online learning through project-based learning during the 2020 COVID-19 pandemic," 2021.

[9] A. A. Sihombing, S. Anugrahsari, N. Parlina, and Y. Kusumastuti, "Merdeka Belajar in an online learning during the COVID-19 outbreak: Concept and implementation," *Asian Journal of University Education*, vol. 17, no. 4, pp. 35–48, 2021.

[10] J. Li, H. Luo, L. Zhao, M. Zhu, L. Ma, and X. Liao, "Promoting STEAM education in primary school through cooperative teaching: A design-based research study," *Sustainability*, vol. 14, no. 8, Art. no. 4348, 2022.

[11] Y. Li and H. Wagenaar, "Revisiting deliberative policy analysis," *Policy Studies*, vol. 40, no. 3–4, pp. 325–335, 2019.

[12] P. Tarc, A. M. Tarc, and X. Wu, "Anglo-Western international school teachers as global middle class: Portraits of three families," *Discourse: Studies in the Cultural Politics of Education*, vol. 40, no. 4, pp. 535–548, 2019.

[13] A. Poole, "Decoupling Chinese internationalised schools from normative constructions of the international school," *Compare: A Journal of Comparative and International Education*, vol. 49, no. 4, pp. 573–590, 2019.

[14] H. Kim and E. Mobrand, "Stealth marketisation: How international school policy is quietly challenging education systems in Asia," *Globalisation, Societies and Education*, vol. 17, no. 2, pp. 252–266, 2019.

[15] L. M. Dos Santos, "Recruitment and retention of international school teachers in remote archipelagic countries: The Fiji experience," *Education Sciences*, vol. 9, no. 2, Art. no. 132, 2019.

[16] F. D. Davis, "Perceived usefulness, perceived ease of use, and user acceptance of information technology," *MIS Quarterly*, vol. 13, no. 3, pp. 319–340, Sep. 1989.

[17] V. Venkatesh, M. G. Morris, G. B. Davis, and F. D. Davis, "User acceptance of information technology: Toward a unified view," *MIS Quarterly*, vol. 27, no. 3, pp. 425–478, Sep. 2003.

[18] B. Liu, *Sentiment Analysis and Opinion Mining*. San Rafael, CA, USA: Morgan & Claypool Publishers, 2012.

[19] A. Tarhini, K. Hone, and X. Liu, "Factors affecting students' acceptance of e-learning environments in developing countries: A structural equation modeling approach," *International Journal of Information and Education Technology*, vol. 3, no. 1, pp. 54–59, 2013.

AI-Driven Personalized Recommendations in Digital Banking: Examining Privacy, Trust, and Loyalty from a FinTech Perspective

Haiting Liu[1] and Ahmad Yahya Dawod[2*]

[1,2]International College of Digital Innovation, Chiang Mai University, Chiang Mai, 50200, Thailand
E-mail: haiting_liu@cmu.ac.th, ahmadyahyadawod.a@cmu.ac.th
(*corresponding author)

Abstract

As digital banks expand their FinTech services, AI-driven personalized recommendations have become an important tool for enhancing customer experiences and strengthening customer relationships. Despite the growing adoption of AI-enabled personalization, concerns regarding privacy and security remain a critical challenge for financial institutions. This study examines the effects of AI-driven personalized recommendations on customer trust and customer loyalty, with privacy and security perceptions serving as a mediating mechanism. Drawing upon Privacy Calculus Theory, the Technology Acceptance Model, and Trust-Commitment Theory, this research develops an integrated framework to explain customer relationship formation in digital banking environments. Primary data obtained from 284 digital banking users residing in mainland China were analyzed using PLS-SEM. The results reveal that AI-driven personalized recommendations positively influence privacy and security perceptions, customer trust, and customer loyalty. Privacy and security perceptions also exert significant positive effects on trust and loyalty while partially mediating the relationship between personalization and customer relationship outcomes. This study provides insights into the FinTech sector by demonstrating that customer responses to AI-driven personalization depend on both perceived service value and evaluations of data protection practices. The findings further suggest that effective personalization and privacy protection operate together in supporting customer relationship development within digital banking services. The study provides practical insights for financial institutions seeking to balance personalization effectiveness with responsible data governance in increasingly data-driven financial ecosystems.

KEYWORDS: Digital Banking, AI-driven personalization, Privacy and Security Perceptions, Customer Trust, Customer Loyalty

1 Introduction

The rapid advancement of Artificial Intelligence (AI) and Financial Technology (FinTech) has fundamentally reshaped the operational landscape of digital banking. Financial institutions have progressively adopted AI-powered systems to enhance service personalization and strengthen customer engagement. Among these innovations, AI-driven personalized recommendations (AIPR) have emerged as an important mechanism for analyzing customer behavior, preferences, and transaction patterns to deliver customized financial products and services [1]. Prior research has demonstrated that AI implementation in financial services contributes to improvements in operational efficiency and service quality [2,3]. Empirical studies have shown that AI-driven personalization enhances customer satisfaction and trust and fosters long-term loyalty by improving service relevance and convenience [4].

Nevertheless, the extensive deployment of AI-driven personalization has also intensified concerns about data privacy and security. Personalized financial services depend substantially on customer information, behavioral tracking, and algorithmic profiling, processes that heighten customers' anxiety regarding potential data misuse and unauthorized information disclosure [5]. This concern is particularly acute in the FinTech sector, where AI-driven personalization routinely involves large-scale data collection and continuous digital monitoring. Earlier studies indicate that effective privacy management is fundamental to building trust and providing high-quality services to users [6]. Furthermore, indiscriminate data collection has been shown to undermine user engagement with personalized banking services [7]. The increasing complexity of cybersecurity threats and algorithmic decision-making in FinTech systems has further amplified concerns about transparency, ethical governance, and the trustworthiness of AI-driven financial services [8,9].

According to the Privacy Calculus Theory (PCT), customers evaluate information disclosure based on a trade-off between perceived benefits and risks. When AIPR provides relevant financial advice, improves decision-making efficiency, and enhances service convenience, customers often perceive greater value in sharing their personal data. Furthermore, high-quality personalized recommendations can be viewed as evidence of responsible data management and secure information processing, indicating that financial institutions possess strong data governance capabilities, thereby reducing customers' perceived uncertainty regarding data disclosure. Consequently, effective personalized services may actually reinforce users' perceptions of privacy and security even while making extensive use of personal data, rather than exacerbating privacy concerns.

Previous studies have largely examined, in isolation, the positive effects of AI-driven personalization and the negative consequences of privacy concerns, without integrating these two strands of research. In particular, little attention has been paid to how perceptions of privacy and security mediate the relationship between AI-driven personalization and customer outcomes in digital banking. This research gap carries significant theoretical and practical implications. Theoretically, a deeper understanding of this mediating mechanism can help resolve inconsistent findings in the existing literature on personalized services. Practically, financial institutions urgently need clearer guidance on how to strengthen customer relationships through AI-driven services while safeguarding data privacy and security.

To address the identified research gap, this study formulates three research questions. Research question 1 examines how the implementation of AIPR shapes customers' perceptions of privacy and security (PS). Research question 2 explores to what extent AIPR and PS individually and directly influence CT and CL. Research question 3 investigates how perceptions of privacy and security (PS) mediate the relationship between AIPR and the outcomes of CT and CL.

This study develops an integrated conceptual framework examining the structural relationships among AIPR, PS, CT and CL in digital banking. Drawing upon the Privacy Calculus Theory (PCT), the Technology Acceptance Model (TAM), and the Trust-Commitment Theory, this framework explains how customers evaluate AI-enabled financial services and how these evaluations influence relationship outcomes. The PCT explains how customers balance perceived benefits and perceived risks when evaluating information disclosure [7,10]. The TAM provides insight into how customers assess the usefulness and value of AI enabled services [11]. The Trust-Commitment Theory explains how these evaluations contribute to the development of customer trust and long-term loyalty [12]. A quantitative survey was conducted among digital banking users in China, and Partial Least Squares Structural Equation Modeling (PLS-SEM) was deployed to test the proposed hypotheses and mediation relationships. This analytical approach facilitates the examination of complex relationships among multiple latent constructs and provides empirical evidence regarding customer behavior in digital financial environments.

This study contributes to the existing literature in three ways. First, it advances understanding of AI-driven personalization in digital banking by integrating PCT, TAM, and the Trust-Commitment Theory into a unified theoretical framework. Second, it identifies PS as a critical psychological mechanism through which AIPR influence CT and CL. Third, it provides new theoretical insight into how effective AI-driven personalization may strengthen privacy and security perceptions through positive evaluations of institutional competence and data governance capabilities.

2 Research Methodology

2.1 Research Framework

This study proposes an integrated theoretical model to explore how AIPR influence CT and CL within digital banking. The framework bridges three established theoretical perspectives to explain the psychological mechanisms underlying customer behavior in AI-enabled financial services.

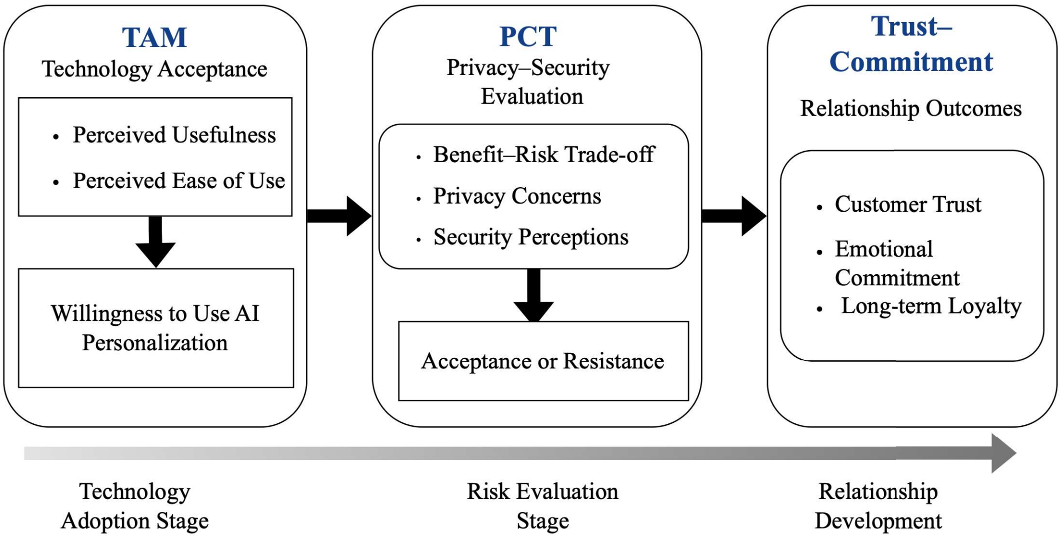

Figure 1: *An Integrated Theoretical framework of AI-driven personalization Based on TAM, PCT, and Trust-Commitment Theory*

As shown in Figure 1, the theoretical model delineates a linear three-stage process of customer relationship development. The first stage focuses on technology acceptance, guided by the TAM, which provides the theoretical rationale for customers' willingness to engage with AI-driven personalization technologies. The second stage represents the evaluation process grounded in PCT, where customers assess the benefits of personalized services against potential privacy and security risks. These evaluations are reflected in customers' privacy and security perceptions, which serve as a key mechanism linking AI-driven personalized recommendations to subsequent relationship outcomes. The third stage, focusing on long-term relationship development. Rooted in Trust-Commitment Theory, this concluding phase translates customer cognitive assessments into solid relationship outcomes, specifically manifested through customer trust, emotional commitment, and long-term loyalty. This integrated path provides a comprehensive explanation of customer psychology in modern FinTech environments.

Based on these theories, this study develops a conceptual model consisting of one independent variable (AIPR), one mediator (PS), and two dependent variables (CT and CL). This conceptual framework explores the direct and indirect effects of AI-driven personalization on customer trust and loyalty within digital banking contexts.

As shown in Figure 2, the framework maps the research questions and hypotheses across specific structural pathways. Research Question 1 (RQ1) addresses the link between AIPR and the mediator, leading to Hypothesis 1 (H1). Research Question 2 (RQ2) encompasses both the direct paths from AIPR to the dependent variables, evaluated through H4 and H5, and the subsequent impacts of PS on trust and loyalty, evaluated through H2 and H3. Research Question 3 (RQ3) specifically covers the mediating mechanisms addressed in H6 and H7. This framework suggests that effective AI-driven personalization enhances customer trust and loyalty by simultaneously delivering functional service efficiency and strengthening privacy-security assurances. This model provides a process-based explanation of the personalization-privacy paradox in AI-driven financial services[4,10].

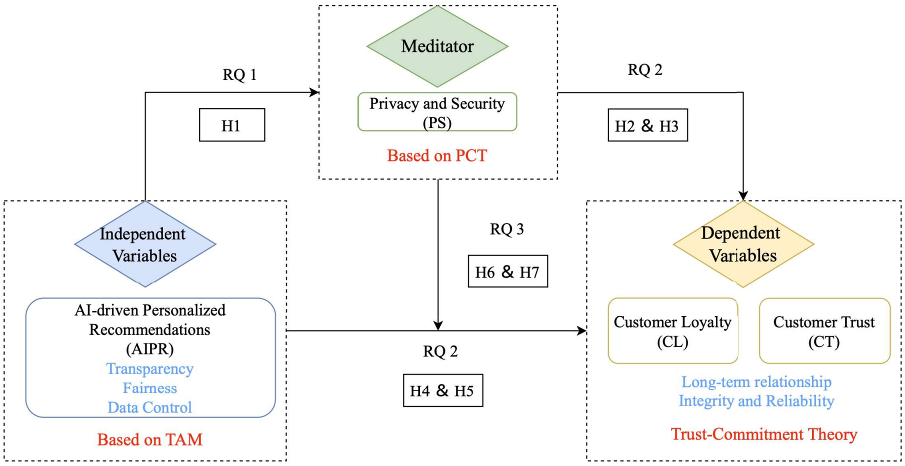

Figure 2: *Conceptual framework of the Impact of AI-Driven Personalized Recommendations on Customer Trust and Loyalty*

2.2 Research Hypotheses

Based on the theoretical discussion above, this study proposes seven hypotheses to examine the effects of AIPR on customer perceptions and relationship outcomes in digital banking and FinTech services.

H1: AIPR have a positive effect on PS.
H2: PS have a positive effect on CL.
H3: PS have a positive effect on CT.
H4: AIPR have a direct positive effect on CL.
H5: AIPR have a direct positive effect on CT.
H6: PS mediates the relationship between AIPR and CL.
H7: PS mediates the relationship between AIPR and CT.

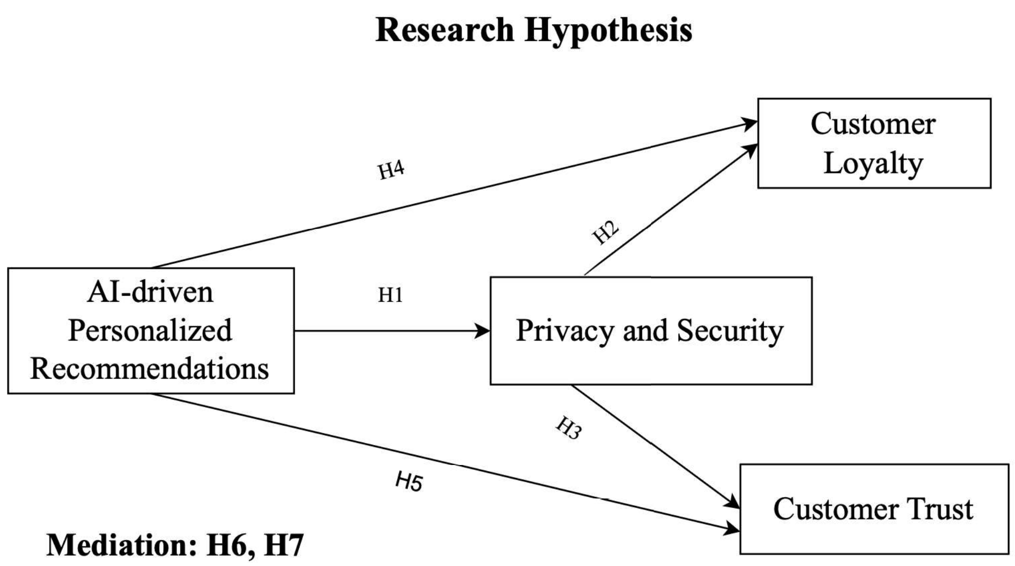

Figure 3: *Research Hypothesis for Model for AI-Driven Personalization and Customer Relationship Management*

As shown in Figure 3, PS perceptions serve as a mediating factor between AI-driven personalization and customer trust and loyalty. This framework helps explain customer responses to AI-driven financial services in digital banking environments.

3 Data Collection

The research instrument was developed based on established literature to ensure reliability and validity. To achieve conceptual and linguistic equivalence for respondents in Mainland China, the questionnaire was translated using a back translation procedure (English-Chinese-English) and reviewed by a banking professional. The questionnaire included demographic information and measurement items for AIPR, PS, CT, and CL. All measurement items were assessed using a 7-point Likert scale ranging from "Strongly Disagree" to "Strongly Agree".

Data were collected online through the Credamo platform. Before the formal survey, a pilot study involving 30 respondents was performed to test for questionnaire clarity and initial reliability using SmartPLS 4.0 [13]. The minimum sample size required for this study was calculated using G*Power [14,15]. The results indicated that at least 107 valid responses were necessary to achieve adequate statistical power ($\alpha = 0.05$, power = 0.99, effect size $f^2 = 0.15$). After confirming measurement quality, two rounds of formal surveys were conducted, resulting in 300 responses.

Two methods were used to enhance data quality during the screening process. Firstly, any questionnaire response taking fewer than 100 seconds was deleted due to previous studies, which indicated that an appropriate time to complete self-report questionnaires is at least 100 seconds [16,17]. Secondly, answers from questionnaires that showed strong consistency among most of their responses were excluded because these types of answers might indicate careless answering and increase the chance of common method variance [18]. After the screening process, 284 valid questionnaires were retained for further analysis.

3.1 Data Analysis

This study uses partial least squares structural equation modeling (PLS-SEM) with SmartPLS 4.0 to examine the proposed research model and test the hypothesized relationships among the constructs. PLS-SEM was selected because it is suitable for complex models, mediation analysis, and studies with relatively small sample sizes. In addition, this method has been widely applied in digital banking and FinTech research. Following the approach suggested by Hair et al. [13], the analysis includes measurement model assessment and structural model assessment.

2.4.1 Measurement Model Assessment

The measurement model was evaluated in terms of reliability and validity. Indicator reliability was confirmed with factor loadings > 0.70. Internal consistency was assessed using Cronbach's alpha (α) and composite reliability (CR), with acceptable values > 0.70. Convergent validity was verified through average variance extracted (AVE > 0.50). Discriminant validity was assessed using the Fornell-Larcker criterion and HTMT values (HTMT < 0.90) [13,19].

2.4.2 Structural Model Assessment

The structural model was evaluated by examining path relationships among the constructs. Multicollinearity was assessed using variance inflation factor values (VIF < 3.3) [20-22]. Bootstrapping with 5,000 resamples was conducted to test the proposed hypotheses. Path coefficients, t -values, p -values, R^2, and Q^2 were used to evaluate the significance, explanatory power, and predictive relevance of the model. Mediation analysis was performed to examine the mediating effect of privacy and security perceptions.

4 Research Results and Discussions

4.1 Sample Demographic Characteristics Analysis

The final sample comprised predominantly female participants (62.68%), with 78.52% aged between 18 and 35. Most respondents had relatively high educational backgrounds, including 65.85% holding a bachelor's degree or above and 22.89% holding a master's degree or above. In addition, 59.15% were corporate employees, and 38.38% reported monthly disposable incomes above 8,001 yuan.

The respondents also demonstrated strong engagement with digital banking services. A total of 91.90% mainly used state owned commercial banks, 83.45% had purchased non-deposit financial products, and 60.21% used banking services frequently. Furthermore, 70.07% had used digital banking services for more than three years, indicating substantial experience with AI-driven banking services.

4.2 Common method bias

To assess common method bias, the full collinearity approach proposed by Kock [20–22] was applied. In this test, all latent constructs were regressed on the remaining constructs to obtain variance inflation factor (VIF) values. All VIF values ranged from 1.000 to 1.662, well below the recommended threshold of 3.3, indicating that common method bias is unlikely to be a significant concern in this study. Detailed VIF values are presented in Table 3. subsectionMeasurement model assessment Table 1 presents the results of the reliability and validity assessment. The internal consistency reliability was demonstrated by Cronbach's alpha coefficients ranging from 0.797 to 0.919, and composite reliability (CR) values ranged from 0.868 to 0.934, both exceeding their respective thresholds of 0.7. For convergent validity, all measurement items exhibited outer loadings above 0.7; the average variance extracted (AVE) for each construct, with values ranging from 0.622 to 0.644, was consistently above the acceptance level of 0.50 [23]. Discriminant validity was measured using the heterotrait-monotrait (HTMT) ratio and Fornell-Larcker Criterion (see Table 2). All HTMT values were under 0.90, the values ranged from 0.723 to 0.899, and each construct's square root of AVE exceeded its correlations with the other constructs, meeting the Fornell-Larcker criterion. These results confirm the adequate distinction between the constructs [13,19].

4.3 Structural model assessment

The structural model assessment followed a systematic two-phase approach as advised by Becker et al. [24] and Hair et al.[13]. Initially, a base model without mediators was estimated to examine direct effects, followed by treating PS as a mediating variable (see Table 3). The analysis employed 5,000 bootstrap samples.

The evaluation began with an examination of multicollinearity among the predictor variables. The Variance Inflation Factor (VIF) values for all path combinations ranged from 1.000 to 1.662, falling well below the threshold of 3.3 [19], indicating no critical levels of multicollinearity.

Path analysis revealed significant relationships across all hypothesized connections. AIPR has a substantial positive influence on PS ($\beta = 0.631, \mathrm{t} = 14.832, 95\%\mathrm{CI}[0.538, 0.705], \mathrm{p} < 0.01$, supporting H1) and CL ($\beta = 0.631, \mathrm{t} = 12.376, 95\%$CI [0.527, 0.726], $\mathrm{p} < 0.01$, supporting H4) and CT ($\beta = 0.330, \mathrm{t} = 5.059, 95\%$ CI [0.211, 0.467], $\mathrm{p} < 0.01$, supporting H5). PS has a substantial positive influence on CL($\beta = 0.214, \mathrm{t} = 3.584, 95\%\mathrm{CI}[0.094, 0.326], \mathrm{p} < 0.01$, supporting H 2) and CT($\beta = 0.567$, $\mathrm{t} = 9.102, 95\%\mathrm{CI}[0.432, 0.678], \mathrm{p} < 0.01$, supporting H3). The effect size analysis based on f^2 values indicated varying impacts. The path corresponding to H1 exhibited a large effect ($\mathrm{f}^2 = 0.662$), H3 demonstrated a large effect ($\mathrm{f}^2 = 0.580$), and

Table 1: *Construct reliability and validity*

Measurements		Factor loading
AI-driven personalized recommendations and $\alpha = 0.919, CR = 0.934, AVE = 0.638$		
AIPR1	I think the bank's services are tailor-made for me.	0.845
AIPR2	I think banks are able to forecast my future financial requirements and offer guidance accordingly.	0.820
AIPR3	I believe my user experience has been improved by the bank's tailored recommendations.	0.797
AIPR4	The bank will recommend different products based on my life stage (e.g., student, working	0.711
AIPR5	Personalized features make me more willing to explore the bank's new services.	0.779
AIPR6	I think the banks recommend products that actually meet my needs.	0.829
AIPR7	I think the personalized recommendations provided by the bank are based on my spending habits.	0.763
AIPR8	I am satisfied with the bank's personalized service.	0.838
Privacy & Security and $\alpha = 0.816, CR = 0.879, AVE = 0.644$		
PS1	The bank gave me a detailed explanation of how they gather and use my data.	0.825
PS2	The bank provides sufficient security features (such as two-factor authentication) to protect my	0.780
PS3	I trust that the bank will comply with data protection regulations.	0.801
PS4	The bank will explicitly ask me whether I consent to the use of my data for personalized services.	0.805
Customer Loyalty and $\alpha = 0.797, CR = 0.868, AVE = 0.622$		
CL1	I recognize the (commonly used) value of this bank more than others.	0.761
CL2	I would consider this bank first (my primary bank) when I need new financial products.	0.814
CL3	I have purchased multiple products from this bank (wealth management products, credit cards, etc.).	0.777
CL4	I may increase my usage or investment with this bank in the future.	0.801
Customer Trust and $\alpha = 0.904, CR = 0.924, AVE = 0.634$		
CT1	I believe the bank has been honest and transparent in handling my personal data.	0.810
CT2	I trust that banks will prioritize protecting customer privacy over their own interests.	0.798
CT3	I believe the AI technology used by banks was designed with privacy and security protections	0.787
CT4	The bank's commitment to data security aligns with its actual actions, which makes it credible to me.	0.813
CT5	I feel confident entrusting my financial data to this bank because I trust its security systems.	0.790
CT6	I think the technical system of the bank is safe and secure	0.765
CT7	The way the bank uses my data makes me feel it is a trustworthy institution.	0.810

*Reverse coded
Source(s): Crafted by authors

H4 demonstrated a large effect $\left(f^2 = 0.621\right)$. The remaining hypotheses $(\mathrm{H2}, \mathrm{H5})$ showed small effects, with f^2 values ranging from 0.071 to 0.197 .

The model demonstrated robust explanatory power with R^2 values. The results indicate that CT achieved an R^2 of 0.667 , showing that AIPR and PS explain 66.7% of its variance. CL reported an R^2 of 0.614 , indicating that 61.4% of the variance is explained by AIPR and PS. PS achieved an R^2 of 0.398 , meaning that AIPR explains 39.8% of its variance. Overall, the model demonstrates moderate to substantial explanatory power across all endogenous variables, consistent with the standards for exploratory quantitative research.

The predictive significance of the model was confirmed by the PLS prediction. The Q^2 values for all endogenous variables in this study are greater than 0 , ranging from 0.388 to 0.579 . These results meet the criterion established by Hair [13] and confirm that the model has adequate predictive relevance for CL, CT, and PS.

4.4 Mediation analysis

As shown in Table 3, the mediation analysis reveals significant indirect effects for both H6 and H7 pathways. H6 proposed that PS mediates the relationship between AIPR and CL. The results demonstrate a significant indirect effect $(\beta = 0.135, \mathrm{t} = 3.389, 95\%\mathrm{CI}[0.060, 0.215], \mathrm{p} < 0.01)$, providing strong support for H 6 . The confidence interval excludes zero, confirming that

Table 2: *Discriminant validity*

	AIPR	CL	CT	PS
HTMT				
AIPR				
CL	0.889			
CT	0.749	0.797		
PS	0.723	0.759	0.899	
Fornell-Larcker criterion				
AIPR	0.799			
CL	0.766	0.789		
CT	0.688	0.675	0.796	
PS	0.631	0.612	0.755	0.803
Source(s): Crafted by authors				

PS serves as a significant mediator in the AIPR-CL relationship. H7 examined whether PS mediates the relationship between AIPR and CT. The analysis shows a significant indirect effect ($\beta = 0.358, t = 7.554, 95\%$ CI $[0.263, 0.450], p < 0.01$). The confidence interval does not contain zero, indicating that PS significantly mediates the relationship between AIPR and CT. Therefore, H7 receives empirical support. Comparing H6 and H7 reveals that PS plays a considerably stronger mediating role in the personalization-to-trust pathway ($\beta = 0.358$) than in the personalization-to-loyalty pathway ($\beta = 0.135$).

4.5 Discussion and Implications

The findings support all seven hypotheses and provide important insights into how AI-driven personalized recommendations influence customer trust and loyalty in the FinTech based digital banking environment. The results show that personalization quality, privacy and security perceptions, trust, and loyalty are strongly interconnected in shaping customer relationships within digital financial services.

First, AIPR has a strong positive effect on PS$(\beta = 0.631)$. Earlier studies frequently emphasized the potential privacy risks associated with AI-driven personalization, arguing that extensive data collection may heighten customer concerns about surveillance and the misuse of personal information. This findings reveal a different pattern in digital banking services. Customers associate high-quality personalized recommendations with professional data management capabilities. When recommendations are accurate, relevant, and aligned with individual financial needs, customers interpret such services as evidence of responsible handling of personal information. This observation extends the Privacy Calculus Theory by suggesting that the perceived benefits of personalization can actively mitigate privacy risk perceptions in highly regulated financial environments.

Second, AIPR significantly influences both CL $(\beta = 0.631)$ and CT $(\beta = 0.330)$. The comparatively stronger path to loyalty suggests that customers in digital banking environments are primarily responsive to the practical utility of personalized services, including convenience, relevance, and efficiency in financial decision support. This observation resonates with the core propositions of the Technology Acceptance Model, particularly the role of perceived usefulness in driving continued service engagement. The positive relationship between personalization and trust further indicates that customer evaluations of AI-enabled services are not limited to functional performance. Consistently relevant recommendations strengthen perceptions of competence, reliability, and service quality.

Third, the role of PS varies significantly across different customer relationship outcomes. The indirect effect of AIPR on CT through PS ($\beta = 0.358$) is higher than its indirect effect on CT ($\beta = 0.135$). This difference suggests that trust formation relies heavily on customer evaluations of data protection and information security. Loyalty, by contrast, is more resilient and experiential, driven concurrently by direct service value, convenience, and accumulated trust. Consequently, privacy and security perceptions function fundamentally as a protective baseline for establishing trust, while customer loyalty develops through a combination of practical service value, emotional security, and satisfying user experiences. This distinction refines Trust-Commitment Theory by separating the safety prerequisites of cognitive trust from the experiential drivers of customer loyalty.

Finally, the relatively R^2 values for CT and CL confirm the high explanatory power of the integrated framework, proving that the structural model accounts for a significant portion of variance in digital banking relationship outcomes. This strong explanatory capacity suggests that predicting long-term customer relationships in FinTech environments requires a simultaneous focus on both functional utility and risk barriers. Traditional technology acceptance models often generate limited explanatory power in financial contexts because they overlook data vulnerabilities. By incorporating privacy and security perceptions alongside perceived usefulness, this integrated model creates a comprehensive predictive framework, capturing both the practical incentives and the safety prerequisites that drive modern digital banking interactions.

This study offers several important theoretical insights for researching AI-driven financial services. First, the results reshape the application boundaries of Privacy Calculus Theory within highly regulated environments. When personalized recommendations exhibit high quality, customers reframe data sharing as a reassuring indicator of professional financial management rather than a surveillance risk. Second, this study advances the Technology Acceptance Model by showing that perceived usefulness in AI-enabled banking is a dynamic assessment. This evaluation changes over time, interacting closely with privacy-security perceptions as users accumulate service experience. Finally, the distinct causal pathways driving trust and loyalty refine Trust-Commitment Theory. The findings show that institutional trust depends heavily on governance signals, whereas customer loyalty responds more directly to functional service value. Therefore, future FinTech models should treat these two constructs as asymmetric relational outcomes rather than interchangeable dependent variables.

