pISSN: 1906 - 3296 © 2020 AU-GSB e-Journal.
eISSN: 2773 – 868x © 2021 AU-GSB e-Journal.
http://www.assumptionjournal.au.edu/index.php/AU-GSB/index

Driving Factors of Behavioral Intention to Use Japanese Language Learning Apps Among Non-Japanese Major Students in Chengdu, China

Jingyi Zhang*

Received: October 17, 2023. Revised: February 19, 2024. Accepted: February 22, 2025.

Abstract

Purpose: The study analyzes the factors affecting non-Japanese major students' behavioral intention to use Japanese learning apps in Chengdu, China. A conceptual framework comprises three theoretical models and seven variables, which are perceived enjoyment, perceived usefulness, perceived ease of use, attitude, task-technology fit, information quality, and behavioral intention. **Research design, data, and methodology:** A quantitative approach was employed to survey a sample of 500 non-Japanese major students from eight universities situated in Chengdu. Prior to data collection, the study utilized the Item-Objective Congruence (IOC) index and conducted a pilot test with a sample of 50 participants to establish the validity and reliability of the research tools. Subsequently, the collected data were subjected to analysis through the application of confirmatory factor analysis (CFA) and Structural Equation Modeling (SEM). **Results:** Perceived enjoyment has a significant influence on perceived ease of use. Perceived enjoyment and percived ease of use significantly influence perceived usefulness. Perceived usefulness and percived ease of use significantly influence attitude towards behavioral intention. Additionally, task-technology fit and information quality significant influence behavioral intention. **Conclusion:** Ultimately, prioritizing the user experience is paramount to ensure that the Japanese language learning app's interface design, functional operation, and content presentation align with user expectations and needs, thus elevating overall user satisfaction.

Keywords: Japanese Learning App, Perceived Enjoyment, Perceived Usefulness, Attitude, Behavioral Intention

JEL Classification Code: E44, F31, F37, G15

1. Introduction

One of the most important factors that China's higher education institutions consider when it comes to foreign language instruction is the development of their students' overall quality and knowledge. Japanese is regarded as the most prevalent language in the country, and its importance is growing as the country and Japan expand their communication. According to the "2018 Survey Results of Overseas Japanese Language Education Institutions" released by the Japan International Exchange Fund in 2019, the number of Japanese learners in China has reached 1,004,625 (Shimauchi, 2018).

In terms of the number of people who learn Japanese in China, it is ranked first globally. Also, the country's researchers and teachers account for over a quarter of the world's total. Therefore, it can be seen from the figures alone that the number of Japanese learners and Japanese teachers in China occupies the first place in the world (Zhao, 2020). In major universities in China, Japanese is offered as a second language for students studying other languages. It can also be used in various academic programs, such as general studies and Japanese culture.

According to the statistics of the Southwest Branch of the

1*Jingyi Zhang, Southwest Minzu University, China. Email: momoko391@126.com

China Association of Japanese Language Teaching and Learning, there are 24 universities in Sichuan Province offering college Japanese, Japanese as a second foreign language, and other Japanese-related courses, including Sichuan University, University of Electronic Science and Technology, Southwest Jiaotong University, Southwest University for Nationalities, Xihua University, Chengdu University of Technology, Sichuan Normal University. Chengdu College of Sichuan International Studies University, Chengdu University of Traditional Chinese Medicine, Sichuan University of Light Chemical Engineering, Yibin College, Southwest University of Science and Technology, Leshan Normal College, Sichuan Tourism College, Sichuan International Vocational College and Chengdu University have more than 5,000 students studying Japanese (Yoshikawa, n.d.).

Besides the usual universities, several training and educational institutions are related to Japan. These include the Shinkansen Japanese, Ohara Japanese, and Kaguru Japanese. Around 20,000 learners are studying Japanese in the province. The field of education has become more complex due to the increasing number of network technology applications. One of the most popular methods of learning is through mobile learning. This type of technology is very portable and can be used by students at various levels. Developing effective and high-quality mobile learning apps in Japan is very important for the country's students. Japanese learning apps allow users to learn at their own pace and time, and they can take advantage of their available time. They can also arrange their learning according to their needs, allowing them to develop active learning capabilities. Besides being able to learn at their own pace, these apps can additionally supplement the learning materials that they have been taught in class (OECD, 2015).

