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CHIANG MAI UNIVERSITY

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PROCEEDINGS

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Conference 12th October 2024 at International College Digital Innovation, Chiang Mai University
Organized by
International College Digital Innovation, Chiang Mai University

Introduction

The DIFT 2024-2 Conference is organized by International College Digital Innovation, Chiang Mai University, International College Digital Innovation Building, Chiang Mai, Thailand on 12^{th} October 2024

The conference aims to bring together policy makers, researchers, and experts in the domain of policy making to share their ideas, experiences, and insights. We welcome experts, researchers and practitioners from academia, industries, research institutions, R&D enterprise services and governmental organizations to exchange innovative contributions around the topics.

All papers were reviewed by members of the DIFT 2024-2 Committee for rating and presentation content. Further details in accordance with the instructions of provided at: `https://icdi.cmu.ac.th/dift/2024-2/`

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Conference Schedule

Room number 1 (ICB1102)
Morning Session, Chairpersons: Dr. Siva Shankar Ramasamy
Afternoon Session, Chairpersons: Asst. Prof. Dr. Ahmad Yahya Dawod
Committees: Asst. Prof. Dr. Kittawit Autchariyapanitkul, Asst. Prof. Dr. S P Gayathri, and Dr. Siva Shankar Ramasamy

Time	Topic
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10:50 - 11:10	The Influencing Factors for Tourist'S Decision Making on Tourism Route Selection in the Context of Smart Tourism. By Jiayuan Sun and Naret Suyaroj and Pintusorn Onpium
11:10-11:30	The Impact Of Digital Payment Systems on Customer Satisfaction in the Hospitality Industry: The Mediating Role of Online Travel Agencies. By Yanan Wang and Pintusorn Onpium
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13:30-13:45	Leveraging Online Innovations: Improving HIV and STIs Prevention and Treatment Services in Major Cities of Thailand. By Panyaphon Phiphatkunarnon and Worawit Tepsan
13:45-14:00	Factors Influencing Student' Acceptance of General Artificial Intelligence in Higher Education: Using the UTAUT Model. By Tianjing Xin and Worawit Tepsan
14:00-14:15	A Hybrid Genetic-Fuzzy Ant Colony Optimization Algorithm for Automatic K-Means Clustering in Urban Global Positioning System. By Xiaojuan Ran and Naret Suyaroj and Worawit Tepsan
14:15-14:30	Gain Insights into Immersive Language Leaners' Sentiment and Opinion Based on the Large Language Model. By Lin Bao and Piyachat Udomwong

Room number 2 (ICB1211)
Morning Session, Chairpersons: Asst. Prof. Dr. Thacha Lawanna
Afternoon Session, Chairpersons: Dr. Naret Suyaroj
Committees: Dr. Watcharin Sarachai, Asst. Prof. Dr. Thacha Lawanna, and Dr. Naret Suyaroj

Time	Topic
10:30 - 10:50	An Ensemble Machine Learning Approach for Cryptocurrency Price Prediction using Variational Mode Decomposition and Wavelet Denoising. By Liping Zhang and Ahmad Yahya Dawod
10:50 - 11:10	Hybrid Algorithmic Trading Strategies Performance Study on Crypto Markets. By Kollavath Charoengan and Nathee Naktnasukanjn
11:10-11:30	Feasibility Study of Remote Drug Dispensing System via Automatic Machine. By Saowaros Nopnithipat and Anukul Tamprasirt and Naret Suyaroj
11:30-11:45	Modernizing Thailand's Power System for Renewable Integration and Energy Transition. By Muhammad Ilyas and Naret Suyaroj and Chakkrapong Kuensaen
11:45-13:00	**Lunch Break**
13:00-13.15	Predicting Students' Academic Performance in Blended Learning based on Flipped Classroom Approach. By Xiaoxia Wen and Ahmad Yahya Dawod
13:15-13:30	A Semantic Analysis and Sentiment Mining of User Experience Changes on Online Teaching Platforms During and After the Pandemic Based on Review Data. By Wang Mei and Siva Shankar Ramasamy
13:30-13:45	Evaluating User Influence in Blockchain-Based Social Networks: A Comparative Study of Hybridization Centrality and Traditional Metrics. By Xinke Li and Nathapon Udomlertsakul
13:45-14:00	Enhancing the Paymaster Mechanism: Advances in ERC-4337 Implementation with Account Abstraction Contract. By Huifeng Jiao and Nathapon Udomlertsakul and Anukul Tamprasirt
14:00-14:15	Online Barter Trade Model Based on Traceability by Blockchain Technology. By Jianlei Qian and Napat Harnporncha
14:15-14:30	The Impact of Personalized Recommendation based on Tourism Decision-Making. By Hongmei Duan and Ahmad Yahya Dawod

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The Impact of Social Media Influencers on Travel Decision-Making and Tourism Behavior

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Abstract

As the tourism industry becomes increasingly connected digitally, Social Media Influencers play a key role in shaping travelers' preferences and behaviors. This study collected data from 254 respondents using a quantitative method to evaluate the impact of travel-related content shared by social media influencers on travel decisions. The results showed that social media played a key role in the decision-making process, with 48% of respondents checking travel information every two to three weeks and 18.1% checking it every day. Among them, customized travel packages and unique travel experience content were the most attractive to users, while travel notes and reviews effectively enhanced social identity. In addition, the authority and credibility of social media platforms were the main determinants of user trust, and user reputation and the quality of content shared in the past also played an important role in the decision-making process. Using trustworthy platforms and personalized marketing content can significantly increase user engagement and trust, thereby influencing their travel decisions. This study further emphasizes the core role of high-quality, credible content in driving consumer behavior and effectively promoting destinations, providing valuable insights for social media influencers and marketers in the tourism industry. At the same time, the study discusses limitations and future research directions and recommends introducing more diverse samples and exploration of influencing factors in future research.

KEYWORDS: Digital Tourism, Travel Decision-Making, Social Media Influencers, Destination Branding, Tourism Marketing

1 INTRODUCTION

This study uses quantitative methods to statistically analyze the influence of social media influencers on travel decisions, providing important insights into tourism marketing strategies and consumer behavior. In the context of the global tourism industry's rapid digitization, which has made it a force to be reckoned with in the travel market, the role of social media influencers (SMIs) is also growing in importance within the digital tourism sector. In particular, there hasn't been much study done on how these influencers' approaches and interaction styles play a part in how individual travel experiences and destination brand image construction are taken into account. While the study by Bigne et al.'s. (2020) examines the influence of SMIs on tourism through the analysis of blog content and user research, little is known about how travel bloggers affect the public's travel decisions and shape the perception of destinations. Although Gholamhossein Zadeh, et al.'s (2021). used the Netnography methodology to offer a systematic way of observing and analyzing social media communication externally, it was unable to assess the effectiveness of travel bloggers' long-term impact on destination image. Additionally, the study did not go deeply enough into the exploration of personal experiences and internal feelings. The objective is to present a comprehensive analysis of social media influencers' tactics and patterns of behavior from an insider's viewpoint, as well as how they use user-generated content (UGC) models to influence travel trends and destination branding. This study will use quantitative research to analyze the impact of social media influences on tourism destinations and how they change the public's travel preferences. The results will provide insights into marketing strategies and behavioral insights related to the tourism industry. The rapid growth of social media has significantly transformed how people gather information, share experiences, and make decisions, particularly in travel (Pencarelli, 2020). With platforms like Instagram, XiaoHongShu, TikTok, YouTube, and Facebook becoming integral parts of everyday life, travelers now have access to a vast array of content that shapes their perceptions and choices Femenia-Serra, et al., 2022. Among the myriads of content available, social media influencers have emerged as key players in the tourism industry, leveraging their online presence to impact their followers' travel decision-making processes Bastrygina et al., 2024. Social media influencers, defined by their large followings and the trust they build with their audience, often share user-generated content (UGC) such as reviews, travel vlogs, photos, and itineraries Vlahov et al., 2021. This content serves as a virtual guide for many potential travelers, providing them with insights that traditional marketing and advertising may not offer. The authenticity and relatability of influencers' experiences make their recommendations highly persuasive, often leading to changes in travel preferences and destination selection Rao Hill, & Qesja, (2023). This paper explores how social media influencers shape travel decision-making through their user-generated content. It examines the ways in which influencers create compelling narratives, build destination imagery, and influence travelers' attitudes and behaviors. By understanding this dynamic, the research aims to highlight the growing power of social media in the tourism sector and its implications for both travelers and industry stakeholder.

2 LITERATURE REVIEW

Wider et al. (2023) analyzed 1,079 articles from the Web of Science database. Their bibliometric analysis revealed the main trends in digital tourism, identifying three main clusters: smart tourism destinations and tourists, the evolution of e-tourism, and personalized smart tourism experiences. These findings highlight the impact of technology on travel behavior and emphasize the importance of destination management, as well as the application of new technologies. The study advocates for a focus on socio-cultural preservation amid technological advancement to ensure the sustainability of digital tourism. However, the reliance on a single database, Web of Science, has many limitations and may overlook diverse perspectives and interdisciplinary insights that could be captured through broader datasets. Although this study comprehensively focuses on technology and data analysis methods, it neglects the human factor, particularly the impact of social media personalities on travel trends and consumer behavior. The influence of these individuals may be an important driver in the travel industry's adoption of new technologies such as augmented reality and artificial intelligence, which the study highlights but does not explicitly link to influencer activity. The travel industry is an area where social media influencers have significant influence. This study aims to fill this gap and provide insights into how influencers contribute to the development and dissemination of smart tourism experiences and technologies. Social media influencers share and communicate with viewers through user-generated content. In a study by Mira Mayrhofer et al.'s it was noted that user-generated content is more likely to increase viewers' willingness to engage. UGC platforms contribute to online co-creation and destination experiences (Lam et al.'s 2020) On media platforms, social media influencers need to focus on the editing of user-generated content for destination promotion to enhance tourists' willingness to travel to the destination. The study conducted by Pop et al.'s (2021). offers insights into how consumer trust in social media influencers positively affects each phase of travel decision-making. The article explores the role of the customer journey structure in mediating the interrelationship between social media influencer trust and customer journey dimensions. The core point of the literature is to analyze how trust in social media influencers (SMIs) affects tourism consumers at each stage of the entire decision-making process. However, this study did not consider other influencing factors: in addition to trust in social media influencers, many other factors may influence consumers' travel decisions, such as personal preferences, economic factors, etc., which may not have been fully considered in the study. Javed et al.'s (2020). found that social media channels significantly impact tourists' behavioral intentions and actual behavior, leading them to select certain destinations and make travel-related decisions. Influencers are an important new interme·diary between consumers and suppliers, substantially affecting the tourism marketing agenda. (Yılmaz al.'s 2020b). Influencers are significant new actors that can substantially affect the trajectories of tourism consumption. (Ghlamhosseinzadeh, et al.'s 2021). Regarding the studies of Pop R.-A et al.'s (2021) and Ghlamhosseinzadeh, et al.'s (2021), both literatures emphasize the importance of social media and SMIs in the modern tourism industry. (Pop et R.-A et al. 2021) used customer journey theory to explore the relationship between social media influencer trust and consumer decision-making through statistical analyses. The influence of social media influencers throughout the tourism decision-making process is emphasized, especially in building consumer trust. (Gholamhosseinzadeh et al. 2021) revealed travel bloggers' role in shaping a destination's image.

3 METHODOLOGY

This study adopts quantitative analysis and aims to reveal how tourism-related content on social media platforms affects consumers' travel choices and behavior patterns. Approach to examine how tourism-related content on Chinese social media platforms, including Weibo, Douyin (TikTok), and Xiaohongshu (Little Red Book), influences consumers' travel choices and behavior patterns. All financial data in the study are reported in Chinese currency (RMB).

3.1 Research Design

The quantitative study will evaluate social media users' perceived influence and preference for travel posts and how these posts affect their travel decisions by designing a questionnaire. This study focuses on travel posts on social media and their impact on the decision-making process of travel consumers. Target Population: This study targets a wide range of social media users, with a particular focus on those who actively interact with tourism-related content.

3.2 Survey Design

A questionnaire is developed and implemented to quantify the impact of social media content on users' travel decisions. Sample Extraction and Analysis: A representative sample is selected from social media users using random sampling methods, and statistical analysis techniques are applied to evaluate the data and extract insights. This research pays attention to how social media influencer content affects public perceptions and preferences for travel destinations. First, select the sample: identify social media user groups, taking into account audience characteristics (gender, age, income). This study proposes a research framework on how social media influencer content affects travel decisions. By analyzing influencer content, audience response, and final travel choices, the role of social media in travel decisions is understood. Step 1, the travel-related content shared by influencers (such as pictures, videos, and personal comments) is taken as an independent variable. This content will affect the audience's emotional response and attitude. To collect data, focus on their characteristics (gender, age, income level, and social media usage habits) as moderating variables to evaluate the different responses of different groups to the content. Step 2, the audience's emotional response is assessed through a questionnaire survey, that is, their excitement, interest, and desire to travel after watching the influencer content. After the emotional response is used as a mediating variable, the impact of likes, comments, and shares on the decision-making process is analyzed to understand how these interactions strengthen the audience's trust in the content. Finally, through the analysis of the audience's emotional response and social proof, the dependent variable of travel decision is proposed, whether the audience decides to travel to the promoted tourist destination after being exposed to the social media influencer content. It aims to reveal how social media affects travel decisions shown in Figure 3.1.

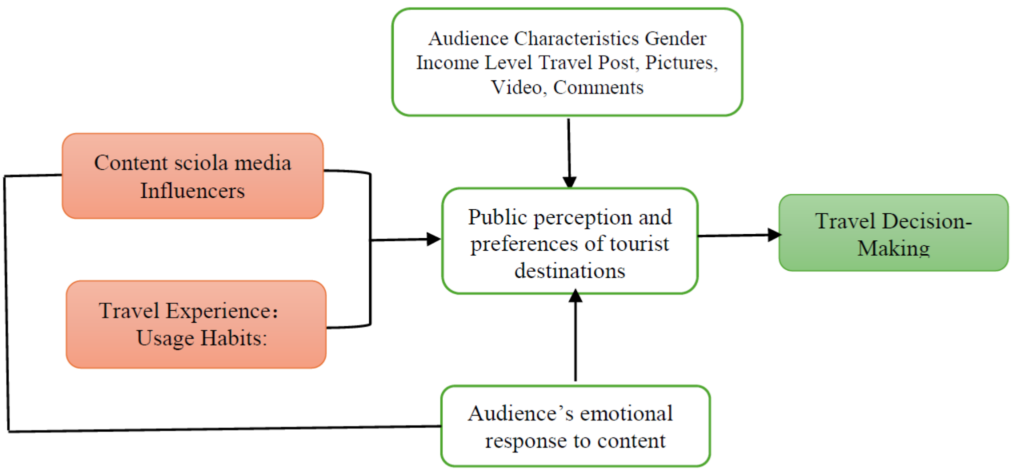

Figure 3.1: *Conceptual Framework for Travel Decision-Making and Tourism Behavior.*

3.3 Data Collection and Processing Tools

Quantitative Analysis Using SPSS: Questionnaire data is directly imported into the program. After cleaning, the data is checked for consistency errors, outliers, and missing values. The basic properties of the dataset were described through descriptive statistical analysis, including frequency, mean, and standard deviation. The correlation analysis function in SPSS examined the association between the frequency of social media use and travel choice. The regression analysis method examines the impact of independent variables (social media motivation influencing factors) on the dependent variable (travel experience). Collect data: To analyze content posted by social media influencers. Survey or track social media users' reactions to this content, as well as their relationships with influencers, travel experiences and social media usage habits. Operationalize variables: Determine how to measure each variable, using questionnaires to measure the audience's emotional response to content, using frequency surveys to measure social media usage habits, etc. Implementation research: Conducting an actual survey, experiment, or data collection to ensure that controlled variables do not affect the results. Data analysis: Use statistical software to analyze data to see how well social media influencer content correlates with public perceptions and preferences for travel destinations. Analyze how moderator variables affect this relationship and how affective reactions mediate this effect. Interpret the results: Based on the results of your data analysis, explain the specific impact of influencer content on audience perceptions and preferences, and how other variables moderate or mediate this impact.

3.4 Hypotheses

Social media plays a key role as a source of information to help tourists in all stages of travel decision-making, and social media is an important tool and platform for sharing data in real time. (Nilashi et al., 2021) The public can share travel information on social media and learn about destinations in real-time. The electronic word of mouth (IWOM) generated by travel content in social media allows travelers to overcome the ambiguity associated with travel planning. IWOM plays an important role in travel decision-making. (Nilashi et al. 2022) In social media, one can participate in the distribution and dissemination of travel information by replying, retweeting, commenting, linking, and liking, which makes travel information spread more widely and quickly. ((Zhang, Chen, & Fu, 2023) There is a positive correlation between travel motivation and tourists' destination attitudes influenced by destination image. (Pereira, Gupta, & Hussain, 2019), (Zhang, Gao, Cole, & Ricci, 2020) Social media influencers display and share tourism information on social media through user-generated content (UGC), and the way tourists share, and access household-generated content (UGC) significantly affects the attractiveness of a destination. Tourists can access destination information through the comments of other users on social media. Therefore, social media content about tourism may have an impact on tourists' destination choices. In light of this, it can rightly be hypothesized that:

- Hypothesis 1: Positive Influencer Content on Attitude Formation The more positive the travel-related content shared by social media influencers, the more favorable the attitudes of followers towards the promoted destination. This hypothesis is based on the idea that influencer content can shape perceptions and attitudes, leading to a more favorable view of the destination they showcase.

- Hypothesis 2: Positive Influence of Engagement on Travel Intentions Higher levels of engagement (likes, comments, shares) with travel influencers' content are positively correlated to visiting the featured destinations. Active engagement with an influencer's content indicates a higher interest level, which can translate into a stronger intention to make a travel decision.
- Hypothesis 3: Positive Social Proof on Decision-Making Exposure to travel content from social media influencers, combined with positive social proof (e.g., likes, comments, testimonials), significantly increases the likelihood of followers choosing the promoted travel destinations. This hypothesis leverages the concept of social proof, suggesting that people are more likely to make travel decisions when they see positive reactions from others shown in Figure 3.2.

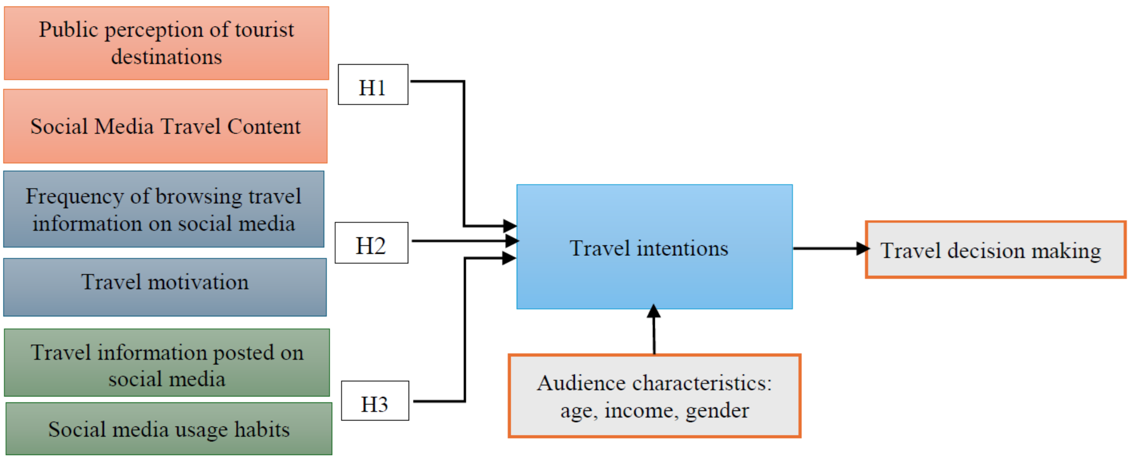

Figure 3.2: *A conceptual model for Travel Decision-Making and Tourism Behavior.*

4 RESULT AND DISCUSSION

4.1 Quantitative research findings

A total of 254 valid questionnaires were collected. Among the respondents, 48.8% were male and 51.2% were female. Most of the respondents were aged between 27 and 40, accounting for 53.1%, followed by those aged 40 and above, accounting for 24.8%. 78% of the respondents had a monthly income of more than $5000, According to data from the National Bureau of Statistics (2020). This shows that most of the respondents have a high level of income. 47.6% of the respondents have an annual travel budget of more than RMB 5,000, and 22.8% have a budget of between RMB 3,001 and RMB 5,000, which shows that the respondents have a strong ability to spend on traveling, while 12.6% of the respondents have an annual travel budget of less than RMB 1,000. It is interesting to note that 100% of the respondents said they get travel information through social media before traveling, which shows the importance of social media in travel decision-making. Regarding the frequency of social media use, 48%

of respondents viewed travel information every 2-3 days and 18.1% viewed it every day, indicating that social media is their main channel for obtaining travel information. These results show that social media plays an important role in tourism information acquisition and decision-making. Respondents generally have high income and travel budgets spend a lot of time browsing travel information on social media and are frequently exposed to social media influencer content shown in Table 1.

Name	Option	Frequency	Percentage
Gender	male	124	48.8
Gender	women	130	51.2
Age	18-22years	23	9.1
Age	23-26years	33	13
Age	27-40 years	135	53.1
Age	40 years or more	63	24.8
Your monthly income	Less than 3,000 yuan	14	5.5
Your monthly income	3000-5000 yuan	27	10.6
Your monthly income	5000-8000 Yuan	15	5.9
Your monthly income	8000 or more	198	78
Your annual budget for travel	Less than $1,000	32	12.6
Your annual budget for travel	1001-3000 yuan	43	16.9
Your annual budget for travel	3001-5000 yuan	58	22.8
Your annual budget for travel	5001 or more	121	47.6
Did you learn about travel through social media before you traveled	yes	254	100
Did you learn about travel through social media before you traveled	no	0	0
How often do you usually use social media to browse travel information	at least once a day	46	18.1
How often do you usually use social media to browse travel information	once every two or three days	122	48
How often do you usually use social media to browse travel information	once a week	51	20.1
How often do you usually use social media to browse travel information	once every few months	35	13.8
How long do you usually spend on social media platforms to get travel information	less than 1 hour	68	26.8
How long do you usually spend on social media platforms to get travel information	1-3 hours	111	43.7
How long do you usually spend on social media platforms to get travel information	3-5 hours	46	18.1
How long do you usually spend on social media platforms to get travel information	More than 5 hours	29	11.4

Table 1: *Demographic Results of the Participants (n=254)*

4.2 Influence of Engagement on Travel Intentions

By analyzing the interactive behavior of users, the response rate and reach of users to different personalized tourism marketing content are demonstrated using the stacked bar chart (Table 2). It can be seen that customized travel packages and offers and unique travel experience content are the most interactive ones, with a response rate of 24.434% and 21.683%, respectively. The calculation formulas for response rate and prevalence (coverage) rate are:

$$Response\ Rate(\%) = \frac{Number\ of\ Responses\ for\ a\ Content\ Type}{Total\ Number\ of\ Responses} \times 100\% \tag{1}$$

$$Prevalence\ Rate\ (Coverage\ Rate)(\%) = \frac{Number\ of\ Respondents\ for\ a\ Content\ Type}{Total\ Respondents} \times 100\% \tag{2}$$

The response rate for self-recommended content based on users' interests is relatively low at 17.314%, but its coverage rate is still relatively high. Users' real travelogues and reviews have a response rate of 18.285%, which is comparable to personalized recommendations, but users' trust in such content accounts for 44.488%. This indicates that user travelogues and reviews can effectively increase social recognition, as shown in Table 2.

4.3 Social Proof and Decision-Making

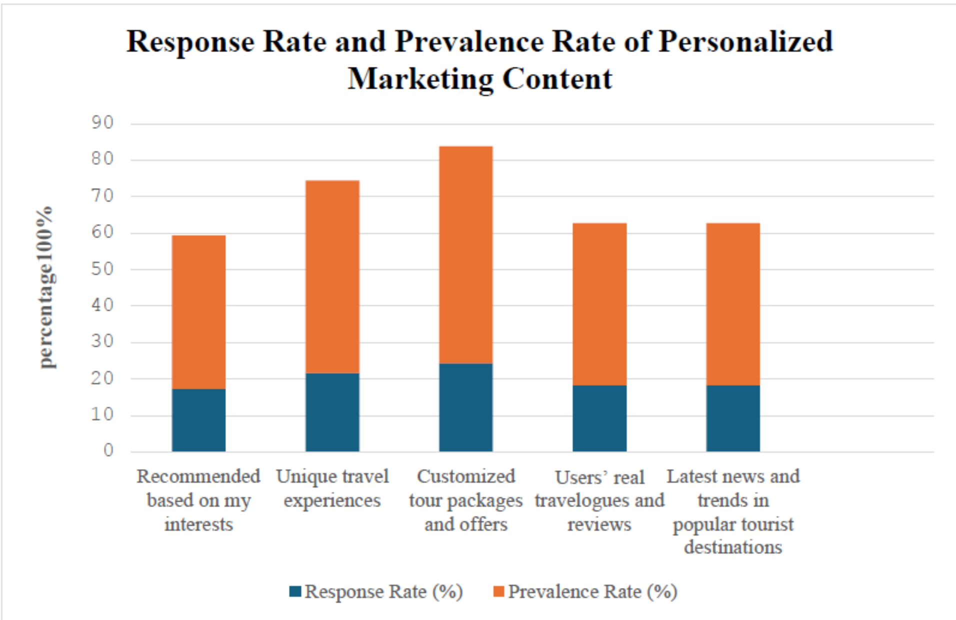

Figure 4.3: *Response rates and popularity of personalized marketing content.*

This interaction not only helps to enhance the attractiveness of the destination but also increases users' trust and willingness to participate through the social identity effect. This trust mechanism will further motivate users to be more inclined to make travel decisions after seeing positive reviews from other users. The latest news and trends of popular tourist destinations have a slightly lower response rate of 18.285%, but a coverage rate of 44.488%, which reveals that timely tourism information can attract user participation, and the content of tourism posts can further increase users' willingness to travel through a large number of users' likes, comments, and shares shown 4.3.