From a practical standpoint, the findings address a strategic tension that financial institutions frequently mismanage. Many banks and FinTech firms handle personalization investments and privacy compliance as separate, competing operational priorities. This study proves that such separation reduces business effectiveness. Consumers respond positively to personalization precisely because they connect accurate recommendations with competent data governance. Consequently, transparent data protection serves as a valuable commercial asset, meaning that institutions must communicate their privacy practices clearly to users alongside internal technical implementation. Additionally, with personalization quality exert-

Table 3: *Structural model path coefficients and hypothesis testing*

Hypothesis	Path	β	t-V	p	95% CI		f^2	VIF
Direct Effects								
H1	AIPR →PS	0.631	14.832	0.000	0.538	0.705	0.662	1.000
H2	PS → CL	0.214	3.584	0.000	0.094	0.326	0.071	1.662
H3	PS → CT	0.567	9.102	0.000	0.432	0.678	0.580	1.662
H4	AIPR →CL	0.631	12.376	0.000	0.527	0.726	0.621	1.662
H5	AIPR →CT	0.330	5.059	0.000	0.211	0.467	0.197	1.662
Indirect Effects (Mediation)								
H6	AIPR →PS→CL	0.135	3.389	0.001	0.060	0.215		
H7	AIPR → *PS* → CT	0.358	7.554	0.000	0.263	0.450		

Note(s): $p < 0.01, \beta =$ Path Coefficient, t-V = T-Statistics, $p = p$-value, 95% CI = Bootstrapping 95% BC CI, VIF = The VIF of inner model
Source(s): Crafted by authors

ing a stronger direct impact on loyalty than on trust, financial institutions must recognize that convenience-driven customer retention creates a vulnerable relationship, prompting them to approach personalization capabilities and privacy governance as complementary investments to prevent rapid customer churn during security incidents.

5 Conclusions

This study examined how AI-driven personalized recommendations shape customer trust and loyalty in digital banking, with privacy and security perceptions serving as a mediating variable. Using PLS-SEM analysis of data from 284 Chinese digital banking users, and grounded in Privacy Calculus Theory, the Technology Acceptance Model, and Trust-Commitment Theory, all seven hypotheses received empirical support. The results confirm that high-quality personalized recommendations significantly improve customer privacy and security perceptions, demonstrating that users interpret precision services as evidence of competent data governance rather than as privacy threats.

Furthermore, the structural framework proves that while personalized recommendation features act as the primary driver of continuous customer loyalty, privacy and security perceptions remain the central determinant for establishing institutional trust. This study advances the existing FinTech literature by dismantling the traditional dichotomy between service customization and data safety, proving their strong complementarity in digital financial interactions.

This study has several limitations that suggest productive pathways for future inquiry. The reliance on a cross-sectional design and a single-country sample of Chinese users may constrain the generalizability of these insights. Future academic endeavors should expand these boundaries by incorporating variables such as algorithmic fairness, AI ethics, and user digital literacy. Additionally, implementing longitudinal designs or comparative analyses across diverse regulatory jurisdictions would capture the dynamic, long-term impacts of emerging generative AI and real-time behavioral analytics on evolving consumer behavior.

References

[1] U. Noreen, A. Shafique, Z. Ahmed, and M. Ashfaq, "Banking 4.0: Artificial intelligence (AI) in banking industry & consumer's perspective," *Sustainability*, vol. 15, p. 3682, 2023, doi: 10.3390/su15043682.

[2] T. A. Abdulsalam and R. B. Tajudeen, "Artificial intelligence (AI) in the banking industry: A review of service areas and customer service journeys in emerging economies," *Bus. Manage. Compass*, vol. 68, pp. 19–43, 2024, doi: 10.56065/9hfvrq20.

[3] A. Turner, "How marketing leaders are experimenting with, and benefitting from, artificial intelligence in banking," *ABA Banking J.*, 2024. [Online]. Available: https://bankingjournal.aba.com/2024/12/how-marketing-leaders-are-experimenting-with-and-benefitting-from-artificial-intelligence-in-banking/. Accessed: Aug. 22, 2025.

[4] M. Ashrafuzzaman, R. Parveen, M. A. Sumiya, and A. Rahman, "AI-powered personalization in digital banking: A review of customer behavior analytics and engagement," *Amer. J. Interdiscip. Stud.*, vol. 6, pp. 40–71, 2025, doi: 10.63125/z9s39s47.

[5] R. B. Ikhsan *et al.*, "An empirical study on the use of artificial intelligence in the banking sector of indonesia by extending the TAM model and the moderating effect of perceived trust," *Digit. Bus.*, vol. 5, p. 100103, 2025, doi: 10.1016/j.digbus.2024.100103.

[6] J.-G. Martínez-Navalón, M. Fernández-Fernández, and F. P. Alberto, "Does privacy and ease of use influence user trust in digital banking applications in spain and portugal?" *Int. Entrep. Manage. J.*, vol. 19, pp. 781–803, 2023, doi: 10.1007/s11365-023-00839-4.

[7] J. Lappeman, S. Marlie, T. Johnson, and S. Poggenpoel, "Trust and digital privacy: Willingness to disclose personal information to banking chatbot services," *J. Financ. Serv. Mark.*, vol. 28, pp. 337–357, 2023, doi: 10.1057/s41264-022-00154-z.

[8] K. D. Martin and P. E. Murphy, "The role of data privacy in marketing," *J. Acad. Mark. Sci.*, vol. 45, pp. 135–155, 2017, doi: 10.1007/s11747-016-0495-4.

[9] E. Mogaji and N. P. Nguyen, "Managers' understanding of artificial intelligence in relation to marketing financial services: Insights from a cross-country study," *Int. J. Bank Mark.*, vol. 40, pp. 1272–1298, 2022, doi: 10.1108/IJBM-09-2021-0440.

[10] H. H. H. Aldboush and M. Ferdous, "Building trust in fintech: An analysis of ethical and privacy considerations in the intersection of big data, AI, and customer trust," *Int. J. Financial Stud.*, vol. 11, p. 90, 2023, doi: 10.3390/ijfs11030090.

[11] M. Rahman, T. H. Ming, T. A. Baigh, and M. Sarker, "Adoption of artificial intelligence in banking services: An empirical analysis," *Int. J. Emerg. Markets*, vol. 18, pp. 4270–4300, 2023, doi: 10.1108/IJOEM-06-2020-0724.

[12] L. Kim, T. Jindabot, and S. F. Yeo, "Understanding customer loyalty in banking industry: A systematic review and meta analysis," *Heliyon*, vol. 10, p. e36619, 2024, doi: 10.1016/j.heliyon.2024.e36619.

[13] J. F. Hair, G. T. M. Hult, C. M. Ringle, and M. Sarstedt, *A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM)*, 3rd ed. in *Int. J. Res. Method Educ.*, vol. 38, pp. 220–221, 2021, doi: 10.1080/1743727X.2015.1005806.

[14] D. Lakens, "Sample size justification," *Collabra: Psychol.*, vol. 8, p. 33267, 2022, doi: 10.1525/collabra.33267.

[15] F. Faul, E. Erdfelder, A. Buchner, and A.-G. Lang, "Statistical power analyses using G*power 3.1: Tests for correlation and regression analyses," *Behav. Res. Methods*, vol. 41, pp. 1149–1160, 2009, doi: 10.3758/BRM.41.4.1149.

[16] J. A. Krosnick, "Survey research," *Annu. Rev. Psychol.*, vol. 50, pp. 537–567, 1999, doi: 10.1146/annurev.psych.50.1.537.

[17] M. K. Ward and A. W. Meade, "Dealing with careless responding in survey data: Prevention, identification, and recommended best practices," *Annu. Rev. Psychol.*, vol. 74, pp. 577–596, 2023, doi: 10.1146/annurev-psych-040422-045007.

[18] P. M. Podsakoff, N. P. Podsakoff, L. I. Williams, Huang C, and J. Yang, "Common method bias: It's bad, it's complex, it's widespread, and it's not easy to fix," *Annu. Rev. Organ. Psychol. Organ. Behav.*, vol. 11, pp. 17–61, 2024, doi: 10.1146/annurev-orgpsych-110721-040030.

[19] J. F. Hair, J. J. Risher, M. Sarstedt, and C. M. Ringle, "When to use and how to report the results of PLS-SEM," *Eur. Bus. Rev.*, vol. 31, pp. 2–24, 2019, doi: 10.1108/EBR-11-2018-0203.

[20] N. Kock, "Common method bias in PLS-SEM: A full collinearity assessment approach," *Int. J. e-Collab.*, vol. 11, pp. 1–10, 2015, doi: 10.4018/ijec.2015100101.

[21] N. Kock, "Harman's single factor test in PLS-SEM: Checking for common method bias," *Laredo, TX, USA: ScriptWarp Systems*, Tech. Rep., 2021.

[22] M. A. Memon, T. Ramayah, J.-H. Cheah, H. Ting, F. Chuah, and T. H. Cham, "Pls-sem statistical programs: A review," *J. Appl. Struct. Equ. Model.*, vol. 5, pp. i–xiv, 2021, doi: 10.47263/JASEM.5(1)06.

[23] C. Fornell and D. F. Larcker, "Evaluating structural equation models with unobservable variables and measurement error," *J. Marketing Res.*, vol. 18, pp. 39–50, 1981, doi: 10.2307/3151312.

[24] J.-M. Becker, J.-H. Cheah, R. Gholamzade, C. M. Ringle, and M. Sarstedt, "PLS-SEM's most wanted guidance," *Int. J. Contemp. Hosp. Manag.*, vol. 35, pp. 321–346, 2023, doi: 10.1108/IJCHM-04-2022-0474.

The Evolution of Governance Discourse in Uniswap DAO By Using BERTopic

Miao Peng[1*] and Nathapon Udomlertsakul[2]

[1,2]International College of Digital Innovation, Chiang Mai University, Chiang Mai, 50200, Thailand
E-mail: miao_p@cmu.ac.th, nathapon.u@cmu.ac.th
(*corresponding author)

Abstract

This paper examines how governance discourse evolves within decentralized autonomous organizations (DAOs). Using a dataset of 405 Uniswap governance forum discussions from 2020 to 2026, the research applies BERTopic to identify dominant governance themes and examines their distribution across four governance periods. The results show clear shifts in discussion priorities. Early discourse focuses more on fee switches, treasury governance, proposal procedures, and participation, while later periods show greater attention to protocol deployment, delegation, governance coordination, and ecosystem management. These findings indicate that governance discourse becomes more differentiated as Uniswap DAO develops. The paper contributes to DAO governance research by demonstrating how topic modeling can be used to study discourse evolution in decentralized governance forums.

KEYWORDS: Decentralized Autonomous Organization (DAO), DeFi Governance; Governance Discourse, Topic Modeling, Uniswap

1 Introduction

Decentralized autonomous organizations (DAOs) have emerged as an important governance form in blockchain ecosystems. Although DAO governance is often associated with token voting and smart-contract procedures, governance also develops through public discussions where participants debate proposals, set priorities, and interpret emerging challenges.

Uniswap DAO provides a useful case for studying this process. As one of the most influential decentralized finance protocols, its governance forum contains extensive public discussions on proposals, delegation, treasury decisions, and protocol development. This dataset allows governance discourse to be examined across multiple periods.

Recent developments in decentralized finance (DeFi) have also increased the importance of regulatory and legal concerns in DAO governance. As DeFi protocols expand and attract wider public adoption, regulators have begun to scrutinize issues related to securities law, compliance responsibility, anti-money laundering obligations, and liability attribution. In the case of Uniswap, public regulatory events such as the SEC inquiry and the Wells Notice issued to Uniswap Labs have drawn significant attention from the broader crypto community. These developments suggest that DAO governance discussions may increasingly incorporate legal and regulatory considerations alongside technical and organizational concerns. Governance forums, therefore provide not only a space for coordination and proposal deliberation, but also a venue where participants interpret and respond to changing external regulatory environments.

Existing studies have examined DAO governance and blockchain-based coordination, but less attention has been given to how governance discourse evolves over time. In particular, limited research has traced how governance topics shift or how regulatory concerns appear in governance discussions.

This study addresses this gap through a longitudinal analysis of Uniswap DAO forum discussions using BERTopic. The research asks: How does governance discourse in the Uniswap DAO forum evolve over time?

2 Literature Review

Research on DAOs has primarily examined governance outcomes using on-chain indicators such as voting participation, token distribution, and delegation behavior. Empirical studies show that participation is uneven and that voting power often concentrates among a limited number of token holders [1]. Delegation mechanisms have been introduced to address low participation, yet they frequently channel influence toward active delegates [2,3]. As a result, governance in large DeFi protocols displays structured coordination even though decision rights remain formally open. While this literature provides evidence about participation structure, it mainly evaluates governance after decisions are made and provides limited insight into how governance choices are discussed and justified beforehand.

A separate body of work focuses on the regulation of decentralized finance. Legal scholarship describes DeFi as operating in an environment of jurisdictional uncertainty and evolving enforcement expectations [4]. Regulatory attention often concerns liability attribution, compliance responsibility, and the legal status of development teams or affiliated organizations[5]. However, most of this work studies DeFi from an external legal perspective. It says less about how regulatory concerns appear inside DAO governance discussions themselves. In large DeFi protocols such as Uniswap, regulatory concerns may gradually become part of governance discourse as participants respond to a changing external environment. Examining governance discussions, therefore, helps reveal when and how such concerns become more visible over time.

Methodologically, computational text analysis has been widely applied to political and organizational communication. Automated content analysis enables researchers to detect recurring themes and track discussion dynamics across large document collections [6]. Topic modeling methods identify latent thematic structures in textual corpora [7], and recent neural approaches improve semantic coherence in heterogeneous online discussions [8]. Despite the availability of public governance forums, these approaches have rarely been used to examine DAO governance longitudinally. Most empirical DAO research relies on transaction data and voting records, while governance discussions remain underexplored as a data source.

This paper connects these strands of research by examining the evolution of governance discourse in Uniswap DAO over time using BERTopic and by tracing the emergence of regulatory concerns across different governance periods. BERTopic was selected because it combines transformer-based document embeddings, dimensionality reduction, density-based clustering, and class-based TF-IDF topic representation. This architecture enables the model to group documents according to semantic similarity and generate interpretable topic representations, which are suitable for analyzing heterogeneous online forum discussions. Previous methodological research shows that BERTopic can generate coherent topic representations by combining transformer embeddings with class-based TF-IDF, and comparative studies have also demonstrated its usefulness for analyzing social media and other heterogeneous online texts [8,9]. Compared with traditional bag-of-words models such as LDA, BERTopic is appropriate for this study because it represents documents using contextual embeddings rather than relying only on word co-occurrence patterns. Given the relatively small and noisy nature of DAO forum data, the topic modeling results were further interpreted through manual inspection of representative keywords and representative documents.

3 Research Methodology

3.1 Research Design

This study adopts a longitudinal text analysis design to examine how governance discourse in Uniswap DAO evolves over time. The analysis focuses on governance forum discussions, which record proposal debates, governance coordination, and institutional developments within the DAO. These discussions provide observable evidence of how governance concerns emerge and change during different stages of organizational development. The research design identifies major discussion topics within the corpus and then examines how these topics are distributed across governance periods. This approach makes it possible to trace shifts in governance priorities and observe how the focus of discussion evolves over time.

3.2 Data Source and Unit of Analysis

The empirical data comes from the Uniswap Governance Forum, the primary public platform where community members discuss governance proposals and institutional issues. The dataset covers the period from September 8 2020, to January 18 2026, and initially includes 920 forum posts. After removing duplicates, empty entries, and non-substantive texts, the final corpus contains 405 documents. Each document is treated as a unit of analysis in the topic modeling process.

3.3 Data Preparation

Before topic modeling, the corpus is preprocessed to improve consistency. The preprocessing procedure includes removing duplicate entries, filtering non-substantive texts, and cleaning formatting noise. Basic normalization is applied to prepare the documents for embedding and clustering.

3.4 Periodization

To analyze the temporal evolution of governance discourse, the dataset was divided into four governance periods. The period boundaries were defined according to major public events that changed the institutional and organizational environment of the Uniswap ecosystem. This event-based periodization allows the study to compare governance discussions across different stages of DAO development and to connect internal governance discourse with broader changes in the regulatory and organizational context of decentralized finance.

Table 1: *Governance Periodization*

Period	Time Range	Boundary Event
P1: Governance Formation	8 September 2020-2 September 2021	No publicly visible regulatory scrutiny associated with the protocol
P2: Governance Expansion	3 September 2021-9 August 2022	Public reporting of SEC inquiry
P3: Institutional Adjustment	10 August 2022-9 April 2024	Create the Uniswap Foundation proposal and foundationbased ecosystem coordination
P4: Governance Stabilization	10 April 2024-18 January 2026	Public disclosure of SEC Wells Notice to Uniswap Labs

P1 represents the initial governance formation stage, covering the period before publicly visible regulatory scrutiny associated with Uniswap Labs. During this stage, governance discussions mainly concerned foundational issues such as proposal procedures, treasury governance, voting rules, and participation mechanisms.

P2 begins on 3 September 2021, when public reporting indicated that the U.S. Securities and Exchange Commission had opened an inquiry into Uniswap Labs [10]. This event is used as a boundary because it marked the emergence of visible external regulatory attention toward the Uniswap ecosystem. Therefore, P2 is interpreted as a governance expansion period in which Uniswap governance developed under increasing external scrutiny and began on 10 August 2022, when the "Create the Uniswap Foundation" proposal entered the governance discussion process at the consensus-check stage [11]. This event is used as a boundary because the proposed foundation represented a shift from early governance formation toward more formalized ecosystem coordination, grant allocation, governance support, and institutional capacity building. The Uniswap Foundation was designed to support builders, researchers, organizers, academics, analysts, and other contributors in growing the protocol and planning for its future. Therefore, P3 is interpreted as an institutional adjustment period in which governance discussions increasingly moved beyond basic voting procedures and treasury debates toward ecosystem development, organizational support, and governance coordination.

P4 begins on 10 April 2024, when Uniswap Labs publicly disclosed that it had received a Wells Notice from the SEC [12]. This event is used as a boundary because it represented a more direct enforcement-stage regulatory development and intensified the legal and institutional context surrounding Uniswap governance. Therefore, P4 is interpreted as a governance stabilization period in which governance discussions occurred under stronger regulatory visibility and increasing institutional pressure.

The purpose of this periodization is not to claim that these events mechanically determined governance discourse. Instead, these events are used as observable temporal markers for comparing how governance priorities changed across different stages of Uniswap DAO's institutional development.

3.5 Topic Modeling with BERTopic

This study uses BERTopic modeling to identify recurring themes in Uniswap DAO governance discourse. It first converts the cleaned forum texts into semantic embeddings with the pre-trained all-MiniLM-L6-v2 sentence transformer model. Next, the analysis applies UMAP for dimensionality reduction and HDBSCAN for clustering. In the clustering step, the model sets min_cluster_size=10 to reduce very small clusters and improve topic stability. For topic representation, the analysis uses a CountVectorizer with stop_words = "english," ngram_range = (1, 2), and min_df = 3. This setup removes common English stop words, keeps both single words and two-word phrases, and excludes terms that appear in fewer than three documents.

The model also uses calculate_probabilities = True, so each document receives both a topic assignment and a topic probability score. After the model generates the topic clusters, the analysis reviews the representative keywords and representative texts for each topic. Based on this review, the study assigns a final topic name to each cluster. It then uses these in the longitudinal analysis to compare topic prevalence across governance periods and trace how governance discourse changes over time.

3.6 Longitudinal Topic Analysis

After topic extraction, the identified topics were analyzed across governance periods. This step examines the temporal distribution of topics and compares their relative

3.7 Reliability and Validation

Several steps were taken to improve the reliability of the analysis. The data preparation process, embedding model, and main BERTopic settings were reported clearly to ensure the procedure's transparency. Topic names were assigned through manual review of representative keywords and representative texts so that each topic reflected a coherent discussion theme. The study also compared outputs from alternative model settings during the exploratory stage to check whether the main topics remained broadly stable. In addition, period-level interpretations were checked against the original forum texts to ensure that the reported discourse shifts were supported by the underlying discussions.

4 Research Results and Discussions

4.1 Topic Identification

BERTopic identifies ten dominant topics in the Uniswap governance forum discussions. The model generated multiple clusters. The outlier topic (-1) was treated as noise and excluded from the final topic interpretation and period-level proportion analysis. Among the 405 documents, 98 documents were classified as outliers, representing 24.2% of the corpus. The remaining 307 documents were used to calculate topic distributions across governance periods.

After removing the outlier cluster (-1) and examining topic coherence, ten interpretable topics were retained for analysis. Each topic reflects a recurring theme in governance debates. The topics capture discussions related to protocol upgrades, treasury management, governance procedures, delegation mechanisms, and ecosystem coordination.

Figure 1 presents the two-dimensional UMAP projection of documents generated by the BERTopic model. Each point represents an individual governance proposal document, while colors indicate different topic clusters identified by the model.

The visualization shows that most topics form relatively distinct semantic clusters, indicating strong topic coherence and effective separation among governance discussion themes. Topics such as Topic 3 and Topic 1 exhibit dense and compact distributions, indicating highly focused discussions within these governance areas. In contrast, several topics located near the center, including Topic 9, display partial overlap with neighboring clusters, reflecting broader governance discussions that share semantic similarities with multiple topics.

Table 2: *BERTopic Modeling Procedure*

Process	Formula / Model	Parameter	Purpose
Data Preprocessing	Text Cleaning	Removal of URLs, code blocks, HTML tags, and markdown formatting; conversion of text to lowercase; whitespace normalization	Improve corpus consistency
Text Embedding	Sentence-BERT	all-MiniLM-L6-v2 (Sentence Transformer model generating 384-dimensional embeddings)	Transform documents into semantic vectors
Dimensionality	UMAP	n_neighbors = 15, n_components = 5, min_dist= 0.0, metric="cosine", random_state= 42	Reduce dimensionality while preserving semantic neighborhood structure
Topic Clustering	HDBSCAN	min_cluster_size = 10; metric= "euclidean"; cluster_selection_method= "eom"; prediction_data=True	Reduce very small clusters and improve topic stability
Noise Detection	HDBSCAN outlier detection	$c_i = -1$	Remove non-coherent documents
Topic Representation	c-TF-IDF	stop_words = "english"; ngram_range = (1,2); min_df = 3	Extract representative topic keywords
Topic Probability Estimation	$P(c_i = k \mid d_i)$	calculate_probabilities = True	Generate topic probability scores for each document
Topic Interpretation	Manual Review	Representative keywords and documents	Assign interpretable topic names

Notation.
c_i refers the topic assignment of document i;
d_i refers document i;
k refers to a topic cluster.
$c_i = -1$ indicates that the document is classified as noise or an outlier by HDBSCAN.

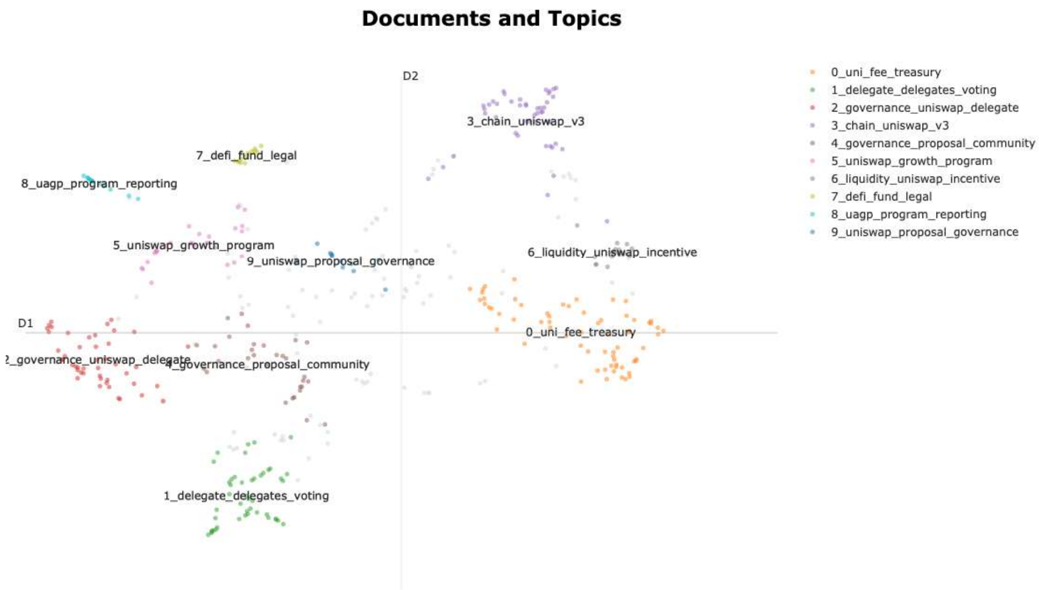

Figure 1: *UMAP Projection of BERTopic Document Clusters*

Topic interpretation is based on the examination of representative keywords and representative documents for each cluster. Table 3 presents the final topic names and their main keywords. Figure 2 visualizes the top 5 keyword importance scores across topics.

Several topics appear prominently in the corpus. Fee Switch and Treasury Governance (Topic 0) is the largest topic, followed by the DAO Governance Structure and Delegates (Topic 2), Delegation, Voting and Participation Incentives (Topic 1), and Protocol Deployment and Cross-Chain Expansion (Topic 3). Governance Proposal Procedures and Voting Rules (Topic 4) also appear frequently. These topics show that Uniswap governance discussions cover financial governance, protocol expansion, representation, procedural coordination, and institutional development.

The topic structure further indicates that governance discourse extends beyond formal voting. Forum discussions frequently address resource allocation, participation mechanisms, delegate coordination, and ecosystem initiatives. The diversity of governance themes suggests that DAO governance increasingly functions as a multidimensional coordination process rather than a purely token-voting mechanism.

The coexistence of procedural, technical, financial, and regulatory topics also indicates that governance functions within the DAO become increasingly differentiated as the ecosystem matures. As governance expands beyond proposal voting and treasury allocation, discussions gradually incorporate broader forms of organizational coordination and ecosystem management.

Table 3: *Topic Keywords Summary and Name*

Topic	Count	Top 5 keywords	Final topic name
0	65	uni, fee, treasury, uniswap, switch,	Fee Switch and Treasury Governance
1	45	delegate, delegates, voting, delegation, participation	Delegation, Voting, and Participation Incentives
2	45	governance, uniswap, delegate, dao, proposals	DAO Governance Structure and Delegate Ecosystem
3	45	chain, uniswap, v3, network, uniswap v3	Protocol Deployment and Cross-Chain Expansion
4	30	governance, proposal, community, vote, quorum,	Governance Proposal Procedures and Voting Rules
5	25	uniswap, growth, program, ecosystem, incentives	Growth Programs and Grant Allocation
6	16	liquidity, uniswap, incentive, pools, mining	Liquidity Incentives and Pool Reward Design
7	13	defi, fund, legal, regulatory, defense	Legal and Institutional Governance Issues
8	12	uagp, program, reporting, arb, arbitrum	Grant Program Reporting and Ecosystem Coordination
9	11	uniswap, proposal, governance, celo, governor	Foundation and Ecosystem Governance

Note. celo refers to the Celo blockchain ecosystem;
uagp refers to the Uniswap Arbitrum Grant Program;
arb refers to the governance token of the Arbitrum ecosystem.

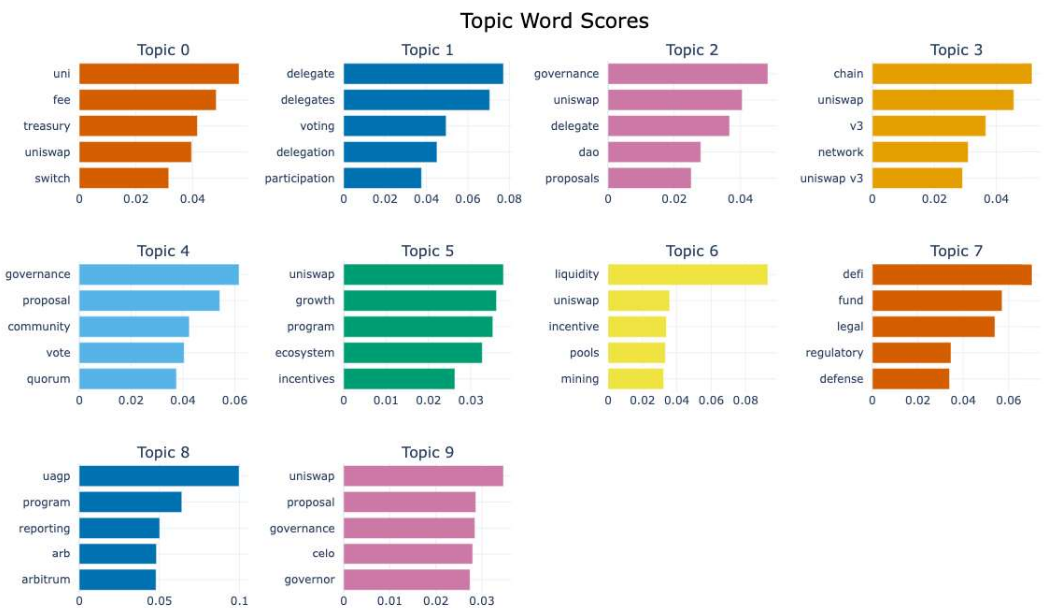

Figure 2: *Topic Keyword Scores Across Identified Topics*

4.2 Topic Composition across Governance Periods

The distribution of topics changes over time, with some governance concerns appearing more prominently in earlier stages and others becoming increasingly important in later periods. This pattern suggests that the focus of governance discussions shifts alongside the institutional development of the Uniswap DAO.

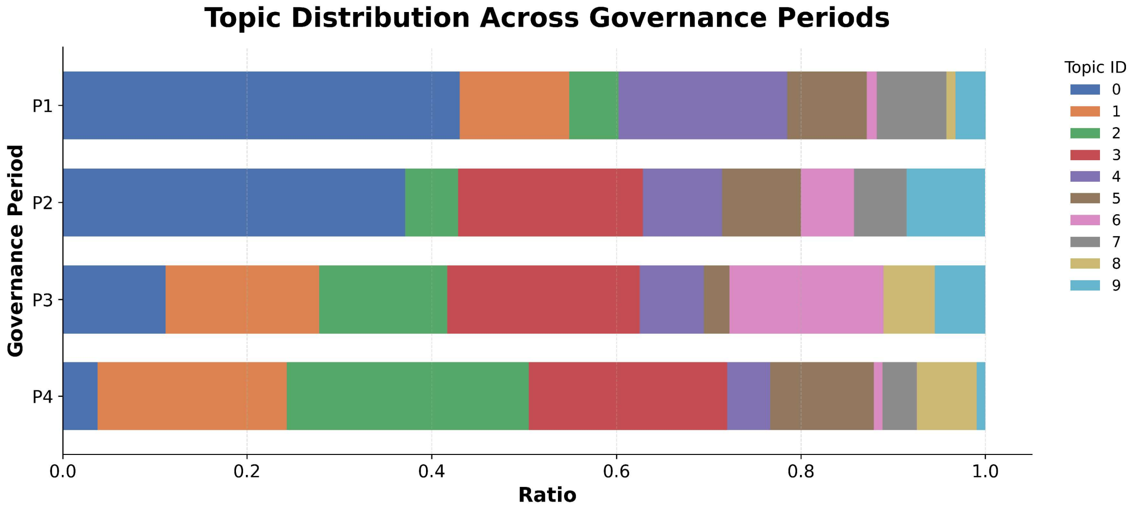

Figure 3: *Evolution of Topic Proportions Across Governance Periods*

Figure 3 shows that governance discourse evolves across different governance periods.