In order to collectively assess the combined effect of different trust factors on users' decision-making, we conducted a multiple responses analysis to analyze the performance of

Content-Type	Response Rate (%)	Prevalence Rate (%)
Recommended based on my interests	17.314	42.126
Unique travel experiences	21.683	52.756
Customized tour packages and offers	24.434	59.449
Users' real travelogues and reviews	18.285	44.488
Latest news and trends in popular tourist destinations	18.285	44.488

Table 2: *Response rate and reach of personalized tourism marketing content*

"authority and credibility of social media platforms," "reputation and quality of past shares," and "common interests or experiences" in terms of response rate and coverage rate. The calculation formulas used for response rate and prevalence (coverage) rate are:

$$Response\ Rate(\%) = \frac{Number\ of\ Responses\ for\ a\ Trust\ Factor}{Total\ Number\ of\ Responses} \times 100\%. \tag{3}$$

$$\text{Prevalence Rate (Coverage Rate)}(\%) = \frac{Number\ of\ Respondents\ for\ a\ Trust\ Factor}{Total\ Respondents} \times 100\% \tag{4}$$

The results show that the authority and credibility of social media platforms have a 35.476% response rate and a 54.331% prevalence rate, making it the primary factor influencing users' trust. (Table 3) exhibits that the authority of the platform plays a significant role in enhancing users' trust and prompting them to make travel decisions. Users prioritize platform credibility when assessing the trustworthiness of travel-related content. Therefore, travel brands and social media influencers should prioritize social platforms with high authority among user groups to promote destinations and increase their influence. Secondly, user reputation and the quality of past shares show a 32.905% response rate and 50.394% reach, indicating that reputation also plays a critical role in decision-making.

Trust Factor	Response Rate (%)	Prevalence Rate (%)
Reputation of users and quality of history sharing	32.905	50.394
Shared interests or experiences with users	31.62	48.425
Authority and credibility of social media platforms	35.476	54.331

Table 3: *Key Factors Influencing User Trust, Response Rates and Coverage Rates*

Compared to platform authority, although the user's reputation has a slightly lower response rate, the difference in its reach is not significant, suggesting that the social media influencer's reputation and the quality of past shares have an equally strong influence on fans' trust. Posting high-quality content helps to maintain fans' attention and trust and increases their acceptance of recommended destinations. Shared Interests or Experiences The response rate of 31.620% and coverage rate of 48.425% are low compared to the influence of other factors, although social media influencers sharing similar interests and experiences with their fans can also help to increase trust and interaction, which in turn influences their travel decisions exposed Figure 4.4.

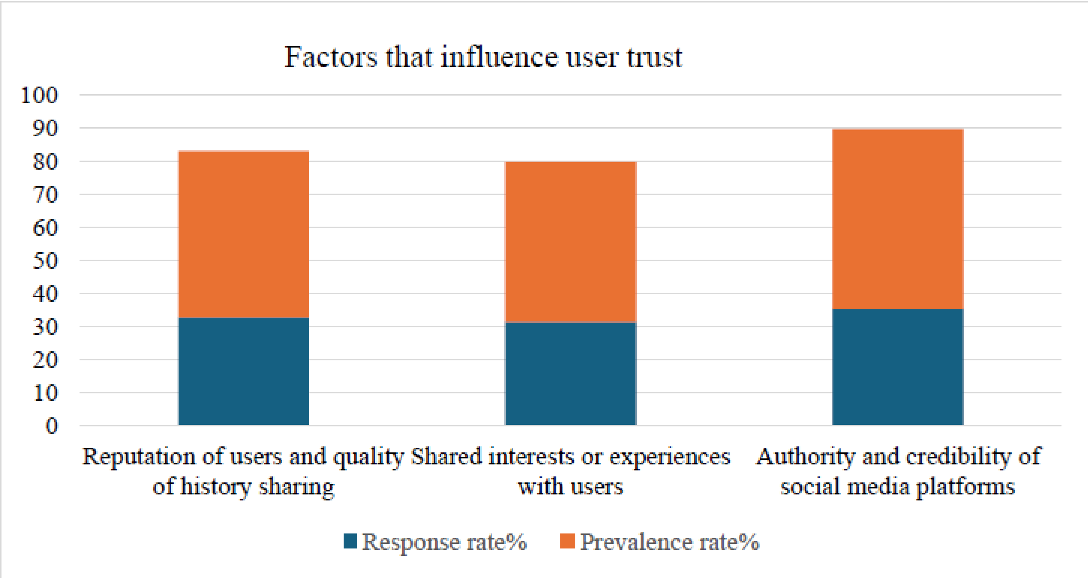

Figure 4.4: *Stacked Bar Chart of Response Rate and Coverage for Different Trust Factors.*

4.4 Reliability Analysis

Cronbach's alpha coefficient formula: I rely on influencer recommendations when choosing travel destinations to inform my travel decisions. To verify the reliability of this statement and others related to the impact of social media on tourism motivation, the corrected total correlation value (CITC) and Cronbach's alpha coefficient analysis were conducted. A reliability analysis was performed to evaluate the consistency of the responses, and the calculation formula used for Cronbach's alpha is:

$$\alpha = \frac{N}{N-1}\left(1 - \frac{\sum_{i=1}^{N}\sigma_i^2}{\sigma_T^2}\right) \tag{5}$$

The analysis showed that the reliability coefficient of the questionnaire was 0.886, indicating a high degree of consistency in the data collected, with each item contributing to the overall reliability.

5 DISCUSSION

This study reveals the important role of social media in travel decision-making. As a digital platform, social media affects the way consumers obtain travel information and make decisions at all stages. The results show that all respondents obtain information through social media before making travel decisions, indicating that social media has gradually replaced traditional

Name	CITC (Total correlation of correction items)	Alpha Coefficient of the deleted entry	Cronbach Alpha Coefficient
Impact of social media on travel motivation - I often use social media for travel information	0.637	0.874	0.886
Travel information on social media social media inspires my urge to travel	0.666	0.871	0.886
I think social media has a positive impact on my choice of travel destination options	0.63	0.874	0.886
User reviews and recommendations on social media play an important role in my travel decisions	0.672	0.871	0.886
I would judge the popularity of a place based on the likes and comments of travel shares on social media	0.626	0.875	0.886
Likes and comments on social media enhance my expectation and longing for the travel experience	0.617	0.875	0.886
Travel content shared on social media is authentic and reliable	0.635	0.874	0.886
Travel tips and real travel experiences shared on social media increase my enthusiasm and urge to travel	0.638	0.874	0.886
Word-of-mouth about a place on social media influences my decision to travel	0.61	0.876	0.886

Table 4: *Reliability analysis of the impact of social media on tourism motivation*

sources of information. The authority and credibility of the platform play a key role in building user trust, and users tend to choose platforms they believe to be credible to obtain travel information (Guerreiro, Viegas, & Guerreiro, 2019). Especially in the era of Tourism 4.0, the impact of digital technology is more significant, and traditional tourists are gradually transformed into digital and intelligent travelers (Pencarelli, 2020). Through the analysis of 254 valid questionnaires, this study further explored the interactive behavior of users with travel content. 48% of the respondents browsed travel information every 2-3 days, and 18.1% of the respondents browsed it every day, indicating that social media platforms play an important role in providing timely and relevant travel content. Personalized marketing content significantly increased user engagement, specially customized travel packages and unique experience content, which reached 24.434% and 21.683% response rates, respectively, becoming the most interactive content. This shows that personalized content can not only stimulate user interest but also enhance the attractiveness and trust of the platform. Trust factors occupy a central position in this study, especially the authority and credibility of the platform. Studies have found that platforms that users trust tend to have consistency, transparency, and security, which significantly increase users' acceptance of content (Saini, Kumar, & Oberoi, 2023). In addition, the frequency of content generation and sharing, the proportion of influencers' fans, and comment replies also constitute the prerequisites for trust and directly affect users' travel decisions. The study also fills the empirical gap in the existing literature on platform trust, proving that users are more inclined to trust social platforms that show high consistency in content publishing and interaction.

In addition to platform trust, user-generated content (UGC) such as travel stories and comments also play an important role in building trust. The data shows that the coverage rate of users' real travel notes and comments is 44.488%, which indicates that social proof effects (such as likes, comments, and positive recommendations) have a significant impact on users' decisions. Users have a higher degree of trust in these UGCs, which further enhances their interest and willingness to recommend destinations.

However, relying solely on UGC or destination-generated content may not be enough to fully gain user trust. Research by Sano et al. (2024) shows that in the process of building trust, in addition to the authority of the platform and content, merchants and social media influencers need to adopt more strategies to meet the needs and trust expectations of tourists in different situations. Therefore, merchants and influencers should give priority to cooperating with highly authoritative platforms while ensuring the continuous production of high-quality and reliable content to meet users' expectations and further promote their travel decisions. The degree of influence of the trust factor can be seen in the relative role of platform authority and UGC. Although the credibility of the platform is the primary factor affecting user trust, personalized content, and user interactions (such as comments and sharing) also play an important role in the decision-making process by enhancing social proof. Customized travel packages and unique travel experience content, due to their high interactivity and personalization, can further promote user trust and participation, and ultimately drive their travel decisions.

6 CONCLUSION

This study explores the impact of social media on travel decision-making by analyzing the behaviors, preferences, and trust factors of 254 respondents. The results emphasize the critical role that social media plays in shaping users' travel intentions and decisions. The role of social media as a primary source of information has become increasingly significant, influencing users' access to travel-related content (Figure 3.1). The data shows that respondents frequently use social media to obtain information before making travel decisions, confirming that it is an essential channel for up-to-date travel content. This reinforces the findings from earlier studies on image formation (e.g., Pop, Săplăcan, Dabija, & Alt, 2021) Respondents use social media to obtain travel information before making travel decisions. Social media is an important channel for frequent updates of travel-related content. This reinforces the results of earlier image formation studies (e.g. Pop, Săplăcan, Dabija, & Alt, 2021,). Personalized marketing content such as tailored travel packages and unique travel experiences (Figure 3.2) generates the highest levels of user interaction. This suggests that users prefer content that matches their personal preferences or offers novel experiences. The findings suggest that creating personalized content is an effective way to enhance user engagement and influence travel decisions. In addition, the authority and trustworthiness of social media platforms are the most important factors influencing users' decision-making, with users showing a strong preference for platforms they consider trustworthy. Although this study offers valuable insights into the influence of social media on travel decisions, it is not without limitations. While the sample size is useful, it may not be fully representative of the broader population. Furthermore, the study concentrated on influencers and personalized content, thereby neglecting other potential influencing factors. Future research should investigate a wider range of variables and consider a wider range of influencers. In conclusion, social media can be considered a powerful tool for the tourism industry, as it can influence travel intentions through several factors, including frequent interactions, the provision of personalized content, and the establishment of trust. It is of the utmost importance for travel brands and influencers to concentrate their efforts on the creation of engaging, reliable, and tailored content on reputable platforms. This approach is essential for the effective promotion of their products and services and for influencing travel decisions.

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The Influencing Factors for Tourist'S Decision Making on Tourism Route Selection in the Context of Smart Tourism

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Abstract

This study aims to analyze the influencing factors of tourists' travel route selection decisions in the context of smart tourism. Data was collected through questionnaire surveys, and statistical methods such as descriptive statistics and correlation analysis were used to analyze the data. The research hypotheses were verified through regression analysis. Through the research analysis, the influencing factors of tourists' travel route selection decisions in the context of smart tourism were identified, and corresponding recommendations were proposed. In addition, the concepts of smart tourism and travel decision-making were defined and summarized, and existing research was reviewed and summarized. The research results that personal needs and preferences are the most important factors affecting the choice of travel routes , combining the cognition of smart tourism provide a foundation and innovative point for further research in the field of smart tourism and summarize the main innovations of the research, as well as provide prospects for future research.

KEYWORDS: Smart Tourism, Travel Route Selection, Tourist Decision-Making, Influencing Factors, Questionnaire Survey

1 INTRODUCTION

This study aims to explore the influencing factors of tourism route selection decisions in the context of smart tourism. In the context of smart tourism, there have been some changes in the influencing factors of tourism decision-making. Collect data through questionnaire surveys and statistical analysis methods to analyze the influencing factors of tourism route selection decisions in the context of intelligent tourism. The research results will provide theoretical basis and reference for further research and practice of tourism routes in the field of smart tourism, provide better tourism experience for tourists, help tourists intelligently choose tourism routes, and provide data support for tourism enterprises to better design and plan routes.

2 LITERATURE REVIEW

In domestic and international research, important research results have been achieved in the field of smart tourism. Foreign research mainly focuses on defining the concept of smart tourism, designing and applying smart tourism platforms and services. However, domestic research focuses more on the development and application of smart tourism, as well as the impact of smart tourism on tourist behavior and tourism formats. Zheng Xiangmin (2013) pointed out that smart tourism is a new tourism development concept that serves tourists, tourism enterprises, and destination governments. Deng Hui (2015) proposed that smart tourism is a distinctive creative tourism activity that is based on intelligence, led by creativity, supported by technology, attracted by smart creations, and characterized by experiencing creative success and inspiring people's smart creativity. Zhao Lihua (2016) believes that smart tourism is a new tourism development model that uses emerging technologies and network terminals to collect various tourism information and make scientific plans for the arrangement and adjustment of tourism plans.

3 Research Designs, Scope and Methods

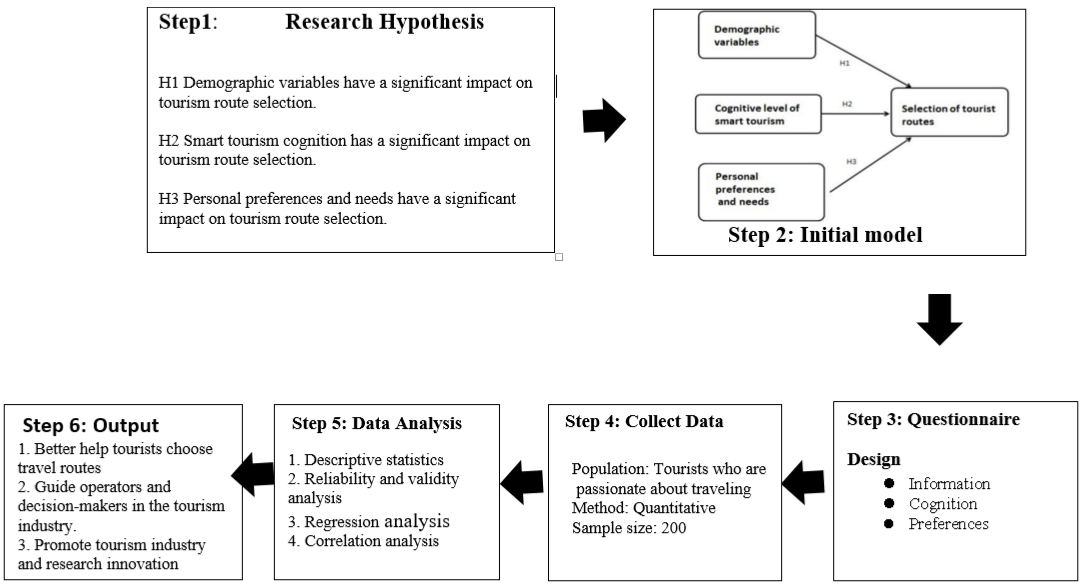

Figure 3.1: *Research framework.*

In order to analyze the influencing factors of tourist travel route selection decisions in the context of smart tourism, the conceptual framework is as follows:

3.1 Formulate Research Hypotheses

Formulate research hypotheses by reading the literature. There are a total of 3 research hypotheses in this article. H1is Demographic variables have a significant impact on tourism route selection. H2 is Smart tourism cognition has a significant impact on tourism route selection. H3 is Personal preferences and needs have a significant impact on tourism route selection.

3.2 Build a model for the research hypothesis

Build a model for the research hypothesis. There are four variables, personal preferences and needs, cognitive variables of smart tourism route selection and demographic variables are independent variables, Selection of tourist routes is are dependent variable.

3.3 Questionnaire design

This section is about survey questionnaire design. This study will use a questionnaire survey method for data collection. The questionnaire design will combine relevant concepts such as personal needs, cognitive factors, and personal background factors, as well as existing literature research results, to construct a survey questionnaire. The sample scope is national tourism enthusiasts, with a sample size of 200.

3.4 Data Collection

This study uses a questionnaire survey method to hypothesize and investigate tourists' travel intentions and smart tourism applications.

3.5 Data Analysis

The questionnaire analysis first conducted reliability and validity analysis, followed by descriptive analysis, regression analysis, and correlation analysis (SPSS). The research hypothesis was validated and analyzed, and the correlation between factors affecting tourism route selection was further elaborated.

3.6 Output

Better assist tourists in choosing travel routes, bring better tourist experiences, and increase tourist satisfaction. Guide tourism industry operators and decision-makers to provide data and information for tourism enterprises to make better route planning. It can promote innovative development of the tourism industry and provide support for tourism research.

4 Data analysis and results

4.1 Reliability

According to the analysis results, the demographic variables, smart tourism cognition, and personal preferences and needs involved in the study all show high internal consistency in their impact on tourism route selection, with Cronbach's alpha coefficients exceeding 0.8. In particular, the alpha coefficients of personal preferences and needs are as high as 0.979, indicating their dominant role in tourism selection. This indicates that consumers' age, gender, income, and awareness of smart tourism will significantly affect their travel decisions.

Dimension	Item Count	Sample Size	Cronbach α
Demographic Variables' Impact on Travel Route Selection	8	200	0.896
Impact of Smart Tourism Awareness on Travel Route Selection	8	200	0.967
Impact of Personal Preferences and Needs on Travel Route Selection	8	200	0.979

Table 1: *Reliability*

MO Sampling Adequacy Measure		0.823
Bartlett's Test of Sphericity	Approx. Chi-Square	1408.03
	Degrees of Freedom	36
	Significance	0

Table 2: *The impact of demographic variables on tourism route selection*

4.2 Validity

From the perspective of validity analysis, the KMO values of all three dimensions exceed 0.7, indicating good sample suitability and suitability for factor analysis. Among them, the KMO value for personal preferences and needs is the highest, at 0.937, indicating a stronger correlation. The Bartlett sphericity test results were all significant (p=0), supporting sufficient correlation between variables and suitable for further statistical analysis. This indicates that demographic variables, smart tourism cognition, and personal preferences and needs have good validity in influencing tourism route selection, providing a solid foundation for subsequent research.

4.3 Regression analysis

This study conducted an in-depth analysis of different demographic variables, and the results showed that age, education level, labor type, and income level have a significant impact on tourism choices. The impact of different demographic variables on tourism route selection can be significantly numerically analyzed through regression analysis. These data clearly reflect the profound impact of different demographic characteristics on tourism choices, providing valuable market strategy references for related industries.

4.4 Correlation analysis

MO Sampling Adequacy Measure		0.92
Bartlett's Test of Sphericity	Approx. Chi-Square	2325.362
	Degrees of Freedom	36
	Significance	0

Table 3: *The impact of smart tourism cognition on tourism route selection*

MO Sampling Adequacy Measure		0.937
Bartlett's Test of Sphericity	Approx. Chi-Square	2890.908
	Degrees of Freedom	36
	Significance	0

Table 4: *The influence of personal preferences and needs on travel route selection*

The influence of personal preferences and needs on travel route selection It indicates that various factors of smart tourism significantly affect tourists' travel route choices. Overall, enhancing tourists' awareness of smart tourism will further improve satisfaction. It is recommended that the tourism industry integrate these factors to optimize marketing strategies and service design.

The impact of smart tourism cognition on tourism route selection Cultural characteristics, leisure needs, and emotional experience needs are key factors that influence tourists' choices of travel routes. Meanwhile, the popularity, geographical location, and climate conditions of tourist destinations have relatively little impact on the choice. Tourism operators should pay attention to these significant factors in order to design products that better meet the needs of tourists and enhance the overall tourism experience.

5 Conclusions and recommendation

Research has shown that individual needs and preferences play a dominant role in travel choices. Consumers' age, gender, income, and awareness of smart tourism will significantly affect their travel decisions. In short, personal preferences and needs have the greatest impact on the choice of travel routes. Cultural characteristics, leisure needs, and emotional experience needs are key factors that influence tourists' choices of travel routes. Population variables have an impact on tourism routes, and corresponding tourism plans can be developed based on different age groups, education levels, income levels, and labor types, fully considering the differences between different groups of people. There is also the awareness of smart tourism, which can use intelligent technology and platforms to provide better services and experiences for tourists, increasing their stickiness. The research findings of this study can provide targeted recommendations and decision support for tourism enterprises and destination managers, helping them better understand the needs and preferences of tourists. Then tourists will receive suitable travel route suggestions to meet personalized travel needs. In further research in the field of smart tourism, the results of this study can also serve as a reference and inspiration for promoting the development of smart tourism theory and practice.

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	Unstandardized Coefficients	Standard Error	Standardized Coefficients	t	Significance
	B		Beta		
(Constant)	1.073	0.301		3.563	0
1. Young people tend to prefer challenging and adventurous travel routes	0.168	0.072	0.181	2.319	0.021
2. Older adults tend to prefer quiet and comfortable travel environments	0.278	0.083	0.262	3.36	0.001
(Constant)	0.587	0.205		2.866	0.005
3. People with higher education tend to prefer travel routes with cultural heritage and academic value	0.157	0.049	0.232	3.236	0.001
4. People with lower cultural education levels place more importance on travel routes with entertainment value	0.226	0.054	0.299	4.18	0
(Constant)	1.091	0.104		10.464	0
5. People engaged in mental labor are more likely to seek relaxation and pursue natural scenery	0.089	0.036	0.228	2.447	0.015
6. People engaged in physical labor are more likely to choose leisure and entertainment travel routes	0.094	0.04	0.218	2.339	0.02
(Constant)	1.05	0.271		3.875	0
S1	0.463	0.067	0.44	6.885	0

Table 5: *The impact of demographic variables on tourism route selection*

		10	11	12	13	14	15	16	17	18
Cognitive level of smart tourism	Pearson correlation	.315**	.388**	.402**	.291**	.316**	.353**	.304**	.309**	.402**
	Sig. (Double tail)	0	0	0	0	0	0	0	0	0
	Number of cases	200	200	200	200	200	200	200	200	200

Table 6: *Pearson analysis of the cognitive impact of smart tourism*

		19	20	21	22	23	24	25	26	27
Personal preferences and needs	Pearson correlation	.471**	.475**	.451**	.480**	.479**	.469**	.445**	.417**	.343**
	Sig. (Double tail)	0	0	0	0	0	0	0	0	0
	Number of cases	200	200	200	200	200	200	200	200	200

Table 7: *Pearson analysis of the influence of personal needs and preferences*

The Impact Of Digital Payment Systems on Customer Satisfaction in the Hospitality Industry: The Mediating Role of Online Travel Agencies.

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Abstract

This study investigates the impact of digital payment systems on customer satisfaction in the hospitality industry, with a particular focus on the mediating role of Online Travel Agencies (OTAs). The study utilized a questionnaire to collect data from users of OTA platforms to assess their perceptions of digital payment systems, online travel agencies, and overall customer satisfaction. The results suggest that improving the convenience of the payment system, ensuring transaction security, and increasing the speed of payment can be effective in improving customer satisfaction, and that OTA platforms should prioritize improvements in these three areas when designing their digital payment systems in order to increase overall customer satisfaction. However, the intermediary effect of OTA is also obvious. Among OTA platforms, there are obvious differences in service experience and user feedback among different platforms and Booking and Ctrip have stronger advantages in market competition. Therefore, the role of each OTA platform in improving customer satisfaction is obviously different. Booking has the highest influence, followed by Ctrip, while Agoda has a relatively weak influence. These findings suggest that OTA platforms should focus on optimizing the key factors affecting customer satisfaction, especially the service features offered by Booking, when developing their market strategies in order to improve customer experience, enhance customer loyalty, and ultimately capture a larger share of the competitive market. The results of this study provide valuable insights for hospitality companies and OTAs to optimize their digital payment strategies and improve customer satisfaction.

KEYWORDS: Digital Payment Systems, Customer Satisfaction, Hospitality Industry, Consumer Experience, Digital Finance

1 INTRODUCTION

Fintech services is an umbrella term for advanced technology that facilitates financial services and has brought about extraordinary digital financial system advancements mainly in developed and developing countries. (Mention, A.L. 2019 Jin, C.C.; Seong, L.C.; Khin, A.A.2019) There has been a widespread recognition that "the digital revolution has dramatically changed the operation and management of hotels, and digital technologies have been recognised as the primary sources of efficiency and competitive advantage in the hotel sector" (Wynn, M., & Jones, P. 2022) Digital payment systems are extensively used for digital application-based transactions and payments because consumers view this method as advantageous (Gokilavani, R., Kumar, D. 2018) The use and adoption of information and communication technologies have demonstrated that online travel agencies have a crucial competitive advantage for tourism and hotel organizations. In this dynamic environment, online travel agencies must highlight a range of digital tools to be able to meet the expectations and requirements of connected tourists. Online Travel Agencies (OTAs) are online platforms such as Booking, Skyscanner and Expedia that offer travel-related products and services, such as hotel rooms, flights, crossings and travel packages, facilities and tourism activities to customers. (El Archi, Y., & Benbba, B. 2022). OTAs act as intermediaries between the tourism value chain and customers by helping them sell and buy products and services (Kumar et al., 2022). The evolution of digital payment systems is not merely a technological progression but a societal shift towards a convergence of physical and digital infrastructures to adapt to changing consumer preferences and technological advancements. To improve the customer experience, fintech services combine new processes with the creation and delivery of personalized, 24/7 financial services (Pollari, I.; Gomber, P.;2019 2020). While customers are dwelling in digital societies, their expectations of products and services quality increase and ultimately reflected in customer satisfaction (Tran & Vu. 2019). Thailand's tourism and hospitality segment generated up to 20% of country's GDP (Inthasang et al. 2021) and the survey by Statista (2022) on the comparison between offline and online hotel booking in Thailand revealed that 79.3% had booked their accommodation online while only 20.7% had booked their accommodation offline. The hotel industry in Thailand still has room for growth soon after nevertheless, study on the impact of digital payment systems of the hotel industry and OTAs on customer satisfaction is needed to provide practitioners with a broader perspective. prevoius tudies on the Thai hotel industry have only focused on the online booking process, the use of OTAs, the impact of digital marketing on hotel performance, and online purchase intention (Chubchuwong, 2019; Wongkhajornpaibul & Sornsaruht, 2019; Inthasang et al., 2021; Chubchuwong, 2022; Phumpa et al. 2022), However, The discussion on customer satisfaction brought about by OTA digital payment systems is still neglected. This study will be helpful for hotel management, especially OTA-hotel cooperation. In the process of measuring customer satisfaction, payment methods, OTA platforms, etc. will be compared. Therefore, this study proposed to understand the impact of OTA platform digital payment systems on customer satisfaction.

2 LITERATURE REVIEW

Silvia Ratna, S. Saide et al. (2023) showed that the impact of digital financial technology service has dramatically changed the landscape of financial services in both developed and developing countries (Silvia Ratna, S. Saide. 2023). The of digital payment systems is particularly beneficial to consumers because it improves payment efficiency and simplifies the payment process (Shruti Mandlik. 2023). The customer satisfaction have been identified as key factors in the hospitality industry, and a positive customer experience contributes to revenue growth and reduction in service costs (Kyryliuk & A. Blahopoluchna. 2023) The need for broader research on the willingness to increase visitor loyalty through fintech services and the mediating role of consumer experience and attitudes within the hospitality industry in relation to customer satisfaction (Tuti Awaliyah, Nurul Safitri, et al.2023). The existing research literature by Silvia Ratna, S. Saide, et al. (2023) provided valuable insights into The impact of FinTech innovations on customer satisfaction, loyalty and overall efficiency of payment systems in the hospitality industry. The study emphasized the potential of fintech and knowledge management to create new markets and opportunities in the tourism and hospitality industry. Digital payment systems and Online Travel Agencies (OTAs) have gained significant popularity in recent years, impacting customer satisfaction and purchasing decisions. Studies showed that factors such as perceived usefulness, ease of use, trust, and security influence the adoption of digital payment systems (Shailza & Madhulika P. Sarkar. 2019; K. Vinitha & S. Vasantha. 2018). Customer satisfaction with OTAs is closely linked to the certainty of benefits, convenience in transactions, and alignment with expectations regarding prices and promotions (Didit Iswahyuniarto. 2023). To ensure customer satisfaction, digital payment systems and OTAs must focus on building trust, improving consumer interaction, enhancing service delivery, and maintaining robust security measures (K. Vinitha & S. Vasantha. 2018). In summary, the current literatures demonstrate the profound impact of digital payment systems on the hospitality industry and OTAs, emphasizing the important role of customer satisfaction. These studies provide valuable insights for industry stakeholder and pave the way for future research aimed at further understanding the impact of advances in digital payment systems on the hospitality industry and OTA platforms.

3 RESEARCH METHODOLOGY

3.1 RESEARCH DESIGNS

This study collected primary data by distributing questionnaires to respondents who had used OTA apps to purchase travel products (e.g., booking rooms). This study adopted a non-probability sampling method (Hair, J. 2010 & Subiyanto, I. 2000)The questionnaire was distributed to 200 respondents, but only 150 respondents were available for further analysis. The data was analyzed using multiple regression analysis (MRA). A quantitative approach will be employed to collect and analyze numerical data, allowing for statistical analysis and generalization of findings. Quantitative research: Distribute questionnaires to respondents who use OTA applications to purchase travel products (such as booking rooms) to collect primary data, collect data on payment system usage and customer satisfaction non-probability sampling (Tansey 2007) A quantitative approach will be employed to collect and analyze numerical data, allowing for statistical analysis and generalization of findings.

3.2 RESEARCH SCOPE AND METHODS

The aims of this investigation are as follows.:
OBJECTIVE 1: To explore direct impact of digital payment systems on hotel customer satisfaction:
RESEARCH QUESTION 1: How digital payment systems such as Alipay, WeChat Pay, credit card payment, etc. affect the overall satisfaction of hotel customers by improving convenience, transaction security, payment speed, etc.?

OBJECTIVE 2: To analyze the role of online travel agents (OTAs) in digital payment and customer satisfaction:
RESEARCH QUESTION 2: How OTAs such as Ctrip, Booking, etc. as participants in hotel booking platforms affect the effectiveness of digital payment systems regulate or amplify the impact of digital payment systems on customer satisfaction?
VARIABLES
INDEPENDENT VARIABLE:
Digital payment system (Ali Pay, WeChat Pay, Credit Card Payment): Convenience, Transaction Security, Payment speed. OTAs platforms (Ctrip, Booking.com, Agoda): The effectiveness of digital payment systems (Service experience, User feedback)
DEPENDENT VARIABLE: Customer satisfaction: Measured using a validated customer satisfaction scale, including dimensions such as overall satisfaction, perceived value.
CONCEPTUAL FRAMEWORK

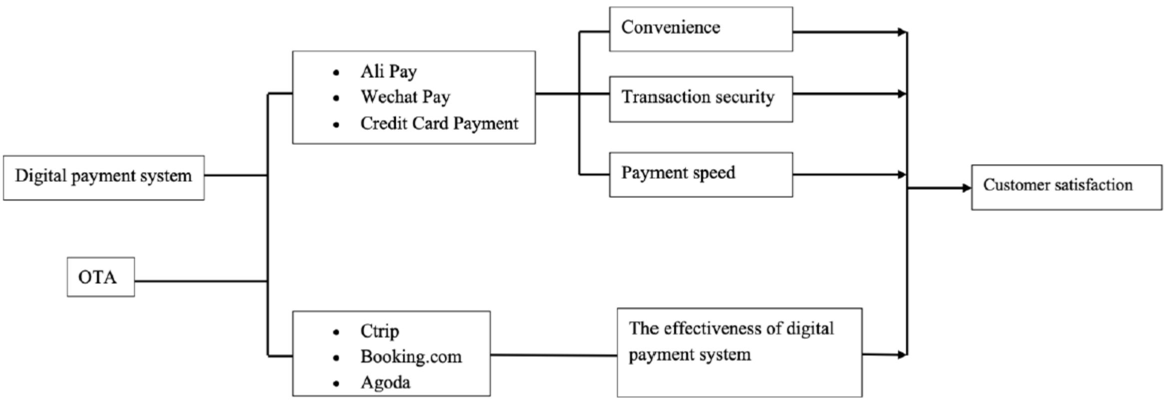

Figure 3.1: *CONCEPTUAL FRAMEWORK*

RESEARCH HYPOTHESES
Hypothesis1: The type of digital payment system used will significantly influence hotel customer satisfaction. Digital payment systems affect the overall satisfaction of hotel customers by improving convenience, transaction security, payment speed.

4 DATA ANALYSIS AND RESULT

This study used a quantitative research method. Data was collected from questionnaires, then processed through Excel, and finally analyzed through SPSS, which is a commercial distributed data management and statistical analysis software Through advances in usability and data access, SPSS technology makes difficult analytical tasks easier, allowing more people to benefit from using quantitative techniques for decision making (SPSS Inc.) The reliability of the hypothesis will be analyzed. This study assumes that digital payment systems have an impact on customer satisfaction and efficiency, and that digital system payment types have an impact on customer satisfaction in the hotel industry. Finally, multiple regression analysis is used to determine the extent of the impact.

4.1 REGRESSION ANALYSIS BETWEEN CONVENIENCE, TRANSACTION SECURITY, PAYMENT SPEED AND CUSTOMER SATISFACTION

The coefficient of determination of the model is 0.355, which means that the combination of independent variables in the model can explain 35.5% of the variance in customer satisfaction, while the adjusted R-squared value is 0.344. The adjusted R-squared value takes into account the effect of degrees of freedom and is usually slightly lower when the number of independent variables increases.

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.596[a]	.355	.344	.8317

a. Predictors: (Constant), Payment Speed, Convenience, Transaction Security

Table 1: *REGRESSION ANALYSIS BETWEEN CONVENIENCE, TRANSACTION SECURITY, PAYMENT SPEED AND CUSTOMER SATISFACTION*

4.2 ANOVA

ANOVA analysis shows that the combination of these three independent variables statistically significantly predicts customer satisfaction, with an F value of 31.875 and a significance level Sig. of .000, which is much less than 0.05. Therefore, we reject the null hypothesis and consider the model is valid.

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	66.146	3	22.049	31.875	.000[b]
	Residual	120.359	174	.692		
	Total	186.505	177			

a. Dependent Variable: Customer Satisfaction

b. Predictors: (Constant), Payment Speed, Convenience, Transaction Security

Table 2: *ANOVA*

4.3 COEFFICIENTS

In the coefficient analysis, convenience has the most significant impact on customer satisfaction, with a standardized coefficient of 0.568, indicating that it contributes the most to satisfaction; while the standardized coefficients of transaction security and payment speed are 0.306 and 0.301 respectively, both showing positive To influence. These results show that improving the convenience of the payment system, ensuring transaction security and increasing payment speed can effectively enhance customer satisfaction. In particular, convenience plays a key role, indicating that consumers attach great importance to it when choosing hotels. Smoothness of the payment process. Therefore, OTA platforms should prioritize improving these three aspects when designing digital payment systems to improve overall customer satisfaction.

Model		Unstandardized Coefficients		Standardized Coefficients		
		B	Std. Error	Beta	t	Sig.
1	(Constant)	1.834	.241		7.597	2.553
	Convenience	.660	.299	.568	2.205	.029
	Transaction Security	.361	.347	.306	1.043	.009
	Payment Speed	.350	.216	.301	1.622	.007

a. Dependent Variable: Customer Satisfaction

Table 3: *COEFFICIENTS*

4.4 REGRESSION ANALYSIS BETWEEN OTAS PLATFORM (CTRIP, BOOKING, AGODA) AND CUSTOMER SATISFACTION

The R Square of the model is 0.454, which means that about 45.4% of the customer satisfaction variation can be explained by these three independent variables, indicating that the explanatory power of the model is relatively strong.

4.5 ANOVA

The ANOVA analysis results show that the F value is 48.166 and the significance level (Sig.) is 0.000, which indicates that the regression model is highly significant overall and supports the hypothesis of the influence of independent variables on dependent variables.

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.674a	.454	.444	.7652

a. Predictors: (Constant), Agoda, Ctrip, Booking

Table 4: *REGRESSION ANALYSIS BETWEEN OTAS PLATFORM (CTRIP, BOOKING, AGODA) AND CUSTOMER SATISFACTION*

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	84.615	3	28.205	48.166	.000b
	Residual	101.890	174	.586		
	Total	186.505	177			

a. Dependent Variable: Customer Satisfaction

b. Predictors: (Constant), Agoda, Ctrip, Booking

Table 5: *ANOVA*

4.6 COEFFICIENTS

In the coefficient analysis, the unstandardized coefficient of the constant term is 1.937, indicating the baseline level of customer satisfaction when other independent variables are zero. The unstandardized coefficient of Ctrip is 0.766, and its standardized coefficient is 0.651, indicating that there is a strong positive relationship between Ctrip's services and customer satisfaction. Customer satisfaction increases significantly when using Ctrip. The unstandardized coefficient of Booking is 1.100, and the standardized coefficient reaches 0.969, which shows that Booking has the most prominent contribution in affecting customer satisfaction. Its influence is nearly twice that of Ctrip, which means that the service features provided by Booking can more effectively induce customer satisfaction. feel. The unstandardized coefficient of Agoda is 0.329 and the standardized coefficient is 0.284. Although the impact on customer satisfaction is relatively small, it still shows a positive and positive relationship. This result shows that in OTA platforms, there are obvious differences in service experience and user feedback between different platforms, and Booking and Ctrip have stronger advantages in market competition. Therefore, the role of each OTA platform in improving customer satisfaction is obviously different. Among them, Booking stands out with the highest influence, followed by Ctrip, while Agoda's influence is relatively weak. These findings suggest that when formulating market strategies, OTA platforms should focus on optimizing the key factors that affect customer satisfaction, especially the service features provided by Booking, so as to improve customer experience, enhance customer loyalty, and ultimately occupy a greater share in the fiercely competitive market. favorable position.

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	1.937	.221		8.771	.353
	Ctrip	.766	.227	.651	3.381	.001
	Booking	1.100	.271	.969	4.064	.000
	Agoda	.329	.353	.284	.932	.001

a. Dependent Variable: Customer Satisfaction

Table 6: *COEFFICIENTS*

4.7 REGRESSION ANALYSIS BETWEEN DIGITAL PAYMENT SYSTEM AND OTAS PLATFORM

The R Square of the model is 0.369, indicating that about 36.9% of the variation in customer satisfaction can be explained by the two independent variables of digital payment system and OTA platform. This proportion shows that the model has a certain explanatory power.

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.608a	.369	.362	.8199

a. Predictors: (Constant), OTAs platform, Digital Payment System

Table 7: *REGRESSION ANALYSIS BETWEEN DIGITAL PAYMENT SYSTEM AND OTAS PLATFORM*

4.8 ANOVA

The ANOVA analysis results show that the F value of the regression model is 51.200, and the corresponding significance level Sig. is .000, which is much smaller than the conventional significance level of 0.05. This shows that the independent variables in the model have a significant impact on customer satisfaction. prediction effect.

4.9 COEFFICIENTS

In the coefficient analysis, the unstandardized coefficient of the constant term is 1.800, which represents the baseline value of customer satisfaction when both the digital payment system

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	68.847	2	34.423	51.200	.000b
	Residual	117.658	175	.672		
	Total	186.505	177			

a. Dependent Variable: Customer Satisfaction

b. Predictors: (Constant), OTAs platform, Digital Payment System

Table 8: *ANOVA*

and the OTA platform are zero. The unstandardized coefficient of the digital payment system is 0.673 and the standardized coefficient is 0.566, which shows that there is a significant positive relationship between factors such as the convenience and security of the digital payment system and customer satisfaction, indicating that improving the digital payment experience can improve customer Satisfaction. The unstandardized coefficient of the OTA platform is 1.357, and the standardized coefficient reaches 1.154, showing that the OTA platform has a more significant impact on customer satisfaction, indicating that customer satisfaction when using the OTA platform is significantly higher than the baseline level, especially when Convenience and transparency in the booking process. Therefore, both digital payment systems and OTA platforms have a positive impact on customer satisfaction, with OTA platforms having a significantly higher impact than digital payment systems.

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	1.800	.237		7.583	.182
	Digital Payment System	.673	.385	.566	1.747	.005
	OTAs platform	1.357	.381	1.154	3.564	.000

a. Dependent Variable: Customer Satisfaction

Table 9: *COEFFICIENTS*

5 CONCLUSIONS AND RECOMMENDATION

This study investigates the impact of digital payment systems on customer satisfaction in the hospitality industry, focusing on the mediating role of online travel agencies (OTAs). The findings suggest that both digital payment systems and online travel agencies contribute significantly to customer satisfaction, and that the provision of convenient and secure payment methods through OTAs plays a crucial role in influencing customer satisfaction with the hotel experience. Based on these findings, several recommendations can be made for hotel companies and OTAs:

For hoteliers: Offer a variety of secure and convenient digital payment options to cater to different customer preferences. Partner with OTAs that offer a seamless payment experience and have a strong customer base. Ensure that the online booking process is smooth and user-friendly, including clear payment information and secure transaction gateways. Use the data provided by OTAs to understand customer preferences and customize services accordingly.

For OTAs: Implement strong security measures to protect customer payment information and instill confidence in online transactions. Offer a range of payment options, including installment and other payment methods, to meet different customer needs. Ensure seamless integration of the OTA platform with hotel reservation systems to streamline the payment process. Clearly communicate payment terms, fees and refund policies to avoid misunderstandings and improve customer satisfaction.

By implementing these recommendations, hospitality businesses and OTAs can further leverage the benefits of By implementing these recommendations, hospitality businesses and OTAs can further leverage the benefits of digital payment systems and OTAs to enhance customer satisfaction and drive revenue growth.

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Development Strategy of Rural E-commerce Live Broadcast under Digital Economy.

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Abstract

This report explores the potential of the business model of direct selling of agricultural products in Douyin. We showed the comprehensive survey results of consumers, sellers/farmers and platform operators who used live broadcast of agricultural products in Douyin This study examines consumer behaviors and willingness, the effectiveness of various sales strategies and functions, and the challenges and opportunities related to this growing trend of e-commerce. Our research shows that consumers give priority to product quality, price and interaction with sellers when shopping in Douyin. By grasping the psychological characteristics of the live audience, live interaction significantly increases the purchase intention, among which the interaction with the host (including auxiliary virtual objects) and other customers is the most influential factor. Product display is the most effective sales strategy for sellers. However, attracting audiences and overcoming technical difficulties remain major challenges. Platform support will positively affect the enthusiasm of sellers and highlight the importance of continuous cooperation between sellers and platform operators.

KEYWORDS: E-Commerce Live Broadcast, Consumer Behaviors And Intention, Seller'S Sales Strategy, Audience Psychology, Rural E-Commerce Status, Live Broadcast Platform Technology

1 INTRODUCTION

The e-commerce revolution has dramatically changed consumer buying habits, affecting almost every industry, including agriculture (Luo et al., 2018). Consumers are increasingly turning to online platforms because they offer convenience, product variety, and competitive prices (Wang et al., 2020). As an important part of the county economy, the e-commerce production and marketing of agricultural products plays an important role in the revitalization of rural industries and talents. (Zhang Ruihua, 2024) Therefore, the research on the e-commerce economy of agricultural products has high social significance and economic value.

Live streaming, a real-time interactive video format, has gained tremendous traction on social media platforms, particularly in China, where it has become a major driver of e-commerce sales (Luo et al., 2019). While there is limited research on the use of Douyin live streaming for agricultural products, anecdotal evidence suggests that it is growing in popularity. The rise of live-streaming e-commerce has revolutionized the sale of agricultural products. For example Bloomberg Wealth reports Jin Guowei, better known as internet sensation Brother Pomegranate, made Rmb300m (US$46m) in sales in 2020. He once sold Rmb6m worth of pomegranates in 20 minutes. Many successful cases have proved that live broadcasting not only solves the limitations of traditional sales channels, but also provides farmers with a new source of income and promotes the upgrading of the agricultural industry.

In order to ensure the efficiency and reliability of the research, we chose the Douyin platform as the research object, mainly because it provides a large user base and rich data resources, which is convenient for extensive sample collection and multi-angle analysis. Douyin's real-time interaction function and efficient algorithm recommendation mechanism not only improve the timeliness and prediction accuracy of research, but also make data collection and user feedback fast and convenient. In addition, Douyin's significant influence and practical contributions to agricultural product marketing, cultural trend shaping, and economic development provide important market, cultural, and economic value to research, making it an attractive research platform in the social sciences. This study aims to bridge this knowledge gap by investigating consumer behaviors, seller experience, platform functionality, and the overall effectiveness of Douyin's live stream of agricultural product sales. Through a comprehensive survey design, we explored how consumers search for and buy produce on Douyin Live, the most effective sales strategies for sellers, and the challenges and support systems offered by the platform itself. By examining these different aspects, this report aims to provide valuable insights for stakeholders in the agriculture sector seeking to harness the potential of Douyin livestreaming.

2 LITERATURE REVIEW

E-commerce has undergone major changes, and e-commerce live broadcast has become a powerful tool to influence consumer behaviors and business strategy (Sun et al., 2020). This literature review uses the recent empirical research and theoretical framework (Huang et al., 2021) to study the influence of ecommerce live broadcast on consumers' purchase intention, behaviors, satisfaction and sellers' sales strategies and challenges. E-commerce live broadcast combines real-time video broadcasting with online shopping, providing a dynamic and interactive shopping experience. This form allows consumers to contact the seller directly, ask questions and get an immediate reply, thus improving the overall shopping experience. The immediacy and interactivity of live broadcast distinguish it from traditional e-commerce by creating a sense of urgency and excitement.
Purchase intention is an important indicator of potential sales and market success. One of the important reasons why the new network red economy can establish a brand-new link between manufacturers, sellers and consumers is the prevalence of participatory culture, and its ultimate impact depends largely on the characteristics of fan consumption, such as inducement, integration, and personalization. At the same time, research shows that e-commerce live broadcast significantly enhances consumers' purchase intention (Sun et al., 2020). According to Sun et al. (2020), the interactive nature of live broadcast, combined with real-time feedback and product demonstration, increases consumers' confidence and willingness to buy. The sense of urgency generated by limited-time discounts and real-time discounts also promoted the purchase intention (Wang He and Li, 2019).
Customer satisfaction is critical to customer retention and long-term business success. Live

streaming provides a platform for consumers to see the actual situation of the product, ask questions, and get instant feedback, thus improving satisfaction (Li and Wu, 2020). A study by Li and Wu (2020) showed that live streaming significantly increased customer satisfaction by providing a more personalized and engaging shopping experience. E-commerce live streaming requires sellers to adjust their sales strategies to effectively leverage the advantages of the platform. Sellers must develop new skills for live demonstrations, engage with audiences in real time, and create compelling content to drive sales (Wang and Zhang, 2019). (Wang and Zhang, 2019) point out that successful live streaming strategies often involve collaboration with influencers, personalized interactions, and strategic use of limited time offers.

The technology of the e-commerce platform itself is also a productivity that stimulates the potential of consumers and the vitality of sellers. Through data mining, machine learning, natural language processing and other technical means, artificial intelligence technology can quickly process and analyze massive data, mine the laws and values behind the data, and provide scientific basis and intelligent support for the marketing strategy of e-commerce platform. In addition, the e-commerce platform also needs to use artificial intelligence technology to realize the refinement and intelligence of marketing strategy and improve the effect of advertising and return on investment (ROI). (Luo, Sun, 2024) At the same time, the auxiliary virtual role technology is also very important to help sellers. Virtual digital people live with goods is an innovative business model, which combines virtual digital people technology and live sales methods. It uses artificial intelligence and computer graphics to create a virtual anchor with human image and voice and recommends and sells goods or services to the audience through the live broadcast platform. Virtual digital people are not limited by time and space and can cover audiences all over the world. Virtual digital people can provide personalized recommendation and promotion according to the audience's preferences and buying behavior through machine learning and intelligent algorithms and improve the sales conversion rate. In addition, virtual digital people are absolute loyal to the enterprise, and there are no problems such as job-hopping and salary requirements, and there will be no moral and legal risks.

At the same time, we should also consider the impact of major social events such as international conflicts, epidemics and other environmental factors on e-commerce. (Zhang, 2022)

While e-commerce live streaming offers many benefits to rural economies, it also brings challenges. One of them is the challenge of poverty alleviation mechanism: there is a gap between industrial poverty alleviation policies and actual results, and grass-roots work is difficult. Live streaming e-commerce relies on government guidance, and it is difficult to independently respond to market changes, and when the government is insufficient, the project effect decreases significantly. Another is the upward challenge of agricultural products: the sales cost of agricultural products into cities is higher than that of consumer goods into the countryside. Fierce competition in livestream drives down the value of agricultural products, logistics problems occur frequently, and transportation costs in poor areas are high, leading to after-sales difficulties and loss of consumer trust. (Huang Yuexiu, 2020)

E-commerce live broadcast has a far-reaching impact on consumers and sellers. It enhances consumers' purchasing intention, behaviors and satisfaction, and at the same time urges sellers to adjust their sales strategies and face new challenges. Empirical evidence of recent research (Sun et al., 2020; Huang et al., 2021; Li and Wu (2020) confirmed these findings and emphasized the important role of live broadcast in modern e-commerce. Considering the rapid progress of technology, the constant change of consumers' preferences and the change of potential social environment, future research should continue to explore the development trend of this phenomenon.