In P1, discourse is strongly dominated by Fee Switch and Treasury Governance (Topic 0), which accounts for 43.01% of all discussions. Governance Proposal Procedures and Voting Rules (Topic 4) represents 18.28%, while Delegation, Voting, and Participation Incentives (Topic 1) accounts for 11.83%. Discussions in this stage focus primarily on foundational governance issues such as treasury decisions, proposal formation, and participation mechanisms. This pattern reflects the early-stage governance priorities of the DAO, where establishing core governance structures and decision-making processes becomes the central concern.

In P2, governance discussions expand beyond foundational governance concerns and increasingly involve Protocol Deployment and Cross-Chain Expansion (Topic 3), which accounts for 20.00% of discussions. Although Fee Switch and Treasury Governance (Topic 0) remain the dominant topics at 37.14%, their relative prominence declines compared with P1. Governance Proposal Procedures and Voting Rules (Topic 4), Growth Programs and Grant Allocation (Topic 5), and Foundation and Ecosystem Governance (Topic 9) each account for 8.57% of discussions. This shift suggests that governance priorities gradually extend from internal governance formation toward ecosystem growth and protocol expansion.

In P3, governance discourse becomes more diversified. Protocol Deployment and Cross-Chain Expansion (Topic 3) becomes the largest topic, representing 20.83% of discussions. Delegation, Voting, and Participation Incentives (Topic 1) and Liquidity Incentives and Pool Reward Design (Topic 6) each account for 16.67%, while DAO Governance Structure and Delegate Ecosystem (Topic 2) accounts for 13.89%. No single topic dominates the period, indicating increasing governance complexity and broader organizational coordination concerns.

Governance discussions during this stage cover a wider range of technical, organizational, and incentive-related issues.

In P4, governance discourse increasingly reflects institutional coordination and ecosystem management. DAO Governance Structure and Delegate Ecosystem (Topic 2) becomes the most prominent topic, accounting for 26.17% of discussions. Protocol Deployment and Cross-Chain Expansion (Topic 3) represents 21.50%, while Delegation, Voting, and Participation Incentives (Topic 1) account for 20.56%. In contrast, Fee Switch and Treasury Governance (Topic 0) declines to only 3.74% of discussions. This pattern suggests that governance discussions gradually shift from foundational governance formation toward more institutionalized forms of coordination involving specialized governance actors, governance management processes, and ecosystem-level coordination.

The increasing visibility of delegation-related discussions in later periods also suggests that governance increasingly depends on semi-formal governance structures and active governance participants. Rather than relying solely on open voting participation, governance coordination appears to become increasingly structured around delegates, governance contributors, and ecosystem coordination mechanisms.

4.3 Topic Concentration and Temporal Shifts

Figure 4 provides a clearer view of topic concentration across periods and highlights several important temporal dynamics in Uniswap DAO governance discourse.

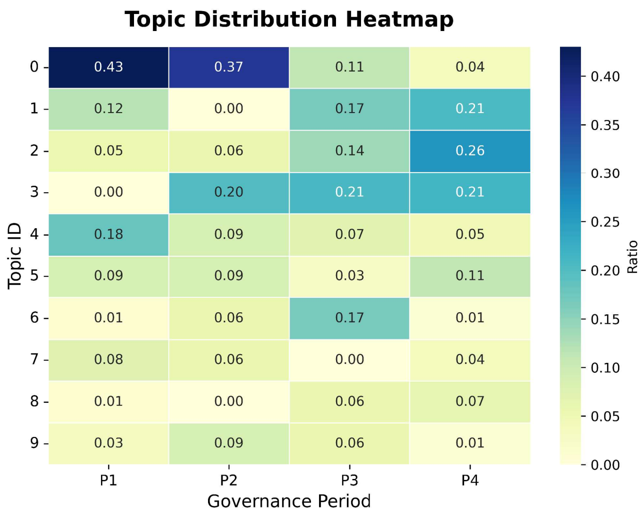

Figure 4: *Heatmap of Topic Concentration Across Governance Periods.*

First, Fee Switch and Treasury Governance (Topic 0) is highly concentrated in P1 and then declines steadily in later periods. This pattern suggests that treasury governance and fee allocation were central concerns during the early governance formation stage of the DAO.The decline of this topic in later periods may indicate that foundational treasury governance becomes relatively less contested once core governance procedures and treasury management mechanisms stabilize.

Second, Protocol Deployment and Cross-Chain Expansion (Topic 3) receives relatively limited attention in P1 but becomes increasingly prominent from P2 onward and remains highly visible in P3 and P4. This trend suggests that governance priorities gradually shift toward managing ecosystem scalability, protocol deployment, and cross-chain coordination as the DAO ecosystem expands. Governance discussions increasingly focus on coordinating growth across different blockchain infrastructures and maintaining broader ecosystem integration.

Third, Delegation, Voting, and Participation Incentives (Topic 1) and DAO Governance Structure and Delegate Ecosystem (Topic 2) become more prominent in the later governance periods, particularly in P3 and P4. The growing visibility of these topics suggests increasing attention to delegation systems, governance coordination, and organizational management. This pattern reflects a gradual institutionalization of governance within the DAO. Governance discussions increasingly focus on delegation systems, governance coordination mechanisms, voting participation, and the role of active governance actors. This pattern reflects a gradual institutionalization of governance, where governance increasingly depends on specialized participants and semi-formal coordination structures. The growing importance of delegation-related discourse also aligns with previous studies suggesting that governance participation in DAOs often becomes concentrated among active delegates and governance contributors. Although governance rights formally remain open to token holders, governance coordination increasingly appears to rely on a smaller group of active governance participants.

Fourth, several topics show more concentrated visibility during specific governance stages. Liquidity Incentives and Pool Reward Design (Topic 6) become more visible in P3. Legal and Institutional Governance Issues (Topic 7) do not follow a simple upward trend. Instead, this topic appears intermittently across the governance timeline, with visible proportions in P1, P2, and P4, while being absent or marginal in P3. This pattern suggests that legal and institutional concerns may be event-sensitive rather than gradually increasing over time. In contrast, Grant Program Reporting and Ecosystem Coordination (Topic 8) becomes more visible in the later periods, especially after the development of foundation- and grant-related ecosystem coordination mechanisms. Although these topics occupy a smaller share of overall discussions, their increasing visibility suggests that governance concerns gradually expand beyond technical decision-making to include regulatory adaptation, institutional legitimacy, and ecosystem accountability.

4.4 The Evolution of Governance Priorities

A longitudinal view of the results suggests an observable evolution in governance priorities within the Uniswap DAO. In the early stage, governance discourse is mainly organized around treasury decisions, fee switch discussions, proposal procedures, and voting rules. These topics reflect a voting-centered governance model, in which the central problem is how to establish legitimate decision-making procedures and mobilize token-holder participation.

As the DAO develops, governance discourse moves beyond basic voting procedures and increasingly focuses on delegation, governance structure, protocol deployment, and ecosystem coordination. This shift indicates that governance capacity becomes more important than voting participation alone. Delegates and active contributors begin to function as coordination actors who translate community preferences into operational decisions, proposal development, and ecosystem management.

In the later stages, governance discourse further reflects institutional adaptation. The increasing prominence of delegation, governance structure, and ecosystem coordination suggests that Uniswap DAO gradually develops semi-formal coordination mechanisms. This does not necessarily mean that decentralization has failed. Rather, it suggests that decentralized governance may require specialized roles and structured coordination mechanisms in order to operate at scale.

Legal and institutional governance discussions remain relatively small compared with the major governance topics, but their presence suggests that DAO governance is not isolated from external institutional environments. Rather than showing a simple upward trend, Topic 7 appears intermittently across the governance timeline, indicating that legal and regulatory concerns may be event-sensitive. Regulatory issues therefore did not dominate Uniswap DAO governance discourse, but they formed a secondary institutional layer that occasionally entered governance discussions when external pressure became more visible.

Overall, the evolution of Uniswap DAO governance can be understood as a transition from voting-centered governance toward institutionally coordinated governance. This finding contributes to DAO governance research by showing that decentralization does not eliminate organizational structure. Instead, decentralized governance may produce new forms of coordination that combine open participation with delegation, specialization, and institutional adaptation.

5 Conclusion

This paper examines the evolution of governance discourse in Uniswap DAO through a longitudinal topic modeling analysis of governance forum discussions from 2020 to 2026. Using BERTopic modeling, the study identifies major governance themes and analyzes how governance priorities change across different governance periods.

The findings show that governance discourse in Uniswap DAO evolves from foundational governance concerns toward more complex forms of institutional coordination. Early discussions focus mainly on treasury governance, fee switch decisions, proposal procedures, and participation mechanisms, while later discussions increasingly involve protocol deployment, delegation systems, and ecosystem management. Legal and institutional issues also appear as a smaller but recurring theme, suggesting that regulatory concerns form part of the broader institutional context of DAO governance rather than a dominant discussion focus.

More importantly, the findings suggest that DAO governance cannot be understood merely as token-based voting. As governance develops, coordination increasingly depends on delegates, ecosystem contributors, and semi-formal governance structures. This raises an important question about the nature of decentralization: DAOs may begin as open and community-driven systems, but their long-term operation often requires specialization, representation, and organizational coordination.

This does not necessarily mean that decentralization has failed. Rather, it suggests that decentralized governance may evolve into a hybrid organizational form. In this form, open participation remains important, but governance efficiency, scalability, and institutional stability increasingly depend on structured coordination mechanisms. The evolution of Uniswap DAO, therefore, reflects a broader tension between decentralized participation and the practical need for governance capacity.

The limited but recurring visibility of legal and institutional governance discussions further suggests that DAOs do not operate outside broader institutional environments. Although legal and regulatory issues did not dominate the forum discourse, their intermittent appearance indicates that external regulatory pressure can enter DAO governance as a secondary but institutionally relevant concern. In this sense, DAO governance is not only a technical or community-based process but also an evolving institutional process shaped by both internal coordination needs and external regulatory pressures.

Methodologically, this paper demonstrates the usefulness of BERTopic for longitudinal governance discourse analysis in decentralized organizations. The findings also show the value of governance forums as an empirical data source for studying institutional evolution within DAOs.

The study has several limitations. The analysis focuses on a single DAO and relies on governance forum discussions as the primary data source. Topic interpretation also involves the researcher's judgment and may be influenced by subjective interpretation. Future research can extend this approach to multiple DAOs and combine discourse analysis with on-chain governance data to better understand the relationship between discussion and governance outcomes.

References

[1] R. Fritsch, M. Müller, and R. Wattenhofer, "Analyzing voting power in decentralized governance: Who controls DAOs?" *Blockchain: Research and Applications*, vol. 5, p. 100208, 2024, doi: 10.1016/j.bcra.2024.100208.

[2] D. Bongaerts, T. Lambert, D. Liebau, and P. Roosenboom, "Vote delegation in DeFi governance," Social Science Research Network, Rochester, NY, 2025, doi: 10.2139/ssrn.5177022.

[3] L. Weidener, "Delegated voting in decentralized autonomous organizations: A scoping review," *Frontiers in Blockchain*, 2025, doi: 10.3389/fbloc.2025.1598283.

[4] D. A. Zetzsche, D. W. Arner, and R. P. Buckley, "Decentralized finance," *Journal of Financial Regulation*, vol. 6, pp. 172–203, 2020, doi: 10.1093/jfr/fjaa010.

[5] C. Brummer, "Disclosure, Dapps, and DeFi," Social Science Research Network, Rochester, NY, 2022, doi: 10.2139/ssrn.4065143.

[6] J. Grimmer and B. M. Stewart, "Text as data: The promise and pitfalls of automatic content analysis methods for political texts," *Political Analysis*, vol. 21, pp. 267–297, 2013, doi: 10.1093/pan/mps028.

[7] D. M. Blei, A. Y. Ng, and M. I. Jordan, "Latent Dirichlet Allocation," *Journal of Machine Learning Research*, vol. 3, pp. 993–1022, 2003.

[8] M. Grootendorst, "BERTopic: Neural topic modeling with a class-based TF-IDF procedure," arXiv:2203.05794, 2022. [Online]. Available: https://arxiv.org/abs/2203.05794

[9] R. Egger and J. Yu, "A topic modeling comparison between LDA, NMF, Top2Vec, and BERTopic to demystify Twitter posts," *Frontiers in Sociology*, vol. 7, p. 886498, 2022, doi: 10.3389/fsoc.2022.886498.

[10] D. Michaels and A. Osipovich, "Regulators investigate crypto-exchange developer Uniswap Labs," *Wall Street Journal*, Sep. 3, 2021. [Online]. Available: https://www.wsj.com/finance/regulation/regulators-investigate-crypto-exchange-developer-uniswap-labs-11630666800

[11] D. Walsh, "Create the Uniswap Foundation," *Uniswap Governance Forum*, Aug. 10, 2022. [Online]. Available: https://gov.uniswap.org/t/consensus-check-create-the-uniswap-foundation/17457

[12] Uniswap Labs, "Wells Notice Response," Uniswap Labs, May 21, 2024. [Online]. Available: https://blog.uniswap.org/wells-notice-response.pdf

Automated Transaction Risk Scoring in Cryptocurrency Exchanges with a KYT Model for FATF Compliance

Xuan He[1*] and Nathapon Udomlertsakul[2]

[1,2]International College of Digital Innovation, Chiang Mai University, Chiang Mai, 50200, Thailand
E-mail: xuan_h@cmu.ac.th, nathapon.u@cmu.ac.th
(*corresponding author)

Abstract

This paper develops a Know Your Transaction (KYT) risk scoring model for cryptocurrency exchange inflow monitoring under the Financial Action Task Force (FATF) risk-based approach. The study focuses on USDT/ERC-20 inflows on Ethereum, using a 60-day observation window and one- to three-hop upstream paths. The central problem is how to translate the FATF risk-based approach, industry address labels, and observable on-chain structures into an explainable scoring process. The model defines five first-level risk entries: Obfuscation / Mixing, Cross-chain Layering, Darknet Interaction, Sanctioned Inflow, and High-risk Cluster Exposure. The five entries are selected according to three criteria: regulatory or industry basis, on-chain identifiability, and independent measurement function. The model then calculates risk through Exposure Aggregation, Flow Dynamics, and a Strong Trigger Mechanism, and maps the final score into Low, Medium, High, and Severe tiers. Three real ERC-20 address cases show that the model can distinguish a high-volume low-risk address, a high-risk-cluster-dominated address, and a mixer-related address. The case outputs are broadly consistent with external KYT tools in risk direction. The model is not proposed as a replacement for commercial KYT systems or human compliance judgment. Its value lies in providing a transparent, reviewable, and auditable inflow risk scoring model.

KEYWORDS: KYT, cryptocurrency exchange, transaction risk scoring, FATF, USDT, address labels, anti-money laundering

1 Introduction

Virtual asset transactions allow funds to move quickly across wallets, exchanges, bridges, decentralized finance (DeFi) protocols, and custodial services. On-chain records are visible, but the real controller of an address, the source of funds, and the intermediate transaction path are often unclear. This creates a compliance problem for exchanges that need to assess inflow risk rather than only customer identity. The Financial Action Task Force (FATF) is an intergovernmental AML/CFT standard-setting body established by the G7 in 1989. Its mandate later expanded from money laundering to terrorist financing and other illicit-finance risks. FATF does not operate exchange compliance systems. It issues standards and risk-based guidance that countries use to design regulation and that virtual asset service providers use to structure internal controls. In the virtual asset sector, FATF guidance requires VASPs to identify, assess, and mitigate risks related to customers, jurisdictions, products, services, and transactions [1]. The U.S. Treasury identifies DeFi-related illicit-finance exposure as a policy concern, including risks linked to decentralized services, cross-chain mechanisms, and anonymity-enhancing tools [2]. Network-analysis studies also show that token transfers can be represented as address nodes and transaction edges [3,4]. These sources support the same methodological point: virtual asset risk can be studied through both regulatory risk categories and observable on-chain structures.

Know Your Customer (KYC) is a basic part of exchange compliance. It verifies customer identity and supports customer-risk assessment. In virtual asset markets, however, risk may appear after onboarding. A customer may pass KYC while the deposit address still receives funds from a mixer, a darknet market, a sanctioned entity, a phishing wallet, a stolen-funds cluster, or another high-risk address. Hannan et al. argue that blockchain-based e-KYC can improve identity management, but it still faces limits in standardization, fraud control, and privacy protection [5]. KYC therefore cannot by itself explain the on-chain source and transaction-path risk of deposited funds.

Know Your Transaction (KYT) extends compliance attention from customer identity to transaction behavior, source of funds, and fund-flow paths. In the exchange inflow monitoring context of this study, KYT risk scoring is operationalized through four observable dimensions: the type of upstream address, the number of hops between the risk source and the target address, the value of the exposed funds, and the share of high-risk funds in the inflow structure. A reviewable KYT scoring model should also explain how the risk tier is formed, rather than providing only an opaque score.

Existing research provides a technical basis for on-chain risk analysis. Somin et al. study ERC-20 transactions through network analysis and show that token transfers can be represented as address nodes and transaction edges [3]. Papadimitriou et al. analyze crypto-asset market structure from a complex-network perspective and identify dynamic relationships among crypto-assets [4]. Huang et al. use graph-structured methods to detect misbehavior in anonymous cryptocurrency and show that on-chain relational structures can support abnormal-pattern detection [6]. These studies show that blockchain transactions are not isolated records. They can be modeled as network structures.

There is still a gap between existing research and industry practice. FATF documents provide regulatory principles, but they do not provide directly executable variables, weights, thresholds, or scoring procedures for exchanges [1]. Commercial KYT tools already use address labels, entity attribution, and path tracing, but their internal variable structures and escalation rules are usually not fully disclosed [7,8]. Academic studies discuss anomaly detection, graph classification, and illicit-transaction identification, but pay less attention to how regulatory risk, industry labels, and deposit paths can be translated into a transparent scoring model [3,4,6].

This paper addresses that gap by developing a KYT risk scoring model for cryptocurrency exchange inflow monitoring. The model translates FATF risk logic, industry address labels, and observable on-chain structures into a computable, explainable, and reviewable scoring process. It focuses on risk scoring and compliance prioritization rather than the enumeration of all forms of virtual asset crime or the replacement of commercial KYT systems.

The core contribution of the study is threefold. First, it defines five first-level risk entries for exchange inflow KYT scoring and explains why these entries are sufficient for the study scope. Second, it converts these entries into a stepwise scoring model covering Direct Exposure, Indirect Exposure, Exposure Aggregation, Flow Dynamics, Continuous Risk Aggregation, and Strong Trigger adjudication. Third, it tests the model through three real ERC-20 address cases, external KYT directional checks, and weight-sensitivity scenarios. The main output is a 0-100 explainable risk score with a risk-tier interpretation that can support alert prioritization, compliance review, and audit documentation.

2 Research Methodology

2.1 Research Scope and Unit of Analysis

The study focuses on USDT/ERC-20 inflow transactions on Ethereum. USDT/ERC-20 is selected to keep the asset type and value measurement consistent. The paper excludes other tokens, outbound transactions, off-chain behavior after cross-chain transfers, and internal exchange account movements. This boundary is used to build a reproducible baseline model and leaves other assets or transaction directions for later extensions.

The model uses the address as the unit of analysis. For each target address, it collects USDT/ERC-20 inflows within a 60-day observation window and constructs one- to three-hop upstream paths in the direction of fund origin. Let the target address be D. If C sends USDT to D, C->D is a one-hop inflow. If B sends USDT to C, B->C->D is a two-hop path. If A sends USDT to B, A->B->C->D is a three-hop path. The three-hop boundary is an operational design choice. It preserves direct and near-upstream exposure while limiting attribution decay, path noise, and excessive expansion into ordinary background activity. Paths beyond three hops may still contain useful information, but their evidential certainty and computational burden are lower for a reproducible case-based model.

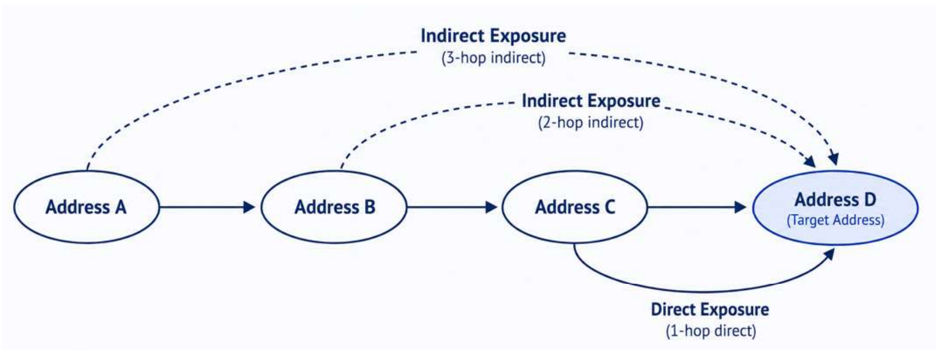

Figure 1: *The three-hop inflow tracing structure*

2.2 Selection Basis for the Five First-level Risk Entries

The model retains five first-level risk entries based on three criteria: regulatory or literature basis, industry label observability, and independent measurement function. The purpose of this classification is not to enumerate all crime names. It is to define a compact set of risk entries that can be observed on-chain, connected to industry labels, and converted into scoring variables.

Table 1 separates regulatory / literature basis from industry label basis. This separation reduces overlap in the source explanation and shows how each first-level risk entry can be operationalized through commonly used KYT labels.

Table 1: *Risk Entry Taxonomy and Retention Rationale*

Risk entry	Regulatory / literature basis	Industry label basis	Measurement function	Retention rationale
Obfuscation / Mixing	FATF identifies anonymity-enhancing tools, mixers, and weakened fund traceability as virtual-asset red flags [1].	mixer; privacy tool; obfuscation service; privacy wallet	Measures source-of-funds concealment and weakened transaction traceability.	Retained because it captures active concealment of fund origin. Without this entry, the model cannot separately explain traceability loss before exchange inflow.
Cross-chain Layering	FATF discusses complex transaction patterns and layering risk; Elliptic reports the use of bridges, DEXs, swaps, and chain-hopping in cross-chain crime [1, 9].	bridge; DEX; swap; chain-hopping	Measures path fragmentation, asset conversion, and attribution disruption within the stated Ethereum ERC-20 scope.	Retained because it captures path-structure risk. It differs from Obfuscation / Mixing: the former focuses on attribution disruption through movement and conversion, while the latter focuses on source concealment.
Darknet Interaction	FATF risk logic covers source-of-funds and counterparty risk; Chainalysis tracks darknet-market activity as a cryptocrime category [7, 8].	darknet market; illicit marketplace; darknet service	Measures exposure to explicit illicit-market origin.	Retained because darknet exposure has a clearer illicit-market meaning than a generic risky address label. Merging it into a general high-risk cluster would weaken source-of-funds explanation.
Sanctioned Inflow	FATF requires VASPs to consider geographic, customer, product, service, and transaction-related risk factors; industry practice monitors sanctioned entities and addresses [1, 8].	sanctioned entity; sanctioned jurisdiction; sanctioned address	Measures exposure to regulatory designation or sanctions-related compliance sensitivity.	Retained because sanctions exposure has noncompensatory compliance meaning. It may require enhanced due diligence, compliance escalation, or jurisdiction-specific handling, so it should not be treated as an ordinary high-risk label.
High-risk Cluster Exposure	Industry risk-label systems used by Chainalysis, TRM Labs, and similar providers identify entity clusters linked to scams, ransomware, hacks, stolen funds, illicit gambling, and high-risk platforms [8, 10].	scam; ransomware; hack; stolen funds; illicit gambling; high-risk platform	Measures label-based high-risk entity exposure through external labels, entity attribution, and address clusters.	Retained because it provides a unified entry for label-based entity risk. It avoids oversplitting first-level categories by crime name when the onchain identification logic is similar.

Table 1 explains why the model retains five first-level risk entries. The entries are not five separate formula sets. They are five risk-interpretation categories.

Obfuscation / Mixing captures weakened traceability of fund origin. Cross-chain Layering captures path fragmentation and attribution disruption caused by bridges, swaps, and multi-path transfers. These two entries may share the same exposure, amount, and ratio variables, but they explain different mechanisms. Darknet Interaction, Sanctioned Inflow, and High-risk Cluster Exposure may also share the same measurement variables. They are retained separately because their compliance meanings differ. Darknet Interaction points to illicit-market provenance. Sanctioned Inflow points to regulatory-designation and sanctions exposure. High-risk Cluster Exposure covers label-based risks such as scams, phishing, hacks, stolen funds, ransomware, and high-risk platforms.

The five-entry structure is used to avoid two problems. If the model is reduced to four entries, distinct risks such as sanctions exposure and general high-risk clusters may be merged. If the model is expanded to six or seven entries, similar label-based risks may be over-split. Scam, ransomware, hack, stolen funds, and illicit gambling differ as crime types, but they are usually identified through the same label-based entity-attribution logic. For this reason, the model keeps five semantic risk entries while allowing them to share measurement variables.

This keeps the scoring process simple enough to audit, while preserving the main compliance distinctions needed for manual review.

This structure also makes the FATF alignment reviewable. Figure 2 visualizes the same alignment in a process form, showing how FATF-related risk logic is translated into observable on-chain or label-based indicators, first-level KYT risk entries, and scoring components.

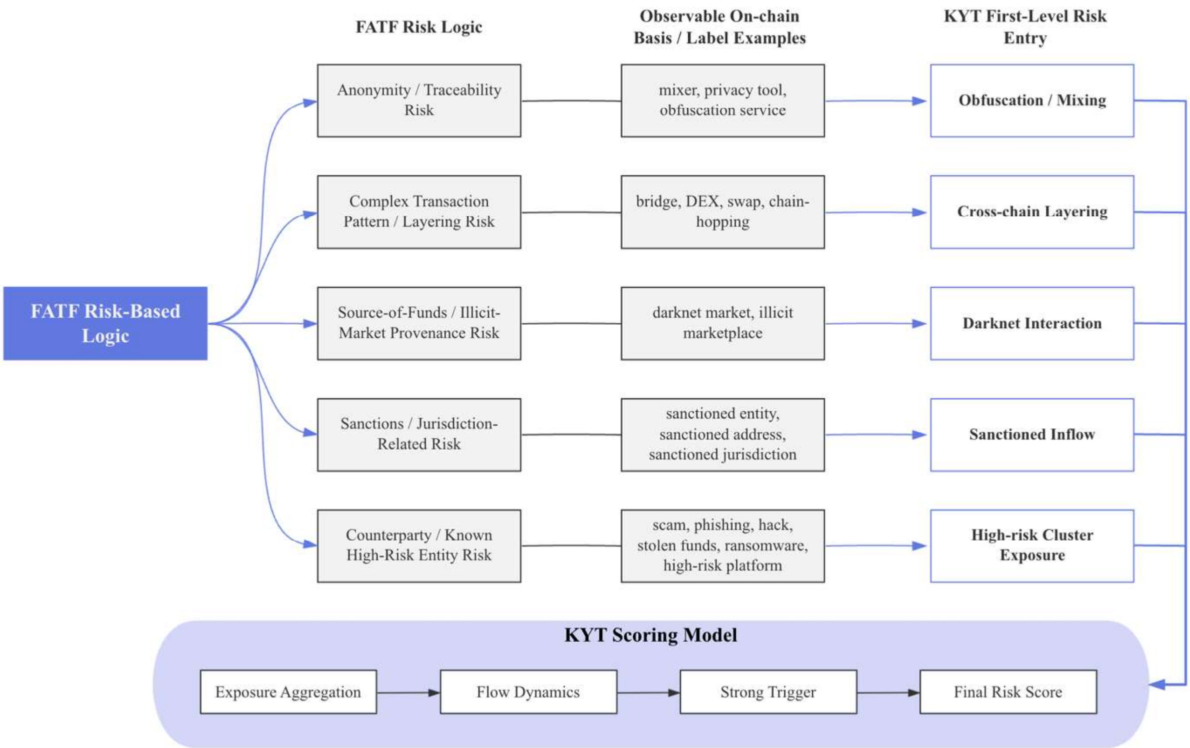

Figure 2: *Mapping Between FATF Risk-Based Logic and the KYT Scoring Model*

The figure is intended as a conceptual mapping rather than a formal classification of FATF Recommendations. It shows that FATF-related risk concerns are operationalized through risk-entry selection, label-based observability, exposure measurement, flow dynamics, and strong-trigger adjudication. In the baseline model, the Strong Trigger applies only to Darknet Interaction, Sanctioned Inflow, and High-risk Cluster Exposure.

2.3 Risk Measurement Components and Scoring design

Under the five risk entries, this study calculates address-level inflow risk through three core scoring components: Exposure Aggregation, Flow Dynamics Scoring, and the Strong Trigger Mechanism. Exposure Aggregation consists of two sub-dimensions, Direct Exposure and Indirect Exposure, and measures the degree of path-based contact between the target address and high-risk fund sources. Flow Dynamics Scoring consists of two sub-dimensions, Cumulative Amount Scoring and Flow Ratio Scoring, and measures the scale and proportion of high-risk funds within the target address's inflow structure. The Strong Trigger Mechanism is used to identify high-severity risk signals that should not be diluted by weighted averaging.

Based on these three core components, this study further divides the overall scoring

Table 2: *Direct Exposure Score Mapping Table*

Risk Category	1-hop Single Amount	1-hop Direct Exposure Score
	[0,100)	20
Obfuscation / Mixing	[100, 1,000)	40
Cross-chain Layering	[1,000, 5,000)	70
	[5,000, + ∞)	85
	[0, 50)	20
Darknet Interaction Sanctioned Inflow	[50, 100)	40
High-risk Cluster Exposure	[100, 1,000)	70
	[1,000, + ∞)	85

procedure into nine sequential steps. Each scoring step first states its calculation objective, and then provides the corresponding formula and score mapping table. The score mapping tables convert observable on-chain values into normalized risk scores on a 0–100 scale. The final risk bands refer to the four-band risk structure used by Zone21 and are reinterpreted for the KYT inflow monitoring context [11].

2.3.1 Exposure Scoring

Exposure Scoring measures the degree of path-based contact between the target address and high-risk fund sources. This study divides path exposure into Direct Exposure and Indirect Exposure. Direct Exposure refers to one-hop inflow contact, where the target address directly receives funds from a labelled high-risk address. Indirect Exposure refers to two-hop and three-hop upstream paths, where the target address does not directly transact with the labelled high-risk source but its upstream funding path contains high-risk nodes.

Step 1: Direct Exposure Scoring

Direct Exposure Scoring calculates the direct high-risk exposure score at the one-hop level. For each risk category r, the model identifies the maximum single high-risk inflow amount observed at the one-hop level within the observation window. This value is then mapped to a normalized risk score using the Direct Exposure ScoreTable. The model retains the highest score across all risk categories to represent the strongest one-hop exposure signal.

$$S_{\text{direct}} = \max \left\{ \text{ScoreTable}\,_{r,1}^{D}\left(\alpha^{*}_{r,1}\right) \mid r \in \mathcal{R} \right\} \tag{1}$$

Formula notation:

- $\alpha^{*}_{r,h}$ denotes the maximum high-risk inflow amount observed for risk category r at hop level h.
- $\mathcal{R}$ denotes the set of risk categories, covering the on-chain high-risk behaviors defined in this study.
- ScoreTable $_{r,1}^{D}$ denotes the predefined score-mapping function used for Direct Exposure Scoring for risk category r at the one-hop level.

This step retains the strongest direct exposure signal. It prevents a high-severity one-hop inflow from being diluted by lower-risk or non-risk transactions in other categories.

Step 2: Indirect Exposure Scoring

Table 3: *Indirect Exposure Score Mapping Table*

Risk Category	2-hop Single Amount	2-hop Indirect Exposure Score	3-hop Single Amount	3-hop Indirect Exposure Score
	[0, 1,000)	20	[0, 5,000)	20
Obfuscation / Mixing	[1,000, 5,000)	40	[5,000, 10,000)	40
Cross-chain Layering	[5,000, 10,000)	70	[10,000, 50,000)	70
	[10,000, + ∞)	85	[50,000, + ∞)	85
Darknet Interaction	[0, 100)	20	[0, 1,000)	20
Sanctioned Inflow	[100, 1,000)	40	[1,000, 5,000)	40
High-risk Cluster	[1,000, 5,000)	70	[5,000, 10,000)	70
Exposure	[5,000, + ∞)	85	[10,000, + ∞)	85

Indirect Exposure Scoring calculates indirect high-risk exposure through two-hop and three-hop upstream paths. These paths can capture upstream risk sources, but their attribution certainty is weaker than one-hop transactions. For this reason, indirect exposure is calculated separately from direct exposure and is scored using an independent Indirect Exposure ScoreTable.

For each risk category r and hop level h, the model identifies the maximum single high-risk inflow amount observed at the corresponding hop level and maps it to an indirect exposure score. The model then retains the highest score across all risk categories and across two-hop and three-hop paths.

$$S_{\text{indirect}} = \max\left\{ \text{ScoreTable}_{r,h}^{ID}\left(\alpha_{r,h}^{*}\right) \mid r \in \mathcal{R}, h \in \{2,3\}\right\} \tag{2}$$

Formula notation:

- $\text{ScoreTabler}_{r,h}^{ID}$ denotes the predefined score-mapping function used for Indirect Exposure Scoring for risk category r at hop level h.

This design retains upstream risk signals while avoiding the treatment of two-hop and three-hop exposure as equivalent to one-hop direct exposure.

Step 3: Exposure Aggregation Scoring

Exposure Aggregation Scoring combines the Direct Exposure score and the Indirect Exposure score into a path-based exposure score. Direct Exposure is assigned a higher weight because one-hop transactions have stronger evidentiary proximity. Indirect Exposure remains part of the score but is discounted through the aggregation parameter.

$$S_{\text{exposure}} = \alpha S_{\text{direct}} + (1-\alpha) S_{\text{indirect}} \tag{3}$$

where α is the weighting parameter, set to 0.6 in the baseline configuration. This setting is grounded in the risk proximity principle, which states that risk signals originating from closer transactional relationships generally exhibit higher certainty.

2.3.2 Flow Dynamics Scoring

Flow Dynamics Scoring measures the scale and concentration of high-risk funds in the target address's inflow structure. This study divides flow-dynamic risk into two sub-dimensions: Cumulative Amount Scoring and Flow Ratio Scoring. The former measures the absolute scale of high-risk inflows, while the latter measures the proportion of highrisk inflows within total inflows. These two signals capture different risk information and are not interchangeable.

Step 4: Cumulative Amount Scoring

Table 4: *Cumulative Amount Score Mapping Table*

Risk Category	1-hop Cumulative Amount	1-hop Cumulative Amount Risk Score
	[0, 1,000)	20
Obfuscation / Mixing	[1,000, 5,000)	40
Cross-chain Layering	[5,000, 10,000)	70
	[10,000, + ∞)	85
	[0, 100)	20
Darknet Interaction Sanctioned Inflow	[100, 500)	40
High-risk Cluster Exposure	[500, 1,000)	70
	[1,000, + ∞)	85

Cumulative Amount Scoring calculates the cumulative scale of one-hop high-risk inflows received by the target address. For each risk category r, the model calculates the cumulative one-hop high-risk inflow amount within the observation window and maps it to a normalized risk score using the Cumulative Amount ScoreTable. The highest category-level cumulative amount score is retained.

$$S_{CA} = \max\left\{ \text{ScoreTable}\,^{CA}_{r,1}\,(CA_{r,1}) \mid r \in \mathcal{R}\right\} \tag{4}$$

Formula notation:

- $CA_{r,1}$ denotes the cumulative high-risk inflow amount for risk category r at the one-hop level.
- $ScoreTable^{CA}_{r,1}$ denotes the predefined score-mapping function used for Cumulative Amount Scoring for risk category r at the one-hop level.

This step identifies addresses that receive a material amount of high-risk funds. Even when high-risk funds are split across multiple transactions, the cumulative amount score captures the total scale of risk.

Step 5: Flow Ratio Scoring

Flow Ratio Scoring measures the proportion of high-risk inflows in the target address's total inflow structure. The model divides the total one-hop high-risk inflow amount actually received by the target address by the total one-hop inflow amount within the same observation window. The resulting ratio is then mapped to a normalized risk score using the Flow Ratio ScoreTable.

$$S_{FR} = \text{ScoreTable}\,^{FR}\left(\frac{I_{\text{risk}}}{I_{\text{total}}}\right) \tag{5}$$

Formula notation:

- I_{risk} denotes the amount of high-risk inflows received by the target address during the observation window.
- I_{total} denotes the total inflow amount received by the target address during the same observation window.

This step identifies addresses whose inflow structure is highly concentrated in high-risk sources. Even when the absolute amount is small, a high risk-inflow ratio may still indicate a higher review priority.

Table 5: *Flow Ratio Score Mapping Table*

High-Risk Deposit Ratio	Flow Score (S_FR)
<1%	0
$1\%- < 20\%$	20
$20\%- < 40\%$	40
$40\%- < 70\%$	70
$\geq 70\%$	85

Step 6: Flow Dynamics Scoring

Flow Dynamics Scoring combines the Cumulative Amount score and the Flow Ratio score into a flow-dynamics score. Cumulative Amount reflects the absolute scale of high-risk funds, while Flow Ratio reflects the dominance of high-risk funds in the address-level inflow structure. A large but proportionally small high-risk inflow and a small but highly concentrated high-risk inflow may imply different risk interpretations and review priorities.

$$S_{\text{flow}} = \beta S_{CA} + (1-\beta) S_{FR} \tag{6}$$

In the baseline specification, this section adopts an equal-weight configuration ($\beta = 0.5$). This choice is grounded in the principle of methodological neutrality: in the absence of external supervisory labels or prior information, symmetric weighting serves as an unbiased specification, helping to avoid parameter-induced bias in risk ranking outcomes.

2.3.3 Continuous Risk Aggregation

Step 7: Continuous Risk Aggregation

Continuous Risk Aggregation combines the path-based exposure score and the flow-dynamics score into a continuous risk score. This score represents the integrated risk level before the Strong Trigger Mechanism is applied. Exposure Aggregation mainly captures path contact and distance from high-risk sources, while Flow Dynamics Scoring captures the scale and structural concentration of high-risk inflows.

$$S_{\text{cont}} = \omega_1 S_{\text{exposure}} + \omega_2 S_{\text{flow}} \tag{7}$$

In the baseline configuration, this section adopts $(\omega_1, \omega_2) = (0.6, 0.4)$. This setting reflects a methodological balance: on the one hand, assigning greater weight to exposure risk strengthens the model's ability to identify source-driven risk; on the other hand, retaining a non-negligible weight for Flow Dynamics ensures that persistent and cumulative risk patterns are adequately captured. This prevents the model from relying excessively on single transactions or isolated significant events.

2.3.4 Strong Trigger Mechanism

Step 8: Strong Trigger Mechanism Check

The Strong Trigger Mechanism is applied only to Darknet Interaction, Sanctioned Inflow, and High-risk Cluster Exposure in the baseline specification. These categories contain higher-certainty sensitive signals: explicit illicit-market origin, external regulatory designation, or known high-risk entity exposure. Obfuscation / Mixing and Cross-chain Layering are serious risk indicators, but they mainly describe traceability loss and path disruption. A high mixing ratio or bridge-related pattern may require review, but it does not always provide the same

Table 6: *Strong Trigger Score Mapping Table*

Risk Category	1-hop Trigger Condition	1-hop Escalation Score	2-hop Trigger Condition	2-hop Escalation Score	3-hop Trigger Condition	3-hop Escalation Score
	Flow Ratio $\geq 70\%$	85	Flow Ratio $\geq 80\%$	80	Flow Ratio $\geq 90\%$	75
Darknet Interaction	Cumulative Amount $\geq 1,000$	85	Cumulative Amount $\geq 5,000$	80	Cumulative Amount $\geq 10,000$	75
Exposure	Cumulative Amount $\geq 5,000$	100	Cumulative Amount $\geq 10,000$	95	Cumulative Amount $\geq 50,000$	90

evidential certainty as sanctioned, darknet, or known high-risk entity exposure. Excluding them from the baseline trigger therefore prevents structural ambiguity from automatically producing the highest severity levels. Institutions may define a stricter policy variant by adding trigger rules for mixing or cross-chain layering when their risk appetite, jurisdiction, or supervisory expectations require it. The Strong Trigger Mechanism handles high-severity risk signals that should not be diluted by weighted averaging. For each risk category and hop level subject to the Strong Trigger Mechanism, the model checks the ratio-based trigger condition and the amount-based trigger conditions defined for that hop level. If any condition is satisfied, the corresponding candidate escalation score is assigned according to the Strong Trigger ScoreTable. If multiple conditions are satisfied at the same risk category and hop level, the highest candidate escalation score is retained. The model then takes the maximum value across all candidate escalation scores as the account-level strong trigger score.

$$S_{\text{strong}} = \max\left\{S_{r,h}^{esc} \mid r \in \mathcal{R}_{\text{strong}}, h \in \mathcal{H}\right\} \tag{8}$$

Formula notation:

- R_{strong} denotes the set of risk categories subject to the Strong Trigger Mechanism.
- $h \in \mathcal{H} = \{1, 2, 3\}$ denotes the set of hop levels considered in this study.
- $S_{r,h}^{esc}$ denotes the candidate escalation score assigned by the Strong Trigger ScoreTable for risk category r at hop level h. If multiple trigger conditions are satisfied for the same risk category and hop level, $S_{r,h}^{esc}$ takes the highest escalation score among them. If no trigger condition is satisfied, then $S_{r,h}^{esc} = 0$.

Note: The Strong Trigger Mechanism follows an OR logic. If any trigger condition is satisfied, the corresponding escalation score is assigned. Cumulative Amount refers to the cumulative high-risk inflow amount for the corresponding risk category and hop level within the observation window.

2.3.5 Final Adjudication and Risk Tier Mapping

Step 9: Strong Trigger Adjudication Mechanism

The Strong Trigger Adjudication Mechanism compares the continuous risk score with the strong trigger score and retains the higher value as the final risk score. This rule follows a non-dilutive design. If the continuous risk score is higher, the model retains the continuous result. If the strong trigger score is higher, the model upgrades the result based on the trigger output.

$$S_{\text{final}} = \max\left(S_{\text{strong}}, S_{\text{cont}}\right) \tag{9}$$

After the evaluated risk score is obtained, the model maps the $0 - 100$ output into four risk tiers: Low, Medium, High, and Severe. This tiering is used to support alert ranking and manual review prioritization. A score from 0 to 30 is classified as **Low**, indicating that no material high-risk on-chain exposure is observed and that routine monitoring may be sufficient.

Table 7: *Scoring Results for Case 1 (Address 0x74...f44e)*

Scoring item	Value / Evidence	Score
Data records collected	Collected data records: 11,785	
Direct Exposure Scoring	No 1-hop risky inflow observed.	0
Indirect Exposure Scoring	Maximum 2-hop risky inflow = 0.001 USDT; behavior = High-risk Cluster Exposure	20
Exposure Aggregation Scoring	$0.6\times$ Direct (0) $+0.4\times$ Indirect (20)	8
Cumulative Amount Scoring	No cumulative 1-hop risky inflow amount.	0
Flow Ratio Scoring	1-hop risky inflow / total 1-hop inflow $= 0/1,054,609,656.89 =$ 0.000000%	0
Flow Dynamics Scoring	$0.5\times$ Amount score (0) $+0.5\times$ Ratio score (0)	0
Continuous Risk Aggregation	$0.6\times$ Exposure (8) $+0.4\times$ Flow (0)	4.8
Strong Trigger Mechanism Check	Hop 1: strong-risk inflow = 0 USDT; ratio = 0.000000%; triggered = 0	0
Strong Trigger Adjudication Mechanism	max(continuou_score 4.8 , strong_trigger_score 0) = 4.8; tier = Low	4.8 / Low
KYT Tool Trustformer		**Good credit**
KYT Tool MistTrack		**Low / No Risk Data**

A score above 30 and up to 60 is classified as **Medium**, indicating limited or localized risk exposure that may require enhanced monitoring or follow-up review. A score above 60 and up to 80 is classified as **High**, indicating more evident direct exposure, indirect exposure, or flow-structure risk, and therefore requiring prioritized manual review. A score above 80 and up to 100 is classified as Severe, indicating serious risk signals or activation of the strong-trigger mechanism, which may require senior compliance review.

These tiers are used for alert ranking and review prioritization. Further compliance handling should be assessed together with the customer profile, transaction context, institutional policy, and applicable jurisdictional requirements.

3 Research Results and Discussion

The paper evaluates model behavior using three real ERC-20 address cases. All cases use the same 60-day USDT/ERC-20 observation window, the same path depth, and the same parameter table. External KYT tool results are used only for directional plausibility checking. They are not used to calibrate model scores. For readability, the real addresses are presented in shortened form and discussed as Case 1, Case 2, and Case 3.

Case 1 serves as a high-volume, low-risk reference case. The address has a large inflow volume within the observation window, but it has no one-hop high-risk inflow. The high-risk inflow ratio is 0%. The model classifies this case as Low. This result shows that the model does not mechanically increase the risk level because of transaction volume. The risk level is driven by high-risk sources, path distance, and inflow structure, rather than total inflow volume alone. External KYT results classify the address as Good credit, Low, or No Risk Data, which is consistent with the model output.

Case 2 tests the role of the Strong Trigger Mechanism. The one-hop high-risk inflow amount is only 0.006715 USDT, but the high-risk inflow ratio reaches 96.07%. The address also has direct exposure to a high-risk entity. The model classifies this case as Severe. The severe classification is not driven by the absolute amount. It is driven by the dominance of high-risk inflows in the address-level inflow structure. This result matches the KYT alert logic: a small-value address can still present severe risk when its inflows are highly concentrated in high-risk sources. External KYT tools also classify the address as Severe / Risky and report

Table 8: *Scoring Results for Case 2 (Address 0x88...2dbb)*

Scoring item	Value / Evidence	Score
Data records collected	Collected data records: 4,877	
Direct Exposure Scoring	Maximum 1-hop risky inflow = 0.00181 USDT; behavior = Highrisk Cluster Exposure	20
	Maximum 2-hop risky inflow = 0.001 USDT; behavior = High-risk	
Indirect Exposure Scoring	Cluster Exposure	20
Exposure Aggregation Scoring	0.6× Direct (20) +0.4× Indirect (20)	20
Cumulative Amount Scoring	Maximum cumulative 1 -hop risky inflow = 0.006715 USDT; behavior = High-risk Cluster Exposure	20
Flow Ratio Scoring	96.065808%	85
Flow Dynamics Scoring	0.5× Amount score (20) +0.5× Ratio score (85)	52.5
Continuous Risk Aggregation	0.6× Exposure (20) +0.4× Flow (52.5)	33
Strong Trigger Mechanism Check	Hop 1: strong-risk inflow = 0.006715 USDT; ratio = 96.065808%; triggered = 1	85
Strong Trigger Adjudication Mechanism	max(continuous_score 33 , strong_trigger_score 85) = 85; tier = Severe	**85 / Severe**
KYT Tool Trustformer	labels include suspected money laundering, phishing, and drainerrelated risk.	**Severe**
KYT Tool MistTrack	labels include illicit activity / high-risk entity exposure.	**Risky**

Table 9: *Scoring Results for Case 3 (Address 0x69...e89s)*

Scoring item	Value / Evidence	Score
Data records collected	Collected data records: 228	
Direct Exposure Scoring	Maximum 1-hop risky inflow = 990.51641 USDT; behavior = Obfuscation / Mixing	40
	Maximum 2-hop risky inflow = 1,000 USDT; behavior =	
Indirect Exposure Scoring	Obfuscation / Mixing	40
Exposure Aggregation Scoring	0.6× Direct (40) +0.4× Indirect (40)	40
	Maximum cumulative 1 -hop risky inflow = 5,941.511554 Cumulative Amount Scoring USDT; behavior = Obfuscation / Mixing	
	1-hop risky inflow / total 1-hop inflow = 5,941.511554 /	70
Flow Ratio Scoring	5,941.531993 = 99.999656%	85
Flow Dynamics Scoring	0.5× Amount score (70) +0.5× Ratio score (85)	77.5
Continuous Risk Aggregation	0.6× Exposure (40) +0.4× Flow (77.5)	55
Strong Trigger Mechanism Check	Hop 1: strong-risk inflow = 0 USDT; ratio = 0.000000%; triggered = 0	0
Strong Trigger Adjudication Mechanism	max (continuous_score 55, strong_trigger_score 0) = 55; tier = Medium	**55 / Medium**
		Risky / Severe or designationrelated risk
KYT Tool Trustformer KYT Tool MistTrack	Direct mixer exposure / mixer-related label.	**Risky**

labels such as suspected money laundering, phishing, drainer, and illicit activity. The model output is consistent with the external results in terms of risk direction.

Case 3 reflects mixing-related exposure and differences in external labels. The address has direct and indirect Obfuscation / Mixing exposure. Its one-hop high-risk inflow is approximately $5,941.512$ USDT, and the high-risk inflow ratio is 99.99%. The model classifies this case as Medium. This result shows that the model can identify mixer-related exposure, but it does not automatically escalate the address to High or Severe solely because the high-risk inflow ratio is close to 100%. The main risk signal in this case comes from Obfuscation / Mixing rather than from strong-trigger categories such as Sanctioned Inflow, Darknet Interaction, or High-risk Cluster Exposure. Under the final parameter setting, the strong-trigger mechanism is not activated, so the final tier is determined by the continuous risk score.

Across the three cases, the two external KYT tools are used as directional comparison references rather than calibration benchmarks. The comparison focuses on three types of information: broad risk direction, reported risk labels, and general severity interpretation. The external outputs are not used to calibrate the model score and are not treated as ground-truth labels, because commercial KYT tools differ in label coverage, entity attribution, risk taxonomy, threshold settings, and escalation rules. For this reason, the comparison is used only to assess directional plausibility.

The three real-world cases show that the model can distinguish different risk situations based on observable on-chain inflow structures. Case 1 shows that high transaction volume alone does not lead to risk escalation. Case 2 shows that the Strong Trigger Mechanism can identify small-value addresses with highly concentrated sensitive risk sources. Case 3 shows

Table 10: •

Scenario	Direct/indirect weight	Amount/ratio weight	Exposure/flow weight	Case 1	Case 2	Case 3
A Baseline	**0.6 / 0.4**	**0.5 / 0.5**	**0.6 / 0.4**	**4.8 / Low**	**85 / Severe**	**55 / Medium**
B Balanced	0.5 / 0.5	0.5 / 0.5	0.5 / 0.5	5.0 / Low	85 / Severe	58.75 / Medium
C Proximityprioritized	0.7 / 0.3	0.5 / 0.5	0.7 / 0.3	4.2 / Low	85 / Severe	51.25 / Medium
D Propagationenhanced	0.5 / 0.5	0.5 / 0.5	0.6 / 0.4	6.0 / Low	85 / Severe	55 / Medium
E Flow-ratioprioritized	0.6 / 0.4	0.4 / 0.6	0.5 / 0.5	4.0 / Low	85 / Severe	59.5 / Medium
F Amountprioritized	0.6 / 0.4	0.6 / 0.4	0.5 / 0.5	4.0 / Low	85 / Severe	58 / Medium

that the model can detect mixer-related exposure while allowing reasonable severity differences from external KYT tools. In this study, external KYT results are used to assess consistency in risk direction, not to require numerical or tier-level equivalence with commercial systems.

Since the proposed model contains several weighting parameters, including the direct/indirect weight, amount/ratio weight, and exposure/flow weight, the final score may be affected by parameter settings. It is therefore necessary to examine whether the risk tiers of the three cases remain stable under alternative weight configurations. Table 10 reports the scoring results under six parameter scenarios and is used to assess the model's sensitivity to key weighting choices.

The sensitivity results show that the risk tiers of the three cases remain stable under six weight configurations. Case 1 is always Low, Case 2 is always Severe, and Case 3 is always Medium. This does not prove statistical robustness. It does show that the classifications in these three cases are not accidental results of a single weight setting.

4 Limitations

The results are case-based. They are not a large-sample statistical validation. The three cases can show model behavior, but they cannot estimate accuracy, recall, false-positive rate, or superiority over commercial KYT tools. Future research should use larger labeled samples, low-risk reference addresses, and manually reviewed compliance outcomes.

The model depends on external address labels. Limited coverage, delayed updates, entity-attribution errors, or differences in label definitions can affect scoring. Case 3 already shows that different KYT systems may assign different severity levels because of different label coverage.

The paper analyzes only USDT/ERC-20 inflows. Multi-chain flows, outbound transactions, internal exchange account movements, and off-chain customer background are not included. This limitation keeps the method boundary clear, but it also limits model completeness.

5 Conclusions and Recommendations

This paper proposes a KYT risk scoring model for cryptocurrency exchange inflow monitoring. The model translates regulatory risk logic, industry address labels, and on-chain deposit structures into five first-level risk entries, and then produces a 0-100 risk score through Exposure Aggregation, Flow Dynamics, and a Strong Trigger Mechanism.

The paper gives a specific explanation for the five first-level risk entries. The five entries are not arbitrary and they are not a list of crime names. They correspond to source concealment, path layering and attribution disruption, illicitmarket origin, regulatory designation exposure, and label-based high-risk entity exposure. Reducing them to four would merge different risk mechanisms. Expanding them to six or seven would split label-based risks that use similar measurement logic. Within the scope of this study, the five-entry design is better for explanation, audit, and parameter calibration.

The three real cases show that the model can distinguish a high-volume low-risk address, a high-risk-clusterdominated address, and a mixer-related address. The outputs are broadly aligned with external KYT tools in risk direction, but external tools are not used as calibration targets. The model is intended to support initial risk triage, alert prioritization, compliance review, and audit documentation.

From an AML regulatory perspective, the study suggests three practical implications. First, exchanges should combine Know Your Customer (KYC) and Know Your Transaction (KYT) controls rather than relying on identity verification alone, because verified customers may still receive funds from high-risk transaction paths. Second, regulators may encourage risk-based KYT scoring models with explainable variables, so that exchanges can document how risk alerts are generated, ranked, and reviewed. Third, strong-trigger cases should receive enhanced review based on customer context, transaction background, institutional policy, and jurisdictional requirements. These recommendations support a more transparent and reviewable approach to virtual asset AML monitoring.

Future research should address three issues. First, the sample size should be expanded, and more blockchains and asset types should be included. Second, future studies should compare the classification stability of the model under different observation windows, such as 30 days, 60 days, and 90 days, as well as under different path depths, weight settings, and threshold configurations. The amount thresholds, ratio thresholds, and strong-trigger escalation scores used in this study are model design parameters. They are used to construct an interpretable scoring rule and should not be understood as statistically optimal parameters validated by large-scale data. Third, when data are available, model outputs should be systematically compared with compliance review outcomes and commercial KYT results. These comparisons can support further calibration of the thresholds and score-mapping rules.

References

[1] FATF, "Updated Guidance for a Risk-Based Approach to Virtual Assets and Virtual Asset Service Providers," Financial Action Task Force, Paris, France, 2021.

[2] U.S. Department of the Treasury, "Illicit Finance Risk Assessment of Decentralized Finance," U.S. Department of the Treasury, Washington, DC, USA, 2023.

[3] S. Somin, G. Gordon, A. Pentland, E. Shmueli, and Y. Altshuler, "ERC20 transactions over Ethereum blockchain: Network analysis and predictions," 2020.

[4] T. Papadimitriou, P. Gogas, and F. Gkatzoglou, "The evolution of the cryptocurrencies market: A complex networks approach," *Journal of Computational and Applied Mathematics*, vol. 376, p. 112831, 2020.

[5] M. A. Hannan, M. A. Shahriar, M. S. Ferdous, M. J. M. Chowdhury, and M. S. Rahman, "A systematic literature review of blockchain-based e-KYC systems," *Computing*, vol. 105, no. 10, pp. 2089–2118, 2023.

[6] S. Huang, X. Yang, L. He, X. Hao, and W. Ren, "An analysis model for detecting misbehaviors in anonymous cryptocurrency," *Computer Standards & Interfaces*, vol. 83, p. 103669, 2023.

[7] Chainalysis, "The 2024 Crypto Crime Report," Chainalysis, 2024.

[8] Chainalysis, "The 2025 Crypto Crime Report," Chainalysis, 2025.

[9] Elliptic, "The State of Cross-Chain Crime 2025," Elliptic, 2025.

[10] TRM Labs, "The 2025 Crypto Crime Report," TRM Labs, 2025.

[11] Zone21, "Bitcoin-Backed Lending and Transaction Risk Scoring," Zone21, 2025.

Digital Twin-Based Multi-Source Fusion for Real-Time Health Management and Remaining Useful Life Prediction of Industrial Equipment

Peiyan Guo[1] and Ahmad Yahya Dawod[2*]

[1,2]International College of Digital Innovation, Chiang Mai University, Chiang Mai, 50200, Thailand
E-mail: peiyan_guo@cmu.ac.th, ahmadyahyadawod.a@cmu.ac.th
(*corresponding author)

Abstract

Industrial equipment operating under complex environments requires reliable health assessment and lifetime forecasting to support predictive maintenance. Existing methods generally rely on simple feature concatenation or parallel multi-task learning architectures, which limit source-level interpretability and weaken the explicit correlation between Health Index (HI) and Remaining Useful Life (RUL) prediction. To address these limitations, this study develops a Digital Twin-based Masked-Gated Multi-Source HI-guided Transformer, named DT-MGMSHI Transformer. The proposed model integrates heterogeneous information from vibration, temperature, humidity, pressure sensors, and PLC operational logs. A source-level masking and gating strategy is introduced before Transformer encoding to identify valid data sources and adaptively reweight their contributions. The predicted HI is further incorporated into the RUL prediction branch to enhance degradation-aware lifetime estimation. Experiments conducted on the Edge-AI industrial sensor dataset show that the proposed model achieves a MAE of 0.755 , an RMSE of 1.239 , and an R^2 of 0.901 for RUL prediction. The results demonstrate that multi-source fusion and HI-guided learning can effectively improve RUL prediction performance while providing interpretability support for intelligent industrial maintenance.

KEYWORDS: Digital twin, multi-source fusion, health index, remaining useful life, Transformer

1 Introduction

With the rapid development of intelligent manufacturing and industrial automation, equipment failures may result in production interruptions, maintenance cost growth, and safety risks. Therefore, predictive maintenance and equipment health management have become important research topics in Prognostics and Health Management (PHM). Among these tasks, remaining useful life (RUL) estimation plays a key role in predicting equipment degradation trends and supporting maintenance decision-making [1]. Deep learning techniques have recently shown strong capability in extracting degradation information from industrial monitoring data [2].

In practical applications, equipment operating conditions are usually reflected by multiple heterogeneous data sources rather than a single signal. Sensor measurements such as vibration, temperature, humidity, and pressure describe physical operating states, while PLC logs contain control actions and operational events [3]. Digital twin technology provides an effective way to integrate physical equipment and virtual monitoring systems, enabling real-time condition assessment and predictive maintenance [4, 5]. Compared with single-source monitoring, multi-source fusion can provide more comprehensive degradation information and improve prediction reliability [6].

Although existing studies have achieved certain progress in deep learning, digital twin, and multi-source data fusion, several deficiencies still exist in the real-time health management of industrial equipment and remaining useful life (RUL) prediction. Many methods still rely on direct feature concatenation without considering source-level importance differences [3, 6]. In addition, most multi-task approaches treat Health Index (HI) and RUL prediction as parallel objectives, while the degradation relationship between them is not fully utilized [7]. Existing Transformer-based methods also mainly focus on temporal attention modeling and lack adaptive source selection mechanisms for heterogeneous industrial data [8, 9].

To overcome these limitations, this study proposes a Digital Twin-based Masked-Gated Multi-Source HI-guided Transformer (DT-MGMS-HI Transformer). The proposed model integrates heterogeneous sensor and PLC information through a masked gated fusion strategy and introduces HI-guided learning to enhance RUL prediction performance. Experimental results on the Edge-AI industrial sensor dataset demonstrate the effectiveness of the proposed approach for industrial health management and lifetime prediction.

2 Literature Review

2.1 Deep Learning and Transformer-based RUL Prediction

Deep learning approaches have been widely used in RUL prediction because they can automatically learn nonlinear degradation features from multivariate industrial time-series data [10, 11]. Attention mechanisms further improve the identification of important degradation features, while Transformer-based models show strong capability in long-range temporal dependency modeling for multivariate sequence prediction [10-12]. Recent studies have also introduced temporal embedding, multi-scale self-attention, and dual-scale Transformer structures to enhance degradation representation across different operating stages [13-15]. However, most Transformer-based RUL methods mainly focus on temporal dependency extraction and pay limited attention to source-level reliability and importance differences before self-attention.

2.2 Multi-source Fusion and Digital Twin-based Prognostics

Multi-source data fusion can provide more comprehensive degradation information than single-sensor monitoring because heterogeneous sensors and PLC logs describe equipment conditions from different perspectives [16, 17]. Such fusion can reduce the influence of sensor noise, drift, or local signal failure, thereby improving the robustness of health assessment. Digital twin technology further supports predictive maintenance by linking physical equipment with virtual representations for condition monitoring, health assessment, and lifetime prediction [18]. However, many existing studies still rely on direct feature concatenation or unified input modeling, while the reliability and contribution differences among heterogeneous data sources are rarely explicitly considered [16-18].

2.3 HI-RUL Joint Learning

HI and RUL are closely related in degradation modeling because HI reflects the current health condition, while RUL estimates the remaining operating time before failure [19]. Multi-task learning provides a useful framework for jointly modeling HI assessment and RUL estimation by sharing degradation-related representations [20]. However, many HI-RUL methods use a shared encoder with parallel output branches, where the guiding role of HI in RUL prediction is usually implicit and not fully exploited [19-21]. In summary, existing studies still have three limitations: simple multi-source concatenation, insufficient source-level reliability modeling before Transformer encoding, and limited explicit guidance from HI to RUL. To address these gaps, this study develops the DT-MGMS-HI Transformer with digital twin-based multi-source representation, masked-gated fusion, and HI-guided RUL prediction.