3 RESEARCH DESIGN, SCOPE AND METHODS

3.1 Put forward hypotheses

For the research objects of rural e-commerce live broadcast consumers, live broadcast hosts or farmer sellers, and rural e-commerce platform operators, the following are some hypotheses that can be analyzed through survey methods:
Assumptions about consumers:
Hypothesis 1: The interactivity in live broadcasting (including the interactive experience of virtual live broadcast technology) significantly improves the immersion and purchase intention of consumers and the efficiency of sellers. It has significantly increased consumers' willingness to buy.
Hypothesis 2: Consumers' satisfaction with the Douyin recommendation system used in the live broadcast is positively correlated with their purchase frequency and average order value (including discount activities) during the live broadcast.
Assumptions for live hosts or farmer sellers:
Hypothesis 3: The level of training received by the live broadcast host is positively correlated with its live broadcast sales performance.
Hypothesis 4: Farmer sellers leverage multi-channel live sales strategies on social media and short video platforms to significantly increase their product exposure and sales.
Assumptions for rural e-commerce platform operators:
Hypothesis 5: The new online trading technology introduced by the platform improves the transparency and security of transactions and significantly enhances the willingness of farmer sellers to participate in live sales.
Hypothesis 6: The operational efficiency and user friendliness of the platform are positively correlated with consumer loyalty to the platform.

3.2 Scope and methods

These hypotheses can be effectively tested by designing relevant survey questions to collect data, such as consumer perceptions of live stream interaction and quality, live stream hosts' training experiences and sales strategies, and evaluations of the platform's technical support. After collecting the questionnaire data, statistical methods were used to analyze the data and test the validity of each hypothesis. For example, regression analysis is used to examine the correlation between live broadcast quality and consumption frequency. The analysis of the survey results will help to verify these hypotheses and provide empirical evidence for the development of rural e-commerce live streaming.

4 DATA ANALYSIS AND RESULTS

The survey of 400 respondents covered a variety of genders, ages and occupational backgrounds, of which 58.75% were male and 41.25% were female. The age group is mainly between 18 and 34 years old, accounting for 56.75% of the total number of people. In terms of educational background, 42.75% of the respondents have a bachelor's degree, and 30.5% of the respondents have a college degree, showing a high level of education. Occupations are also widely distributed, with 44.25% of respondents being students, 31.75% being corporate employees, and a small number of farmers, freelances and entrepreneurs. Overall, the survey group was diverse in gender, age, education, and occupation, providing a wealth of data to support the study hypothesis.

trait	Option	frequency	Percentage (%)	Cumulative percentage (%)
gender	male	235	58.75	58.75
	female	165	53.23	100.00
age	Under 18 years old	49	12.25	12.25
	18-24	122	30.5	42.75
	25-34	105	26.25	69
	35-44	67	16.75	85.75
	45-54	23	5.75	91.5
	55 years old and above	34	8.5	100.00
educational level	High school and below	68	17	17
	Junior school	122	30.5	47.5
	Undergraduate	171	42.75	90.25
	Master's degree or above	39	9.75	100.00
occupation	Students	25	44.25	44.25
	Farmers/agricultural workers	87	5.75	50
	Employees	65	31.75	81.75
	Freelancers	90	9.75	91.5
	Entrepreneurs/self-employed	25	5	96.5
	Others (please specify)	18	3.5	100.00
total		400		

Table 1: *Sample distribution data results*

Let's take a closer look at each of these assumptions, combined with the data.
Hypothesis 1: Live interactivity significantly improves consumers' immersion and purchase intention.
The statistical results are shown in the figure 4.1.

It is worth noting that this interaction is not just for entertainment, it profoundly affects the psychological feelings of consumers. During live streaming, 41 percent of respondents "strongly agreed" that interaction improved their immersion, with another 27 percent agreeing. This suggests that when viewers feel they are "noticed" and "responded to" during the interaction, they are more likely to feel emotionally connected, thus increasing the urge to buy. Virtual

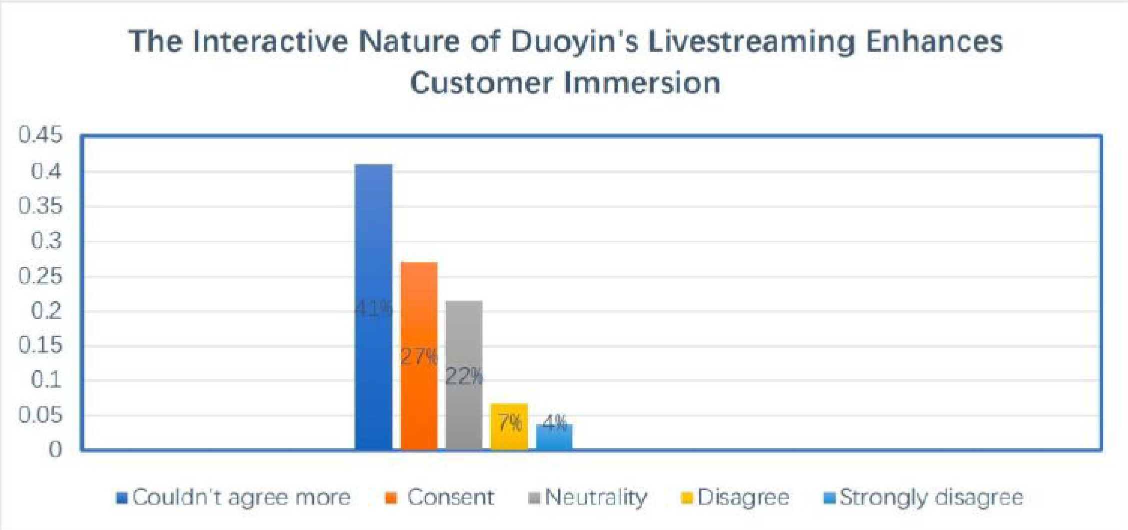

Figure 4.1: *The Interactivity in Douyin Livestreaming Improves Customer Immersion Questionnaire*

anchors enhance interactivity, and 63.25% of respondents like it, which further improves consumers' sense of immersion and purchase intention, especially for audiences sensitive to the two-dimensional culture.

Hypothesis 2: Consumers' satisfaction with the recommendation system is positively correlated with their purchase frequency and order value.

In today's information overload environment, Douyin's recommendation system has become a powerful tool to drive sales by recommending products that meet users' interests through precise algorithms. The data shows that 40.75% of respondents are "very satisfied" with the system, and 73.5% are satisfied overall. More interestingly, 49.25% of respondents said they often make a purchase because of the recommendation system, meaning that the system not only influences their choice, but also directly drives the actual purchase behavior.

Looking further, 37.75% of users said that their average order amount was 50-200 yuan, indicating that the precise push of the recommendation system affected the consumption decision of the medium price to a certain extent. This shows that the system not only improves the frequency of purchase, but also promotes the level of consumption.

Hypothesis 3: The training level of the host is positively correlated with sales performance.

The training of the anchor is not only about the introduction skills of the product, but also about how to build intimacy and trust with the audience through the camera. 60% of anchors have received training, of which 59.58% believe that training has helped sales performance "very much." This not only reflects the effectiveness of the training content, but also shows that well-trained anchors are better at guiding viewers to consume.

Through this training, the anchor learned how to enhance consumer trust, especially in the product recommendation, can more accurately grasp the audience's pain points, so as to improve the conversion rate. This phenomenon is not only reflected in sales figures, but also in the positive feedback of viewers on the live streaming experience. Seller/farmer experience

Hypothesis 4: Farmer sellers' multi-channel strategies significantly increase product exposure and sales. The statistical results are shown in the figure 4.2.

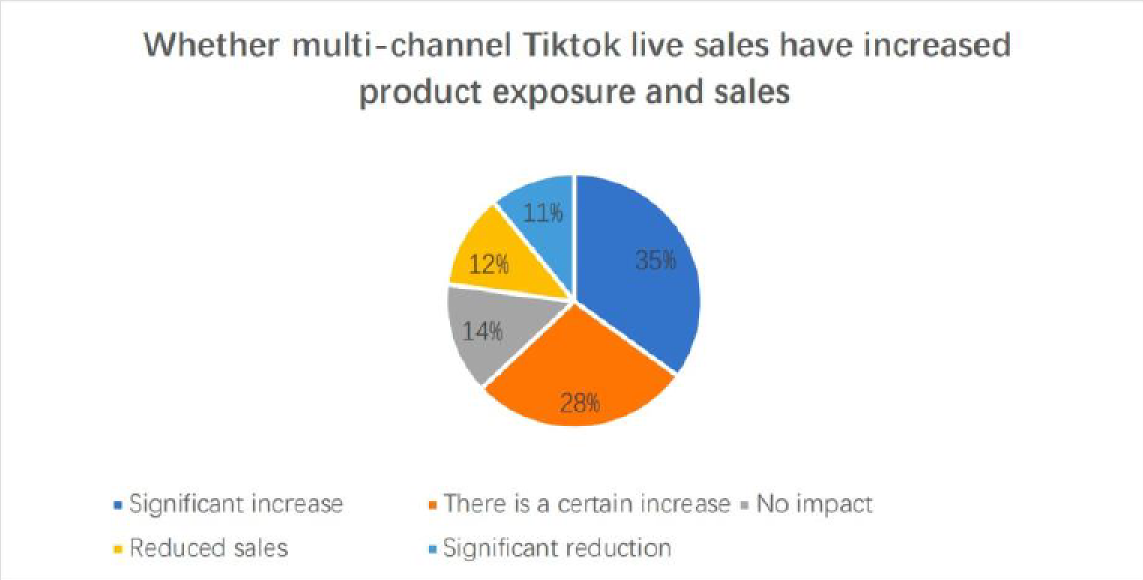

Figure 4.2: *Perceived impact of training on field sales*

For farmer sellers, the use of multiple platforms such as Douyin for live sales has become an important means to expand product exposure. According to the data, 74.17% of sellers are using multiple platforms for live streaming, and 35% of respondents said this strategy has "significantly" increased their product exposure. This isn't just a technical issue, it's a marketing strategy that helps farmer sellers cross the limits of traditional sales channels.
Through multi-channel coverage, farmer sellers can reach more potential consumers, especially in the case of differentiated user habits of different platforms, multi-channel sales can cover different consumer groups to the maximum extent. This makes the sale of agricultural products no longer restricted to a specific consumer group or region.
Hypothesis 5: New technologies introduced by the platform improve transparency and security, and significantly increase sellers' willingness to participate.
In rural e-commerce, the transparency and security of transactions are the focus of sellers. Douyin has effectively improved its performance in this regard by introducing new online trading technologies. 28.33% of respondents said transparency and security of transactions were very good, while another 30% said they were good.
Interestingly, this technological improvement directly affected sellers' willingness to participate. 28.75% of sellers expressed willingness to participate in live sales more frequently because of the transparency and security of transactions on the platform. This means that the platform not only improves trust through technical means, but also further promotes the enthusiasm of sellers, forming a virtuous circle.
Hypothesis 6: Platform operational efficiency and user friendliness are positively correlated. with consumer loyalty.
The statistical results are shown in the figure 4.3.

In the e-commerce platform, user experience is the core factor that determines platform loyalty. According to the data, 32.5 percent of respondents believe that the platform's operational efficiency is high, while 27.75 percent are very satisfied with the friendliness of the user

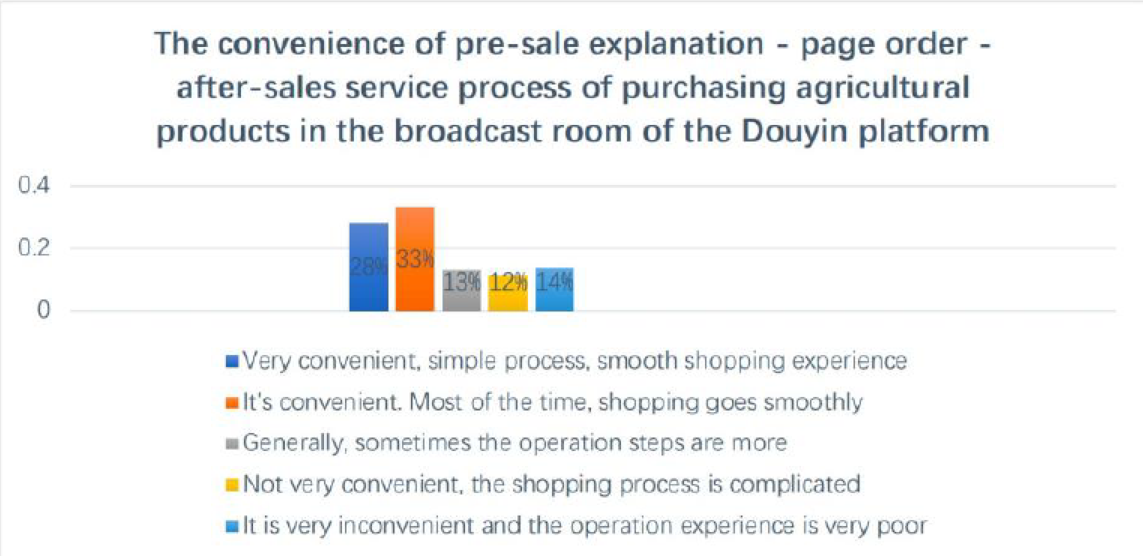

Figure 4.3: *Douyin Platform Purchase Process Convenience questionnaire*

interface. The fluency of operation and ease of use of functions directly affect the frequency of use and shopping intention of consumers.
Looking further, 31% of respondents said they would be inclined to shop on the platform because of its operational efficiency and user friendliness. This loyalty is not only reflected in the improvement of platform functions, but also reflects the trust relationship established between consumers and the platform. This trust makes consumers more willing to make repeated purchases on the same platform, which increases the retention rate of the platform.

5 CONCLUSION AND RECOMMENDATION

Consumers: Choosing a platform with good interactivity and recommendation systems can significantly enhance the produce shopping experience. It is recommended that consumers actively participate in the live interaction, use the recommendation system to find more products of interest, while paying attention to the transparency and security of the platform to ensure the reliability of the transaction, use the interactive function to learn more product information, and contact the seller.
Sellers/farmers: Participate in platform training to improve live streaming skills. Seize the positive influence factors in the psychology of live audience, create attractive content in line with public order and good customs to attract viewers, and effectively display products. Establish a unified business mechanism, prevent vicious competition, and accelerate the formation of independent economic status and scale. Also invest in training to improve sales skills and build consumer trust.
Platform operators: Improving operational efficiency and user friendliness is the key to enhancing consumer loyalty. It is recommended that platforms continue to optimize the user experience and introduce new technologies to improve transaction transparency and security in order to attract and retain users, while promoting sellers' willingness to participate. Through

these measures, the platform can build a benign ecommerce ecosystem and increase efforts to improve rural Internet infrastructure. Content creation training program specifically for sellers/farmers in rural areas. Work with agricultural organizations to provide educational and advocacy content. Meet the needs of all parties.
Obviously, from the above preliminary research, we can find a lot of interesting conclusions. The live broadcast in Douyin provides a promising way to sell agricultural products. Consumers pay attention to the content in the live broadcast, like interaction, pay attention to fresh agricultural products, and have the ability to establish contact with sellers. Sellers's benefit from the expansion of contact, sales growth and platform support. However, challenges such as insufficient gravity to attract audiences and limited rural infrastructure need to be solved. Generally speaking, by promoting the continuous improvement of content quality, technical infrastructure and training plan, all stakeholder can contribute to the success of ecommerce of direct broadcast of agricultural products in Douyin.

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An Ensemble Machine Learning Approach for Cryptocurrency Price Prediction Using Variational Mode Decomposition and Wavelet Denoising

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Abstract

Cryptocurrency prices are highly volatile, posing significant challenges to digital currency stability and drawing substantial attention from both investors and researchers. This volatility is driven by complex, non-linear, and non-stationary price dynamics, making accurate predictions difficult. In this study, we propose a new ensemble machine learning model, including long short-term memory (LSTM), gated recurrent unit (GRU), and extreme learning machine (ELM) models. Combining Variational Mode Decomposition (VMD) with machine-learning models divides cryptocurrency data at different frequencies and analyses an effective data denoising method, wavelet denoising (WD), to improve the accuracy of feature extraction and make the extracted features more reliable and distinguishable by eliminating noise data in cryptocurrency historical price data. We applied the proposed DW-VMD-LSTM-GRU-ELM model to predict BTC, ETH, and XRP and compared its performance with the DW-LSTM model. The results indicated that the DW-VMD-LSTM-GRU-ELM model not only improved R^2 but also significantly reduced RMSE by 33.6%, 56.2%, and 71.2%, respectively. Additionally, MAE decreased by 32.1%, 48.4%, and 54.6%, while MAPE improved by 47.2%, 57.56%, and 62.2%. These findings demonstrate that the DW-VMD-LSTM-GRU-ELM model outperforms the method combining only wavelet denoising with a single model in all metrics, showcasing its superior predictive capability. We compared our proposed method with the VMD-LSTM-GRU-ELM model, these results show that our model significantly outperforms the VMD-LSTM-GRU-ELM model in terms of prediction accuracy, as indicated by the R^2 value, and in error metrics, including RMSE, MAE, and MAPE. Finally, we conclude that the DW-VMD-LSTM-GRU-ELM model delivers the most accurate prediction results.

KEYWORDS: Cryptocurrency, Artificial Intelligence, Machine Learning, Price Prediction, Variational Mode Decomposition, Wavelet Denoising

1 INTRODUCTION

Conventional economic systems depend exclusively on financial institutions acting as intermediaries. It encounters numerous issues, such as restricting transaction amounts and lacking trust, security, transparency, and flexibility. To tackle these challenges, Satoshi Nakamoto introduced the cryptocurrency Bitcoin in 2008, which effectively solves the problems of intermediaries in financial transactions (Patel et al.,2020). Cryptocurrencies have gained global prominence owing to their decentralization, immutability, and security features (Nair et al.,2023). As a part of the world financial system, Cryptocurrencies play an increasingly important role in economic development. In December 2019, the daily trading volume reached $19.45 billion, based on data from CoinMarketCap. By December 2023, the market for cryptocurrencies had grown to a daily trading volume of about $58.49 billion, a remarkable 200% rise. As the first cryptocurrency, the price of Bitcoin has increased dramatically, reaching a high of almost $68,000 in November 2021 from about $65 per coin in 2013. To an incredible rise of more than 1000 times, reaching a peak of over $68,000 in November 2021. Researchers and investors alike have been paying close attention to the sharp increase in the value of Bitcoin (Malsa et al.,2021; Tosunoğlu et al.,2023). However, due to the non-stationary nature of bitcoin price movements, investors now confront much higher investing risks. Traditional statistical methods are widely used in cryptocurrency predictions because they fully consider data characteristics and are easy to implement. However, their ability to make accurate predictions is greatly limited by the inclusion of several assumptions (Khedr et al.,2021). To promote the development of cryptocurrency price prediction, machine learning models such as logistic regression, support vector machine (SVM), recurrent neural network (RNN), and long short-term memory network (LSTM) are widely used (Chen et al.,2020; Tanwar et al.,2021). Although these machine learning models can forecast price patterns, due to the complexity of the changing trend of cryptocurrency prices, current machine-learning algorithms have difficulty adequately addressing the problem of low forecast accuracy (Pintelas et al.,2020). In this study, we focus on processing cryptocurrency price data and optimizing prediction algorithms to improve the accuracy of predicting patterns in cryptocurrency prices.

2 LITERATURE REVIEW

In the dynamic landscape of the cryptocurrency market, the demand for accurate predictions of price fluctuations has surged. Quantitative analysis is to predict cryptocurrency price trends by using mathematical modeling and statistical methods, by discovering patterns and correlations from the market's historical data and making predictions based on these insights, the trends in the cryptocurrency market can be predicted and assessed more accurately(Motamed et al.,2019). Since cryptocurrency market price changes are often affected by the complex interaction of multiple factors, and this relationship is often non-linear, machine learning models can better capture these non-linear relationships and improve the accuracy of predictions. Machine learning is currently the best technology for cryptocurrency price prediction (Khedr et al.,2021). Ammer et al., (2022) utilized the LSTM model to forecast the accuracy of AMP, Ethereum, EOS, and XRP. This study conducted a comparative analysis of the LSTM model against other machine learning models, the findings revealed that LSTM outperformed these models. Mudassir et al.'s research (Mudassir et al.,2020) incorporated various technical indicators as data features and employed four machine learning models, namely artificial neural network (ANN), stacked artificial neural network (SANN), SVM, and LSTM. Ultimately, the study concluded that the LSTM model demonstrated the highest overall performance. Mudassir and Ammer et al. used distinct data features and ultimately established that LSTM outperforms other models. Patel et al., (2020) employ a hybrid cryptocurrency prediction scheme incorporating LSTM and GRU, with a specific focus on two cryptocurrencies, namely

Litecoin and Monero. The analysis utilizes six dataset features, including the average price of the cryptocurrency for the day, the opening price, the closing price, the highest price, the lowest price, and the volume of cryptocurrency traded during the day. Notably, the hybrid model demonstrates enhanced predictive accuracy compared to the standalone LSTM model, and its applicability extends to the price predictions of diverse cryptocurrencies. Based on the existing research results, there is still a lot of room for improvement in the accuracy of cryptocurrency predictions. Cryptocurrency price data is a typical time series, showing strong randomness, periodicity, and trend characteristics (Ibrahim et al.,2021). There are many time series data processing methods, such as VMD, which can decompose time series data into random items, periodic items, and trend items and then analyse the characteristics of each decomposed item separately (Zhang et al.,2023). Luo et al., (2022) employed VMD for data decomposition and utilized a hybrid model comprising LSTM and ELM to forecast bitcoin prices. And VMD-ELM, EMD-ELM, VMD-LSTM, EMD-LSTM, and EMD-LSTM-ELM models were considered for comparison. The outcomes showed that in terms of prediction accuracy, the VMD-LSTM-ELM model performed better than the other models, and the VMD method was better than the EMD method. This underscores the potential for further exploration in combining VMD with multiple models. Wavelet denoising is widely used in signal processing (Halidou et al.,2023). This method can effectively remove random features from the data, making the data "cleaner" and trend features more obvious (Kumar et al.,2019). These advanced data processing methods can effectively enhance the quality of historical cryptocurrency price data, consequently improving forecast accuracy. However, there is little literature on optimizing training data for wavelet denoising. Therefore, we will use data processing methods such as VMD and wavelet denoising to improve the quality of the training dataset, fully consider the impact of multiple factors on cryptocurrency price fluctuations, develop comprehensive and effective machine learning models, and improve prediction accuracy.

3 Methodology

To improve the accuracy of cryptocurrency price prediction, this study used the Pearson correlation coefficient, denoising, decomposition, smoothing, data normalization, and other techniques to optimize the dataset.

3.1 Data Collection

In this section, we will introduce in detail the data sources, collection process, and key steps of data processing. This section lays the foundation for the subsequent training and evaluation of machine learning models, ensuring that the research results are reliable and representative.

Population and sample In this study, the data used is the daily price data of the three popular coins, Bitcoin, XRP, and ETH, obtained from Binance Exchange. The data set is in USD as the unit of measure. These data are divided into a training set and a validation set, accounting for 70% and 30%, respectively. Specifically, the Bitcoin dataset consists of 2,351 samples, the XRP dataset includes 2,081 samples, and the ETH dataset contains 2,369 samples. The study focuses on using daily close price and trading volume as the primary features for prediction.

Data collection and processing tools Quantitative research methods are used in this study. The samples in this study come from Binance Exchange. The API interface provided by Binance Exchange is called through Python to retrieve the daily historical price data of BTC, XRP, and ETH, it consists of five characteristic data: open price, high price, low price, close price, and volume price. This data is used to verify the effectiveness of the time series hybrid prediction model in practical applications. In this study, MATLAB was used to denoise and decompose the data, and then the processed data was fed into a machine-learning model to achieve cryptocurrency price prediction.

3.2 Method of the study

Variational modal decomposition Variational modal decomposition (VMD) is a completely non-recursive signal decomposition method. This method can achieve frequency domain adaptive segmentation of each component of the signal, thereby effectively overcoming the modal aliasing phenomenon caused by EMD decomposition. VMD is an effective method for processing nonlinear and non-stationary signals. Apply the VMD method to decompose modal functions on cryptocurrency price data (Luo et al.,2022; Zhao et al.,2023; Montalvo et al.,2022; Shen et al.,2021) as follows:

$$u_k(t)=A_K(t)\cos(\varnothing_k(t)) \tag{1}$$

Where the $\oslash_k$(t) denotes the non-decreasing function; A_k(t) represents the instantaneous amplitude of the u_k(t); t denotes the time of the u_k(t); u_k(t) denotes the kth mode function; The u_k(t) has center frequencies and limited bandwidths.