3 Research Methodology

3.1 Overall Framework

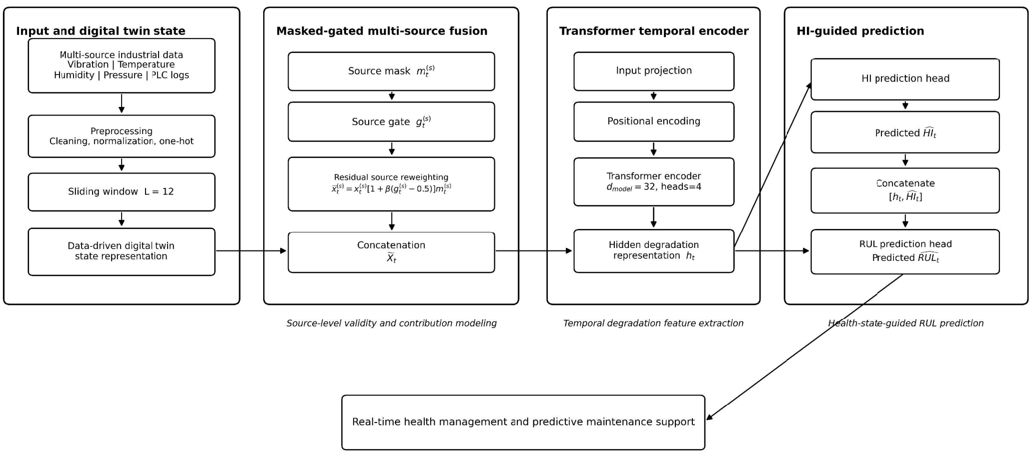

Figure 1: *Detailed architecture of the proposed DT-MGMS-HI Transformer*

Figure 1 presents the detailed architecture of the proposed DT-MGMS-HI Transformer for Health Index (HI) assessment and Remaining Useful Life (RUL) prediction. The framework integrates vibration, temperature, humidity, pressure, and PLC operational logs to describe equipment operating conditions from mechanical, environmental, pressure, and control-event perspectives. After data cleaning, normalization, one-hot encoding, and sliding window construction with L =12, the processed multi-source sequence is mapped into a data-driven digital twin state representation. In this study, the digital twin component is implemented as a virtual state representation constructed from synchronized sensor and PLC data rather than a physical simulation system. Based on this representation, source-level masking and gating are applied before Transformer encoding to identify valid data sources and dynamically adjust their contributions. The reweighted multi-source sequence is then fed into the Transformer temporal encoder to extract degradation-related hidden features h_t. Finally, the HI prediction head estimates the current health state, and the predicted HI is concatenated with h_t to guide the RUL prediction branch, producing HI and RUL outputs for real-time health management and predictive maintenance.

3.2 Dataset and Data Processing

This paper conducts validation using the "Edge-AI Sensor Dataset for Real-Time Fault Prediction in Smart Manufacturing" published by Santosh Kumar on IEEE Dataport in 2025 [22]. It mainly includes vibration, temperature, humidity, pressure and PLC status signals, which describe equipment conditions from mechanical, environmental, and control perspectives.

The multi-source input features at time t are defined as:

$$X_t = \left[x_t^{\text{vib}}, x_t^{\text{temp}}, x_t^{\text{hum}}, x_t^{\text{press}}, x_t^{\text{plc}}\right] \tag{1}$$

where $x_t^{\text{vib}}, x_t^{\text{temp}}, x_t^{\text{hum}}, x_t^{\text{press}}, x_t^{\text{plc}}$ denote the vibration, temperature, humidity, pressure and PLC status features. To reduce the influence of feature scale differences, continuous sensor variables are normalized using Min-Max normalization:

$$x' = \frac{x - x_{\text{min}}}{x_{\text{max}} - x_{\text{min}}} \tag{2}$$

A sliding window strategy with length $L = 12$ is adopted to construct supervised learning samples. For time step t, the model input consists of multi-source features from the past 12-time steps:

$$X_t = [X_{t-L}, X_{t-L+1}, \cdots, X_{t-1}] \tag{3}$$

The corresponding supervised labels are the health index HI_t and remaining useful life RUL_t at the current time step:

$$y_t = [HI_t, RUL_t] \tag{4}$$

3.3 HI and RUL Label Construction

Health Index (HI) and Remaining Useful Life (RUL) are adopted as the supervisory targets for the joint prediction task. HI is used to represent the current degradation condition of equipment within the range $[0, 1]$, where larger values indicate healthier operating conditions and lower values correspond to more severe degradation. RUL represents the remaining operating time before future failure occurs.

In this paper, RUL labels are generated according to the distance between the current time step and the nearest future failure event. Let t_f denote the first failure time after the current time step t, and let the maximum truncated RUL value be $RUL_{\max} = 12$. The definition of the RUL label at time t is formulated as:

$$RUL_t = \begin{cases} \min(t_f - t, RUL_{\max}) & \text{, if a future failure exists} \\ RUL_{\max} & \text{, otherwise .} \end{cases} \tag{5}$$

This truncation limits excessively large RUL values and emphasizes near-failure degradation. The HI label is constructed using both device status information and normalized RUL values. Failure samples are assigned HI values of 0 , warning samples are assigned 0.7 , and normal samples are calculated based on the truncated RUL ratio. Since RUL_t is limited by $RUL_{\max}$, the normalized ratio $\frac{RUL_t}{RUL_{\max}}$ is not greater than 1 . The HI label is defined as:

$$HI_t = \begin{cases} 0 & \text{, if status } = \text{ failure} \\ 0.7 & \text{, if status }_t = \text{ warning} \\ \max\left(0.7, \frac{RUL_t}{RUL_{\max}}\right) & \text{, if status }_t = \text{ normal .} \end{cases} \tag{6}$$

where status_t denotes the device status at time step t. This construction enables HI to reflect the degradation transition from normal to warning and failure while remaining consistent with RUL variation.

3.4 Proposed Model

This study proposes the DT-MGMS-HI Transformer model for joint health index (HI) evaluation and remaining useful life (RUL) prediction using heterogeneous industrial data. The proposed model consists of three main components: a masked-gated multi-source fusion module, a Transformer temporal encoder, and a HI-guided RUL prediction module. Different from the simple feature concatenation, this proposed model introduces source-level masks and gates before Transformer encoding to identify valid data sources and dynamically adjust their contributions. This design improves multi-source fusion effectiveness and provides source-level interpretability.

3.4.1 Masked-Gated Multi-Source Fusion

Let the input of the s-th data source at time step t be denoted as $x_t^{(s)}$, where s corresponds to vibration, temperature, humidity, pressure or PLC. First, the validity of the data source is determined via a source-level mask:

$$m_t^{(s)} = \begin{cases} 1, & \left\| x_t^{(s)} \right\|_1 > 0 \\ 0, & \text{otherwise} \end{cases} \tag{7}$$

where $\| \cdot \|_1$ denotes the L_1-norm. The mask is used to identify whether the corresponding source contains valid nonzero information. Then, the model learns the importance of each data source through a gating network:

$$g_t^{(s)} = \sigma\left(\boldsymbol{W}_2^{(s)} \delta\left(\boldsymbol{W}_1^{(s)} \boldsymbol{x}_t^{(s)} + \boldsymbol{b}_1^{(s)}\right) + \boldsymbol{b}_2^{(s)}\right) \tag{8}$$

where $\sigma(\cdot)$ is the Sigmoid function, $\delta(\cdot)$ is the ReLU activation function, and $g_t^{(s)} \in [0,1]$ denotes the learned importance weight of the s-th data source. To avoid discarding any individual data source, a residual-based source-level reweighting strategy is adopted:

$$\tilde{\boldsymbol{x}}_t^{(s)} = \boldsymbol{x}_t^{(s)} \cdot \left[1 + \beta\left(g_t^{(s)} - 0.5\right)\right] \cdot m_t^{(s)} \tag{9}$$

where β is the gating regulation coefficient. A larger β increases the influence of the learned gate, while a smaller value weakens the reweighting effect. Based on the local hyperparameter search, $\beta = 0.20$ is used in the final model.

3.4.2 Transformer Temporal Encoder

After source-level masking and gating, the reweighted features from all sources are concatenated to form the multisource sequence $\widetilde{\boldsymbol{X}}_t$. The sequence is then fed into the Transformer temporal encoder to extract degradation-related temporal features:

$$\boldsymbol{h}_t = \text{TransformerEncoder}\left(\widetilde{\boldsymbol{X}}_t\right) \tag{10}$$

The Transformer encoder consists of an input projection layer, positional encoding, one Transformer encoder layer, and a final hidden-state extraction operation. The input sequence is first projected into a d_{model} -dimensional representation and then combined with positional encoding to preserve temporal order. The encoded representation of the last time step is used as the degradation state representation $\boldsymbol{h}_t$. In this study, $d_{\text{model}} = 32$, the number of attention heads is 4 , the feed-forward dimension is 64 , and dropout is set to 0.20.

3.4.3 HI-guided RUL Prediction

In the prediction phase, the model first estimates the health condition based on the hidden state $\boldsymbol{h}_t$. Then, the predicted $\widehat{HI}_t$ is concatenated with the hidden state $\boldsymbol{h}_t$ to guide the RUL prediction:

$$\begin{cases} \widehat{HI}_t = \sigma\left(\boldsymbol{W}_{HI}\boldsymbol{h}_t + \boldsymbol{b}_{HI}\right) \\ \widehat{RUL}_t = f_{RUL}\left(\left[\boldsymbol{h}_t, \widehat{HI}_t\right]\right) \end{cases} \tag{11}$$

where $\widehat{HI}_t$ and $\widehat{RUL}_t$ denote the predicted health index and remaining useful life, respectively. $\boldsymbol{W}_{HI}$ and $\boldsymbol{b}_{HI}$ are learnable parameters of the HI prediction head. $f_{\text{RUL}}(\cdot)$ denotes the RUL prediction head implemented by a multilayer perceptron, and $[\cdot,\cdot]$ represents feature concatenation. This structure enables RUL prediction to explicitly use health state information rather than relying only on shared temporal features.

3.4.4 Joint Loss Function

The proposed framework is optimized using a joint loss function defined as:

$$\mathcal{L} = 0.8\mathcal{L}_{HI} + 1.5\mathcal{L}_{RUL} + 0.0005\mathcal{L}_{\text{gate}} \tag{12}$$

where both $\mathcal{L}_{HI}$ and $\mathcal{L}_{RUL}$ adopt the MSE, and $\mathcal{L}_{\text{gate}}$ is introduced as a regularization term for the gating mechanism. This loss design enables the model to focus more on RUL prediction performance while retaining the capability to learn HI-based health states.

In summary, the DT-MGMS-HI Transformer integrates source masking, adaptive gating, Transformer-based temporal modeling, and HI -guided prediction within a unified framework. The predicted HI is further incorporated into the RUL branch to enhance degradation-aware lifetime estimation and improve interpretability for industrial health management.

Table 1: *Experimental Settings*

Item	Setting
Dataset	Edge-AI Sensor Dataset for Real-Time Fault Prediction
Input sources	Vibration, temperature, humidity, pressure, PLC-related signals
Data split	144 observations; 132 supervised samples after $L = 12$ sliding window; 105 training and 27 testing samples
Splitting rule	Chronological split without random shuffling
Targets and metrics	HI and RUL; MAE, RMSE, R^2
Compared models	Single-task RUL Transformer; Vanilla MTL Transformer; HI-guided MTL Transformer; Proposed DT-MGMS-HI Transformer
Architecture	1 Transformer layer; $d_{\text{model}} = 32$; 4 heads; feed-forward dim = 64; dropout = 0.20
Training	Adam; learning rate = 0.0012; batch size = 16; epochs = 300; seed = 100
Loss and gate settings	$\lambda_{HI} = 0.8, \lambda_{RUL} = 1.5, \lambda_{\text{gate}} = 0.0005, \beta = 0.20$

4 Results and Discussion

4.1 Experimental Settings

The experiments are conducted using the Edge-AI industrial sensor dataset to evaluate the effectiveness of the proposed DT-MGMS-HI Transformer for industrial health management and remaining useful life (RUL) prediction. The dataset contains 144 chronological observations, including vibration, temperature, humidity, pressure, PLC signals, actuator states, and control responses. After applying the sliding window strategy with $L = 12$, the first 12 observations are used as historical context for constructing the first prediction window. Therefore, $144 - 12 = 132$ supervised samples are generated. To avoid temporal information leakage, the samples are split chronologically into 105 training samples and 27 testing samples without random shuffling. HI and RUL are selected as the prediction targets. The proposed model is compared with three baseline methods, including the Single-task RUL Transformer, Vanilla Multi-task Transformer, and HI-guided Multi-task Transformer. Prediction performance is evaluated using mean absolute error (MAE), root mean square error (RMSE), and coefficient of determination (R^2).

4.2 Correlation Analysis

To investigate the degradation relationships among heterogeneous industrial signals, Pearson correlation analysis is conducted before model training. Figure 2 presents the correlation heatmap of vibration, pressure, temperature, humidity, PLC signals, Health Index (HI), and Remaining Useful Life (RUL). The results show that HI exhibits a relatively strong positive correlation with RUL, indicating that equipment with healthier operating conditions generally maintains a longer remaining lifetime. In contrast, individual sensor variables present relatively weak direct correlations with RUL because different sensors mainly describe specific aspects of equipment operation, such as mechanical behavior, environmental variation, and control status. Nevertheless, these heterogeneous sources provide complementary degradation information when integrated together. This observation validates the necessity of multi-source fusion and further supports the proposed HI-guided prediction framework for industrial health management and lifetime estimation.

4.3 Multi-Source Ablation Study

To evaluate the effectiveness of multi-source fusion for industrial health management and RUL prediction, ablation experiments are conducted using different input combinations, including

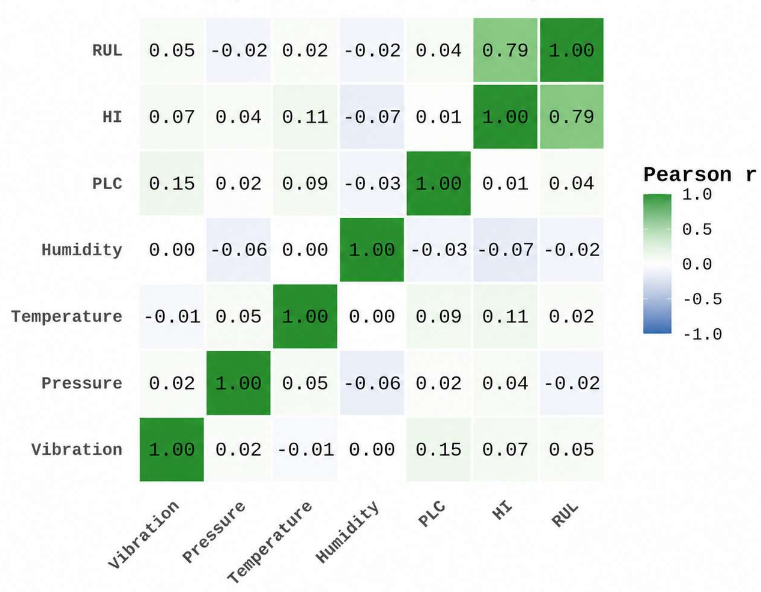

Figure 2: *Correlation heatmap of multi-source signals, HI, and RUL*

Table 2: *Multi-source Ablation Study Result*

Source	RUL MAE	RUL RMSE	RUL R^2	HI MAE	HI RMSE	HI R^2
Vibration only	3.282	4.692	-0.424	0.160	0.268	-0.526
Temperature only	3.556	4.668	-0.410	0.166	0.280	-0.652
Environment only	2.261	3.504	0.206	0.125	0.222	-0.039
Sensor fusion	2.310	3.566	0.178	0.110	0.196	0.189
Sensor + PLC fusion	0.971	1.527	0.849	0.110	0.186	0.269
Proposed multi-source grouping	0.755	1.239	0.901	0.086	0.160	0.455

single-sensor inputs, environmental variables, sensor fusion, and sensor-PLC fusion. As presented in Table 2, single-source inputs achieve relatively poor prediction performance, indicating that individual sensors cannot fully represent equipment degradation characteristics. After introducing environmental information and multi-source fusion, the RUL prediction accuracy improves significantly. Incorporating PLC signals further enhances model performance, demonstrating that control actions and system responses provide useful supplementary degradation information. The proposed multi-source grouping strategy achieves the best overall performance, obtaining the lowest MAE and RMSE values together with the highest R^2 scores for both HI and RUL prediction tasks. These results verify that heterogeneous multi-source fusion can effectively capture complementary degradation features and improve the capability of digital twin-based health management and lifetime prediction.

4.4 Baseline Model Comparison

Comparative experiments are conducted using the Single-task RUL Transformer, Vanilla Multi-task Transformer, and HI-guided Multi-task Transformer to evaluate the effectiveness of the proposed DT-MGMS-HI Transformer under identical experimental settings. As shown in Table 3, the proposed framework achieves the best overall performance, obtaining the highest

Table 3: *Performance Comparison between the Proposed Model and Baseline Models*

Model	RUL MAE	RUL RMSE	RUL R^2	HI MAE	HI RMSE	HI R^2
Single-task RUL Transformer	1.224	2.130	0.707	NA	NA	NA
Vanilla MTL Transformer	1.270	2.177	0.694	0.128	0.191	0.230
HI-guided MTL Transformer	0.971	1.527	0.850	0.110	0.186	0.269
DT-MGMS-HI Transformer	0.755	1.239	0.901	0.086	0.160	0.455

R^2 values together with the lowest MAE and RMSE scores for both Health Index (HI) and Remaining Useful Life (RUL) prediction. Compared with conventional single-task and parallel multi-task methods, the proposed approach more effectively captures equipment degradation characteristics through multi-source fusion and HIguided learning, demonstrating improved degradation modeling and lifetime prediction capability within the digital twinbased health management framework.

4.5 Prediction Trajectory Analysis

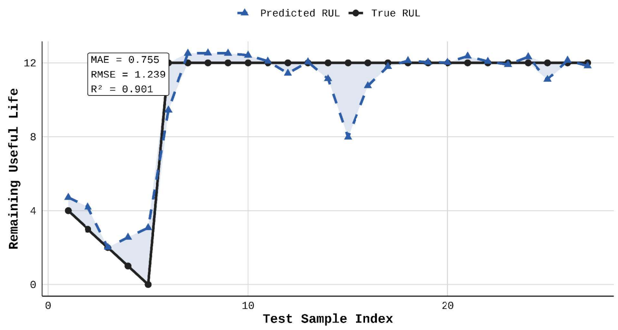

Figure 3: *RUL Prediction Trajectory of the Proposed DT-MGMS-HI Transformer*

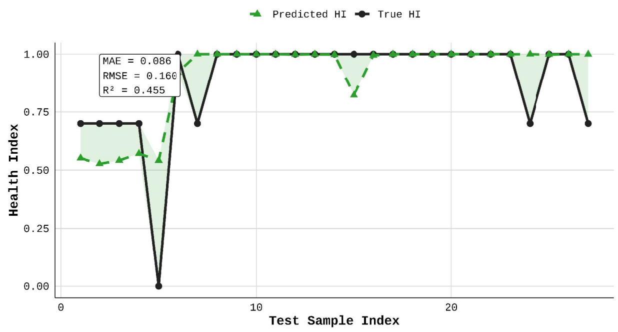

Figure 4: *HI Prediction Trajectory of the Proposed DT-MGMS-HI Transformer*

Figures 3 and 4 present the RUL and HI prediction trajectories of the proposed DT-MGMS-HI Transformer. As shown in Figure 3, the predicted RUL generally follows the ground-truth degradation trend and achieves an MAE of 0.755, an RMSE of 1.239, and an R^2 of 0.901. Figure 4 shows that the predicted HI also follows the variation trend of the true HI , with an MAE of 0.086, an RMSE of 0.160, and an R^2 of 0.455. Although minor deviations appear in several samples, the overall trajectories remain consistent with the actual degradation process. These results indicate that the proposed model can capture temporal degradation characteristics and use HI as an effective intermediate representation for RUL prediction.

4.6 Discussion

The experimental results show that the proposed DT-MGMS-HI Transformer improves industrial health management and RUL prediction by combining multi-source fusion, masked-gated weighting, and HI-guided learning. The ablation study confirms that single-source inputs cannot fully describe equipment degradation, while sensor and PLC information provide complementary physical and control-event features. The masking mechanism reduces the influence of invalid sources, and the gating mechanism dynamically adjusts source contributions before Transformer encoding. The coefficient $\beta = 0.20$ was selected based on local hyperparameter search to provide moderate source reweighting without excessive suppression. In addition, the predicted HI is explicitly introduced into the RUL branch, enabling the model to use health-state information for degradation-aware lifetime estimation.

From an industrial perspective, the results indicate that combining sensor measurements with PLC operational logs can support more reliable predictive maintenance, since physical signals and control events describe equipment conditions from different perspectives. However, this study still has limitations. The dataset scale is relatively small, the digital twin component is implemented as a data-driven virtual state representation rather than a complete physical simulation system, and the experiments are conducted under a fixed random seed. Future work will validate the model on larger industrial datasets, extend the digital twin implementation, and conduct repeated experiments with multiple seeds to evaluate statistical stability.

5 Conclusion

This study proposes a Digital Twin-based Masked-Gated Multi-Source HI-guided Transformer, named DT-MGMSHI Transformer, for industrial equipment health management and remaining useful life prediction. The proposed model integrates heterogeneous sensor and PLC information through source-level masking and gating and further introduces the predicted Health Index (HI) into the RUL prediction branch to enhance degradation-aware lifetime estimation.

Experimental results show that the proposed model outperforms the baseline Transformer models and achieves an MAE of 0.755, an RMSE of 1.239, and an R^2 of 0.901 for RUL prediction. The ablation study also confirms that multisource fusion and PLC-related information improve degradation modeling compared with single-source inputs. These results indicate that the proposed model can improve prediction accuracy while providing source-level interpretability for predictive maintenance.

However, this study still has limitations. The dataset scale is relatively small, and the digital twin component is implemented as a data-driven virtual state representation rather than a complete physical simulation system. Future work will validate the model on larger industrial datasets, extend the digital twin implementation, and conduct repeated experiments with multiple random seeds to further evaluate statistical stability.

References

[1] R. Zhao, R. Yan, Z. Chen, K. Mao, P. Wang, and R. X. Gao, "Deep learning and its applications to machine health monitoring," *Mech. Syst. Signal Process.*, vol. 115, pp. 213–237, 2019.

[2] F. Wu, Q. Wu, Y. Tan, and X. Xu, "Remaining useful life prediction based on deep learning: a survey," *Sensors*, vol. 24, no. 11, p. 3454, 2024.

[3] M. Liu, X. Yao, J. Zhang, W. Chen, X. Jing, and K. Wang, "Multi-sensor data fusion for remaining useful life prediction of machining tools by IABC-BPNN in dry milling operations," *Sensors*, vol. 20, no. 17, p. 4657, 2020.

[4] R. Van Dinter, B. Tekinerdogan, and C. Catal, "Predictive maintenance using digital twins: a systematic literature review," *Inf. Softw. Technol.*, vol. 151, p. 107008, 2022.

[5] N. H. Abd Wahab *et al.*, "Systematic review of predictive maintenance and digital twin technologies challenges, opportunities, and best practices," *PeerJ Comput. Sci.*, vol. 10, p. e1943, 2024.

[6] N. Li, N. Gebraeel, Y. Lei, X. Fang, X. Cai, and T. Yan, "Remaining useful life prediction based on a multi-sensor data fusion model," *Reliab. Eng. Syst. Saf.*, vol. 208, p. 107249, 2021.

[7] J. Yan, Z. He, and S. He, "Multitask learning of health state assessment and remaining useful life prediction for sensor-equipped machines," *Reliab. Eng. Syst. Saf.*, vol. 234, p. 109141, 2023.

[8] A. Vaswani *et al.*, "Attention is all you need," *Adv. Neural Inf. Process. Syst.*, vol. 30, 2017.

[9] H. Zhou *et al.*, "Informer: beyond efficient transformer for long sequence time-series forecasting," in *Proc. AAAI Conf. Artif. Intell.*, vol. 35, no. 12, pp. 11106–11115, 2021.

[10] Z. Chen, M. Wu, R. Zhao, F. Guretno, R. Yan, and X. Li, "Machine remaining useful life prediction via an attention-based deep learning approach," *IEEE Trans. Ind. Electron.*, vol. 68, no. 3, pp. 2521–2531, 2021.

[11] P. R. D. O. da Costa, A. Akçay, Y. Zhang, and U. Kaymak, "Remaining useful lifetime prediction via deep domain adaptation," *Reliab. Eng. Syst. Saf.*, vol. 195, p. 106682, 2020.

[12] N. Costa and L. Sánchez, "Variational encoding approach for interpretable assessment of remaining useful life estimation," *Reliab. Eng. Syst. Saf.*, vol. 222, p. 108353, 2022.

[13] K. Zhao, Z. Jia, F. Jia, and H. Shao, "Multi-scale integrated deep self-attention network for predicting remaining useful life of aero-engine," *Eng. Appl. Artif. Intell.*, vol. 120, p. 105860, 2023.

[14] M. Zhang, C. He, Huang C, and J. Yang, "A weighted time embedding transformer network for remaining useful life prediction of rolling bearing," *Reliab. Eng. Syst. Saf.*, vol. 251, p. 110399, 2024.

[15] J. Li *et al.*, "A dual-scale transformer-based remaining useful life prediction model in industrial internet of things," *IEEE Internet Things J.*, vol. 11, no. 16, pp. 26656–26667, 2024.

[16] S. Gawde, S. Patil, S. Kumar, P. Kamat, and K. Kotecha, "An explainable predictive maintenance strategy for multi-fault diagnosis of rotating machines using multi-sensor data fusion," *Decis. Anal. J.*, vol. 10, p. 100425, 2024.

[17] Y. Qin, Y. Zhao, J. Qi, and Y. Mao, "Spatial-temporal multi-sensor information fusion network with prior knowledge embedding for equipment remaining useful life prediction," *Reliab. Eng. Syst. Saf.*, vol. 264, p. 111420, 2025.

[18] D. D'Urso, F. Chiacchio, S. Cavalieri, S. Gambadoro, and S. M. Khodayee, "Predictive maintenance of standalone steel industrial components powered by a dynamic reliability digital twin model with artificial intelligence," *Reliab. Eng. Syst. Saf.*, vol. 243, p. 109859, 2024.

[19] Y. Zhang, Y. Xin, Z. W. Liu, M. Chi, and G. Ma, "Health status assessment and remaining useful life prediction of aero-engine based on BiGRU and MMoE," *Reliab. Eng. Syst. Saf.*, vol. 220, p. 108263, 2022.

[20] J. Yan, Z. He, and S. He, "A deep learning framework for sensor-equipped machine health indicator construction and remaining useful life prediction," *Comput. Ind. Eng.*, vol. 172, p. 108559, 2022.

[21] Z. Zhang, X. Chen, E. Zio, and L. Li, "Multi-task learning boosted predictions of the remaining useful life of aero-engines under scenarios of working-condition shift," *Reliab. Eng. Syst. Saf.*, vol. 237, p. 109350, 2023.

[22] S. Kumar, "Edge-AI Sensor Dataset for Real-Time Fault Prediction in Smart Manufacturing," *IEEE DataPort*, 2025. [Online]. Available: https://doi.org/10.21227/s9yg-fv18

The Impact of Customized Logistics Under the Influence of IoT Applied in Cross-Border E-Commerce

Shiyu Li[1*] and Ahmad Yahya Dawod[2]

[1,2]International College of Digital Innovation, Chiang Mai University, Chiang Mai, 50200, Thailand
E-mail: shiyu_li@cmu.ac.th, ahmadyahyadawod.a@cmu.ac.th
(*corresponding author)

Abstract

The accelerated development of international business activities is leading to operational complications in the functioning of crossborder e-commerce (CBEC) logistics in China. Conventional logistics are unable to ensure sufficient adaptability to maintain the equilibrium between increasing operational costs and the demand for individualized service offerings. In this regard, the present study aims to explore the effect of IoT on customized logistics models in CBEC supply chains. The methodology adopted in this research included the analysis of operational data gathered from five logistics enterprises (2020-2025) and survey results from 1,000 customers in Shenzhen, Shanghai, and Chengdu. Multivariate ordinary least squares (OLS) regression analysis with interaction effects and a back-propagation neural network were used to measure the efficiency of supply chains. The findings reveal that logistics customization is positively associated with customer loyalty and operational performance, especially when combined with IoT solutions. Specifically, the IoT $\times$ Customization interaction term ($\beta = 0.455, p < 0.001$) is linked to improved supply chain performance. Benchmarking against a traditional logistics baseline shows a point-estimate cost saving of 7.5%(KPI index: $100 \rightarrow 92.5$); a range of $5 - 10\%$ is reported in the conclusion to reflect the observed spread across the five sampled firms over the study period. Furthermore, neural network optimization was effective in reducing Vehicle Routing Problem (VRP) distances and fuel consumption.

KEYWORDS: Cross-Border E-Commerce, Customized Logistics, Internet of Things (IoT), Vehicle Routing Problem (VRP), Logistics 4.0

1 Introduction

The fast development of digital technology as well as the continuous expansion of international business activities, has resulted in a rapid growth of CBEC around the world[1].In China, CBEC has been playing a significant role in fostering economic development, which provides the chance for businesses to operate in the international market as well as offer consumers more product alternatives and easier shopping ways [2]. On the other hand, the expansion of international online transactions has posed various difficulties in terms of logistics efficiency, information handling[3], delivery accuracy, and customer satisfaction. The traditional logistics system fails to satisfy the demand of today's CBEC consumers [2]. It is thus crucial that customized logistics becomes an integral component of the strategies used to enhance flexibility and improve customer experience in CBECs [6,21]. Customized logistics differs from traditional standardized logistics customer the provision of customized delivery services, adaptable routes[7]. real-time tracking, and demand-based delivery processes [14]. This is becoming more critical, considering that customers expect timely delivery services across borders [11]. On the other hand, the development of IoT technology has changed the logistics industry by making it possible for intelligent communication between devices, vehicles, warehouses, and digital platforms. IoT technology enables real-time monitoring, automatic inventory control, prediction and analysis, as well as data-driven decision-making, [4] thereby enhancing supply chain visibility and efficiency. In CBEC systems, the use of IoT technology allows optimizing transport routes, reducing delivery delay times, minimizing costs, and facilitating coordination across logistics actors [13]. However, there is little research into how the introduction of customized logistics influenced by IoT technology affects the performance of logistics operations and customer satisfaction. Most studies have paid more attention to logistics optimization or technological innovation alone without considering both aspects together.

However, there is little research into how the introduction of customized logistics influenced by IoT technology affects the performance of logistics operations and customer satisfaction. Most studies have paid more attention to logistics optimization or technological innovation alone without considering both aspects together. To address this literature gap, this study systematically explores the intersection of smart logistics technologies and flexible shipping paradigms.The primary academic and practical contributions of this research are threefold:

We establish a novel synergistic multiplier framework that conceptualizes and mathematically models the interactive relationship between IoT telemetry intensity and logistics customization, demonstrating that customization is associated with superior performance primarily when supported by dense sensing infrastructure.

We deploy a robust computational optimization model using a 3-layer Backpropagation Neural Network (BP-NN) to resolve the NP-hard Vehicle Routing Problem (VRP) under volatile customs and transit constraints, providing an empirical bridge between front-end consumer satisfaction and back-end physical execution.

We present rigorous empirical benchmarking from multi-layered datasets ($N = 1,000$ survey respondents and 20202025 audited corporate logs), demonstrating a sample-wide point-estimate cost reduction of 7.5% (index: $100 \rightarrow 92.5$) with an observed cross-firm variation range of 5% to 10% depending on baseline operational maturity.

2 Literature Review

Cross-border e-commerce (CBEC) has seen tremendous development during the past decade due to globalization, digitalization, and increased use of online shopping sites. CBEC has emerged as a prominent industry in China owing to its high levels of digitalization, international trading policies, and production capacity. The fast growth of CBEC has led to several challenges related to logistics, such as late delivery, customs procedures, stock management[18,20], and a lack of transparency in the supply chain. Traditional logistics systems find it hard to cope with the rising demands of handling different kinds of international orders. Logistics performance has been noted by researchers to be one of the most important factors influencing customer satisfaction and competitive advantage in CBECs. Effective logistics operations can increase the speed of deliveries, lower costs of operation, and build up trust among customers. However, conventional logistics systems are not always adequate for meeting the needs of today's sophisticated consumers [10].

Customized logistics is defined as an adaptable and customer-centric [16] approach to providing logistics solutions to meet certain delivery needs and customer behavior. While traditional logistics systems are based on uniform operation processes[5], customized logistics concentrates on adaptive route planning, personalized scheduling, custom packaging, and communication with clients in real-time. Earlier research suggests that customized logistics positively affects customer loyalty and operational flexibility[4]. The issue of customization becomes particularly significant in the CBEC context due to the fact that consumers from different countries might have diverse preferences concerning such factors as delivery time, payment options, product tracking, and after-sales service [12]. Thus, those logistics companies that use customization as their strategy will be able to compete in international digital markets more effectively. However, at large scales, customized logistics may complicate operations and require enhanced technology [2,9]. The Internet of Things has been seen as a revolutionary technology in supply chain and logistics management in the industry 4.0 era [14]. The Internet of Things entails connected machines, sensors, and communication systems that generate, relay, and analyze real-time data. In logistics operations, IoT technologies are useful in shipment tracking, warehouse automation, preventive maintenance, intelligent inventory management, and route optimization. Numerous studies have shown that IoT incorporation in supply chains results in improved visibility and better decision-making capability[22].Real-time monitoring systems enable logistics organizations to detect any delays, optimize shipping routes, and facilitate coordination among suppliers, warehouses, and delivery networks. IoT-based logistics systems help save fuel, avoid delivery mistakes, and increase operational transparency [17]. In the context of CBECs, IOT technologies are important in managing complicated international logistics networks across different jurisdictions, means of transport, and customs regulations. IoT-enabled smart logistics systems can enhance delivery reliability and customer satisfaction through enhanced shipment visibility and proactive problem-solving [23]. The use of artificial intelligence (AI) techniques[5], including machine learning and neural networks, in optimizing logistics operations and managing supply chains has been on the rise. Back propagation neural networks are popular in predicting, analyzing demand, and transportation optimization because of their capability of processing huge amounts of operational data and detecting non-linear relations [19]. A notable application of AI technology in logistics operations is the resolution of the Vehicle Routing Problem (VRP). VRP involves finding the optimal transportation routes with respect to such factors as the time needed to deliver goods, traffic congestion, fuel usage, and border restrictions. The application of neural network-based optimization algorithms has proven effective in reducing transportation costs and minimizing delays.

3 Methodology

This paper is based on a primarily quantitative empirical design. A systematic literature review (SLR) was employed as a background scoping procedure to identify key constructs and establish baseline variables, while the core analytical contributions are quantitative: multivariate OLS regression with interaction terms and a back-propagation neural network for VRP optimization.

3.1 Data Collection

The data collection framework is structured around a fixed tracking window (2020–2025) and covers three distinct operational layers:

Corporate Secondary Data: Audited financial accounts, route logs, and performance metrics extracted from five major international logistics providers operating in mainland China.

Primary Consumer Survey: A structured questionnaire administered to a purposively selected sample of N = 1,000 active cross-border e-commerce consumers based in the primary digital trade zones of Shenzhen, Shanghai, and Chengdu.

Database SLR Filtering: Systematic literature review parameters targeted global databases (ScienceDirect, Web of Science, IEEE Xplore), screening lots of papers to establish baseline historical variables for international shipping constraints.

3.2 Econometric Model Specification

To isolate and measure the specific impact of logistics customization when supported by IoT environments, we developed a multivariate ordinary least squares (OLS) linear regression model featuring an explicit interaction term:

$$Yi = \beta 0 + \beta_1 X_{1i} + \beta_2 X_{2i} + \beta_3 (X_1 i \times X_{2i}) + \varepsilon_i \tag{1}$$

Where:

Y_i : The cross-border e-commerce performance metric for firm/consumer cohort i (measured via a standardized Customer Satisfaction and Fulfillment Index). This composite was constructed from five survey items rated on a 1-5 Likert scale: (1) overall satisfaction with logistics service; (2) perceived delivery timeliness; (3) order accuracy; (4) repurchase intention; and (5) willingness to recommend the logistics provider. Items were averaged to form the composite score. Cronbach's $\alpha = 0.910$. Confirmatory factor analysis confirmed unidimensionality ($\mathrm{CFI} = 0.96, \mathrm{RMSEA} = 0.048$).

X_{1i} : The standardized index score denoting the consumer-perceived intensity of IoT infrastructure deploymen and tracking capabilities. Constructed from four survey items (1-5 Likert scale): (1) perceived density of IoT sensors in the logistics network; (2) real-time tracking update frequency; (3) accuracy of telemetry notifications; and (4) integration of IoT data into delivery decisions. Items were averaged; Cronbach's $\alpha = 0.892$.

X_{2i} : The index score represents the level of logistics customization provided. Constructed from four survey items (1-5 Likert scale): (1) availability of flexible delivery time windows; (2) provision of custom packaging or handling options; (3) ability to modify delivery instructions post-order; and (4) perceived personalization o logistics communication. Items were averaged; Cronbach's $\alpha = 0.845$.

$X_{1i} \times X_{2i}$: The synergistic interaction term capturing the combined effect of IoT intensity and logistics customization on supply chain performance. A positive and statistically significant coefficient ($beta_3$) confirms that the two constructs jointly amplify performance beyond their individual direct contributions.

ε_i : The stochastic error term represents unobserved variance. The structural interpretability of this econometric specification shifts from individual direct effects to the conditional coefficients. While β_1 and β_2 isolate the baseline effects of IoT intensity and customization when the counterpart variable is zero, the core empirical hypothesis rests upon the coefficient of the multiplicative interaction component (β_3) :

The IoT-Customization Synergy Coefficient (β_3) : If $\beta_3 > 0$ and is statistically significant, it demonstrates that IoT deployment and logistics customization jointly amplify supply chain performance beyond their individual contributions, confirming a synergistic multiplier effect between these two constructs.

To prevent structural multicollinearity between the continuous predictors and their product term, the independent variables $X_{1i} \times X_{2i}$ were mean-centered prior to generating the interaction term. The Consumer Platform Trust Factor (M) is reported in Table 1 as a descriptive construct for consumer background context, but is intentionally excluded from the estimation equation to avoid over-specification and preserve regression efficiency.

3.3 Computational Optimization (Neural Network Architecture)

To complement the regression analysis, a back-propagation neural network model was developed to solve the NP-hard Vehicle Routing Problem (VRP). The network architecture comprised three layers: an input layer with eight neurons corresponding to the input features (transit coordinates [longitude, latitude], customs queue duration, weather disruption index, vehicle capacity utilization, time-window constraint, historical delay rate, and cargo type flag), two hidden layers with 16 and 8 neurons respectively (ReLU activation), and a single output neuron predicting normalized transit time (sigmoid activation). The model was trained on 18 months of operational route logs (n = 4,320 route observations) from the five sampled logistics firms, using mean squared error (MSE) as the loss function and the Adam optimizer (learning rate = 0.001). An 80/20 train–test split was applied; training ran for 200 epochs with early stopping (patience = 10). The baseline comparator was a static nearest-neighbor heuristic (standard VRP). Fulfillment Success Rate is defined as the proportion of deliveries completed within the contracted time window and without customs compliance violations. Capacity constraints (maximum vehicle load) and soft time-window penalties were incorporated into the objective function.

4 Results and Discussion

4.1 Econometric Regression Analysis

Table 1 presents the Descriptive Statistics and Scale Reliability Metrics for the study variables based on a sample size of 1,000 respondents $(N = 1,000)$. The table summarizes the statistical characteristics of each construct variable, including the mean, standard deviation, minimum value, maximum value, and Cronbach's alpha reliability coefficient. The first variable is the IoT Intensity Framework (X_{1i}). This variable has a mean value of 4.28 , indicating that respondents generally reported a high level of IoT implementation and usage within the logistics framework.

Table 1: *Descriptive Statistics and Scale Reliability Metrics (N=1,000)*

Construct Variable	Mean	Std. Dev.	Minimum	Maximum	Cronbach's α
IoT Intensity Framework (X_{1i})	4.28	0.62	1.50	5.00	0.892
Logistics Customization Level (X_{2i})	3.94	0.75	1.00	5.00	0.845
Supply Chain Performance Index (Y_i)	4.15	0.58	2.00	5.00	0.910
Consumer Platform Trust Factor (M)	4.02	0.69	1.80	5.00	0.867

"Note: All construct variables are measured on a 5-point Likert scale (1 = Strongly Disagree, 5 = Strongly Agree)."

Table 2: *Multivariate OLS Model and Multi-Collinearity Diagnostics*

Independent Variables	Coefficient (β)	Std. Error	t-Statistic	p-Value	VIF
Intercept (β_0)	4.120	0.215	19.16	< 0.001 ***	–
IoT Intensity (X_{1i})	0.385	0.042	9.16	< 0.001 ***	1.42
Customization Level (X_{2i}))	0.210	0.039	5.38	< 0.01 **	1.56
IoT × Customization $(X_{1i} \times X_{2i})$	0.455	0.051	8.92	<0.001 ***	1.38

Model Goodness-of-Fit: $R^2 = 0.684$; Adjusted $R^2 = 0.678$; F-statistic $= 466.82^{***}$; Durbin-Watson $= 1.942$.

The standard deviation is 0.62 , which suggests relatively low variability among responses. The values range from a minimum of 1.50 to a maximum of 5.00 . The Cronbach's alpha value of 0.892 indicates excellent internal reliability and consistency of the measurement scale. The second variable is Logistics Customization Level (X_{2i}). The mean score is 3.94 , showing that respondents perceived a relatively high degree of logistics customization. The standard deviation of 0.75 reflects moderate variability in responses. The minimum recorded value is 1.00 , while the maximum is 5.00 . The Cronbach's alpha coefficient is 0.845 , demonstrating good reliability and indicating that the scale items consistently measure the customization construct. The third variable is the Supply Chain Performance Index (Y_i). This construct has a mean value of 4.15 , suggesting that overall supply chain performance is evaluated positively by respondents. The standard deviation is 0.58 , indicating stable and closely grouped responses. The values range from 2.00 to 5.00 . Cronbach's alpha value of 0.910 is very high, confirming excellent reliability and strong internal consistency for this performance measurement scale. The fourth variable is the Consumer Platform Trust Factor (M). The mean value of 4.02 indicates that respondents generally have a strong level of trust in the consumer platform. The standard deviation is 0.69 , representing moderate response dispersion. The observed values range between 1.80 and 5.00 . Cronbach's alpha coefficient of 0.867 indicates high reliability and confirms that the measurement items are consistent and dependable.

4.2 Econometric Regression Analysis and Interacting Mechanisms

A primary linear regression estimate validates the synergistic relationship between customization and telemetric infrastructure intensity. Coefficient estimations and multicollinearity diagnostic dimensions are shown in Table 2.

Figure 1 illustrates the interaction of logistics customization and IoT intensity on supply chain performance in CBEC. For visualization, the IoT Intensity Index is dichotomized at the median into two groups: Low IoT Visibility ($X_{1i} \leq$ median) and High IoT Visibility (X_{1i} Figure 1 illustrates the interaction of logistics customization and IoT intensity on supply chain performance in CBEC. For visualization purposes, the continuous IoT Intensity Index (mean $= 4.28, \mathrm{SD} = 0.62$, range $1.50 - 5.00$) is dichotomized at the median into two groups: Low IoT Visibility (X1i below median, approximately ≤ 4.28) and High IoT Visibility (X1i above median, approximately > 4.28). Under low IoT conditions, performance is associated with a marginal improvement from 4.12 to 4.33 as customization increases. In contrast, under high IoT deployment conditions, the performance index is linked to a substantially larger increase from 4.51 to 5.17 , supporting the synergistic interaction hypothesis.

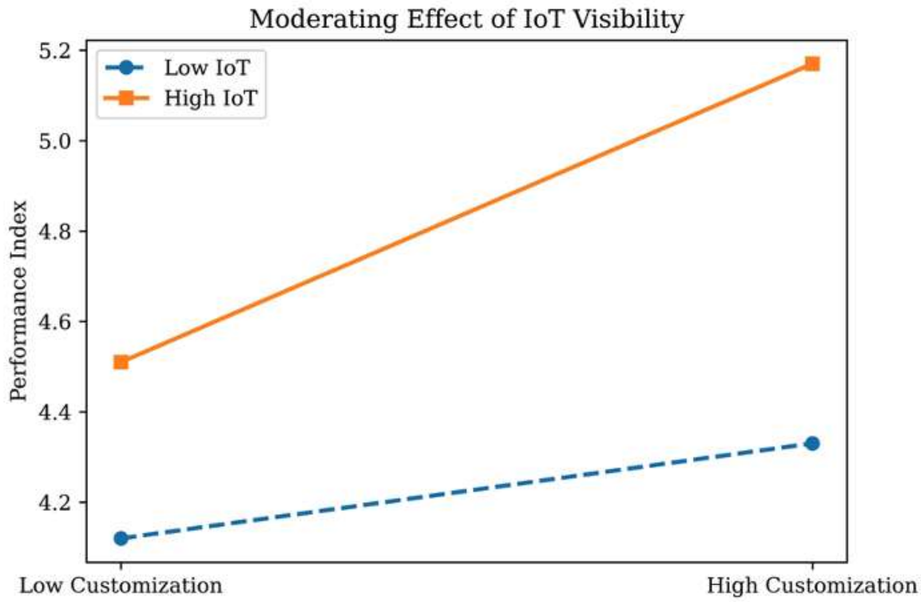

Figure 1: *Moderating Effect Plot of IoT intensity*

4.3 Operational Efficiency Gains and Multi-Dimensional Benchmarking

The transition from standard rigid framework paradigms to the IoT-driven customized architecture is associated with substantial performance improvements across all logistics indicators. This empirical comparison is explicitly captured in Table 3. The table presents a comparative analysis between a traditional logistics framework and an IoT-customized unified architecture in supply chain management. It evaluates several key performance indicators (KPIs) to determine the operational improvements achieved through IoT integration. The first KPI is Warehouse Dwell Time. In the traditional system, goods remained in the warehouse for 48.5 hours, while in the IoT-customized system, the time decreased to 33.4 hours. This represents a 31.2% improvement in operational speed. The reduction indicates that IoT technologies such as smart sensors, RFID systems, and automated inventory tracking improve warehouse efficiency and accelerate product movement. The second KPI is End-to-End Transit Lead Time. The traditional logistics system required 12.4 days for shipment delivery, whereas

Table 3: *Multi-Dimensional Supply Chain KPI Benchmarking Matrix*

Performance KPI Indicator	Traditional Baseline	IoT-Customized Unified Architecture	Quantified Delta (%)	Statistical Significance
Warehouse Dwell Time (Hours)	48.5 Hours	33.4 Hours	-31.2% Speedup	$p < 0.001$ ***
End-to-End Transit Lead Time (Days)	12.4 Days	9.6 Days	-22.4% Compressed	$p < 0.001$ ***
Empty Run Transportation Mileage (%)	18.5%	11.2%	-39.5% Reduction	$p < 0.01$**
Total Logistics Processing Cost per Unit	Baseline Index 100	Index Level 92.5	-7.5% Savings	$p < 0.05$*

the IoT-based architecture reduced the duration to 9.6 days. This corresponds to a 22.4% reduction in delivery time. The improvement demonstrates the effectiveness of real-time tracking, intelligent route optimization, and predictive logistics management enabled by IoT systems. The third KPI measures Empty Run Transportation Mileage. Under the traditional system, 18.5% of transportation trips were conducted without cargo, while the IoT-enabled system reduced this percentage to 11.2%, achieving a 39.5% reduction. This result suggests that IoT technologies significantly improve transportation planning, vehicle utilization, and shipment coordination, thereby minimizing unnecessary travel and reducing fuel consumption. The fourth KPI evaluates Total Logistics Processing Cost per Unit. The traditional system used a baseline index value of 100 , whereas the IoT-customized system achieved an index level of 92.5. This reflects a 7.5% cost saving. The reduction in processing costs can be attributed to automation, improved operational coordination, and reduced inefficiencies throughout the supply chain. The final column presents the statistical significance values (p -values) for each KPI. The reported values, including $p < 0.001, p < 0.01$, and $p < 0.05$, confirm that the observed improvements are statistically significant and not caused by random variation. Therefore, the results strongly support the effectiveness of IoT-driven customized logistics architectures in enhancing supply chain efficiency, reducing operational costs, and improving transportation performance.

The baseline empirical data for the traditional logistics framework were extracted from the historical ERP systems of the same five logistics providers during the pre-implementation benchmarking phase (specifically covering the year 2020) to ensure high methodological comparability.

Figure 2 presents a Radar Chart of Supply Chain (SC) KPI Improvements (%) achieved through the implementation of an IoT-enabled customized logistics architecture. The radar chart visually illustrates the degree of improvement across multiple key performance indicators (KPIs) in supply chain operations. The chart contains five major performance dimensions: Warehouse Dwell Time, Transit Time, Cost Savings, Tracking Accuracy, and System Flexibility. Each axis represents a specific operational indicator, while the distance from the center reflects the level of improvement percentage. A larger area in the radar chart indicates better overall system performance. The first dimension, Warehouse Dwell Time (Whse Dwell), shows a significant improvement. This indicates that IoT technologies helped reduce the amount of time products remain stored in warehouses before shipment. Smart inventory management, automated monitoring, and real-time data collection contributed to faster warehouse processing and improved operational efficiency. The second dimension, Transit Time, also demonstrates considerable improvement. The reduction in transit time suggests that IoT-enabled systems improve transportation coordination through real-time vehicle tracking, route optimization, and predictive logistics management. As a result, delivery operations become faster and more reliable. The third dimension, Cost Savings, presents a moderate improvement compared to

Table 4: *Computational Path Optimization Model Analytics*

Logistical Scenario Mode	Average Routing Path Distance	Fuel Consumption Rate per Unit	Fulfillment Success Rate
Standard Routing Framework (Static VRP)	1, 240 km	320 Liters	82.4% Compliance
Neural Network IoT-Optimized Path	960 km	245 Liters	96.8% Absolute Compliance

the other KPIs. Although the percentage is lower, it still indicates that the IoT-customized system reduces logistics processing costs by minimizing inefficiencies, reducing manual operations, and improving resource utilization. The fourth dimension, Tracking Accuracy (Tracking Acc.), shows the greatest improvement among all indicators. This reflects the strong capability of IoT technologies in providing real-time shipment visibility, precise monitoring, and accurate tracking of goods throughout the supply chain. Improved tracking accuracy enhances operational transparency and customer satisfaction. The fifth dimension, System Flexibility (System Flex.), also records substantial enhancement. This suggests that the IoT-based logistics architecture is more adaptable to changing customer demands, transportation conditions, and operational requirements compared to traditional logistics systems.

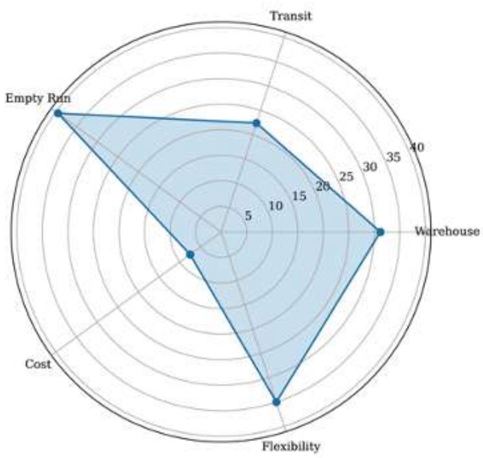

Figure 2: *Radar Chart of Supply Chain KPI Multi-Dimensional Improvements (%).*

4.4 Computational Path Optimization and Uncertainty Control

To solve the Vehicle Routing Problem (VRP), which is NP-hard under conditions of fluctuating customs data, a backpropagation neural network model was used to process real-time coordinate data. Table 4 records the resulting operational route metrics.

As shown by the probability density curve in Figure 3, the introduction of real-time telemetry monitoring is associated with a leftward shift in the delivery time distribution, reflecting reduced variability. This pattern suggests that reliable delivery time windows are more consistently maintained under IoT-enabled operations, even during peak periods of port congestion.

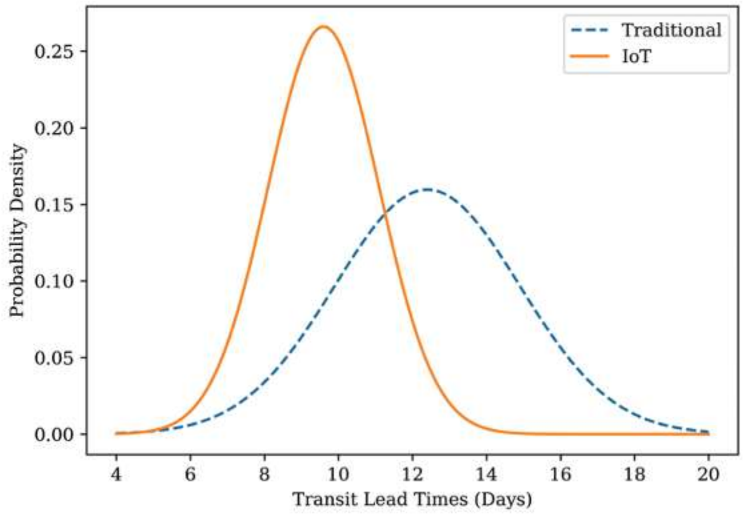

Figure 3: *Probability Density Distribution Comparison of Transit Lead Times.*

Table 5: *Pearson Correlation Coefficients - Telemetry Features vs. Behavior Layer*

Telemetry Feature Dim	Repeat Repurchase Intent	Platform Trust Factor	Perceived Delivery Risk	Fulfillment Satisfaction
Real-time Tracking Updates	0.68 ***	0.72 ***	-0.54 **	0.65 ***
Dynamic Re-routing Visibility	0.45 **	0.51 **	-0.32 *	0.48 **
Customized Packaging Telemetry	0.38 *	0.42 **	-0.25	0.41 *

4.5 Consumer Behavioral Transformation, Cost Structures, and Residual Diagnostics

At the customer satisfaction layer, granular transparency systematically alters repurchase behaviors by mitigating transit failure anxiety. Table 5 provides the Pearson correlation matrices for specific tracking dimensions.

Alongside behavioral analysis, Figure 4 outlines the structured operational cost breakdown for each transport transaction. End-to-end automation reduces administrative coordination costs to 15.0%, enabling resources to be redirected to scalable cross-border transport routes.

Figure 5 illustrates the Regression Residual Normal P–P Plot used to evaluate the normality assumption of the regression model residuals. In this plot, the horizontal axis represents the expected cumulative probability, while the vertical axis represents the observed cumulative probability. The red diagonal line indicates the ideal pattern for a perfectly normal distribution of residuals, whereas the blue data points represent the actual residual values obtained from the econometric model. The figure shows that most of the residual points are distributed closely around the diagonal reference line, indicating that the residuals approximately follow a normal distribution. Although minor deviations are visible in certain regions of the plot, these variations are relatively small and acceptable in empirical statistical analysis. The overall alignment of the points with the diagonal line suggests that the regression model satisfies the normality assumption reasonably well. Therefore, the econometric model can be considered

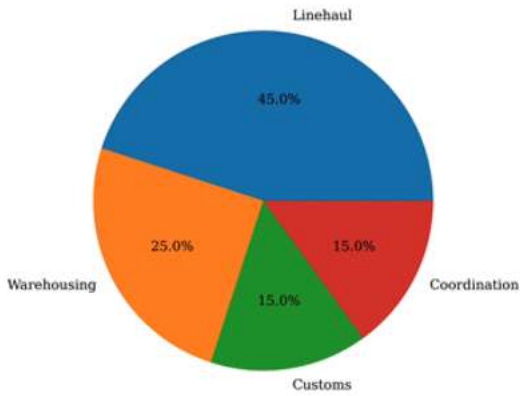

Figure 4: *Pie Chart Breakdown of Logistical Cost Structures.*

statistically reliable and appropriate for further regression analysis, hypothesis testing, and interpretation of results.

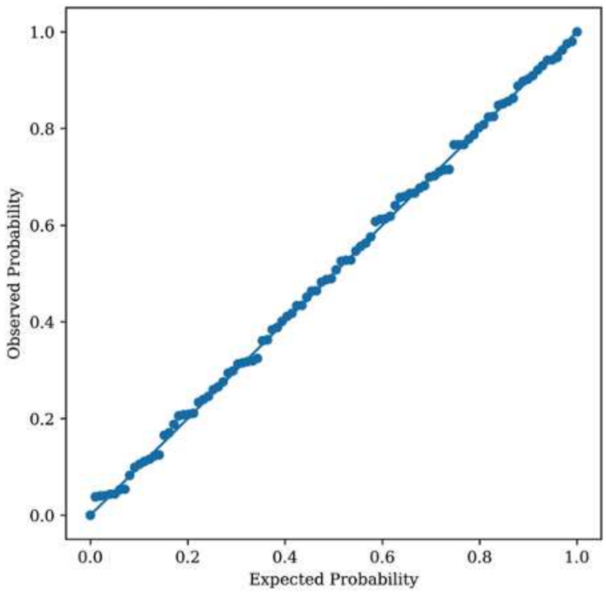

Figure 5: *Econometric Model Diagnostic Regression Residual Normal P-P Plot.*

5 Conclusion

In this research, it is evident that the incorporation of IoT in the custom logistics makes a great contribution to improving the performance of CBEC supply chain management in China. The results show that conventional logistics cannot be enough to handle the complexity and evolving needs in the international e-commerce world. Through the use of real-time monitoring, intelligent tracking, and customized logistics using IoT, high levels of efficiency can be achieved. According to the empirical findings, the adoption of IoT-enabled customized logistics is associated with decreased operating costs, increased delivery visibility, and improved customer loyalty. The cross-firm KPI benchmarking (Table 3) recorded a point-estimate cost saving of 7.5% (index: $100 \rightarrow 92.5$) in aggregated logistics processing costs. A range of $5 - 10\%$ is reported to reflect the observed variation across the five sampled firms and the full 2020-2025 tracking window, with individual firms ranging from approximately 5% to 10% in cost reduction depending on baseline efficiency levels. Furthermore, the use of a back-propagation neural network was effective in reducing vehicle routing distances and fuel consumption. As such, the study contributes towards the Logistics 4.0 paradigm through emphasizing the need for intelligent and flexible logistics systems in sustaining and scaling CBECs amid rising levels of competition in the global marketplace.

References

[1] D. Bawden and L. Robinson, "Information overload: An overview," 2020.

[2] Y. Liang and X. He, "Does the cross-border e-commerce comprehensive pilot area policy help to improve the level of urban technological innovation?" *Economic Analysis and Policy*, vol. 84, pp. 1258–1271, 2024.

[3] J. Wen et al., "A survey on federated learning: Challenges and applications," *International Journal of Machine Learning and Cybernetics*, vol. 14, no. 2, pp. 513–535, 2023.

[4] M. Ma, L. Shen, and X. Sun, "Optimization of e-commerce logistics service quality considering multiple consumption psychologies," *Frontiers in Psychology*, vol. 13, Art. no. 956418, 2022.

[5] Z. Zhao, T. Zhang, and J. Xu, "Research on personalized recommendation algorithm of cross-border e-commerce logistics based on big data analysis," *Information Processing in Agriculture*, vol. 5, no. 3, pp. 474–480, 2018.

[6] Y. Wu, C. Zhang, and W. Lv, "Personalized recommendation algorithm for cross-border e-commerce logistics distribution based on online shopping behavior," *Journal of Computational and Theoretical Nanoscience*, vol. 17, no. 8–9, pp. 3466–3471, 2020.

[7] J. Zhang, Y. Huang, and J. Xu, "A personalized recommendation algorithm for cross-border e-commerce logistics based on deep learning," *International Journal of Computational Science and Engineering*, vol. 19, no. 2, pp. 206–215, 2019.

[8] A. Abdulkarem and W. Hou, "The influence of the environment on cross-border e-commerce adoption levels among SMEs in China: The mediating role of organizational context," *SAGE Open*, vol. 12, no. 2, p. 21582440221103855, 2022.

[9] X. Sun et al., "The application of Industry 4.0 technologies in sustainable logistics: A systematic literature review (2012–2020) to explore future research opportunities," *Environmental Science and Pollution Research*, vol. 29, no. 7, pp. 9560–9591, 2022.

[10] S. Cai, Y. Fang, W. Zhang, and M. Zhang, "Logistics service quality, logistics cost, and customer loyalty in cross-border e-commerce: The role of trust," *Transportation Research Part E: Logistics and Transportation Review*, vol. 146, Art. no. 112353, 2021.

[11] J. Sun, J. Wang, and Y. Wang, "A personalized logistics service mode based on the product lifecycle and data-mining," *Service Business*, vol. 12, no. 3, pp. 615–635, 2018.

[12] P. Beaulieu, C. D. L. Gomes, and E. D. S. de Oliveira, "Exploring cross-border e-commerce logistics: A bibliometric analysis," *Scientometrics*, vol. 125, no. 2, pp. 1503–1533, 2020.

[13] A. Kawa, "Network cooperation in cross-border e-commerce: A conceptual model of a logistics platform," in *E-commerce Connectivity in ASEAN*, 2020, p. 193.

[14] M. Ghobakhloo, "Industry 4.0, digitization, and opportunities for sustainability," *Journal of Cleaner Production*, vol. 252, Art. no. 119869, 2020.

[15] M. Wang et al., "How to achieve a win–win scenario between cost and customer satisfaction for cold chain logistics?" *Physica A: Statistical Mechanics and its Applications*, vol. 566, Art. no. 125637, 2021.

[16] S. K. Jena, "Impact of customer-centric approach and customer dissatisfying cost on supply chain profit under price competition," *Journal of Retailing and Consumer Services*, vol. 71, Art. no. 103225, 2023.