Long short-term memory The Long short-term memory (LSTM) model is an improvement on the RNN model, which solves the gradient explosion and gradient disappearance problems of RNN. The LSTM model uses a gate structure to process data, effectively utilizing current and historical information in time series data. LSTM can better learn past time series data, find out the relationship between time series, and further explore the inherent laws of time series using the function of selective memory. Therefore, the LSTM model is suitable for the prediction of high-frequency data on cryptocurrency prices (Luo et al.,2022). Input gate (i_t), forget gate (f_t), output gate (o_t), and cell state (C_t, C_{t-1}) are introduced by LSTM. The vector of new candidate values is denoted by $\tilde{C}_t$. It is possible to express the three control gates and candidate states as functions of the input eigenvalue x_t and hidden state of the preceding moment h_{t-1} , respectively, in the following ways:

$$\begin{aligned}
i_t &= \sigma\,(W_i\,[\mathrm{h}_{t-1},\mathrm{x}_t] + \mathrm{b}_i),\\
f_t &= \sigma\,(W_f\,[\mathrm{h}_{t-1},\mathrm{x}_t] + \mathrm{b}_f),\\
o_t &= \sigma\,(W_o\,[\mathrm{h}_{t-1},\mathrm{x}_t] + \mathrm{b}_o),\\
C_t &= f_t * C_{t-1} + i_t * \tilde{C}_{t-1},\\
\tilde{C}_t &= \tanh(W_c\,[\mathrm{h}_{t-1},\mathrm{x}_t] + \mathrm{b}_c),
\end{aligned} \tag{2}$$

Where the weights of the input data for the input gate, forget gate, output gate, and new candidate values are denoted by variables W_i, W_f, W_o, and W_c, respectively. The bias weights for the input gate, forget gate, output gate, and new candidate values are b_i, b_f, b_o, and b_c, respectively. where the sigmoid activation function is represented by σ and tanh. The input eigenvalue is denoted by x_t, and the preceding short-term memory function is denoted by h_{t-1}. The long-term memory and the fresh information to be kept in the cell state are expressed by the cell state and candidate state. The output range of the sigmoid activation function σ is between 0 and 1, and most results are close to 0 and 1. After multiplying by 0, the state is cleared, which is the forgotten information. After multiplying by 1, the information is saved.

Gated Recurrent Unit The Gated Recurrent Unit (GRU) is a variant of a Recurrent Neural Network (RNN). Compared with LSTM, GRU has a simpler structure and only contains two gating mechanisms: an update gate and a reset gate. This makes GRU easier to implement and tune. GRU has a certain flexibility in processing data of different frequencies, and it is more suitable for processing medium-frequency and high-frequency data. The function of the update gate Z_t is to control the degree of influence of the hidden state h_{t-1} at the previous moment on the hidden state h_t at the current moment. Its mathematical expression is:

$$z_t = \sigma \left(W_z \cdot [h_{t-1}, X_t] + b_v\right) \tag{3}$$

Where b_v is a deviation vector and W_z is an update gate's weight matrix. σ represents the sigmoid function, and $[h_{t-1}$,$x_t]$ represents connecting the hidden state h_{t-1} of the previous moment and the input xt of the current moment. The function of the reset gate r_t is to control how to mix the hidden state h_{t-1} of the previous moment with the input x_t of the current moment to calculate the candidate hidden state h_t of the current moment. Its mathematical expression is:

$$r_t = \sigma \left(W_r \cdot [h_{t-1}, X_t] + b_i\right) \tag{4}$$

W_r is the weight matrix of the reset gate, and b_i is the bias vector of the reset gate. The current candidate's hidden state Candidate Hidden State is a temporary hidden state calculated at each time step. It is an intermediate result calculated at the current time step based on the current input and the hidden state of the previous time step. Its mathematical expression is:

$$\tilde{h}_t = tanh(W_h \cdot [r_t * h_{t-1}, X_t] + b_h) \tag{5}$$

Where b_h is the deviation vector, represents the current candidate hidden state, W_h is the weight matrix, r_t is the reset gate, h_{t-1} is the hidden state of the previous time step, and X_t is the input of the current time step. The final hidden state is usually the hidden state of the last time step of the sequence. The update rules of the hidden state are controlled through the update gate and candidate hidden states.

$$h_t = (1 - z_t) \times h_{t-1} + z_t \times \tilde{h}_t \tag{6}$$

Where $\tilde{h}_t$ is the candidate hidden state of the last time step of the sequence, represents the final hidden state, h_{t-1} is the hidden state of the penultimate time step of the sequence, and Z_t represents the update gate.

Extreme Learning Machine An Extreme Learning Machine (ELM) is a single hidden layer feedforward neural network, including input, output, and hidden layers. During the training process, only the weight of the output layer is adjusted, while the weight of the hidden layer can be randomly initialized, making the implementation of the ELM model very simple, with fast training, and good generalization performance (Du, et al.,2022). Because low-frequency components are more regular than high-frequency and medium-frequency components, the ELM algorithm has the advantages of fast learning speed and fewer training parameters compared with other algorithms. Therefore, the ELM model may be more suitable for the prediction effect of low-frequency data (Luo et al.,2022). Suppose input samples, where xj and tj, respectively, represent the input vector and the corresponding expected output vector, and xj = [xj1,xj2, . . ., xjn] ε Rm and tj =[xj1, tj2, . . ., tjn]T ε Rm. Let g(w, x, b) denote the activation function of the ELM. The structure of the ELM network consists of n input neurons, N hidden neurons, and m output neurons, which are expressed as follows:

$$\mathrm{t}_j = \sum_{i=1}^{N} \beta_i g_i(w_i \cdot x_j + \mathrm{b}_j) \tag{7}$$

Where W_i and βi represent the weight vectors between the neurons connecting the hidden layer, the input layer, and the output layer. b_j represents the hidden node bias. The expression of the output layer of ELM is as follows:

$$H \beta = \mathrm{T} \tag{8}$$

H stands for the hidden-layer output matrix, and β is the weight matrix from the hidden layer to the output layer. T is the output of the output layer.

Normalization Normalization is a key step in machine learning and data processing. Min-max normalization is a simple and effective preprocessing method, which can improve the performance and stability of the model. Scaling the data to the range [0, 1], ensures that different features have the same scale, thereby avoiding some features having too much influence in model training. In this study, we use the MinMaxScaler class from the scikit-learn library to implement this normalization. The formula for Min-max normalization is as follows:

$$\mathrm{X} = \frac{x - x_{\min}}{x_{\max} - x_{\min}} \tag{9}$$

Model Evaluation Index In this study, four criteria were used to evaluate prediction performance: Root mean square error (RMSE) is the square root of the average of the squared differences between the true value and the predicted value. RMSE can provide a more intuitive evaluation in terms of magnitude. The smaller the value of RMSE, the better the predictive ability of the model. RMSE is defined as:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \tag{10}$$

Mean absolute error (MAE) is an indicator of the mean absolute error of estimates of observed data and describes systematic error or bias. MAE can well reflect the actual situation of the predicted value error. The smaller its value, the higher the accuracy of the prediction model. MAE is defined as:

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|\hat{y}_i - y_i| \tag{11}$$

Mean absolute percentage error (MAPE) is a measure of the error between a forecast model's predicted value and the true value, as well as the ratio of the error to the true value. The smaller its value, the higher the accuracy of the prediction model. MAPE is defined as:

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\frac{|y_i - \hat{y}_i|}{y_i} \times 100\% \tag{12}$$

R^2 is a statistical indicator used to measure the fitting degree of the regression model. SSresidual represents the sum of squares of the residuals, that is, the sum of squares of the difference between the model predicted value and the actual observed value. SStotal represents the total sum of squares, that is, the dependent variable value and its average. The sum of the squares of the differences between values. R^2 ranges from 0 to 1, with closer to 1 indicating a better fit of the model to the data. To assess the accuracy of our predictions, we evaluate the forecasting model using R^2 (Luo et al.,2022). R^2 is defined as:

$$R^2 = 1 - \frac{SS_{residual}}{SS_{total}} \tag{13}$$

3.3 Conceptual Framework

Due to the complex characteristics of cryptocurrency prices, we propose an ensemble machine learning model to predict them. The conceptual framework serves as a theoretical foundation for research, it is crucial to our understanding of cryptocurrency price prediction. Fig. 3.1. shows the particular processes. According to Fig. 3.1. Step 1, my data is numerical, I used quantitative research methods to analyze the data, and I selected open price, high price, low price, close price, and volume as my sample variables. Based on the results of the literature analysis. I preprocessed the sample data, first performing quality checks. Step 2, I utilize wavelet denoising technology to deal with the noise in the raw data and use the VMD method to decompose the denoised data into different parts. The purpose of this is to improve the clarity and interpretability of the data and provide a more reliable data basis for subsequent analysis and modeling. Step 3, I match the decomposed subparts with different machine learning models, including LSTM, GRU, and ELM models. These models have good performance in processing time series data and predictions and can help me predict cryptocurrency price trends more accurately. Step 4, I will use a series of evaluation metrics; to evaluate the prediction accuracy of the model, these metrics can help me quantify model performance and evaluate different models. Through such a research framework, my objective is to improve the accuracy of cryptocurrency price predictions.

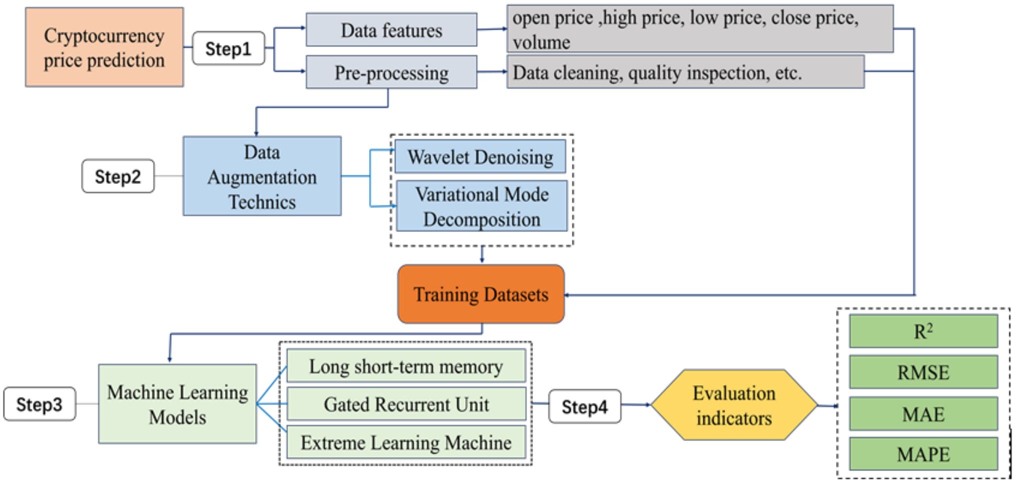

Figure 3.1: *Conceptual Framework for Cryptocurrency Price Prediction*

3.4 Parameter Selection

Hyperparameter selection of the model In this study, we aimed to enhance the accuracy of cryptocurrency price predictions by analysing three cryptocurrencies: BTC, ETH, and XRP. For their high, medium, and low-frequency components, we employed three distinct models: LSTM, GRU, and ELM. We detail the hyperparameter settings for each model below:
LSTM model: The training epoch is set to 100 epochs, with a batch size of 16. The model consists of two layers, each with 64 units. The optimizer is RMSprop, and the loss function is a mean squared error (MSE). A dropout rate of 0.1 is applied after the first layer to prevent overfitting.
GRU model: The training epoch is set to 100 epochs, with a batch size of 16. The model consists of two layers, with 50 and 25 units, respectively. The optimizer is Adam, and the loss function is a mean squared error (MSE).
ELM model: The number of hidden layer neurons is set to 20, the number of output layer neurons is 1, the activation function is Sigmoid, and the weights are initialized randomly.

Selection of Wavelet Denoising Parameters To improve the accuracy of feature extraction and make the extracted features more reliable and distinguishable, this study uses the wavelet denoising method to process the historical price data of cryptocurrency. The parameters of wavelet denoising are selected as follows: In the BTC data processing, a 6-layer wavelet decomposition is used. Using the Sym8 wavelet basis, the Denoising Method is the universal threshold, the Threshold Rule is soft, and the Noise Estimate is Level Dependent. The ETH data processing also uses a 6-layer decomposition but chooses the db5 wavelet basis, keeping other denoising parameters unchanged. The XRP data chooses a 5-layer decomposition and uses the Sym7 wavelet basis, and the other parameters are also Universal Threshold, Soft, and Level Dependent.

Selection of Variational Mode Decomposition Parameters In this study, we decompose BTC, ETH, and XRP data using VMD into low, medium, and high-frequency components. Each frequency band is modeled with an ELM, GRU, or LSTM, respectively. By combining the predictions from these models, we achieve a final prediction that improves forecast accuracy. The decomposition levels for BTC, ETH, and XRP are 5, 6, and 6, respectively.

4 Results and Discussion

4.1 Results

Effectiveness Analysis of WD Combined with VMD In this section, we will conduct a detailed comparison of three different prediction models: LSTM, DW-LSTM, and DW-VMD-LSTM-GRU-ELM. We will first analyze the performance of the standalone LSTM model, then examine the improvements achieved by integrating wavelet denoising (DW) technology into the LSTM model, and finally evaluate the performance of the DW-VMD-LSTM-GRU-ELM model, which combines VMD and multiple models. Through these comparisons, we aim to highlight the differences in prediction accuracy and model performance among the various methods and to reveal the advantages of integrating wavelet denoising and VMD techniques. For BTC, the DW-LSTM model significantly improves upon the LSTM model with reductions of 66.09% in RMSE, 68.27% in MAE, and 68.21% in MAPE, demonstrating the effectiveness of wavelet denoising (see Fig. 4.2). Further, the DW-VMD-LSTM-GRU-ELM model surpasses the DW-LSTM model, achieving additional improvements of 33.6% in RMSE, 32.1% in MAE, and 47.2% in MAPE, highlighting the benefits of combining VMD with ensemble machine learning model.

For ETH, the DW-LSTM model outperforms the LSTM model with a 49.86% reduction in RMSE, 54.36% in MAE, and 53.25% in MAPE, indicating the advantage of wavelet denoising. The DW-VMD-LSTM-GRU-ELM model further enhances accuracy, with reductions of 56.2% in RMSE, 48.4% in MAE, and 57.56% in MAPE compared to DW-LSTM, showcasing the efficacy of integrating VMD and multiple models (see Fig. 4.3).

For XRP, the DW-LSTM model shows a 41.83% improvement in RMSE, 46.59% in MAE, and 48.26% in MAPE over the LSTM model, indicating the advantage of wavelet denoising. The DW-VMD-LSTM-GRU-ELM model offers even greater enhancements, reducing RMSE by 71.2%, MAE by 54.6%, and MAPE by 62.2% compared to the DW-LSTM model, demonstrating the superior accuracy of combining VMD with multiple models (see Fig. 4.4).

Based on the above comparisons, the following conclusions can be drawn, the DW-LSTM model combines wavelet denoising technology and the LSTM model, which makes it perform

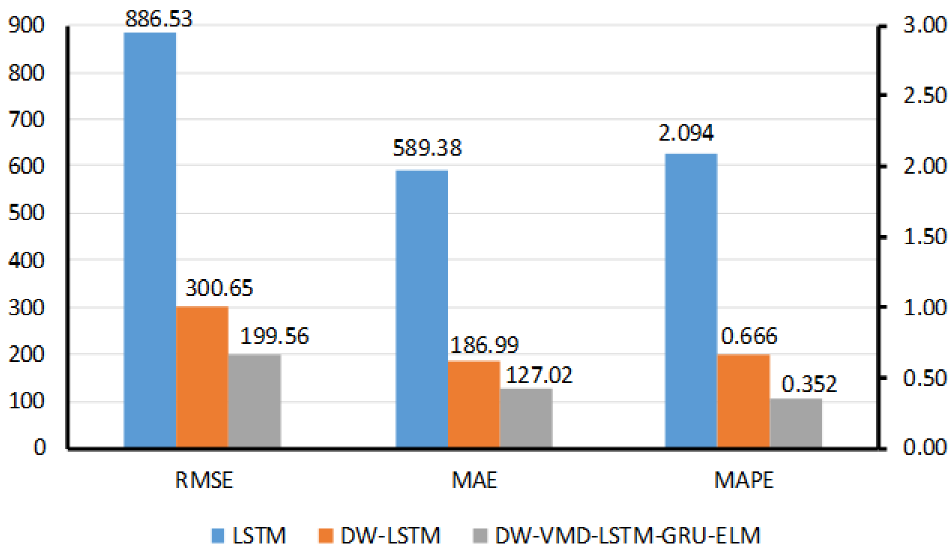

Figure 4.2: *Comparison of LSTM, DW-LSTM, and DW-VMD-LSTM-GRU-ELM on BTC*

better in dealing with noise in the data, which proves the hypothesis that removing the noise data from price data will improve the quality of cryptocurrency historical price data. However, the DW-VMD-LSTM-GRU-ELM model further combines variational mode decomposition and ensemble machine learning models (LSTM, GRU, ELM) to more carefully process and optimize different frequency features. The comparison with the DW-LSTM model shows the performance improvement brought by adding VMD and multi-model integration methods, which proves the hypothesis that the ensemble machine learning models (LSTM, GRU, and ELM) have strong learning abilities for cryptocurrency price data processed by VMD and wavelet denoising methods and will improve cryptocurrency price prediction accuracy.

Comprehensive Comparison of Models in the Study This study compares the performance of various models for Bitcoin (BTC), Ripple (XRP), and Ethereum (ETH) price prediction, including single models (LSTM, GRU, ELM) and ensemble models based on different method combinations. Evaluation indicators include R2, RMSE, MAE, and MAPE. To verify the effectiveness of our proposed DW-VMD-LSTM-GRU-ELM model, we compared its predictive performance against several other models across BTC, XRP, and ETH price datasets. This comparison included individual models, models combined with wavelet denoising, and the VMD-LSTM-GRU-ELM model. We use LSTM as the baseline model and calculate the percentage improvement of other models relative to LSTM in various indicators (RMSE, MAE, MAPE). The calculation formula is:

$$\text{Improvement}(\%) = \frac{\text{Value of Baseline Model} - \text{Value of Other Model}}{\text{Value of Baseline Model}} \times 100\% \tag{14}$$

For BTC prediction, the RMSE of the DW-VMD-LSTM-GRU-ELM model is 199.56, a reduction of approximately 77.5% compared to 886.53 for the LSTM, demonstrating a significant

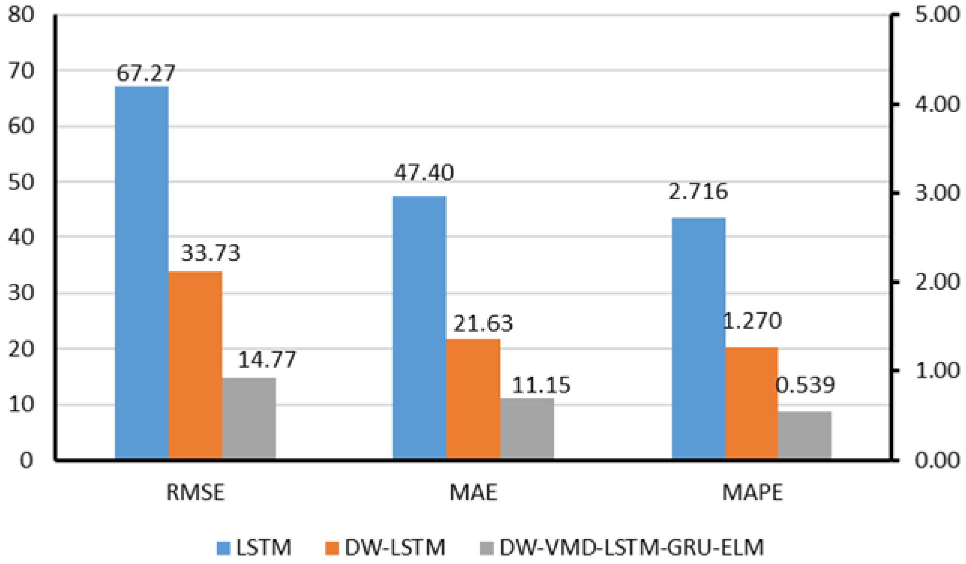

Figure 4.3: *Comparison of LSTM, DW-LSTM, and DW-VMD-LSTM-GRU-ELM on ETH*

advantage in reducing prediction error. The MAE is 127.02, which is about 78.4% lower than the LSTM's 589.38, reflecting an improvement in handling absolute error. The MAPE is 0.352, a reduction of around 83.2% compared to the LSTM's 2.094, indicating a significant improvement in relative error and enhanced prediction stability. The R^2 reaches 99.943%, an increase of about 1.1 percentage points from the LSTM's 98.827%, showing better fitting performance and a marked improvement in the model's explanatory power. Overall, the DW-VMD-LSTM-GRU-ELM model demonstrates extremely high prediction accuracy across all metrics (see Table 2).

BTC	RMSE	Improvement (RMSE) %	MAE	Improvement (RAE) %	MAPE	Improvement (MAPE) %	R^2 (%)
LSTM	886.53	-	589.38	-	2.094	-	98.827
GRU	918.09	-3.6	619.97	-5.2	2.274	-8.6	98.742
ELM	1774.48	-100.2	1352	-129.4	5.011	-139.4	95.299
DW-LSTM	300.65	66.1	186.99	68.3	0.666	68.2	99.865
DW-GRU	537.26	39.4	322.01	45.4	1.438	31.3	99.569
DW-ELM	1634.03	-84.3	1278.6	-116.9	4.572	-118.4	96.014
VMD-LSTM-GRU-ELM	547.73	38.2	387.54	34.2	1.116	46.7	99.354
DW-VMD-LSTM-GRU-ELM	**199.56**	**77.5**	**127.02**	**78.4**	**0.352**	**83.2**	**99.943**

Table 2: *Comparative Analysis of BTC Price Prediction*

For ETH prediction, the RMSE of the DW-VMD-LSTM-GRU-ELM model is 14.767, a reduction of approximately 78% compared to 67.265 for the LSTM. The MAE is 11.155, about

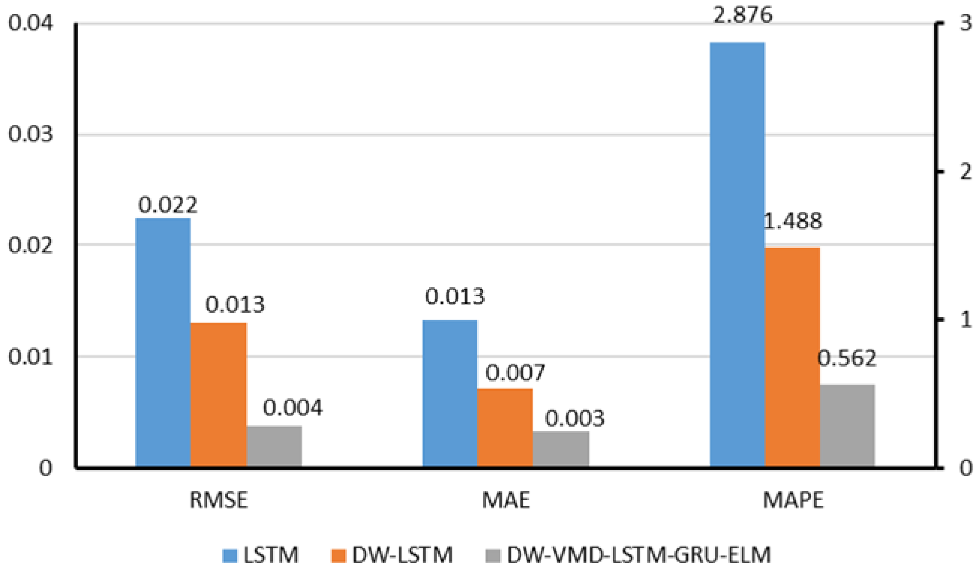

Figure 4.4: *Comparison of LSTM, DW-LSTM, and DW-VMD-LSTM-GRU-ELM on XRP*

76.5% lower than the LSTM's 47.404. The MAPE is 0.539, a decrease of around 80.2% compared to the LSTM's 2.716. The R^2 reaches 99.739%, an improvement of about 1.6 percentage points from the LSTM's 98.14%, demonstrating that the model performs exceptionally well across all metrics (see Table 3).

ETH	RMSE	Improvement (RMSE) %	MAE	Improvement (RAE) %	MAPE	Improvement (MAPE) %	R^2 (%)
LSTM	67.265	-	47.404	-	2.716	-	98.14
GRU	71.972	-7.0	49.318	-4.0	2.815	-3.7	97.871
ELM	127.37	-89.4	99.251	-109.4	5.781	-112.8	93.215
DW-LSTM	33.727	49.9	21.635	54.4	1.270	53.3	99.537
DW-GRU	33.643	50.0	21.547	54.5	1.194	56.1	99.539
DW-ELM	132.22	-96.6	102.72	-116.7	6.053	-122.9	92.688
VMD-LSTM-GRU-ELM	48.059	28.6	32.499	31.4	1.604	40.9	97.354
DW-VMD-LSTM-GRU-ELM	**14.767**	**78**	**11.155**	**76.5**	**0.539**	**80.2**	**99.739**

Table 3: *Comparative Analysis of ETH Price Prediction*

In XRP prediction, the RMSE of the DW-VMD-LSTM-GRU-ELM model is 0.004, a reduction of approximately 83.3% compared to 0.023 for the LSTM. The MAE is 0.003, about 75.7% lower than the LSTM's 0.013. The MAPE is 0.562, a decrease of around 80.4% compared to the LSTM's 2.876. The R^2 reaches 99.439%, an improvement of about 4.03 percentage points from the LSTM's 95.409%, indicating that this model outperforms others in both accuracy and stability (see Table 4).

In conclusion, the DW-VMD-LSTM-GRU-ELM model demonstrated significant accuracy improvements across the BTC, ETH, and XRP prediction tasks, providing optimal forecasting

XRP	RMSE	Improvement (RMSE) %	MAE	Improvement (RAE) %	MAPE	Improvement (MAPE) %	R^2 (%)
LSTM	0.023	-	0.013	-	2.876	-	95.409
GRU	0.024	-4.8	0.013	4.7	2.629	8.6	94.961
ELM	0.028	-24.5	0.018	-37.8	3.797	-32.0	92.910
DW-LSTM	0.013	41.8	0.007	46.6	1.488	48.3	98.447
DW-GRU	0.014	39.6	0.006	53.4	1.305	54.6	98.327
DW-ELM	0.038	-68.3	0.027	-103.1	5.477	-90.5	87.052
VMD-LSTM-GRU-ELM	0.016	31.2	0.011	19.8	1.853	35.6	92.829
DW-VMD-LSTM-GRU-ELM	**0.004**	**83.3**	**0.003**	**75.7**	**0.562**	**80.4**	**99.439**

Table 4: *Comparative Analysis of XRP Price Prediction*

performance.

5 Discussion

Traditional financial systems face intermediary issues such as transaction limits and insufficient security, while cryptocurrencies aim to address these problems. However, the rapid growth and high volatility of the cryptocurrency market pose challenges to the accuracy of traditional statistical prediction methods. Although machine learning models offer some improvements in prediction, their accuracy is still limited due to the influence of various factors. This study focuses on improving prediction accuracy by refining data processing techniques and integrating multiple machine-learning models. In this study, we proposed a novel cryptocurrency price prediction method that combines Variational Mode Decomposition (VMD), wavelet denoising techniques, and an ensemble machine learning model. The study by Luo et al. (2022), which used a VMD-LSTM-ELM model to predict BTC prices, compared with the LSTM model, found that RMSE and MAE decreased by 50.5% and 47.3%, respectively, while R^2 increased from 89.32% to 99.12% (see Table 5). Although the nearly 10% improvement in R^2 is notable, this substantial enhancement may be attributed to the relatively poor performance of their baseline model, leaving significant room for improvement in their approach. In this study, we employed the DW-VMD-LSTM-GRU-ELM model to predict the BTC dataset from August 17, 2017, to January 23, 2024. The results showed that the DW-VMD-LSTM-GRU-ELM model reduced RMSE and MAE by 77.5% and 78.4%, respectively, compared to the LSTM model (see Table 5). This significant improvement is primarily attributed to the use of wavelet denoising during data preprocessing and the application of more suitable models to different frequency components. Although the R^2 improvement is relatively smaller compared to the VMD-LSTM-ELM model proposed by Luo et al., (2022) our model achieved higher optimization on a stronger baseline, demonstrating superior predictive performance.

Second, we compared our results with the CEEMDAN-SVM model proposed by Aggarwal et al. (2020). While Aggarwal et al.'s CEEMDAN-SVM model performed well in terms of MAPE, it had certain limitations in short-term prediction regarding mean squared error

BTC	RMSE	Improvement (RMSE) %	MAE	Improvement (MAE) %	R^2 (%)
LSTM (Our)	886.53	-	589.38	-	98.83
DW-VMD-LSTM-GRU-ELM (Our)	199.56	**77.5**	127.02	**78.4**	**99.94**
LSTM (Luo et al., 2022)	493.91	-	317.33	-	89.32
VMD-LSTM-ELM (Luo et al. 2022)	244.30	**50.5**	167.33	**47.3**	**99.12**

Table 5: *Performance Comparison of DW-VMD-LSTM-GRU-ELM vs. VMD-LSTM-ELM (Luo et al., 2022)*

(MSE). Our DW-VMD-LSTM-GRU-ELM method showed significant improvements in RMSE, MAE, and MAPE, indicating higher prediction accuracy. Although the CEEMDAN-SVM model performed consistently in mid-term to long-term forecasts, the advantages of our approach in noise handling and frequency component optimization led to better overall predictive performance compared to CEEMDAN-SVM. Third, compared to the VMD-AGRU-RESVMD-LSTM method proposed by Jin et al. (2023), which highlights the role of attention mechanisms and residual re-decomposition in enhancing the model's feature-capturing ability, our DW-VMD-LSTM-GRU-ELM method achieves higher prediction accuracy by effectively capturing the characteristics of each frequency component through wavelet denoising and VMD decomposition. While these advanced techniques are promising and warrant further exploration, our approach proves more efficient for feature extraction in this context. Future research could integrate these advanced mechanisms to further enhance the performance of prediction models. Finally, our model holds significant potential for application among investors and cryptocurrency platforms. For investors, the model can analyze vast amounts of market data to provide more accurate market trend predictions and investment advice, thereby aiding in making more informed decisions. Additionally, cryptocurrency trading platforms can leverage this model to optimize trading strategies and mitigate market risks. Through automated risk management and real-time market analysis, the platform can offer users a safer and more reliable trading environment. Although the results are promising, the study's focus on BTC, ETH, and XRP limits the validation of the model's generalizability across a broader range of cryptocurrencies and market conditions, Future research should expand the scope of analysis to include a more diverse set of cryptocurrencies and evaluate the model under various market conditions. Our DW-VMD-LSTM-GRU-ELM model, compared to the LSTM model, incorporates additional steps such as wavelet denoising and VMD, followed by training and predicting on the low, medium, and high-frequency components separately. The final prediction accuracy is achieved by aggregating these individual predictions. Although these steps increase the computational complexity of the model, they have shown a significant improvement in prediction accuracy during experiments. However, our study does not provide specific comparative data on prediction accuracy and computational efficiency. Therefore, it remains unclear how the increase in computational cost balances with the improvement in prediction accuracy. Future work should include detailed analyses of computational time and resource consumption to further evaluate this trade-off, helping decision-makers better understand the cost-effectiveness of the model.

6 Conclusion

This study experimentally verified the significant advantages of the DW-VMD-LSTM-GRU-ELM ensemble model in time series forecasting. The model demonstrated significant improvements in prediction accuracy for ETH, XRP, and BTC prices. Specifically, for BTC predictions, compared to the baseline LSTM model, R^2 increased by 1.1%, while RMSE, MAE, and MAPE improved by 77.5%, 78.4%, and 83.2%, respectively. For ETH predictions, R^2 increased by 1.6%, and RMSE, MAE, and MAPE improved by 78%, 76.5%, and 82%, respectively. For XRP predictions, R^2 increased by 4.03%, and RMSE, MAE, and MAPE improved by 83.3%, 75.7%, and 80.4%, respectively. These results indicate that the model exhibits significant accuracy and error control capabilities across different cryptocurrencies. Although the ELM model performed poorly alone, the combination with LSTM and GRU significantly enhanced the overall prediction ability, verifying the effectiveness of the ensemble model that combines wavelet denoising and VMD methods in processing complex time series data. Our analyzing representative cryptocurrencies such as ETH, XRP, and BTC, this study shows that our model has wide applicability and provides an important reference for the study of other cryptocurrencies. However, the scope of this study is mainly focused on these cryptocurrencies, and the generalizability and stability of the model can be verified in the future under a wider range of datasets and market conditions. Specifically, the model can be tested on high-frequency trading data to handle more complex and fine-grained time series data. Additionally, research could explore integrating external market signals (such as market sentiment) to optimize the model's performance and enhance its applicability and adaptability in practical application scenarios.

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Hybrid Algorithmic Trading Strategies Performance Study on Crypto Markets

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Abstract

The research explores the effectiveness of hybrid algorithmic trading strategies in cryptocurrency markets. Mainly, research about hybrid Long-Short Term Memory (LSTM), Extreme Gradient Boosting (XGBoost), and portfolio management strategies. The hybrid model implement with fundamental and technical analysis techniques used as variables or features to optimize performance and minimize risk. The research use historical data of five major cryptocurrencies which is Bitcoin, Ethereum, Ripple, Litecoin, and Binance coin from 2017 to 2024. Historical data such as price, volume, number of total transaction, market capitalization, fundamental and technical data such as EMA, MACD, RSI, and STO was preprocessed by feature engineering method and implemented into the model. Results demonstrate that the LSTM-XGBoost-Portfolio management strategy outperforms the other model in prediction of price, accuracy, and Root Mean Sauared Error (RMSE). However, the model still cannot capture more volatile cryptocurrencies such as Ripple and Litecoin. The further research suggest that improvement of the portfolio management implemented technique may improve the performance of the model.

KEYWORDS: Hybrid Algorithmic Trading Strategies, Cryptocurrency, Machine Learning, Portfolio Management, LSTM, XGBoost, Algorithmic Trading

1 INTRODUCTION

1.1 Research Background

Quantitative algorithmic trading has emerged as a main topic in today's financial markets, driven by the increasing complexity and volume of data that human traders cannot process effectively. Human limitations, such as the inability to analyze vast amounts of data in real-time and the emotional from fear of losing or even fear from gaining money, have led to the adoption of algorithmic trading systems. Emotions like the fear of losing or even the fear of gaining too much can distort decision-making processes. In contrast, quantitative algorithmic trading employs data-driven models and statistical indicators to automate trading decisions, aiming to optimize profit while minimizing risk. The use of historical data, combined with technical analysis, allows algorithms to make trading decisions that free from the emotional influences that affect human traders. Many hedge funds and financial institutions have successfully implemented algorithmic trading strategies. One of the most well-known is Renaissance Technologies, whose flagship "Medallion Fund" has achieved average annual returns of approximately 66%, largely attributed to its sophisticated algorithmic models.

In the volatile market, such as cryptocurrency market, algorithmic trading play the crucial role to make profit, while optimize risk. Portfolio management also important when dealing with high volatility market to optimze risk control to the model. This study will focus on building hybrid algorithmic trading strategies, mainly on Long-Short Term Memory Networks (LSTMs), Extreme radient Boosting (XGBoost), and portfolio managemet strategies integrated to optimize profit while minimizing risk in cryptocurrency market.

1.2 Problem Statement

Quantitative algorithmic trading strategies come from the fact that humans cannot process the vast of data and cannot concentrate on data required for effective decision making. The other problem is emotional bias, humans have emotion in every trade decision. Quantitative algorithmic trading computes and calculates data, produces algorithms, and takes decisions whether to buy or to sell based on data and statistical indicators instead of human (Briza & Naval, 2011; Y. J. Chen et al., 2018; World Congress on Engineering 2007. Volume 1., 2007). it aims to maximize profit and reduce risk in any transaction made. In the study compare between quantitative algorithmic trading and human have shown that the model using artificial neural network can trade better than humans (by using moving average 15 trading strategy) (Dash & Dash, 2016).

There are several quantitative trading model studies that have positive results (Wei et al., 2011a). However, few have hybrid strategy (such as using both fundamental and technical analysis) and lacking integration with broader financial concepts like portfolio management. Because in real life, humans have no time to concentrate in choosing stock from their model or manage their fund spending on each stock. The study showed hybrid strategies have better performance than single strategy and if the model comes with portfolio management tend to have better performance (Amity University et al., n.d.; Park et al., 2020). Because the model will know how much money to be spent on each stock to maximize the benefit or even reduce risk.

The other challenge in developing quantitative trading strategy model is not the model itself, but rather the lack of efficient hardware (such as GPUs). Insufficient hardware resources and the physical distance between data centers and client can introduce more latency, particularly in high-frequency or minute-by-minute trading (Pricope, 2021). Decentralized finance (DeFi) addresses this issue by eliminating the need for centralized data centers, ensuring all clients receive data simultaneously (Jensen et al., 2021; Schär, 2021a; Zetzsche et al., 2020). Therefore, this research will focus on hybrid algorithmic trading strategies with portfolio management, specifically in cryptocurrency market, addressing gap in current models by exploring how these strategies can improve returns and manage risks.

1.3 Research Objectives

To compare the returns (benefits) and losses of using hybrid strategies with the other hybrid strategies and maximize the benefits and use risk management to reduce risk of losses (risk of ruin) with portfolio management strategies add on hybrid trading strategies.

To determine and measure alpha that shows how well a stock has performed compared with benchmark index, beta which indicates how volatile a stock (cryptocurency, in this research)

has been compared with the market using portfolio management strategies combined.
To explore and answer how hybrid algorithmic trading strategies can be effectively implemented in cryptocurrency market, balancing profitability with robust risk management.

1.4 Research Questions

The study aims to address the following research questions:
What are the differences in performance between hybrid algorithmic trading strategies in cryptocurrency market?
How do hybrid strategies that incorporate more than two approaches, combined with money management, risk management, and portfolio management, compare in terms of profitability and risk reduction?
What are the best practices for implementing hybrid strategies in day-to-day cryptocurrency trading?

2 LITERATURE REVIEW

2.1 Stock market

Stock is one of the most popular investment instruments with high returns that attract more investors to invest. However, it is also increased risk compared to the other instruments. Investors have to analyze all the information to reduce their risk as low as possible. There are three types of stock analysis, the fundamental analysis, the technical analysis, and hybrid analysis. Fundamental analysis is an analysis method to determine a stock's real price or fair value or intrinsic value. The value is calculated by economic value and financial value of the company own the stock. There are a bunch of study about fundamental factor that used to predict the stock price. The research study fundamental factors to predict stock price change using Annual Earning per Share (EPS) found that the stock price reflect to the ability of the company to make positive earning (Nti et al., 2020). The research about relationship between Earning per Share (EPS), Dividend per Share (DPS), and Price-Earning Ratio (PER) with stock price movement using Fuzzy Regression method. The result shows that EPS and DPS significantly related to the stock price movement. Technical analysts identify the trend and analyze the chart by technical indicator. The most important signal is the price and volume because it come from the true value. Price come from real and currently price and volume come from the real transaction occurs either from buyer or seller (Almeida & Vieira, 2023; Chen et al., 2018) The popular indicator used in technical analysis is Moving Average (MA), Moving Average Convergence Divergence (MACD), Relative Strength Index (RSI), and Stochastic Oscillator (K% and D%). Momentum indicator is a term used for the MACD, RSI, and Stochastic oscillator. Momentum is the rate which price are changing, measure how quickly the prices are rising. The momentum indicator can become a leading indicator or telling whether trend slope is changing. When momentum is confirming the price trend, a convergence will occur. When momentum is falling, a divergence will occur. Some momentum also used to identify overbought and oversold conditions and these indicators are used in machine learning to predict the price movement.

2.2 Portfolio management

Modern Portfolio Theory, introduced by Markowitz in 1952, was a main concept for portfolio management. It palys an essential role in optimizing returns and managing risk in trading strategies. Recent advancement have built this theory to address the challenges in cryptocurrency markets such as extreme price volatility, limited historical data, and irregular market behavior (Markowitz, 1991). The principles of diersification and return-risk optimization continue to be central themes in recent studies, esspecially in cryptocurrency markets. Recent developments in artificial intelligence (AI) have resulted in hybrid portfolio management strategies that improve performance by combining various market indicators with machine learning models. Haddadian et al (2022) introduce an AI-based system that optimizes asset allocation and autonomously detect trading opportunities in volatile market(Haddadian et al., 2022). Kocabiyik et al (2024) suggest that using clustering techniques can improve the understanding of market dynamics and help categorize cryptocurrencies with similar behaviors, resulting in more effective portfolio allocation and risk management (Kocabıyık et al., 2024). The research about hybrid decision support system for managing cryptocurrency portfolios, combines big data analytics with decision-making frameworks. This system improve allocation decisions and enhance risk management. Also hightlights the significance of using hybrid method, especially in volatile markets such as cryptocurrencies (Maghsoodi, 2023).The other research combine convolutional neural networks (CNNs) with traditional time-series forecating method to mitigate risk in higly volatile market. The research ensure that data-driven risk forecasting techniques can enhance portfolio management in cryptocurrency trading (Singh & Thavaneswaran, 2022).

2.3 Artificial Intelligence

Artificial Intelligence (AI) is an intelligence machine which can behave like a human, think like humans, and able to make decisions like human. This term was founded during a summer conference at Dartmouth College in the mid of 1950s by John McCarthy, computer and cognitive scientist. And from Alan Turing, mathematician, that published “Computing Machinery and Intelligence” which proposed the idea of the Imitation game, start with a question “Can machine think?” The goal of computer scientist is to make machine can learn like human. One way to achieve that goal is Machine Learning. Machine Learning (ML) is one of a method of data analysis aims to build an automates analytical model based on algorithms. Machine Learning has 3 types which is Supervised Learning, Unsupervised Learning, and Reinforcement Learning. Deep learning is one of the algorithms from machine learning. Deep learning structures algorithms in layers which more than layer of machine learning to create Artificial Neural Network (ANN) that can extract the features, learn, and make intelligent decisions on its own. The neural network of Deep learning comes from the idea which act like biological neural network in human. The structure of Deep learning consists of 3 components, input layer, hidden layer, and output layer. The term “Deep” is refer to the number of hidden layers in neural network. In the old day, traditional neural network only contains 2-3 layers, but Deep learning contains more. This network contains nodes in different ways that are connected and communicated with each other. The most famous and popular Deep learning algorithms are Convolutional Neural Network (CNN), Recurrent Neural Network (RNNs), Long Shot-Term Memory Networks (LSTMs), and Multilayer Perceptron (MLPs).

2.4 Quantitative Algorithmic Trading

Quantitative algorithmic trading is one type of trading strategy that uses mathematical models and statistical techniques to analyse market data and make automated trading decisions. In this approach, many algorithms are programmed to execute trades based on predefined conditions derived from quantitative analysis, such as historical price patterns, market trends, news, or other financial indicators (Loon et al., 2023). The famous algorithm, used in present day, are as follows:

Logistic regression Logistic regression is a supervised machine learning algorithm used for binary classification problems. In our experiment, the logistic regression model aims to classify market movements into two categories: a positive price trend (up) or a negative price trend (down). The model calculates the probability of the dependent variable Y (market movement) based on a set of independent variables X (features such as price, volume, and market sentiment) (Supsermpol et al., 2023). The logistic function, or sigmoid function, is used to capture predicted values to a probability range between 0 and 1, which allows the model to make predictions. The hypothesis for logistic regression is shown as follow.

$$h_\theta(X) = \frac{1}{1+e^{-\theta^T X}} \tag{1}$$

Where:

$h_\theta(X)$ = probability of the event (Price movement)

θ = parameter / weights of the model

X = Input feature to the model

e = Euler's number

Long-Short Term Memory (LSTM) LSTM networks, introduced by Hochreiter and Schmidhuber (1997), are designed to overcome the limitations of traditional RNNs, particularly the vanishing gradient problem (Hochreiter & Schmidhuber, 1997). LSTMs use a system of memory cells or gates to selectively retain or discard information that allowing them to maintain and update relevant information over extended sequences, instead of traditional RNNs, which maintain information in only single hidden state pass through time periods (Loon et al., 2023). LSTM architectures are designed to capture long-term dependencies in sequential data, which make the algorithm well-suite for time series forecasting. The architecture of LSTM cell consists of three types of gates which is: **Forget gate:** the gate that decide which information or feature should be discarded.

$$f_t = \sigma(W_f [h_{t-1}, x_t] + b_f)$$

Where:

f_t is the forget gate activation (2)

W_f is weight of matrix

x_t is the input at time t

Input gate: the useful information will be added by input gate.

$$i_t = \sigma(W_i [h_{t-1}, x_t] + b_i) \tag{3}$$

Output gate: the gate that control the information out from cell to the next hidden state.

$$o_t = \sigma(W_o [h_{t-1}, x_t] + b_0) \tag{4}$$

Finally, cell state C_t which is the key feature of LSTM, is updated by forget gate and input gate.

$$C_t = (f_t * C_{t-1}) + (i_t * \tilde{C}_t) \tag{5}$$

Random Forest (RF The core concept of Random Forest is building a huge number of decision trees, where each tree is trained on a randomly selected subset of the training data (using bootstrap aggregation) and a random subset of features. This approach introduces variety among the trees, which helps lower the model's variance and minimizes the risk of overfitting. For regression tasks, the final prediction is obtained by averaging the outputs of all trees, while for classification tasks, it is determined by majority voting (Supsermpol et al., 2023).

XGBoost XGBoost, stands for Extreme Gradient Boosting, is a machine learning library with ensemble learning method. It implement scalable and distributed gradient boosted decision tree. Moreover, it offer parallel tree boosting (Multiple learner) instead of only gradient boosting. Toledo and Souza (2022) implement gradient boosting algorithm, including XGBoost, to predict signal in cryptocurrency trading. The reserch found that XGBoost can capture complex patterns in trade signals and improve expected return in investment (Toledo et al., 2022). Hafid et al. (2024) and Rahimpour et al. (2024) propose a trading strategies, use XGBoost combine with technical indicators, to capture cryptocurrency trend price. They prove that XGBoost can capture a large volume of data and effectively predict values (Hafid et al., 2024; Rahimpour et al., 2024). The other research introduce hybrid model that combine XGBoost with Capital Asset Pricing Model (CAPM) to optimize portfolio building. The research prove that the integration of machine learning with portfolio management theories can imporve performance of investment (Yang, 2024).

2.5 Cryptocurrencies

Blockchain Blockchain first come with intention to cut off the intermediaries in financial market with token called Bitcoin from unknown person or group called Satoshi Nakamoto in 2008. Bitcoin is the consensus govern, decentralize cryptographic of data stored in block and linked together like a chain that digitally signed the transaction. The transaction is verified by nodes through cryptographic and recorded or stored in distribute ledger. This technology makes Bitcoin immutable. The key concept of blockchain is as follow: Distributed ledger technology, Immutable data, and Smart contract. From the information above proved that Blockchain brings decentralization, transparency, security, and innovation, which have a big impact on financial services (Chang et al., 2020).

Cryptocurrencies A cryptocurrency is a virtual or digital currency that can be used to traded or exchanged between people or users, which is not rely on intermediators (central authority). It uses cryptographic algorithm to increase the security of its storage and transfer processes. This security feature makes cryptocurrencies challenging to counterfeit. Cryptocurrencies are based on blockchain technology so, they acquire the immutability, transparency, and decentralization of the blockchain (Gupta et al., 2020). A lot of cryptocurrencies were developed to make work on the blockchain that they are based on easier. For example, Ethereum's ether which be used as payment for opening blocks and validating transactions. Ripple's XRP which be used to facilitate transfers between different countries (Fang et al., 2022).

3 METHODOLOGY

3.1 Data

The study utilized historical hourly Open-High-Low-Close-Volume (OHLCV) market data for five widely traded cryptocurrency tokens, sourced from the TradingView and Binance platform. The dataset covers past OHLCV data for Bitcoin (BTC), Ethereum (ETH), Ripple (XRP), Binance (BNB), and Litecoin (LTC). The data were collected from 2017 to 2024. The study also utilize the data from CoinMarketCap, including number of transactions, and market capitalization. Data collected in 2-dimension dataframe using python language with pandas library. Dataframe construct with values in rows and variable or feature in columns (represent in X_1,X_2,X_3,...,X_i). Machine learning approached to this study using Scikit Learn library and Keras library.

3.2 Feature Engineering

In the preprocessing stage, the study search for missing values and odd values in the data and impute data with difference methods such as drop the missing data, impute some time series-specific data, and train model to predict the missing data. The study identified substantial differences in the value ranges across various features. Eliminate biases during training and improve the speed of the process by normalized features to fall between 0 and 1 using the Min-Max scaling method. Some feature that tend to be a crucial feature (analyzed by the model) will be punished more than the other feature, by extended range to -1, 1. The transform feature will be labeled to 3 type which is (X_{T1},X_{T2})= (0, 1), (X_{T1},X_{T2}) = (-1, 1), and non-transform X

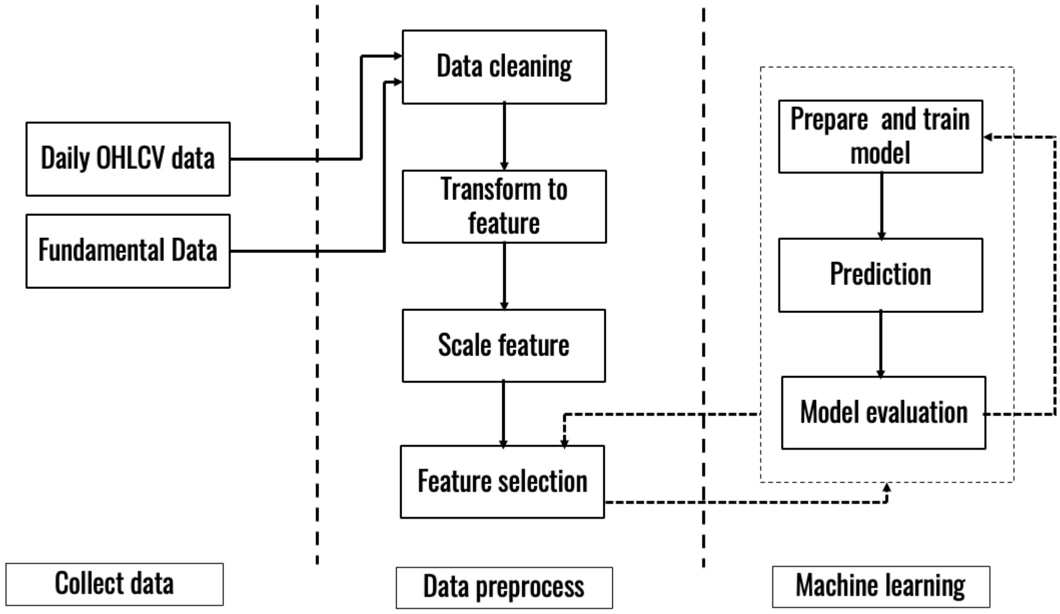

Figure 3.1: *The architecture of hybrid algorithmic trading strategies approach on this research*

(feature with calculated value). The Min-Max scaling method using MinMaxScaler function with formula as follow:

$$X_{\text{scaled}} = \frac{X - X_{\min}}{X_{\max} - X_{\min}}$$

Where:

X is the original feature

X_{scaled} is the scaled feature

$X_{\min}$ is the minimum value of X

$X_{\max}$ is the maximum value of X

(6)

To promote effective model generalization, the study first applied scaling to the training data by determining the max(x) and min(x) values from the training set, and subsequently used these same scaling parameters for the test data.