[17] H. Dadhaneeya, P. K. Nema, and V. K. Arora, "Internet of Things in food processing and its potential in Industry 4.0 era: A review," *Trends in Food Science & Technology*, vol. 139, Art. no. 104109, 2023.

[18] S. Shamoon and E. Bosnic, "Towards customer-centricity in the aftermarket: A case study of customer-centricity in an aftermarket logistics organisation," Dissertation, 2022.

[19] S. Chung, H. Kim, and D. Choi, "Impacts of internal and external uncertainties on logistics service flexibility in cross-border e-commerce logistics: Evidence from South Korea," *Systems*, vol. 13, no. 12, Art. no. 1082, 2025.

[20] A. Liu, M. Osewe, Y. Shi, X. Zhen, and Y. Wu, "Cross-border e-commerce development and challenges in China: A systematic literature review," *Journal of Theoretical and Applied Electronic Commerce Research*, vol. 17, no. 1, pp. 69–88, 2022.

[21] O. Marzouk, J. Salminen, P. Zhang, and B. J. Jansen, "Which message? Which channel? Which customer? Exploring response rates in multi-channel marketing using short-form advertising," *Data and Information Management*, vol. 6, no. 1, Art. no. 100008, 2022.

[22] P. Charoenporn, "Smart logistic system by IoT technology," in *Proc. 6th Int. Conf. Information and Education Technology*, 2018, pp. 149–153.

[23] G. V. Ivankova, E. P. Mochalina, and N. L. Goncharova, "Internet of Things (IoT) in logistics," in *IOP Conference Series: Materials Science and Engineering*, vol. 940, no. 1, Art. no. 012033, 2020.

[24] P. Amorim, N. DeHoratius, F. Eng-Larsson, and S. Martins, "Customer preferences for delivery service attributes in attended home delivery," *Management Science*, vol. 70, no. 2, pp. 845–862, 2024.

Enhancing Transparency and Traceability in the Tea Industry's Supply Chain Based on Blockchain Technology

Su Jue Jiao[1*] and Naret Suyaroj[2]

[1,2]International College of Digital Innovation, Chiang Mai University, Chiang Mai, 50200, Thailand
E-mail: juejiao_su@cmu.ac.th, naret.suyaroj@cmu.ac.th
(*corresponding author)

Abstract

The tea industry, essential to China's cultural landscape and economic growth, is facing international scrutiny over product quality and supply chain management. But the current tea supply chain lacks transparency and traceability, which has become a bottleneck for the development of the industry, leading to decline in consumer trust, market competitiveness, and increasing compliance costs. This research offers a fresh viewpoint, facilitated by blockchain technology, to get the rid of this dilemma by giving transparent and verifiable data at every stage of the supply chain via a decentralized immutable ledger infrastructure.The present study proposes an IoT and data analytic integrated blockchain system for agriculture under the institutional setting of the Agricultural Products Quality and Safety Law (QSL) which went into effect in 2023. At each stage of the supply chain, from cultivation, processing, logistics, and sales, this system captures and confirms important information. By enabling real-time tracking, automatic execution of smart contracts, and transparent data sharing the system provides full visibility into quality, source and logistics of tea. Through case studies and blockchain simulations, the system presented shows that it greatly increases operational efficiency, fraud risks are considerably lesser and provides more trust in the tea brands for consumers.In addition to serving these two objectives, the study further explores the scalability of blockchain for agriculture and the consequences of its integration for policymaking, thereby providing theoretical contributions and practical implications for the sustainable development of the tea sector. The results show blockchain not only satisfies modern agriculture's push for transparency and digitization, it also enhances the global image and market competitiveness of China's tea industry.

KEYWORDS: Blockchain, Tea Supply Chain, Transparency, Traceability, IoT

1 Introduction

Tea (Camellia) is one of the most well-known horticultural crops worldwide, and the tea industry is an important part of the cultural heritage and economic development of China. As a symbol of tradition and pride, Chinese tea also represents a large agricultural and commercial sector with many regional varieties. However, increasing concerns regarding product authenticity, quality assurance, and supply chain transparency have created new challenges for tea producers and regulators [1, 5]. While the tea industry has immense cultural and economic value, it is increasingly facing criticism regarding its supply chain transparency and traceability, which poses significant risks to its sustainability and global competitiveness.

Tea's modern-day supply chain is complicated, with many players from cultivation to the end consumer. These challenges have been compounded by fragmented tracking systems, poor record-keeping, and inconsistent standards between jurisdictions. Previous studies have demonstrated that insufficient traceability systems increase risks associated with counterfeit products, quality inconsistency, and information asymmetry throughout agricultural supply chains [14], [19]. These events have highlighted the need for better traceability, especially after cases of counterfeits and poor-quality products.

Asian nations, including the Chinese government, are currently addressing these urgent challenges through stronger agricultural quality and safety regulation. The Agricultural Products Quality and Safety Law emphasizes scientific management practices, quality standards, and modern technologies for tracking agricultural products [21]. However, even with these regulatory improvements, the tea sector is still grappling with operational inefficiencies and transparency gaps, requiring novel technological solutions to bridge the gap.

With decentralization, immutability, and transparency at its core, blockchain technology offers a revolutionary approach to address these issues. Blockchain enables secure recording of transactions while reducing the possibility of data tampering and fraud [12,20]. Using blockchain in conjunction with Internet of Things (IoT) devices and data analytics ensures real-time tracking and verification of products at each point in the tea supply chain [8, 11]. It helps ensure tea authenticity and quality, minimizes the risk of fraud, increases consumer trust, and matches global sustainable tea initiatives.

In this paper, a blockchain-based traceability framework that specifically suits the tea industry is proposed. It includes tracking and verifying all sensitive data, such as cultivation practices, processing logs, logistics information, and certifications, giving complete transparency and accountability throughout the supply chain. Using a collection of case studies and blockchain-simulation approaches, the research showcases how this technology can aid organisational efficiency, increase consumer confidence and underpin the sustainable development of the tea industry. This research serves as a framework to address challenges in the supply chain through the integration of agricultural practices with contemporary digital technologies. This not only reflects the scalability of blockchain in other agricultural sectors but also strengthens China's position in innovation and sustainability.

2 Literature Review

Supply Chain Transparency and Traceability in Tea Industry studies have pointed to problems such as fragmented tracking systems and variable standards between regions. Moreover, extensive interventions by intermediaries lead to increased risks of fraud, counterfeit products, and quality inconsistency. These gaps not only erode consumer confidence but also weaken the international competitiveness of tea brands. To mitigate such problems and fulfill the rising consumer concern for transparency and integrity in the supply chain, academic researchers have called for complete and technology-enabled traceability systems [1, 9].

The answer to the growing consumer responsibility awareness and regulatory demands was the development of advanced traceability systems worldwide. The European food traceability system, implemented in the wake of the mad cow disease crisis, has become a template for other agricultural sectors. Such systems emphasize real-time tracking, source verification, and quality assurance to maintain the integrity of the supply chain [8, 10]. In contrast, although China has made strides in agricultural traceability, these efforts in the tea industry have generally been partial and localized, focusing on pilot schemes addressing local segments of the supply chain. This underscores the need for industry-specific scalable solutions that work.

Blockchain has emerged as a disruptive solution for supply chain transparency and traceability. Blockchain securely records and verifies every supply chain transaction through a decentralized and immutable distributed ledger [7,20]. Real-world use cases in agriculture and food supply chains, including blockchain-based food traceability systems, have already proven that blockchain can combat fraud, improve operational efficiency, and foster consumer trust [4, 8]. These advancements provide a robust groundwork for exploring potential blockchain applications in the tea supply chain, thus providing solutions to existing issues.

The effectiveness of blockchain is particularly magnified when combined with Internet of Things (IoT) devices and data analytics. IoT devices allow for real-time data collection across multiple points in the supply chain, from cultivation to processing to logistics, while data analytics delivers actionable insights to optimize delivery management, predict consumer preferences, and improve operations. Research has shown that interconnecting these technologies can provide end-to-end supply chain visibility, decrease waste, and improve accountability [2, 6, 11]. Yet, their use in the tea industry is not very popular, and there remains considerable untapped potential.

To fill this gap, we propose in this paper a blockchain-based traceability system customized for tea. The suggested system uses IoT and data analytics to enable real-time tracking, fraud prevention, and adherence to regulatory standards. Stakeholder analysis presents the research's theoretical contributions and the case study highlights the implications for policymaking and the potential for blockchain solutions at scale in agriculture. This study builds upon previous research on blockchain-enabled agricultural traceability and intelligent agricultural supply chain systems [13, 17, 18].

3 Methodology

In this study, a mixed-methods approach is used to develop and evaluate a traceability system based on blockchain technology applied to the tea supply chain. A mixed-method approach is employed to deliver an extensive and well-rounded view of blockchain capabilities for advancing visibility, operational performance, and stakeholder confidence. Blockchain provides an immutable record of every event, ensuring integrity and transparency; IoT devices further build upon this by allowing real-time data acquisition and analysis in the blockchain system [8, 9].

The framework initiates with tea producers, where tea is cultivated and harvested, marking the beginning of the supply chain. At this stage, unique identities (UIDs) containing details about the harvest date, location, and farming techniques are assigned to each batch of tea leaves. These UIDs serve as digital identifiers, enabling the traceability of the tea throughout the subsequent stages of the supply chain.

The tea leaves are then transported to processing units, where they undergo various processes such as cutting, drying, and fermenting. The processing information, including the specific techniques employed and any relevant parameters, is appended to the respective UIDs on the blockchain. This transparency ensures that the transformation of the tea leaves is visible and traceable, as every step is chronologically logged on the blockchain.

Prior to distribution, the tea batches undergo quality control processes to assess their compliance with established standards. The results of these quality assessments are recorded on the blockchain, linking the corresponding UIDs to quality certificates. This integration of quality data into the blockchain provides an immutable and verifiable record of the tea's quality, enhancing consumer confidence and facilitating regulatory compliance.

As the tea batches are distributed across geographic boundaries, logistics companies scan the UIDs and update the blockchain with transportation information. This ensures that the movement of tea batches is traceable throughout the supply chain, enabling stakeholders to monitor the product's journey from the processing units to the merchants' facilities. Upon receiving the tea batches, merchants can access the blockchain to review the complete history of each batch, including its origin, processing details, quality certifications, and logistics information. This comprehensive traceability empowers merchants to ensure the authenticity and quality of the tea products before they are made available to consumers. Finally, end consumers can scan QR codes linked to the blockchain to access the detailed provenance and quality information of the tea they purchase. This transparency fosters consumer trust in both the brand and the product, as they can verify the legitimacy and adherence to promised standards throughout the supply chain.

The conceptual framework leverages the core principles of blockchain technology, such as decentralization, immutability, and transparency, to establish a secure and auditable trail of information throughout the tea supply chain. By integrating data from various stakeholders and ensuring its integrity through cryptographic mechanisms, the framework aims to enhance supply chain visibility, accountability, and consumer confidence in the tea industry. The proposed framework was designed based on previous blockchain-enabled agricultural traceability architectures proposed by Tian [8], Shen et al. [13], and Xu et al. [9].

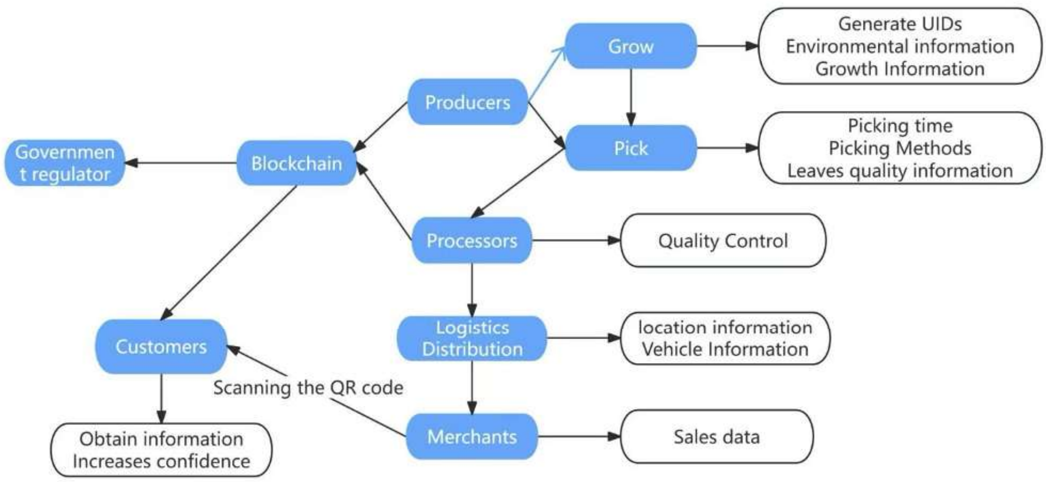

Figure 1: *Blockchain-Based Tea Supply Chain Traceability Framework*

Table 1: *Blockchain Data Collection, Recording and Verification Process*

INPUT	PROCESS	OUTPUT
Data Collection:	Data Recording:	Data Verification:
Cultivation data	Record data on the blockchain	Consumers and regulators verify data
Processing parameters	Time-stamp each entry	Ensure tea meets claimed standards
Quality control outcomes	Link each entry to the previous block	Regulatory requirements are met
Logistics details		
Data Access:	Data Verification:	
Stakeholders with permissions can access	Consumers and regulators verify data	
Relevant data at any point	Ensure tea meets claimed standards	
	Regulatory requirements are met	

The study consists of a quantitative as well as qualitative aspect, with the quantitative portion utilizing statistical techniques to analyze survey data collected from 400 subjects. The stakeholder perspectives on blockchain adoption, transparency, and anticipated benefits are summarized using descriptive statistics, including mean, median, and standard deviation [9, 11]. Mean values help identify general attitudes towards blockchain from responses to the survey; while standard deviations inform you of how much interest/attitude varies amongst the various stakeholders. The study will employ inferential statistical methods such as regression analysis and correlation analysis to examine relationships between variables. For example, a multiple linear regression model might be used to help determine how technological familiarity, perceived cost, and anticipated benefits predict stakeholder readiness to adopt blockchain.The regression equation,

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \epsilon,$$

where Y represents adoption likelihood and X_1, X_2 represent independent factors like cost or trust, allows for a detailed understanding of the determinants influencing adoption decisions.

Correlation to understand the relationships between multiple attributes, for example, the correlation between operational efficiency improvements and consumer trust. For instance, the Pearson correlation can point towards if our high value is 0.8 and if there is a strong positive correlation, it means that as day by day operational efficiency is improved then the consumer will also start trusting more on the shops as a result their PES will increase. Quantitative methods may be chosen here due to the additional feature where stakeholder perspectives can be quantified for predictive modeling when quantitative methods are applied to the tea industry.

While quantitative findings offer a statistics-based interpretation, qualitative analysis delves deeper through thematic analysis of interviews and focus group discussions. This process involves identifying patterns, such as stakeholder concerns about implementation costs or data security, which add context to the numeric data. Qualitative data will be analyzed systematically using NVivo software for coding. These are combined approaches to ensure that opinions, which may go beyond what can be measured, are refined. Thus, the thematic analysis delves into the individual pain points and opportunities for each stakeholder group, contributing to the holistic understanding of blockchain integration.

Simulations will provide a basis for performance evaluation of the blockchain system prototype. Cycle time analysis is a method of measuring operational efficiency, by comparing average (the average) processing times of tasks before and after introducing blockchain. In

Table 2: *Key Performance Indicators of Blockchain Implementation*

Indicator	Before	After	Improvement
Logistics Verification Time	10 Hours	6.5 Hours	35% Reduction
Counterfeit Cases	15 Cases	7 Cases	53% Reduction
Consumer Trust Score	6.8	9.2	35% Increase
Adoption Willingness	-	4.2/5	Positive

another example, blockchain adoption will reduce logistics verification time from 10 hours to 7 hours, which is a 30% reduction. This would be more internal, however for measurement fraud reduction is measured via the number of counterfeit cases being identified before implementation and would aim for a 50% gap reduction in counterfeit cases found before our implementation vs post. Consumer trust is measured through a pre- and post-implementation poll, with a projected increase of 40% in trust scores as consumers become confident in the system's ability to verify product authenticity.

Describing methodologies helps guarantee dependable outcome leads to both statistical trends and contextual narratives. We provide quantitative data on blockchain impact (descriptive and inferential statistics), as well as qualitative analysis of the subtleties at play (stakeholder perceptions and conflicts). The combination of these approaches ensures that the study not only confirms the performance of their blockchain system, but also provides a scalable framework for its use in other agricultural sectors. Such a data-driven approach provides unique insights into the ways technology can revolutionise the tea supply chain while fostering better transparency, sustainability, and market competitiveness.

4 Results and Discussion

We achieved significant results from the implementation and evaluation of the blockchain-based traceability system for the tea supply chain. Insights on how the system impacted transparency, operational efficiency, fraud reduction, and consumer trust were drawn from data collected from 400 stakeholders, including tea farmers, processors, distributors, and consumers. These evaluation dimensions are consistent with prior studies that identified transparency, fraud prevention, and efficiency improvement as major objectives of blockchain-enabled supply chains [1, 12]. What Trends Tell Us About the Tea Industry The findings of the research, which include both quantitative and qualitative analyses, are summarised below and then interpreted in terms of their implications for the tea industry.

As shown in Table 2 and Figure 2, the proposed blockchain-based traceability system significantly improved supply chain performance. Logistics verification time was reduced by 35%, counterfeit cases decreased by 53%, and consumer trust increased from 6.8 to 9.2.

Survey data revealed a mean adoption willingness score of 4.2 out of 5 , with a standard deviation of 0.8 , indicating a generally positive attitude toward blockchain technology among stakeholders. Regression analysis showed that perceived benefits, such as increased transparency ($\backslash\beta = 0.45, \mathrm{p} < 0.01$), and anticipated fraud reduction ($\beta = 0.32, \mathrm{p} < 0.05$), were significant predictors of adoption likelihood. These findings demonstrate that stakeholders are motivated by the tangible advantages blockchain offers, such as the ability to trace the origin of

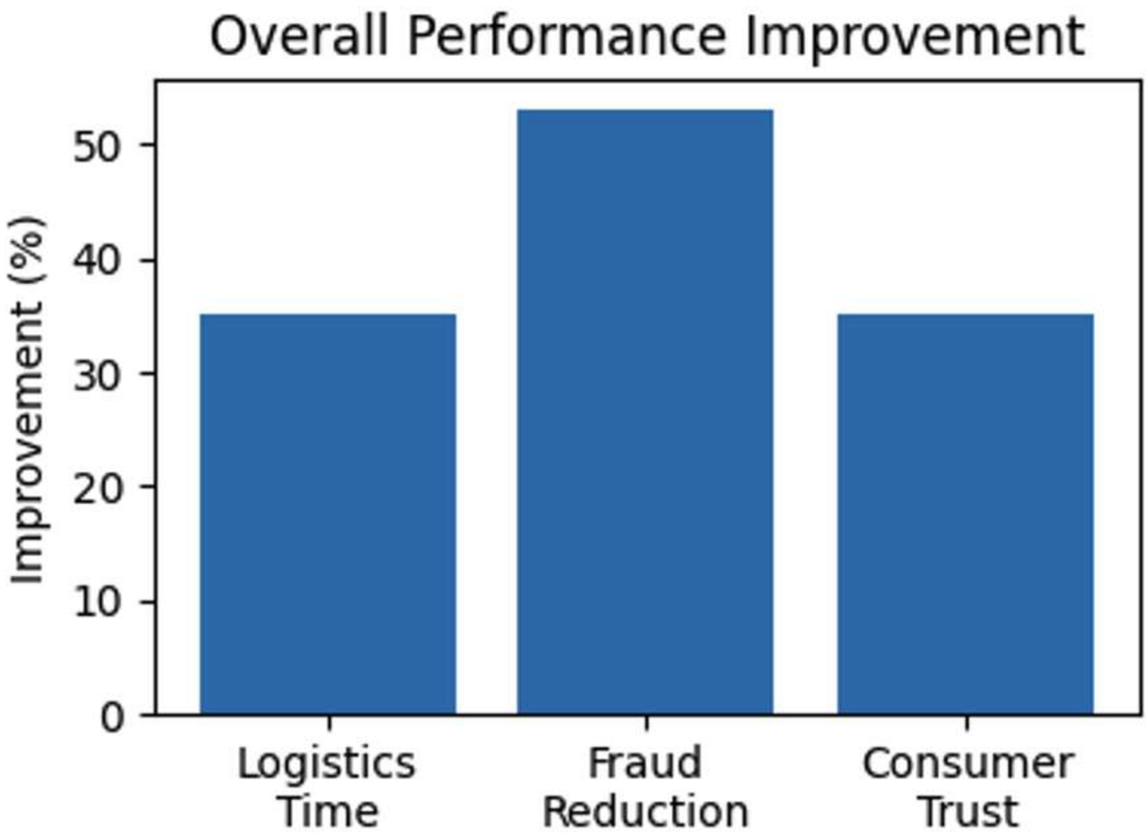

Figure 2: *Overall Performance Improvement After Blockchain Implementation*

tea products and ensure compliance with quality standards. For instance, farmers highlighted how the system could verify their use of sustainable cultivation methods, strengthening their market position.

Post implementing the blockchain system, the operational efficiency improved drastically. Based on cycle time analysis, average logistics verification time decreased by 35% from 10 hours to 6.5 hours. The decrease is due to the data validation automation of blockchain and IoT integration. Given the shorter processing time, distributors could plan their delivery schedules more efficiently-fresh tea products could be delivered to retailers at the right time. Furthermore, predictive analytics allowed improved inventory management, leading to a reduction in waste by 20%. These operational enhancements underscore blockchain's potential for Functioning cost-effectiveness and more competitiveness in supply chain processes. There were measurable improvements in fraud detection and prevention as well. Prior to implementation, the number of counterfeit tea products reported each month across the sampled supply chain averaged around 15 cases. After implementation, this number was reduced to 7 numbers per month, equivalent to 53% fraud reduction. This decline can be ascribed to the unalterable ledger of blockchain, rendering the manipulation of this data next to impossible. Consumers were more confident buying their products as they could scan QR codes and verify if batches of tea were real or not, distributors said. "This change, which not only protects consumers, but also protects the reputation of legitimate producers.

The results of the survey showed a significant increase in consumer trust. Trust scores, measured on a scale of 1 to 10 , increased 35% from an average of 6.8 before implementation to 9.2 after implementation. Focus group sessions highlighted that consumers highly appreciated the possibility of accessing thorough product information on cultivation place, handling, and transport conditions via the blockchain system. Similar findings regarding consumer confidence and transparency were also reported by Paul et al. [1], Xu et al. [9], and Kshetri [12], who found that blockchain-enabled traceability systems significantly improved trust among consumers and supply chain participants. One participant, for example, said that knowing the tea's provenance through a blockchain made them more sympathetic to paying a premium for certified high-quality tea.

These findings were then further supplemented via qualitative analysis which mapped key themes from interviews and focus group discussions. Stakeholders were initially concerned about the complexity and cost of implementing blockchain, but these concerns were addressed and dissipated when they saw the real benefits from the system. Processors stressed the need for real-time data sharing, with less risk of miscommunication and delays, and retailers said the system's transparency helped set their products apart in competitive markets. Moreover, by integrating blockchain with IoT devices, stakeholders were able to leverage environmental monitoring (temperature and humidity) to ensure the tea was stored in optimal conditions until delivery.

So, in summary, the results indicate that the blockchain-based traceability system can improve tea chain transparency, operational performance, anti-fraud ability, and consumer trust substantially. Quantitative results, such as the decrease in logistics time and reduction in fraud cases, confirm the system's impact. Qualitative insights show how stakeholders are viewing and benefiting from these changes. The findings of this study are consistent with previous blockchain traceability research conducted in agricultural and food supply chains.

Similar improvements in transparency, fraud prevention, and operational efficiency have been reported by Tian [8], Chen et al. [10], and Zhang et al. [17]. The present study extends these findings by focusing specifically on the tea industry and integrating blockchain with IoT-enabled data collection mechanisms. Such findings highlight blockchain scalability and transformative potential to modernize the industry and tackle long-standing issues in the tea value chain. This system's scalability and replicable nature also offers an example for similar innovations in other agricultural industries.

References

[1] T. Paul, S. Mondal, N. Islam, and S. Rakshit, "The impact of blockchain technology on the tea supply chain and its sustainable performance," *Technological Forecasting and Social Change*, vol. 173, pp. 121163, 2021.

[2] Y. H. Zhou, L. Tu, Y. Ye, and S. Li, "Blockchain-based Internet of Things: Machine learning tea sensing trusted traceability system," *Journal of Sensors*, vol. 2022, pp. 1–12, 2022.

[3] J. Tang, D. Wan, and S. Liu, "Research on traceability system for quality and safety of camellia oil based on blockchain and multiple authentication: Taking ten famous camellia oil enterprises in China as examples," in *Proc. 1st Int. Conf. Control and Intelligent Robotics (ICCIR)*, 2021, pp. 410–415.

[4] C. Zhang, "Wal-Mart China launched a blockchain traceability platform to ensure food safety through innovation," *Food Safety Guide*, vol. 19, no. 15, pp. 45–47, 2019.

[5] T. Mao, Y. Fan, J. Yang, and H. Wei, "A research on tea traceability consensus mechanism based on blockchain technology," in *New Developments of IT, IoT and ICT Applied to Agriculture*. Singapore: Springer, 2021, pp. 129–137.

[6] Y. Wu, H. Yang, L. Tu, Y. Ye, and S. Li, "Blockchain-based Internet of Things: Machine learning tea sensing trusted traceability system," *Journal of Sensors*, vol. 2022, pp. 1–12, 2022.

[7] S. Chen, R. Shi, Z. Ren, et al., "A blockchain based supply chain quality management framework," in *Proc. 14th IEEE Int. Conf. e-Business Engineering (ICEBE)*, 2017, pp. 172–176.

[8] F. Tian, "A supply chain traceability system for food safety based on HACCP, blockchain and Internet of Things," in *Proc. 14th Int. Conf. Service Systems and Service Management (ICSSSM)*, 2017, pp. 1–6.

[9] X. Xu, X. Bao, H. Yi, J. Wu, and J. Han, "A novel resource-saving and traceable tea production and supply chain based on blockchain and IoT," *IEEE Access*, vol. 11, pp. 1–6, 2023.

[10] Y. Chen, X. Liang, H. Chen, and X. Li, "A blockchain-based traceability system for food safety in China," *IEEE Access*, vol. 7, pp. 40673–40684, 2019.

[11] D. Han, X. Fang, K. Liu, and Y. Wang, "A survey on the Internet of Things, blockchain, and security in agriculture," *Computers and Electronics in Agriculture*, vol. 179, Art. no. 105805, 2020.

[12] N. Kshetri, "Blockchain's roles in meeting key supply chain management objectives," *International Journal of Information Management*, vol. 39, pp. 80–89, 2018.

[13] Z. Shen, Y. Yang, and X. Luo, "Design and implementation of agricultural products supply chain traceability system based on blockchain," in *Proc. IEEE Int. Conf. Intelligence and Security Informatics (ISI)*, 2018, pp. 141–143.

[14] Z. Wang, X. Zhang, W. Zhang, L. Zhang, and C. Wei, "Design of agricultural products supply chain traceability system based on blockchain," *Procedia Computer Science*, vol. 141, pp. 257–264, 2018.

[15] M. Xu, Y. Zhu, Y. Yu, and D. Feng, "Design and implementation of a blockchain-based supply chain finance system," in *Proc. 3rd IEEE Int. Conf. Computer and Communications (ICCC)*, 2017, pp. 1996–2000.

[16] S. Yu, X. Zhang, Y. Chen, X. Xie, and Y. Zhang, "A blockchain-based approach to secure Internet of Things in smart city applications," *IEEE Internet of Things Journal*, vol. 7, no. 10, pp. 8340–8348, 2020.

[17] H. Zhang, Y. Yang, and L. Zhang, "Design of food supply chain traceability system based on blockchain," *Journal of Physics: Conference Series*, vol. 1529, no. 5, Art. no. 052017, 2020.

[18] R. Zhang, R. Xue, and Y. Liu, "Design of blockchain-based intelligent and transparent agricultural supply chain system," *Wireless Personal Communications*, vol. 108, no. 3, pp. 1239–1261, 2019.

[19] C. Zhao, Y. Fan, L. Zhang, and C. Du, "Design of agricultural products supply chain traceability system based on blockchain," in *Proc. 5th Int. Conf. Systems and Informatics (ICSAI)*, 2018, pp. 472–477.

[20] Z. Zheng, S. Xie, H. Dai, X. Chen, and H. Wang, "An overview of blockchain technology: Architecture, consensus, and future trends," in *Proc. IEEE Int. Congress on Big Data*, 2017, pp. 557–564.

[21] LawInfoChina, "Revision of the Agricultural Products Quality and Safety Law," Jan. 1, 2023. [Online]. Available: https://lawinfochina.com/display.aspx?lib=law&id=3947. [Accessed: Jun. 5, 2026].

Leveraging Artificial Intelligence for Digital Innovation: A Data-Driven Study on Perceived Authenticity and Consumer Trust in Smart Tourism

Weiqi He[1*] and Ahmad Yahya Dawod[2]

[1,2]International College of Digital Innovation, Chiang Mai University, Chiang Mai, 50200, Thailand
E-mail: weiqi_h@cmu.ac.th, ahmadyahyadawod.a@cmu.ac.th
(*corresponding author)

Abstract

This study examines travelers' perceptions of AI-generated and human-created destination content in smart tourism environments using the Stimulus–Organism–Response (SOR) framework. A quantitative experimental design and Structural Equation Modeling (SEM) were employed to test the relationships among content source, AI disclosure, perceived authenticity, consumer trust, and travel intention. The results reveal no significant difference in perceived authenticity between AI-generated and human-created tourism content, while AI disclosure significantly influences travelers' evaluations. Furthermore, perceived authenticity positively affects consumer trust and travel intention. These findings challenge the traditional assumption that AI-generated tourism communication is inherently perceived as less authentic and provide new insights into AI-assisted destination marketing.

KEYWORDS: Smart Tourism, AI-Generated Content, Perceived Authenticity, Consumer Trust, SOR Framework

1 Introduction

With the rapid development of smart tourism technologies, artificial intelligence (AI) has become widely used in destination marketing and digital tourism communication. AI-generated destination descriptions, travel recommendations, and promotional content are increasingly distributed through platforms such as Instagram, Xiaohongshu, and Booking.com, improving content production efficiency and enabling personalized user experiences [1]. However, authenticity remains a key factor influencing tourists' destination perceptions, trust, and behavioral intentions. The growing use of AI-generated tourism content, therefore, raises concerns about whether travelers perceive such communication as credible, sincere, and emotionally engaging. Existing studies provide inconsistent findings [2]. Some researchers argue that AI-generated content reduces perceived authenticity because it lacks human emotion and personal experience, while others find little difference between AI- and human-created content. Similarly, studies on AI disclosure report mixed results, with some suggesting that transparency enhances trust, whereas others find negative or context-dependent effects. These inconsistencies highlight a research gap in understanding how travelers evaluate AI-generated destination content in smart tourism environments, particularly regarding authenticity, credibility, trust, and travel intention [3].