3.3 Algorithm/ Strategies

In this section, the study will explore the various algorithmic trading strategies implemented in this research. The hybrid algorithm incorporates both fundamental and technical analysis, also integrates multiple models to optimize performance and minimize risk in cryptocurrency trading. We compare the performance of LSTM standalone, XGBoost standalone, LSTM-XGBoost model, and LSTM-XGBoost-Portfolio management model. Python was the programming language used in all algorithms implemented.

Fundamental and Technical Analysis Integration The study combines Fundamental and Technical to utilize both intrinsic value of the asset and historical price patterns to create more comprehensive trading strategy. In Fundamental, involve key metrics such as number of transactions, data of block size, hash rate, market capitalization, total transaction fees, estimated transaction value, and time between blocks. In Technical, popular indicator such as Moving Average (MA), Moving Average Convergence Divergence (MACD), Relative Strength Index (RSI), and Stochastic Oscillators be utilized to find the momentum and the direction of price trend.

Hybrid Algorithmic Integration The study employed the hybrid model to predict price trend and make the decision whether to buy or to sell. The hybrid model incorporates a fusion of LSTM, XGBoost, and portfolio management algorithm. The data extracted from features engineering process will be preprocessed by LSTM algorithm to find important features that we put into the model. The output, which is important features, fed into XGBoost algorithm as an input to predict price trend, and decide whether to buy or sell in everyday trade. Both algorithms will be fined tune the model before implemented to find the best parameter which is shown in the table (learning rate and epochs will be depend on each time the model run).

Parameter	Best value
colsample_bytree	1
learning_rate	0.01
max_depth	3
n_estimators	200
subsample	0.6

Table 1: *Hyperparameter of XGBoost tunning*

Portfolio management Integration After implementation of hybrid algorithm, using hybrid model to predict the next closing price, using Fundamental data and Technical to identify the trend and entry point. The study also implements portfolio management strategies to improve expected return and reducing volatility. The implementation of portfolio management also helps the model to select and adjust weight or proportion of investing in all cryptocurrencies. The final model of this study is shown in figure 3.2 below. The data were cleaned through feature engineering method to be cleaned features. Cleaned features will be put to XGBoost classifier to extract and analyze feature with feature extraction and ranked the feature by feature important. Portfolio management theories (such as Sharpe ratio) will be calculated and used as a feature in this stage. All features, after calculated and analyzed, will be put to LSTM model to predict target. All targets will be gathered and put to XGBoost regressor model as features. XGBoost model predict the target which is the price next day.

3.4 Model Evaluation

Root Mean Squared error (RMSE) RMSE is a general used metric that used to evaluate the accuracy of model's predictions. It is a square root of the average difference between predicted

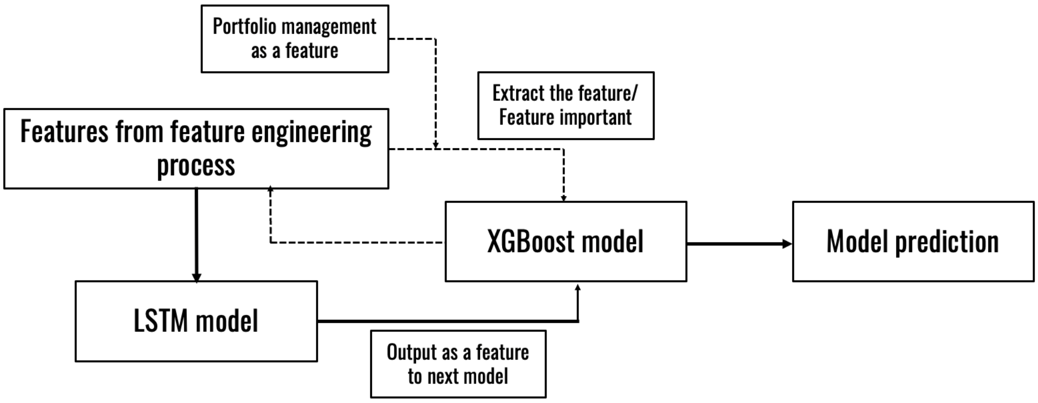

Figure 3.2: *LSTM-XGBoost-Portfolio management architecture*

values and actual values (Standard deviation of the residuals). RMSE represents how well the model can predict the values from feature given to the model. The lower RMSE indicates the better of the model fitting to data, and also indicates overfitting to train dataset. RMSE calculated as follows:

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \tag{7}$$

Where:

n is the number of observation

y_i is the actual value

$\hat{y}_i$ is the pridicted value

Accuracy Accuracy is one of the metric to evaluate a classification models. It measures the proportion of true or correct values made by the model compare to all predict values. A high accuracy indicates how effective of the model to captures underlying patterns in the data.

Return on Investment (ROI) ROI is a key evaluation metric employed in this study, that reflect the net profit or loss resulting from an investment once a trade is completed. ROI is a crucial indicator as it directly measures the financial performance of a trading strategy. ROI was determined using the following formula:

$$\mathrm{ROI} = \frac{\text{Net Profit}}{\text{Cost of investment}} * 100\% \tag{8}$$

Net profit come from Final value of investment subtract by Initial value of investment and Cost of investment is initial cash or the amount of invest in the beginning.

Sharpe ratio Sharpe Ratio (SR) commonly used to evaluate the risk-adjusted performance of an investment or trading strategy. Specifically in cryptocurrencies trading with high volatility, The Sharpe Ratio (SR) evaluates the average return produced by a trading strategy, adjusted for the risk-free rate, in relation to the amount of risk taken. This risk is captured by the standard deviation of the returns. The higher the SR, the better the risk-adjusted return of the strategy. An equation to calculate SR is as below:

$$\text{Sharpe ratio} = \frac{R_p - R_f}{\sigma_p} \tag{9}$$

Where:

R_p = Return of portfolio

R_f = Risk-free rate

σ_p = Standard deviation of the portfolio's return

4 RESULTS

The result of hybrid algorithmic trading strategies implementd in BTC, ETH, XRP, LTC, and BNB. The data of cryptocurrency daily open-high-low-close price and daily volume were collected from TradingView, number of transaction and market capitalization were collected from CoinMarketCap and CoinGecko platform in year 2017 to 2024. The price of each cryptocurrencies are shown in figure 4.3. Each cryptocurrencies price are bound to US Dollar. Bitcoin, Binance, and Ethereum price show same display similar pattern in trend, while Ripple and Lite coin follow distinct pattern. The data collected and transform to 2-dimensional labeled data structure, called dataframe. Rows are values and Columns are type of data, which is price, volume, number of transaction, and market capitalization. Each columns will be use to calculate to be features in machine learning model. Study have 3555 data in rows, and 35 features in columns (represent in X_1,X_2,X_3,...,X_35). The target will be calculate as a return on next days (represent in y).

After collected and extracted the data, we implement the hybrid model (LSTM-XGBoost-Portfolio mangement model) compare with LSTM standalone, XGBoost standalone, and LSTM-XGBoost model. The result are shown in accuracy score, and root mean squared error (RMSE) as a table 2.

Model	Accuracy				
	BTC	ETH	XRP	LTC	BNB
LSTM standalone	0.54	0.52	0.48	0.44	0.54
XGBoost standalone	0.59	0.55	0.51	0.46	0.60
LSTM-XGBoost	0.67	0.66	0.53	0.49	0.66
LSTM-XGBoost-Portfolio management	0.69	0.67	0.53	0.52	0.69

Table 2: *The accuracy of hybrid algorithm strategies compare with the other*

The result from table 2 show that the accuracy of Bitcoin price prediction with LSTM and XGBoost standalone is 0.54 and 0.59 respectively. An accuracy of hybrid LSTM-XGBoost

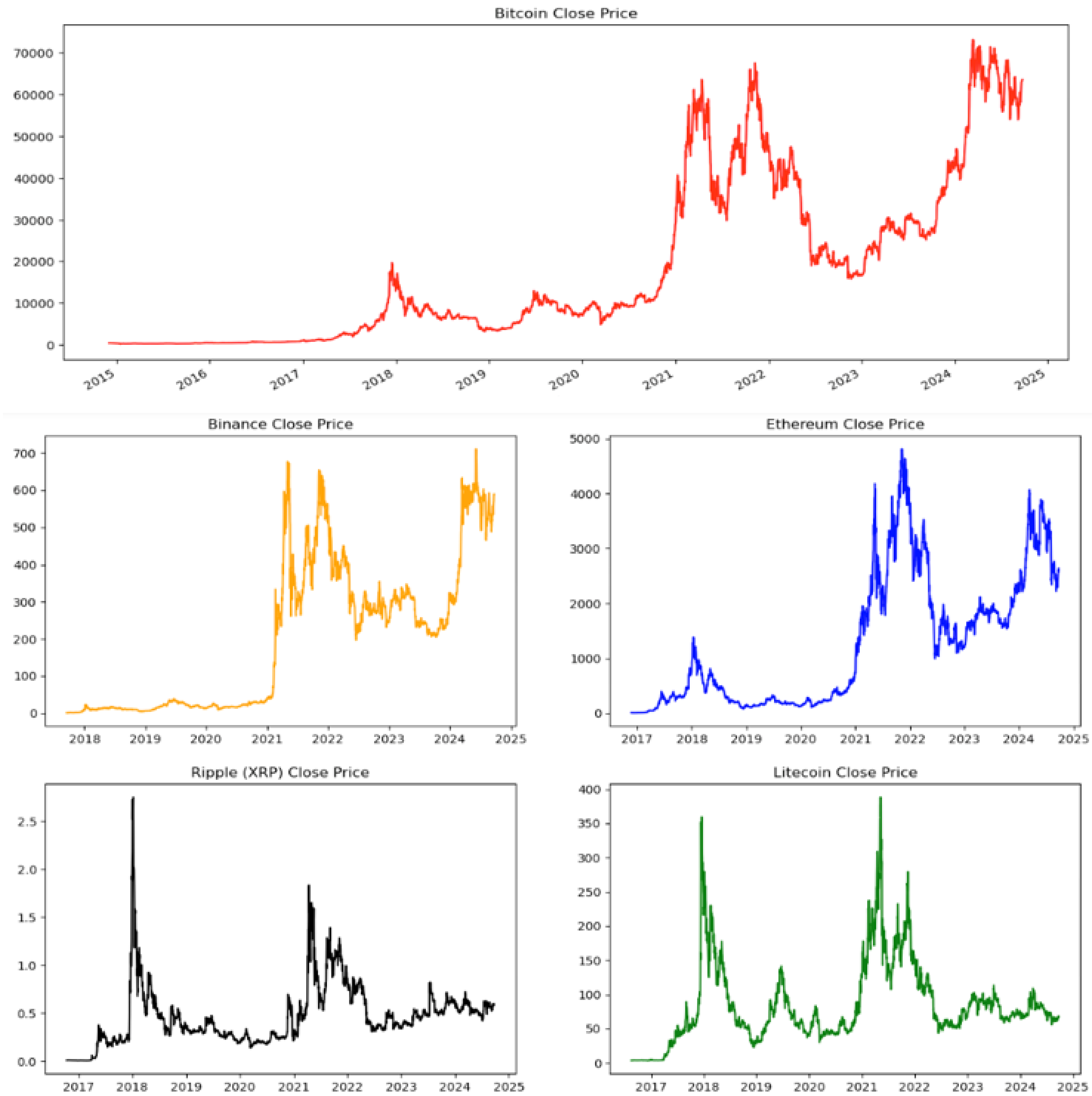

Figure 4.3: *Bitcoin, Binance, Ethreum, Ripple, and Litecoin price chart from 2017 – 2024*

algorithm is 0.67 and 0.69 when combine with portfolio management strategies. The result show in the same direction in Etheruem and Binance coin, but poorly accuracy in Litecoin and Ripple coin. RMSE of predicting Bitcoin price with LSTM and XGBoost standalone is 0.0494 and 0.0353 respectively. The hybrid model show significantly lower RMSE compare with standalone model. The lowest RMSE in this research is shown in Binance coin price prediction with LSTM-XGBoost-portfolio management algorithm. Litecoin and Ripple coin also show badly result in RMSE.

Finally, the model will be implement in trading situation with a capital of 1,000 USD. The table 4 show the cumulative profits and return on investment (ROI) of the model approach, from 1 June 2023 to 1 June 2024. Figure 4.4 shows price prediction from hybrid LSTM-XGBoost-portfolio management model. The model show better performance in less volatile state (around April 2023 – January 2024). Table 4 shows the profit that made from implementing the model

Model	RMSE				
	BTC	ETH	XRP	LTC	BNB
LSTM standalone	0.0494	0.0578	0.3535	0.6899	0.0499
XGBoost standalone	0.0353	0.0499	0.1000	0.5667	0.0355
LSTM-XGBoost	0.0009	0.0009	0.0233	0.1008	0.0009
LSTM-XGBoost-Portfolio management	0.0005	0.0007	0.0100	0.0234	0.0004

Table 3: *Root Mean Squared Error (RMSE) of hybrid algorithm strategies compare with the other*

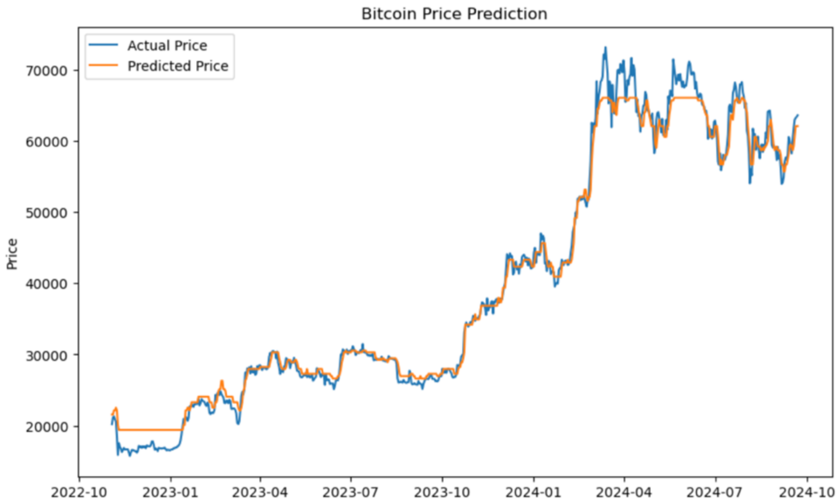

Figure 4.4: *Bitcoin price prediction from hybrid LSTM-XGBoost-portfolio management model*

with a capital of 1,000 USD. The result shows that LSTM-XGBoost-Portfolio management model outperform the other model with 28.9% ROI.

5 CONCLUSION

The research explores the effectiveness of hybrid algorithmic trading strategies in cryptocurrency market, mainly in Bitcoin, Ethereum, Ripple, Litecoin, and Binance coin. Machine learning algorithm such as Long-Short Term Memory (LSTM) and Extreme Gradient Boosting (XGBoost) implement with Fundamental and Technical analysis technique in stock trading. The result shows that the combination of LSTM-XGBoost algorithm, especially integrate with portfolio management strategies, significantly outperforms standalone algorithms in both accuracy and root mean squared error (RMSE). The better result occur in only major cryptocurrency which is Bitcoin, Ethereum, and Binance coin shows that the hybrid algorithm perform a better performance with more trend and less volatile (three majors cryptocurrencies) in a specific time period. Ripple and Litecoin show less trend and more volatile than the other, resulting in poorly performance of the model. The hybrid model with portfolio management strategies also result in enhanced financial outcomes, higher return on investment (ROI) compare to the other strategies. This result comfirm the important of integrating risk management and asset allocation strategies into algorithmic trading, especially in extremely volatile market such

Model	Profit (USD)	Return on investment (ROI, %)
LSTM standalone	-155	-15.5
XGBoost standalone	-191	-19.1
LSTM-XGBoost	168	16.8
LSTM-XGBoost-Portfolio management	289	28.9

Table 4: *Profit and ROI of hybrid algorithm strategies with a capital of 1,000 USD*

as cryptocurrency market. Overall, The hybrid algorithmic trading strategies with portfolio management show better performance compare with the other. However, the model still perform poorly performance. The further research suggest that improvement of the portfolio management implemented technique may improve the performance of the model.

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Feasibility Study of Remote Drug Dispensing System via Automatic Machine

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Abstract

This research examines the feasibility of remote drug dispensing system via automatic dispensing machine in Thailand, focusing on market feasibility and legal and regulatory feasibility. A six-part questionnaire was used to collect data and create descriptive statistics. The market feasibility of the data obtained from 474 respondents was analysed. The results demonstrated that common household medicines, vitamins and supplements, and cosmetics were selected as products that respondents were highly confident in purchasing via automatic machines. Key factors affecting respondent's decision to use automatic machine, including quality, pharmacist consultation, cleanliness, contact channels, payment methods, and service hours. Additional factors suggested by respondents included product expiration date, stability of the machine, medication history, filling out medication allergy, and various drug option. Some concerns raised by respondents included side effects, data security, shelf life of product, product quality, pharmacist consultation, accuracy, and incorrect drug dispensing. The majority of respondents have an overall positive attitude and seem to support the use of remote drug dispensing system. The implementation of the system is in accordance with the Drug Act B.E. 2510 and the announcement about standards and procedures for the Telepharmacy service from the Pharmacy Council of Thailand on June 2, 2020. Currently, businesses that dispense medicines must have a pharmacist on duty during business hours. The Pharmaceutical Profession Act has legal requirements for pharmacists to dispense drugs, even in an automated system, which requires pharmacist to be licensed by the Pharmacy Council of Thailand. Therefore, the remote drug dispensing system via automatic dispensing machine must add remote services named telepharmacy to meet regulatory standards and allow pharmacists to participate. The Pharmacy Council has announced standards and procedures for providing remote services, such as patient registration systems, medical record, patient profile, inform consent, and voice or video record when providing consultation services or following up.

KEYWORDS: Remote Drug Dispensing, Automatic Dispenser, Telemedicine, Telehealth, Telepharmacy, Pharmacy Automation, Feasibility Study, Healthcare Innovation

1 INTRODUCTION

In recent years, the rapid evolution of digital technology has led to significantly transforms in various sectors, including healthcare and medicine. One thing that has seen the development change is telepharmacy and automatic dispensing machines. The COVID-19 pandemic has led to increase adoption of these technologies as social distancing and reduce physical interaction become more important. This has highlighted the need for innovative healthcare solutions that allow patients to access essential medications conveniently and safely without having to visit a pharmacy or hospital. Automatic dispensing machines have emerged as a promising solution for solving these problems. These devices can be used in a variety of settings, including remote locations, nursing homes, pharmacy, and hospitals, to dispense medicines efficiently. These devices provide several benefits, such as reducing patient waiting times, reducing medication errors, and improving inventory management. These systems enable pharmacists to observe the dispensing process and offer remote consultations, ensuring patient safety and following to medication standards by integrating telepharmacy services. In Thailand, the implementation of remote drug dispensing systems faces different challenges, including compliance with the Drug Act B.E. 2510 (1967) and standard and the announcement about standards and procedures for the Telepharmacy service from the Pharmacy Council of Thailand on June 2, 2020. This study purposes to assess the feasibility of implementing remote drug dispensing systems via automatic machines in the Thai healthcare system, focusing on both market feasibility and law and regulatory feasibility. The market feasibility analysis is conducted by assessing the attitudes and perceptions of potential users and identifying key factors affecting the implementation of the system. It also provides valuable insights into the potential for the implementation of this systems to improve access and dispensing of medicines, especially in underserved and rural areas. Finally, the results of this study highlight the opportunities and challenges associated with the implementation of the systems, which provide guidelines for future effort to improve access and efficiency of healthcare in Thailand.

2 LITERATURE REVIEW

In terms of effectiveness, of remote drug dispensing systems and automatic machines has significantly impact on healthcare system, improving medication management, and increasing patient safety across healthcare settings. Automated medication dispensing machine, such as prescription drug units (PDUs) and robotic dispensers, have been proven to significantly reduce medication errors, including wrong dosage, and wrong labeling, by almost 50% in ward environments. Especially, integration with other healthcare technologies such as electronic health record (EHR) systems and barcode medication administration (BCMA) reduces the risk of human errors and improves the overall accuracy and safety of medication management (Garagiola, 2023). Takase demonstrated that the implementation of a robotic dispensing system significantly improved the safety and accuracy of the medication dispensing process. Their research revealed that preventable dispensing errors which were detected by pharmacists before patients get those medicines, such as incorrect strength, dose, or quantity, were reduced by 73.5% to 78.4%. Additionally, unpreventable dispensing errors that were detect by other staff or patients after provided to the patients, were reduced from 66.7% to 86.7% after the robotic system was implemented. The results also showed that the time pharmacists spent dispensing medications was significantly reduced, with the average time per prescription reduced from 60 seconds to 23 seconds (Takase et al., 2022). The economic benefits of automatic dispensing systems were recorded in a study by Becton, which evaluated the impact of replacing manual emergency medication kits with the automatic dispensing cabinet in two long-term care facilities. The results indicated significant productivity gains, with over 6.5 hours saved per day and a 71% reduction in medication pick-up time. Additionally, after-hours medication dispenses were reduced by 96%, resulting in a savings of USD 8,900. Labor costs were also significantly reduced, with pharmacy professional preparing time reduced by 59% and pharmacist spent time reduced by 80%, resulting in over USD 10,000 in savings (Becton, 2024). The introduction of automatic dispensing machine in intensive care units has shown a high return on investment. After implementation, nurses saved an average of 14.7 hours per day on medication-related tasks, while pharmacists spent only an additional 3.5 hours per day to handling medications, resulting in a reduction in overall workload. The net present value of the investment was estimated at 510,494 euro over five years (Chapuis et al., 2015). The global market for automatic drug dispensing systems is expanding rapidly due to the increasing demand for patient safety, efficiency, and medication accuracy. According to PS Market Research, the market was valued at USD 4.98 billion in 2022 and is forecasted to reach USD 9.42 billion in 2030, growing at a Compound Annual Growth Rate (CAGR) of more than 7% (PS Market Research, 2023). Emergen Research projects the global pharmacy automation market to reach USD 11.12 billion by 2030, at a CAGR of 8.3%. Key factors include technological advancements, adoption of robotics, and the require for more efficient healthcare solutions. However, a major challenge is the high cost (Emergen Research, 2023). According to Grandview Research, the market size for pharmacy automation devices, including dispensing, packaging, and storage systems, was valued at USD 5.1 billion in 2021 and is forecasted to grow to USD 9.5 billion by 2028, at a CAGR of 9.3% (Grandview research, 2021).

3 RESEARCH METHODOLOGY

3.1 Research Design

This research purpose to study the feasibility study of the remote drug dispensing system via automatic machine in Thailand by focusing on the market feasibility and law and regulatory feasibility. The legal and regulatory feasibility study used several approaches, including literature review, finding information from the internet, books, journals, conference documents, reports, and other documents, with an emphasis on implementation in Thailand. As for the market feasibility study, a questionnaire was used to collect data from the target sample. The questionnaire was structured into 6 main sections including demographic and geographic data, behavior and experience in using pharmacy services, opinions on remote drug dispensing systems via automatic machines, factors affecting the use of remote drug dispensing systems, concerns about using remote drug dispensing systems, and additional comments and suggestions. The questions were designed to comprehensively understand user's demands, problems, and feasibility of using the system in Thailand. Five-level Likert scales responses were used to measure opinions and concerns. Open-ended questions were also included to allow respondents to provide detailed feedback. Google Forms was chosen for the survey because it was accessible and easy to use, enabling efficient data collection from the target sample, who were mostly located in Thailand.

3.2 Questionnaire Validation

The questionnaires used in research must normally be reviewed for suitability before using in research. This research invited 3 experts in related fields to review. All questions used in the research will be sent to each expert for checking. The scoring criteria are 3 levels: +1, 0, and -1 as follows: +1 means the content can clearly measure the objectives, 0 means the content is unclear, and -1 means the content cannot clearly measure the objectives. The following equation was used to analyse each question and calculate the average score, which is also known as item objective congruence (IOC).

$$
\begin{array}{llll}
 & \text{IOC} & = & \Sigma \text{R} / \text{N} \\
\text{Where} & \text{R} & = & \text{the score of individual experts} \\
 & \text{N} & = & \text{Number of Experts}
\end{array} \tag{1}
$$

An IOC value of greater than or equal to 0.5 is necessary for a useful questionnaire (Turner & Carlson, 2003). Questions with an average score less than 0.5 were considered unacceptable and they will be eliminated from the questionnaire. However, the evaluation results demonstrated that all questions had an IOC value greater than 0.5, none of the questions were eliminated. In addition, the comments and suggestions from those experts were used to improve the questionnaire before use.

3.3 Questionnaire Reliability

After the questionnaire was reviewed and revising according to the part of questionnaire validation, the questionnaire was pilot tested with the first 30 participants to assess the reliability, according to the Cronbach's alpha formula:

$$
\begin{array}{llll}
 & \alpha & = & \frac{K}{K-1}\ 1 - \{ \frac{\Sigma S_i^2}{S_t^2} \} \\
\text{Where} & \text{K} & = & \text{the number of scale items} \\
 & S_i^2 & = & \text{the variance associated with each item} \\
 & S_t^2 & = & \text{the variance associated with the observed total scores}
\end{array} \tag{2}
$$

The range of the Cronbach's alpha coefficient is 0 to 1 (George & Mallery, 2019). The calculations found that the questionnaire had excellent reliability with a Cronbach's alpha coefficient of 0.9065.