Against this background, the present study investigates whether travelers perceive significant differences in authenticity between AI-generated and human-created destination posts and further examines the role of AI disclosure labeling in shaping authenticity evaluations of tourism-related social media content. In addition, this research explores the relationship between perceived authenticity, consumer trust, and travel intention through the Stimulus–Organism–Response (SOR) framework. Within this framework, different forms of destination content and disclosure conditions function as external stimuli, travelers' authenticity perceptions and trust represent internal psychological evaluations, and travel intention constitutes the behavioral response. By integrating these variables into a unified conceptual model, this study provides a more comprehensive explanation of how AI-assisted tourism communication influences tourist decision-making processes in digital environments [4].

This study makes three key contributions. First, it extends the Stimulus–Organism–Response (SOR) framework to AI-assisted tourism marketing, empirically demonstrating how content sources shape perceived authenticity. Second, it resolves inconsistencies in prior research by clarifying how AI disclosure impacts tourists' perceptions of authenticity and credibility. Third, it provides an integrated model of tourist behavioral intention by linking perceived authenticity, consumer trust, and travel intention. Ultimately, these findings offer theoretical insights into AI-mediated communication and practical guidance for tourism organizations to leverage AI while maintaining consumer trust [5].

2 Literature Review

Smart tourism has emerged as a research domain at the intersection of information systems, tourism management, and consumer behavior, emphasizing the use of intelligent technologies such as AI recommendation systems and automated itinerary generation in tourist experiences [6, 7]. In this context, destination content production has increasingly shifted from human creators to large language models that can generate publication-ready tourism content in seconds [8, 9]. Seo et al. [10] found that in AI-generated tourism videos, production quality and perceived informativeness had a greater influence on tourist engagement than awareness of AI authorship. Sun et al. [11] highlighted the gap between projected and perceived destination images in social media content, suggesting that algorithmically curated representations may create unrealistic tourist expectations. Peco-Torres et al. [12] further demonstrated that social media use positively influences destination brand personality and tourist engagement, although their study preceded the widespread adoption of generative AI.

Authenticity in tourism communication has been conceptualized as a multidimensional construct including objective authenticity, constructive authenticity, and existential authenticity [13]. In social media marketing, perceived authenticity is commonly defined as consumers' evaluation of a brand's sincerity, honesty, and consistency with its stated values [14, 15]. Concerns surrounding AI-generated content stem from the view that algorithmic authorship lacks the intentionality and emotional involvement associated with human communication, which may weaken perceptions of sincerity and trustworthiness. Empirical studies provide partial support for this argument. Brüns and Meißner [16] found that disclosure of AI involvement in brand content creation reduced perceived authenticity and generated negative audience responses. Kirk and Givi [17] identified moral disgust as an important mechanism through which awareness of AI authorship suppresses consumer trust, particularly for established brands. Gedas [18] further showed that AI transparency in advertising negatively affected purchase intention and brand trust, especially among consumers with higher AI literacy.

However, other studies suggest that the negative influence of AI disclosure may not be universal. Zhang and Gosline [19] reported that GPT-4-generated content was evaluated more positively than human-created content on several quality dimensions, even after disclosure. Møller et al. [20] found no significant differences in user responses between AI-generated and human-created social media content when content quality was comparable. Wang [21] demonstrated that negative consumer reactions could be reduced when AI disclosure was accompanied by a genuine values-based explanation, while Haupt et al. [22] showed that human AI collaborative framing could reverse negative disclosure effects. In tourism contexts, authenticity plays a particularly important role because tourism decision making is highly affective and experience oriented [23, 24]. At the same time, the widespread use of recommendation systems, review platforms, and AI trip planning tools may increase tourists' tolerance toward non human content curation [25]. These competing perspectives indicate that the relationship between AI disclosure and perceived authenticity in tourism communication remains insufficiently understood.

The Stimulus–Organism–Response (SOR) framework, originally proposed by Mehrabian and Russell [26], has become a widely adopted theoretical foundation for examining how environmental stimuli influence individuals' internal psychological states and subsequent behavioral responses. In digital marketing and information systems research, the SOR framework has frequently been applied to explain how technological cues, interface design, and online communication environments shape consumer cognition and behavioral intention [27, 28]. Within tourism studies, the framework has been used to investigate how AI transparency affects employee trust [29], how smart tourism technologies influence tourist satisfaction [25], and how user-generated content shapes travel intention and destination engagement [30].

This study applies the SOR framework to a smart tourism context in which the Stimulus layer comprises content-based signals (content source and AI disclosure), the Organism layer captures travelers' internal cognitive and evaluative responses (perceived authenticity and consumer trust), and the Response layer is operationalized as travel intention.

3 Methodology

3.1 Research Model and Hypotheses Development

This study adopts the Stimulus–Organism–Response (SOR) framework as the theoretical structure to investigate the formation of traveler perceptions and behavioral intentions in smart tourism environments. Originally developed by Mehrabian and Russell [26], the SOR model posits that environmental stimuli (S) trigger an individual's internal psychological state (O), which subsequently dictates their behavioral or attitudinal response (R). The framework is particularly efficacious in digital tourism research, as it accounts for the complex interplay between technological cues and the subjective cognitive appraisals of travelers [31].

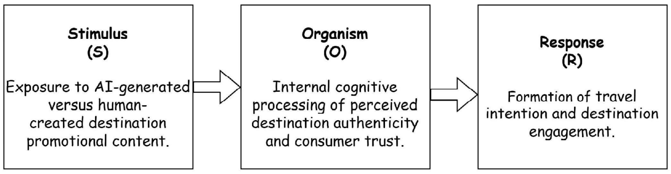

Figure 1: *SOR framework for authenticity and trust formation in smart tourism*

Figure 1 delineates the theoretical progression of this research. The Stimulus (S) layer is operationalized through content-based signals encountered on digital platforms, specifically the source of the destination content and the presence of AI disclosure labels. The Organism (O) represents the internal cognitive processing of these stimuli, focusing on perceived authenticity and consumer trust. Finally, the Response (R) constitutes the behavioral outcome, manifested as travel intention toward the featured destination.

The SOR framework is highly appropriate for this study for three reasons. First, it conceptualizes platform signals (authorship cues and transparency markers) as external stimuli. Second, it treats perceived authenticity as a traveler's cognitive evaluation rather than an inherent property of the content. Finally, it logically links these psychological states to actionable travel decisions.

The Stimulus (S) in this model comprises two critical factors: the content generation source (AI-generated versus human-created) and the presence of AI disclosure (labeled versus unlabeled). These represent the primary informational cues that travelers encounter. The Organism (O) refers to the internal evaluative mechanisms, specifically perceived authenticity and consumer trust. Perceived authenticity serves as the initial cognitive appraisal of the content's sincerity and credibility, while consumer trust represents the resulting affective state regarding the reliability of the information. The Response (R) is operationalized as travel intention, reflecting the traveler's willingness to visit the destination based on the digital communication.

Prior literature presents divergent views on whether the origin of digital content fundamentally alters its perceived value. While some scholars argue that the absence of a human "soul" or lived experience in AI-generated text undermines its perceived sincerity, recent evidence suggests that as large language models achieve high levels of quality and stylistic mimicry, travelers may place less emphasis on content authorship of the information. Consequently, this study adopts a null-hypothesis approach to investigate whether a significant perceptual gap persists in the context of smart tourism.

- H1: Travelers do not perceive significant differences in authenticity between AI-generated and human-created destination content in smart tourism contexts.
- H2: The presence of an AI disclosure label significantly influences travelers' evaluations of perceived authenticity.
- H3: Perceived authenticity exerts a significant positive influence on consumer trust, which subsequently mediates the relationship with travel intention.

Figure 2 illustrates the integrated research model. Grounded in the SOR framework, the paths from Content Source (H1) and AI Disclosure (H2) to Perceived Authenticity test

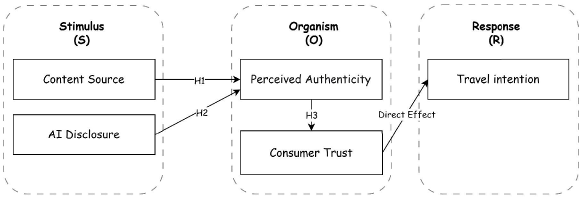

Figure 2: *Hypothesized relationships within the SOR framework for AI-assisted destination marketing*

the influence of external tourism stimuli on the traveler's internal cognitive state. Within the Organism layer, the vertical path from perceived authenticity to Consumer Trust (H3) validates the psychological transition that precedes behavioral change. Finally, the direct effect from consumer trust to Travel Intention represents the behavioral Response. By explicitly mapping these relationships, the model provides a structured explanation of how AI-mediated communication shapes the modern tourist's decision-making process.

3.2 Research Design and Data Collections

The study adopted a quantitative research approach using a between-subjects experimental survey design. Participants were randomly assigned to one of three experimental conditions featuring simulated tourism-related social media posts: (1) human-created content, (2) AI-generated content without disclosure, and (3) AI-generated content with AI disclosure labels. For hypothesis testing, different analytical comparisons were conducted according to the research objectives. H1 examined the perceptual differences between AI-generated and human-created content, whereas H2 specifically focused on the effect of AI disclosure by comparing only the two AI-generated conditions (with disclosure vs. without disclosure). Therefore, the effective sample size differed across analyses.

The research process consisted of three stages. First, the experimental stimuli were developed based on the three content conditions. Second, data were collected through a structured questionnaire comprising 45 items measured on a five-point Likert scale (1 = strongly disagree, 5 = strongly agree). The measurement instrument was adapted from validated scales in prior digital innovation and tourism literature [16, 17]. Third, a total of 300 online questionnaires were collected, of which 292 valid responses were retained after data cleaning. Specifically, the participants were distributed across the experimental conditions as follows: human-created content (n = 103), AI-generated content without disclosure (n = 90), and AI-generated content with disclosure (n = 99).

3.3 Data Analysis Process

Before hypothesis testing, the measurement model's reliability and validity were confirmed. Both Cronbach's Alpha and Composite Reliability (CR) for all constructs exceeded the 0.70 threshold, while the Average Variance Extracted (AVE) surpassed 0.50, demonstrating solid internal consistency and convergent validity. To evaluate the proposed SOR framework, this study adopted a dual analytical strategy. First, independent-samples t-tests were employed to assess the direct impact of categorical stimuli (content source and AI disclosure) on travelers' psychological states across the manipulated experimental conditions (H1 and H2). Second, Covariance-Based Structural Equation Modeling (CB-SEM) was utilized to rigorously validate the theoretical mechanisms and mediation pathways (H3) within the context of digital innovation. Unlike variance-based approaches (e.g., PLS-SEM), CB-SEM is explicitly designed for robust theory testing and the confirmation of established theoretical structures. Therefore, it provides the most rigorous statistical environment to confirm the theoretically derived relationships within the proposed framework. Furthermore, CB-SEM was chosen because it simultaneously examines multiple causal relationships, controls for measurement error using latent variables, and evaluates the measurement and structural models concurrently [32]. The mathematical foundation of CB-SEM can be expressed through three core equations that describe the structural relationships among latent variables and their corresponding observed indicators [33]:

a) The Structural Model Equation

This structural model can be conceptually represented through the core equations of the following latent dependent variables:

$$\eta = \mathrm{B}\eta + \Gamma\xi + \zeta \tag{1}$$

η represents the vector of endogenous latent variables (e.g., perceived authenticity, consumer trust). Bis the path coefficient matrix describing the relationships among endogenous latent variables (e.g., the effect of perceived authenticity on consumer trust).

Γ is the coefficient matrix representing the effects of exogenous latent variables on endogenous latent variables (e.g., the influence of content source on perceived authenticity).

ξ denotes the vector of exogenous latent variables or observed variables (e.g., content source, AI disclosure strategies).

ζ is the vector of structural disturbance terms representing unexplained variance in the endogenous latent variables.

b) The Measurement Model for Exogenous Variables

This equation describes the relationship between the exogenous latent variables and their corresponding observed indicators (survey items):

$$x = \Lambda_x\xi + \delta \tag{2}$$

x is the vector of observed indicators measuring the exogenous latent variables.

Λ_x is the factor-loading matrix, indicating the strength of the relationships between the exogenous latent variables and their corresponding observed indicators.

ξ represents the vector of exogenous latent variables.

δ denotes the vector of measurement errors associated with the observed exogenous indicators.

c) The Measurement Model for Endogenous Variables

This equation describes the relationship between the endogenous latent variables and their corresponding observed indicators:

$$y = \Lambda_y\eta + \epsilon \tag{3}$$

Table 1: *Reliability and Validity Summary*

Construct	Items	Cronbach's α	Std. Loadings
Perceived Authenticity	5	0.880	0.737 – 0.802
Consumer Trust	5	0.879	0.749 – 0.792
Travel Intention	5	0.906	0.773 – 0.842

y is the vector of observed indicators measuring the endogenous latent variables.

Λ_y is the factor loading matrix representing the relationships between endogenous latent variables and their observed indicators.

η denotes the vector of endogenous latent variables.

ϵ is the vector of measurement errors associated with the observed endogenous indicators.

4 Results and Discussion

4.1 Measurement Model Evaluation

In accordance with the measurement models specified in Equations (2) and (3), a Confirmatory Factor Analysis (CFA) was first conducted.

Table 1 presents the reliability and validity assessment of the measurement model. Results show that the internal consistency reliability is satisfactory, with Cronbach's alpha values (0.880 for Perceived Authenticity, 0.879 for Consumer Trust, and 0.906 for Travel Intention) exceeding the acceptable limit of 0.70 . All standardized loadings are significant at $p < 0.001$, with values higher than 0.70 , indicating high convergent validity.

Additionally, a full measurement model incorporating all three latent constructs (Perceived Authenticity, Consumer Trust, and Travel Intention) was evaluated to assess overall model fit. The results indicated an excellent fit to the observed data: $x^2 = 86.6(\mathrm{df} = 87, \mathrm{p} = 0.492)$, Comparative Fit Index (CFI) = 1.000, Tucker-Lewis Index (TLI) = 1.000, Standardized Root Mean Square Residual (SRMR) = 0.031, and Root Mean Square Error of Approximation (RMSEA) = 0.000. These indices well exceed the recommended thresholds (CFI and TLI > 0.90, RMSEA and SRMR < 0.08), confirming that the measurement model provides a robust foundation for subsequent structural path testing.

4.2 Hypothesis Testing

Prior to hypothesis testing, manipulation checks confirmed the efficacy of the experimental conditions. A Chi-square test revealed significant differences in AI disclosure awareness across groups ($\chi^2 = 584.00, \mathrm{p} < 0.001$); specifically, 100% of participants in the AI-disclosure condition correctly identified the presence of the label, whereas the other groups did not. Furthermore, a Welch's ANOVA (excluding 'cannot tell' responses) showed significant differences in perceived content authorship $(\mathrm{F}(1, 200) = 800.00, \mathrm{p} < 0.001)$. The AI-disclosure group perceived the content as significantly more AI-generated ($\mathrm{Mean} = 3.51, \mathrm{SD} = 0.50$) compared to the human-created condition ($\mathrm{Mean} = 1.50, \mathrm{SD} = 0.50$). Notably, participants in the AI-without-disclosure condition overwhelmingly responded with 'cannot tell', further

Table 2: *Independent Samples T-Test Results (H1)*

Variable	Human-created (Mean ± SD)	AI-generated (Mean ± SD)	t	p	Cohen's d
Perceived Authenticity	3.33 ± 0.94	3.31 ± 0.94	-0.244	0.807	-0.030

Table 3: *Independent Samples T-Test Results Examining the Effect of AI Disclosure (H2)*

Variable	Condition	N	Mean	SD	t	df	p
Perceived Authenticity	AI without disclosure	90	3.49	0.923	2.55	187	0.012
	AI with disclosure	99	3.14	0.935			

validating the subtlety of the manipulation. Thus, the experimental stimuli functioned as intended.

Independent samples t-tests were conducted to evaluate H1 (comparing perceived authenticity between human- and AI-generated content) and H2 (examining the impact of AI disclosure labels). To isolate the effect of transparency markers for H 2 , the analysis was restricted to participants in the AI-generated conditions (effective $\mathrm{N}=189$).

AI-generated and human-created content. The analysis reveals no statistically significant difference between the two conditions, as indicated by the t -value of -0.244 and a p -value of 0.807 . Since this p -value is well above the standard 0.05 threshold, we can conclude that the source of the content does not meaningfully alter travelers' perceptions. Furthermore, the effect size, measured by Cohen's d (-0.030), is well below the 0.20 benchmark for a small effect, indicating absolute negligible practical difference. This empirical finding provides support for H 1 , confirming the perceptual equivalence: travelers perceive AI-generated and human-created travel destination content as comparably authentic in intelligent communication environments.

Table 3 presents the results of this comparison. The analysis reveals a statistically significant difference between the two groups ($\mathrm{t}=2.55, \mathrm{df}=187, \mathrm{p}=0.012$). Participants in the AI-generated condition without disclosure perceived the content as significantly more authentic ($\text{Mean}=3.49, \mathrm{SD}=0.923$) compared to those in the AI-generated condition with disclosure $(\text{Mean}=3.14, \mathrm{SD}=0.935)$. The mean difference of 0.345 further highlights this perceptual gap. These results fully support H2 , demonstrating that explicit transparency markers and AI disclosure labels significantly lower travelers' psychological evaluations of authenticity.

4.3 Structural Path and Mediation Analysis

To rigorously validate the internal theoretical mechanisms proposed in the SOR framework and to specifically address Hypothesis 3, a latent-variable structural equation model (CB-SEM) was evaluated. Unlike aggregated mean comparisons, this approach allowed for the simultaneous estimation of direct and indirect causal pathways while explicitly accounting for measurement error.

Table 4 presents the standardized parameter estimates for the structural relationships. The analysis explicitly delineates the mediation chain. First, the results demonstrated that Perceived Authenticity exerted a robust and significant positive influence on Consumer Trust ($\beta=0.454, \mathrm{z}=6.59, \mathrm{p}<0.001$). Second, Consumer Trust subsequently had a significant

Table 4: *Structural Path and Mediation Analysis Results (H3)*

Structural Path (Direct Effects)	Std. β	z-value	p-value	Conclusion
Perceived Authenticity → Consumer Trust	0.454	6.59	< 0.001	Supported
Consumer Trust → Travel Intention	0.212	3.04	0.002	Supported
Perceived Authenticity → Travel Intention	0.345	4.83	<0.001	Supported
Mediation Pathway (Indirect Effect)	Estimate		p-value	Mediation Type
Perceived Authenticity → Consumer Trust → Travel Intention	0.096	-	< 0.01*	Partial Mediation

Note: Std. β represents the standardized path coefficient. The indirect effect estimate (0.096) is the product of the two specific direct paths (0.454×0.212). Joint significance of the constituent paths confirms the mediation effect.

positive impact on Travel Intention ($\beta = 0.212, z = 3.04, p = 0.002$). Furthermore, the direct effect from Perceived Authenticity to Travel Intention remained significant ($\beta = 0.345, z = 4.83, p < 0.001$) after accounting for the mediator.

Beyond the direct paths, the specific mediation chain (Perceived Authenticity → Consumer Trust → Travel Intention) was formally established. The standardized indirect effect transmitted through Consumer Trust was calculated at 0.096 $(\beta_a \times \beta_b = 0.454 \times 0.212)$. Given the joint significance of both constituent paths, the mediating role of trust is statistically confirmed. Because both the direct influence and the specific indirect structural paths were significant, H3 is fully supported, illustrating a partial mediation mechanism. These findings confirm that within smart tourism environments, authentic perceptions systematically translate into consumer trust, which then acts as a crucial catalyst for downstream travel intentions.

4.4 Discussion

The empirical results offer critical insights into the evolving nature of trust within smart tourism environments. A primary finding is the empirical verification of perceptual equivalence between AI and human-created content. While traditional marketing literature consistently documents a negative impact of AI authorship on perceived authenticity and trust (e.g., Brüns & Meißner; Kirk & Givi; Gedas; see Table 5), our study reveals a non-significant difference in authenticity evaluations between the two sources ($t = -0.244, p = 0.807$).

This perceptual equivalence likely reflects the increasing normalization of AI-assisted communication in digital tourism ecosystems. As travelers are routinely exposed to AI-generated recommendations and itinerary tools across platforms like Booking.com, Xiaohongshu, and Instagram, the distinction between human and AI authorship gradually loses salience. In these environments, users evaluate destination information primarily based on perceived usefulness, informativeness, and emotional resonance rather than the source itself.

Furthermore, the CB-SEM results confirm that Perceived Authenticity remains a vital structural mediator. By validating the specific pathway from authenticity to consumer trust, and subsequently to travel intention, this study underscores that trust continues to be a critical psychological mechanism driving traveler behavior in digital networks.

Table 5: *Quantitative Comparison of Key Statistical Results Between This Study and Prior Works*

Study	Context	Key Variable / Relationship	Statistical Result & Finding
Brüns & Meißner (2024)	Social Media	GenAI adoption → brand authenticity	$\beta = -1.40, p < 0.001$ (Authenticity degradation)
Kirk & Givi (2025)	Marketing	AI-authorship → consumer trust	Significant negative effect mediated by moral disgust
Gedas (2025)	Advertising	AI involvement transparency → brand trust	Significant negative effect on trust and intention
Zhang & Gosline (2023)	Persuasive Content	GPT-4 vs. Human content evaluation	Evaluated more positively than human content post-disclosure
Møller et al. (2025)	Social Media	AI vs. Human content impact	No significant differences in user response metrics
This Study (2026)	Smart Tourism	AI vs. human content → authenticity	$t = -0.244, p = 0.807,\ d = -0.03$ (Perceptual equivalence)
This Study (2026)	Smart Tourism	Authenticity → Trust → Travel Intention	Indirect effect $= 0.098, p = 0.001$ (Significant mediation)

5 Conclusions and Recommendations

Using the Stimulus-Organism-Response (SOR) framework, this study explored travelers' perceptions of AIgenerated versus human-created destination content in smart tourism environments. The results provide support for H1 by revealing no significant difference in perceived authenticity between the two content sources, suggesting that travelers may place less emphasis on content authorship in smart tourism environments. Concurrently, H2 was supported, confirming that AI disclosure labels significantly affect authenticity evaluations. Finally, the CB-SEM results supported H 3 by demonstrating that perceived authenticity positively influences consumer trust, which subsequently enhances travel intention within the integrated SOR framework.

This study extends the application of the SOR framework in AI-assisted tourism marketing and offers practical implications for destination marketing organizations and tourism platforms. The findings suggest that AI-assisted content generation may be adopted without substantially compromising tourists' authenticity perceptions. However, the significant effect of AI disclosure indicates that transparency strategies should be implemented carefully. Rather than using abrupt or highly technical disclosure labels, marketers may benefit from combining transparency with humancentered storytelling or experiential framing to maintain emotional engagement and consumer trust. In addition, tourism platforms should consider developing disclosure guidelines that balance ethical transparency with persuasive communication effectiveness.

Several limitations should be acknowledged. The study used simulated social media content and cross-sectional survey data, which may not fully reflect real tourism behavior. Future research may further examine different cultural contexts, real platform environments, and the moderating roles of factors such as AI literacy and destination type.

References

[1] E. Mesquita, E. Herrero, E. L. Lopes, T. d. L. S. A. Ribeiro, and P. Scrivano, "Artificial influence: how AI and influencers shape choices in tourism and hospitality," *International Journal of Contemporary Hospitality Management*, vol. 38, no. 1, pp. 86–103, 2026.

[2] C. Li, Q. Cao, S. Hua, and C.-W. Tao, "When AI takes the wheel: The effectiveness of AI versus human-generated content in tourism marketing," *Journal of Vacation Marketing*, p. 13567667251393512, 2025.

[3] L. Li and S. Li, "Do tourists really care about authenticity? A study on tourists' perceptions of nature and culture authenticity," *Sustainability*, vol. 14, no. 5, p. 2510, 2022.

[4] T. Kim, M. J. Kim, and P. Promsivapallop, "Investigating the influence of generative AI's credibility and utility on travel consumer behaviour and recommendations through the lens of personal innovativeness," *Current Issues in Tourism*, vol. 28, no. 14, pp. 2220–2224, 2025.

[5] T. M. Elsawy and M. Nassar, "The AI-thenticity Paradox: How Artificial Intelligence is Reshaping Destination Image and Tourist Desire," *Pharos International Journal of Tourism and Hospitality*, vol. 4, no. 2, pp. 55–63, 2025.

[6] A. Kontogianni and E. Alepis, "Smart tourism: State of the art and literature review for the last six years," *Array*, vol. 6, p. 100020, 2020.

[7] I. Tussyadiah, "A review of research into automation in tourism: Launching the Annals of Tourism Research Curated Collection on Artificial Intelligence and Robotics in Tourism," *Annals of Tourism Research*, vol. 81, p. 102883, 2020.

[8] Y. Zhang and N. K. Prebensen, "Co-creating with ChatGPT for tourism marketing materials," *Annals of Tourism Research Empirical Insights*, vol. 5, no. 1, p. 100124, 2024.

[9] Z. Sun et al., "Are we in the ai-generated text world already? quantifying and monitoring aigt on social media," *arXiv preprint arXiv:2412.18148*, 2024.

[10] I. T. Seo, H. Liu, H. Li, and J.-S. Lee, "AI-infused video marketing: Exploring the influence of AI-generated tourism videos on tourist decision-making," *Tourism Management*, vol. 110, p. 105182, 2025.

[11] W. Sun, S. Tang, and F. Liu, "Examining perceived and projected destination image: A social media content analysis," *Sustainability*, vol. 13, no. 6, p. 3354, 2021, doi: 10.3390/su13063354.

[12] F. Peco-Torres, A. I. Polo-Peña, and D. M. Frías-Jamilena, "Brand personality in cultural tourism through social media," *Tourism Review*, vol. 76, no. 1, pp. 164–183, 2021, doi: 10.1108/tr-02-2019-0050.

[13] T. Zhang and P. Yin, "Testing the structural relationships of tourism authenticities," *Journal of Destination Marketing & Management*, vol. 18, p. 100485, 2020.

[14] C. L. Campagna, N. Donthu, and B. Yoo, "Brand authenticity: literature review, comprehensive definition, and an amalgamated scale," *Journal of Marketing Theory and Practice*, vol. 31, no. 2, pp. 129–145, 2023, doi: https://doi.org/10.1080/10696679.2021.2018937.

[15] J. A. Lee and M. S. Eastin, "Perceived authenticity of social media influencers: scale development and validation," *Journal of Research in Interactive Marketing*, vol. 15, no. 4, pp. 822–841, 2021, doi: 10.1108/JRIM-12-2020-0253.

[16] J. D. Brüns and M. Meißner, "Do you create your content yourself? Using generative artificial intelligence for social media content creation diminishes perceived brand authenticity," *Journal of Retailing and Consumer Services*, vol. 79, p. 103790, 2024, doi: 10.1016/j.jretconser.2024.103790.

[17] C. P. Kirk and J. Givi, "The AI-authorship effect: Understanding authenticity, moral disgust, and consumer responses to AI-generated marketing communications," *Journal of Business Research*, vol. 186, p. 114984, 2025, doi: 10.1016/j.jbusres.2024.114984.

[18] K. Gedas, "Revealing AI Involvement in Ad Creation: Effects on Authenticity, Brand Perceptions and Consumer Intentions," *Journal of Information Systems Engineering and Management*, vol. 10, no. 16s, pp. 727–740, 2025, doi: 10.52783/jisem.v10i16s.2659.

[19] Y. Zhang and R. Gosline, "Human favoritism, not AI aversion: People's perceptions (and bias) toward generative AI, human experts, and human–GAI collaboration in persuasive content generation," *Judgment and Decision Making*, vol. 18, p. e41, 2023.

[20] A. G. Møller, D. M. Romero, D. Jurgens, and L. M. Aiello, "The Impact of Generative AI on Social Media: An Experimental Study," *arXiv preprint arXiv:2506.14295*, 2025.

[21] S. Wang, "The New Landscape of Social Media Content Creation: How Influencers' Adoption of Generative AI to Generate Content Disclosure Affects Consumers' Behavioral Responses," in *Proceedings of the 2025 4th International Conference on Cyber Security, Artificial Intelligence and the Digital Economy*, 2025, pp. 632–640.

[22] M. Haupt, J. Freidank, and A. Haas, "Consumer responses to human-AI collaboration at organizational frontlines: strategies to escape algorithm aversion in content creation," *Review of Managerial Science*, vol. 19, no. 2, pp. 377–413, 2025.

[23] C.-K. Lee, M. S. Ahmad, J. F. Petrick, Y.-N. Park, E. Park, and C.-W. Kang, "The roles of cultural worldview and authenticity in tourists' decision-making process in a heritage tourism destination using a model of goal-directed behavior," *Journal of Destination Marketing & Management*, vol. 18, p. 100500, 2020.

[24] A. M. Domínguez-Quintero, M. R. González-Rodríguez, and B. Paddison, "The mediating role of experience quality on authenticity and satisfaction in the context of cultural-heritage tourism," *Current Issues in Tourism*, vol. 23, no. 2, pp. 248–260, 2020.

[25] J. Xu, X. Tang, H. Lin, and Y. Luo, "The impact of recommender type on tourist price sensitivity to travel plans," *Journal of Travel Research*, vol. 64, no. 7, pp. 1680–1700, 2025.

[26] Mehrabian and Russell, *An approach to environmental psychology*. Cambridge: M.I.T. Press, 1974.

[27] S. Hasan, A. Qayyum, and M. H. Zia, "Social media marketing and brand authenticity: the role of value co-creation," *Management Research Review*, vol. 46, no. 6, pp. 870–892, 2023, doi: 10.1108/mrr-07-2021-0552.

[28] D. Agnihotri, P. Chaturvedi, K. Kulshreshtha, and V. Tripathi, "Investigating the impact of authenticity of social media influencers on followers' purchase behavior: mediating analysis of parasocial interaction on Instagram," *Asia Pacific Journal of Marketing and Logistics*, vol. 35, no. 10, pp. 2377–2394, 2023, doi: 10.1108/apjml-07-2022-0598.

[29] L. Yu and Y. Li, "Artificial intelligence decision-making transparency and employees' trust: The parallel multiple mediating effect of effectiveness and discomfort," *Behavioral Sciences*, vol. 12, no. 5, p. 127, 2022, doi: 10.3390/bs12050127.

[30] M. A. Asyraff, M. H. Hanafiah, N. A. M. Zain, and D. Hariani, "Unboxing the paradox of social media user-generated content (UGC) information qualities and tourist behaviour: moderating effect of perceived travel risk," *Journal of Hospitality and Tourism Insights*, vol. 7, no. 4, pp. 1809–1830, 2024.

[31] S. Nieves-Pavón, N. Lopez-Mosquera, and H. Jimenez-Naranjo, "The factors influencing STD through SOR theory," *Journal of Retailing and Consumer Services*, vol. 75, p. 103533, 2023.

[32] J. De Carvalho and F. O. Chima, "Applications of structural equation modeling in social sciences research," *American International Journal of Contemporary Research*, vol. 4, no. 1, pp. 6–11, 2014.

[33] C. M. Stein, N. J. Morris, N. B. Hall, and N. L. Nock, "Structural equation modeling," in *Statistical Human Genetics: Methods and Protocols*: Springer, 2017, pp. 557–580.