3.4 Identifying Population and Sample

The study of the feasibility of the remote drug dispensing system via automatic machine studied the population living in Thailand who were consumers using the services of hospitals or pharmacies. The researcher used the assumption that every Thai person above the age of 20 have used the pharmacies or hospital services by themselves. Based on information statistics released by the announcement of the Office of the Civil Registration Administration, the Royal Gazette states reports that total population registered across Thailand as of December 31, 2023 was 66,052,615 people (Thai Government Gazette, 2024). After excluded those under 20 years old, the population is left with 14,729,578 people based on the statistics. Taro Yamane's formula was used to calculate the number of respondents required for this study (Yamane, 1967), as following:

	n	=	N / (1+Ne^2)	
Where	n	=	Sample size	(3)
	N	=	Population size	
	e	=	Margin of error (expressed as a decimal)	

The margin of error for this research, with a confidence value of 95 percent, is 0.05 (e = 0.05).
n = 51,323,037 / [1 + 51,323,037 (0.05)2]
n = 400

The calculations found that the total sample size was 400, with an expected rejection rate of 10%. Based on the rejection rate, an additional 40 respondents were required, resulting in a minimum of 440 respondents.

3.5 Data Analysis

Descriptives statistics were used to analyze the data in this study. The questionnaire responses were used a 5-level Likert scale, the scores will be assigned according to the following levels:

Level	Score
Strongly agree / Major affect / Extreamly concerned	5
Partially agree / Moderate affect / Moderately concerned	4
Neither / Neutral / Somewhat concerned	3
Partially disagree / Minor affect / Slightly concerned	2
Strongly disagree / No affect / Not at all concerned	1

Figure 3.1: *5-level Likert scale*

Each question with 5-level Likert scale answer format was calculated to find mean and interpreted according to the following absolute criteria (Best J, 1981):
4.51 – 5.00 = Strongly agree / Major affect / Extreamly concerned
3.51 – 4.50 = Partially agree / Moderate affect / Moderately concerned
2.51 – 3.50 = Neither / Neutral / Somewhat concerned
1.51 – 2.50 = Partially disagree / Minor affect / Slightly concerned
1.00 – 1.50 = Strongly disagree / No affect / Not at all concerned

4 RESULT

4.1 Market feasibility

Of the 474 respondents who met the criteria, 36.5% were in the range of 30 – 39 age and 63.29% were women. Most respondents resided in the northern and central regions of Thailand, with the majority residing in Chiang Mai (24.89%) and Bangkok (21.94%). The 30 – 39 age group was the largest group of respondents, while the age group above 59 was the smallest. In terms of occupation, 34.03% were business owners, followed by company employees (28.57%), and other participants included government officials, students, unemployed, agriculturists, freelance, and investor. More than 50% of the respondents had a bachelor's degree or higher, and 37.97% had an in income between 20,000 THB and 29,999 THB per month.

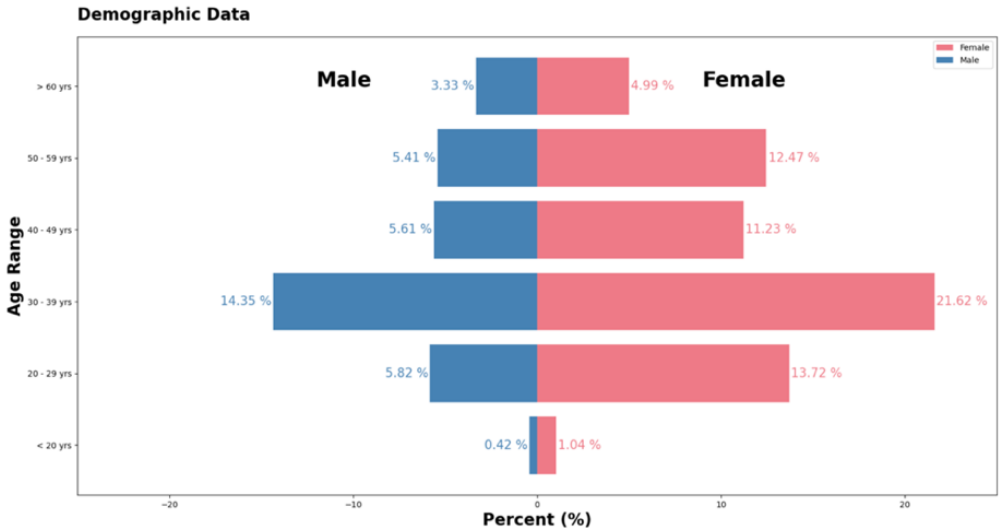

Figure 4.2: *Age and gender of the respondents*

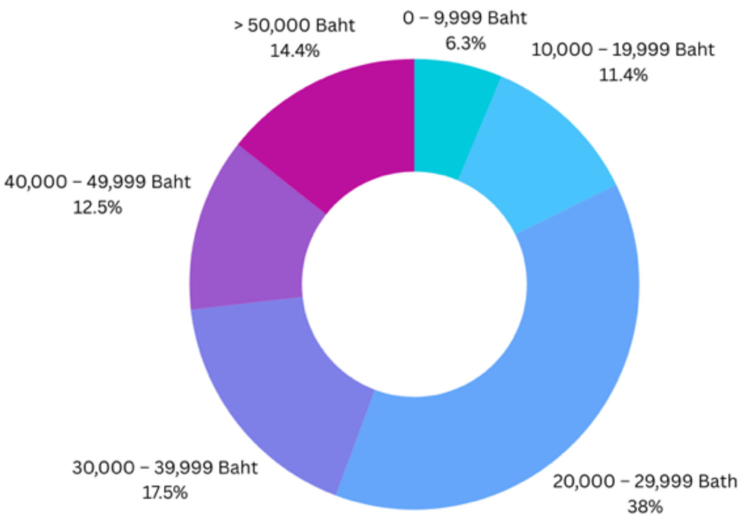

Figure 4.3: *Income per month of the respondents*

The majority of respondents used the pharmacies 1-3 times per month (44.51%) or once a week (32.28%). The last visit was mostly within the past week (46.20%). Most respondents resided within 0 – 1 km (48.31%) of pharmacy, while only a minority of respondents lived 10km or more (7.38%). The majority of respondents spent between 200 – 399 THB (32.07%) per visit, buying items such as modern medicines (28.35%), household remedies (24.04%), and

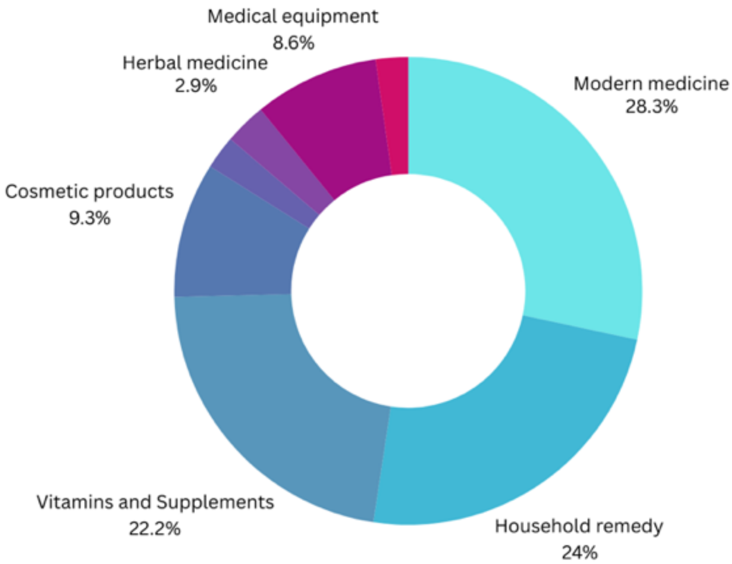

Figure 4.4: *Income per month of the respondents*

vitamins and supplements (22.20%). If the medication that the respondents most frequently purchase are divided by medication category, antihistamine or anti-allergy were purchased the most frequently (17.63%), followed by pain killer (16.57%), muscle relaxants (16.00%), and cold and flu medicine (13.57%). The most frequent time of visit to the pharmacy was between 18.01 – 21.00 PM (41.77%), which may have been due to their convenience after work.

The majority of respondents partially agreed with the introduction of automatic dispensing machine in Thailand (40.30%). They also believed that these machines could dispense medications accurately (35.86%), were safe (36.08%), and were convenient (40.30%). Many respondents also agree that such systems would be particularly useful in rural areas (39.45%) and could reduce waiting times in pharmacies or hospitals (43.36%). The average overall response indicated a positive attitude towards the introduction of these systems, although they still had some concerns about the system, as show in figure 4.6. Respondents had high continence in purchasing household remedy (21.94%), vitamins and supplements (20.94%), cosmetic products (15.40%), modern medicine (13.76%), weight loss products (12.9%), herbal medicine (9.34%), medical equipment (3.56%), and consumer products (2.02%), respectively. Figure 4.7 illustrates the main factors affecting usage of remote drug dispensing system via automatic machine were product quality (48.95%), consultation with a pharmacist (40.30%), contact channels (41.56%) and service hours (42.19%). Additional factors such as variety of product, brand of product, price, location, parking, and language options were considered to have moderate influence. However, the mean values for all the factors can be interpreted as moderate affect. Open-ended answers highlighted other factors that affected the usage of the system such as machine stability, contacts channels in case of problems, display of expiration dates, and drug allergies. Figure 4.8 indicates factors affecting concerns when using the system, the majority of respondents indicated that side effects (42.19%), accuracy (38.82%), shelf-life of product (41.35%), and quality of product (42.41%) were the most concerning factors. Other concern factors included personal data security (38.82%), pharmacist consultation (41.35%),

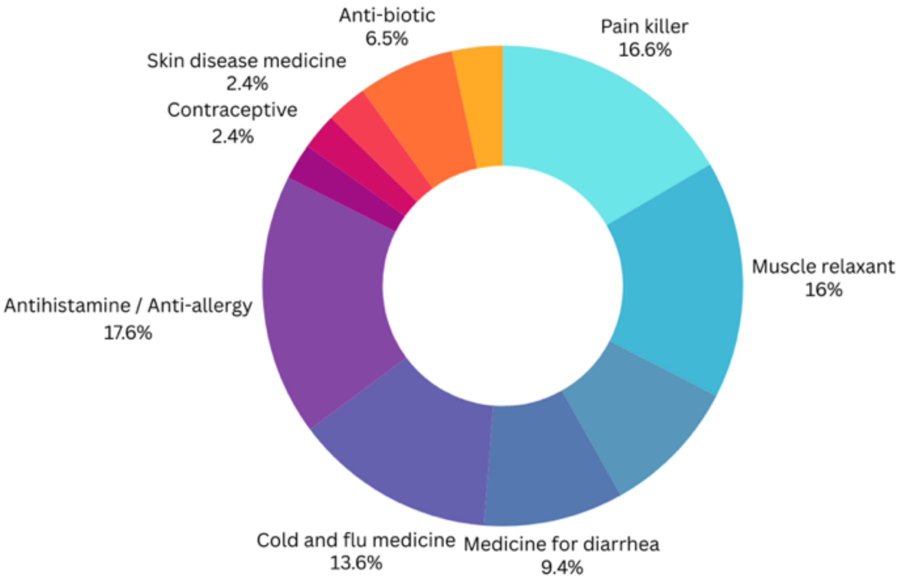

Figure 4.5: *Income per month of the respondents*

and contact after purchasing (38.40%). Respondents were also concerned about dispensing incorrect products, personal data security, and possible malfunctions of the machine. They emphasized the need for clear contact channels and mechanisms for returns or refunds if any problems occur. The final part of the questionnaire asked respondents to provide suggestions for improving remote drug dispensing system via automatic machine on open-ended question. Key recommendations included providing 24/7 real-time online pharmacist consultations, systems to check drug interactions and allergies, and spaces around the machines for maintaining privacy during use. Some respondents suggested limiting the automatic dispensing machine to common household drug, test kits, medical items, or consumer products, rather than prescription medicines. They concern about the system' suitability for dispensing prescription medicines without in-person pharmacist supervision. Some respondents recommended the integration of a system with a mobile app or other system for a better user experience, providing clear medication information, check medication history, prevent drug interaction, allergy alerts, along with an option to store user medical profiles and past purchases. Overall, although respondents recognized the potential benefits of the system such as increased convenience and accessibility, they also emphasized the importance of addressing technical, security, and regulatory issues to ensure that these systems meet the high standards required for healthcare service.

4.2 Law and regulatory feasibility

Although the automatic drug dispensing system via automatic machine is beneficial to consumers, the implementing in Thailand must follow Thai law and regulatory. One important law to regulate the dispensing of medications to patients or recipients is Drug Act B.E. 2510 (1967) ("Drug Act B.E 2510," 1967). This Act clearly defines "drugs" by covering substances used to diagnose, treat or prevent diseases in humans or animal, including chemicals used

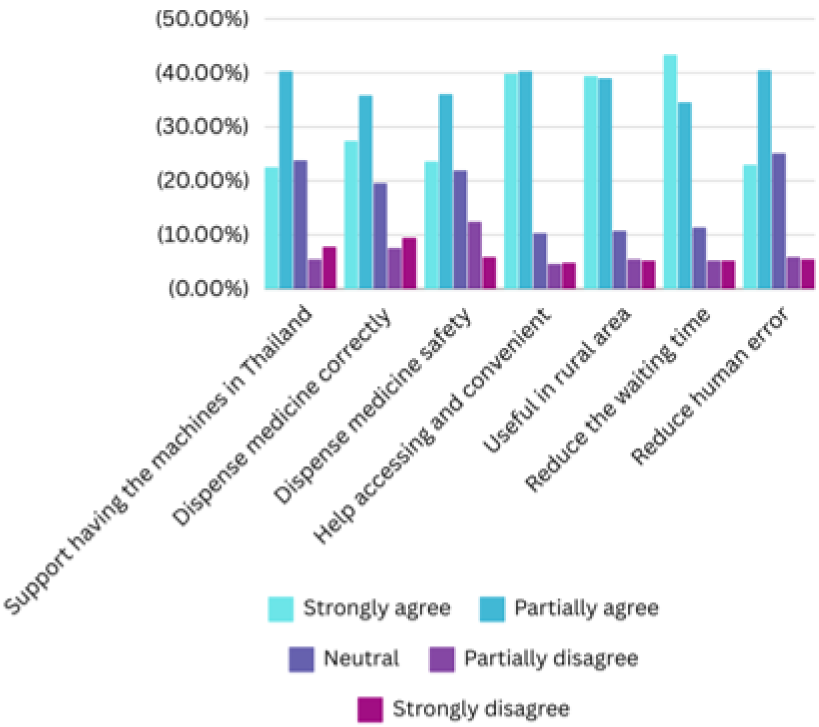

Figure 4.6: *Opinion on remote drug dispensing system via automatic machines*

in pharmaceuticals. Drugs are classified into several categories according to Section 4 in this Act, including modern drugs, traditional drugs, dangerous drugs, common household drugs, specially controlled drug, external use drug, site-specific drug, herbal drug, ready-packed drug, and pharmaceutical chemical. Additionally, the definition of "sale" is also clearly defined, that means retail, wholesale, dispensing, distributing, and even possession for commercial purposes. Therefore, the remote drug dispensing system via automatic machine must comply with this Act according to the definition of selling and dispensing medicine. Section 21 states that selling and dispensing medicines must have a first-class or second-class pharmacist who get licensed by the Pharmacy Council of Thailand on duty during business hours for complying with section 39 (for first-class pharmacists) or section 40 (for second-class pharmacists). This Act also mentioned about duties of licensed pharmacists. Responsibilities of pharmacists related to remote drug dispensing system via automatic machine include to exercise control over the separation of drugs, labeling in accordance, sale of drugs to ensure compliance, delivery of dangerous or specially controlled drugs or prescription drugs, and to provide labels on containers or packages of medicines. These roles requires that only licensed pharmacists can sell and dispense drugs to patients or service recipients.

To ensure that all medication sales and dispensing comply with this law, a new technology called "Telepharmacy" has been integrated into the system and automatic machines. This technology allows pharmacists to remotely monitor and control the sale and dispensing of medicines, including dangerous drugs. Telepharmacy not only addresses compliance issues by involving pharmacists in the dispensing process, but also increases patient access and convenience. It allows patients to consult with pharmacists in real time, receiving expert

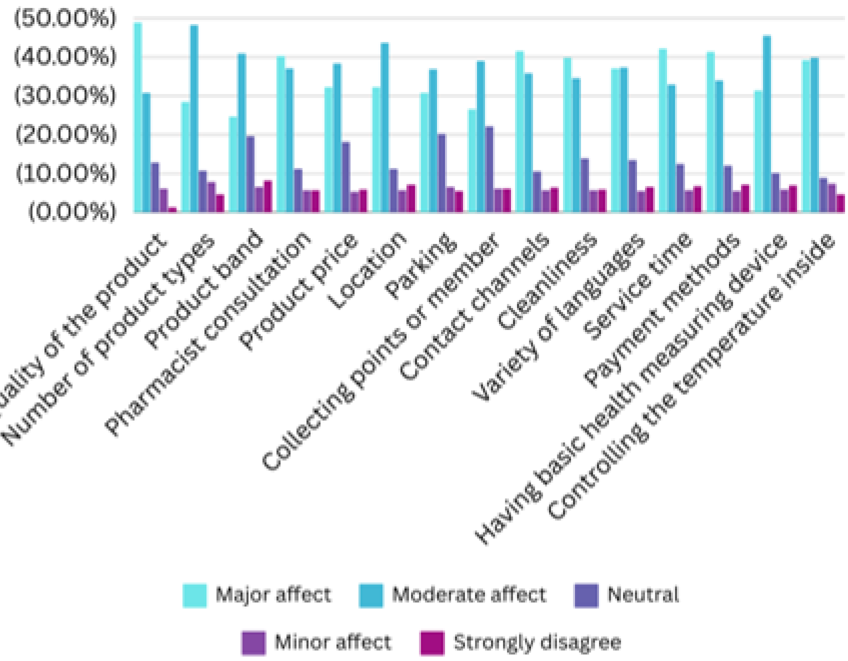

Figure 4.7: *Factors affecting the use of remote drug dispensing system via automatic machine*

advice and guidance on drug use, possible side effects, drug interactions, and so on, with out having to visit a pharmacy in person. However, the use of this technology into the system must comply with regulation issue by the Pharmacy Council of Thailand, as announced on June 2, 2020 (The Pharmacy Council of Thailand, 2020). This announcement consists of standards for remotely pharmacy service and telepharmacy procedures. The standards for remotely pharmacy services requires pharmacists to provide consultations, collect patient information, and analyze prescriptions, including assessment of drug appropriateness, drug interaction risk, and adverse drug reactions. The comprehensive systems are required to follow this regulation including a system for patient registration, patient profile, medical records, voice or video recording during consulting, a system to collect the patients' information, prescription analysis and find drug-related problems, and referral of patients to hospital. Furthermore, the standard also requires appropriate shipping standards to maintain drug quantities and stability including control temperatures, prevent lost medicine, and provide a tracking system to track the parcel. Telepharmacy procedures of telepharmacy service involves creating a patient registration and profile to maintain confidentiality and allow the pharmacist to access the patient's health information. The Pharmacist receives prescriptions from patient via the system, verify patient registration, provide appropriate telepharmacy according to the previously mentioned standard, and make an appointment for parcel delivery. Patients must confirm their name matches the registered name and prescription. If they are relatives, they have to demonstrate their delegation. Then, the pharmacist explains medical information, including medicine names, usage instructions, cautions, and warnings. The pharmacist needs to provide patient profiles, medical records, voice or video recording, and follows up on medication results.

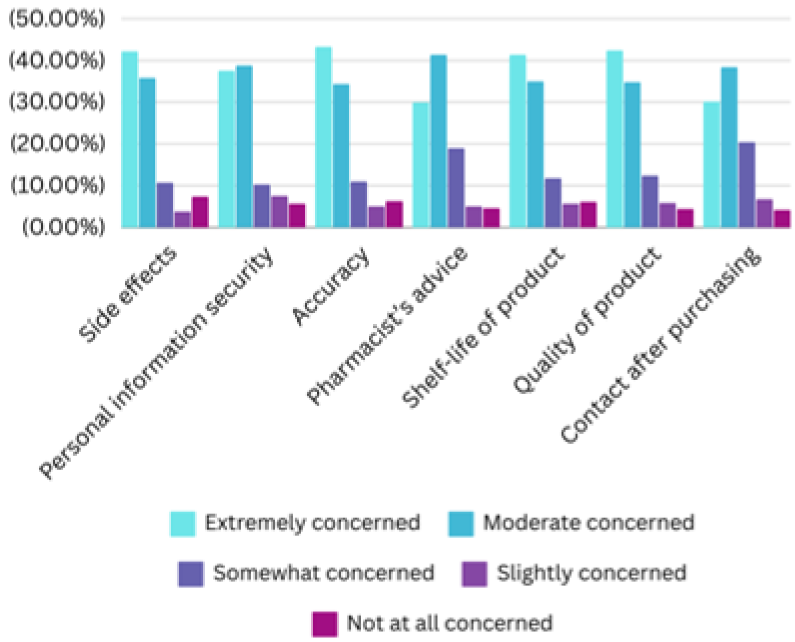

Figure 4.8: *Factors affecting concern when using remote drug dispensing system via automatic machine*

5 CONCLUSION

This framework highlights key components for remote pharmacy system implementation, with an emphasis on market feasibility and legal and regulatory feasibility. Market feasibility encompasses user behavior, product preferences, needs, and location priorities, ensuring that the system is designed to meet user needs with a robust technology infrastructure. Legal and regulatory feasibility focuses on data security compliance, pharmacist involvement, and telepharmacy regulations, ensuring that the system operates within legal boundaries. Integration of patient profiles, voluntary consent, and secure recording methods ensure that the system complies with healthcare standards while maintaining user trust and safety. This framework emphasizes the need for a balanced approach that addresses both market needs and legal requirements for successful implementation. Utilizing the knowledge gained from the market feasibility study and the legal and regulatory feasibility study, it was determined that the remote drug dispensing system via automatic machine could be effectively implemented in Thailand. The market feasibility study found high demand from respondents who frequently use pharmacies and want convenient access to medicines. However, this market feasibility study only considered a certain population, which was mainly in the North and Central regions, makes it inapplicable to other regions of the country. The study includes potentially biased demographics, with the majority of respondents being business owners or well-educated employees. It is unclear how well our results represent the needs or opinions of potential users with low incomes or low education. To be accurate and appropriate for the demands of the target group, another market feasibility study should be conducted at the location where the machine will be installed. A remote drug dispensing systems can be legally and effectively by integrating telepharmacy technology with the system for pharmacist consultations. In

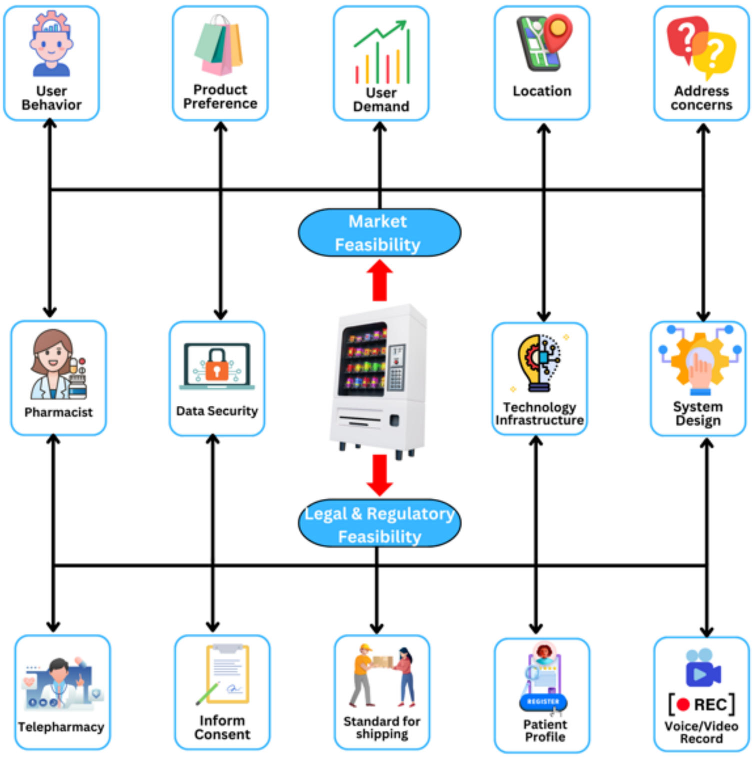

Figure 5.9: *Conceptual framework*

addition, the system requires other technologies to comply legal requirements, such as patient registration systems, medical records, patient profiles, audio or video recording, temperature control system, prescription analysis, and system to get consent form patients. However, further feasibility studies are still required to investigate other fields such as technical feasibility, financial feasibility, cultural feasibility, managerial feasibility, technical feasibility and economic feasibility. This study does not clearly describe the components, technologies, or methods of integration into the system. The study makes a major contribution to the market feasibility, with little attention given to the financial and technical components that would make the project overall sustainable. Security and privacy concerns are certainly important, but need to discuss in more detail how we will address these issues, especially since we are talking about medical data, which is much more sensitive than the other types of data. These are the areas that need to be improved to ensure that the system works properly in the future.

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