Japanese learners have used various learning apps such as Bilibili App, Hujiang Online School, and Moji Japanese Learning. The most downloaded Android app is Hujiang Online School, while the other two are Bilibili App and Moji Japanese Learning. According to a study by Hu and Li (2020), learning software should enhance its functions and content to achieve continuous and systematic learning. Despite the country's rapid growth in this field, more academic studies on online learning in China need to be conducted. According to the country's leading academic website, the CNKI, there were 19,028 research findings related to this subject as of August 2022. These results are mainly comprised of qualitative research and few quantitative studies (Guo & Wan, 2022).

Through quantitative research, limited surveys and analyses are conducted using the Structural Equation Model and the Confirmatory Factor Analysis. When we searched "Japanese," we discovered only 64 papers related to online and Japanese learning. Most of these studies focused on the integration mode of these two types of learning. This study analyzes the factors influencing the development and usage of Japanese learning apps in universities. It also aims to provide references for the design and development of similar learning software. The study is primarily focused on non-Japanese major students within universities. It aims to investigate the key factors that influence the development of learning apps and their usage in educational institutions. In addition, this research will provide references for the design of similar learning software.

2. Literature Review

2.1 Perceived enjoyment

Liaw (2008) noted that increasing people's enjoyment of using a system could improve its acceptability. PE stands for intrinsic motivation. In addition, the researchers noted that intrinsic motivation is related to enjoyment (Ryan & Deci, 2000). Park et al. (2012) noted that intrinsic motivation motivates individuals to act for satisfaction. They also stated that people tend to choose actions for their enjoyment. Activities that are related to a certain system are enjoyable. According to Benmessaoud's group, PE played a significant role in the advancement and growth of information technology (Benmessaoud et al., 2011). Venkatesh (2000) noted that perceived enjoyment refers to the pleasure of using a particular system without considering its possible performance consequences. Venkatesh (2000) noted that PE indirectly affects the choice of a system by influencing the users' attitudes. Huang et al. (2007) noted a causal link between attitude and PE. According to Ward and Abdullah and Ward (2016), perceived enjoyment relates to the perceived usefulness and ease with which people use e-learning software. The study's findings revealed that perceived enjoyment was associated with increased students' willingness to learn using e-learning tools (Hasan et al., 2016). The study also noted that when students are involved in e-learning activities, the convenient facilities are more likely to have favorable effects on perceived ease of use (Siron et al., 2020). Thus, this study indicates that:

H1: Perceived enjoyment has a significant influence on perceived usefulness**.**

H2: Perceived enjoyment has a significant influence on perceived ease of use.

2.2 Perceived ease of use

Researchers claim that the concept of PEOU refers to a level of expectation that learners have when using an online education program (Qin et al., 2019). According to Lee et al. (2007), PEOU can be used as a predictor of consumer trust in mobile commerce. The study also noted that people's perception of ease of use relates to their belief that technology is easy to use (Veríssimo, 2016). A study revealed that certain factors, such as PI, PEU, and SI, can positively affect ATT (Vahdat et al., 2021). Renny et al. (2014) and Suki (2011) obtained similar results in studies in Indonesia and Malaysia, respectively. In a study conducted, Chawla and Joshi (2019) noted that perceptions about ease of use can predict users' intentions toward technology adoption. According to Yip et al. (2020), in the context of technology acquisition management (TAM), the perception of a tangible embodiment of operational excellence (PEOU) significantly affects the PU of consumers. A study conducted in 2017 by Abbas revealed that the perception of PEOU is related to the perceived usefulness of PU. It also directly affects consumers' attitudes toward using e-learning systems (Liu et al., 2009). Studies show that people cultivate a favorable mindset when adopting new technology by developing a sense of ease. Thus, this study indicates that:

H3: Perceived ease of use has a significant influence on perceived usefulness.

H5: Perceived ease of use has a significant influence on attitude.

2.3 Perceived usefulness

According to Davis et al. (1992), the primary determinant of an individual's choice to use a computer is the belief that it is essential. They also stated that the degree to which people hold this belief influences their choice. The level of belief that people have about the advantages of using a computer is also influenced by their expectations of how it will improve their task performance (Bhattacherjee & Sanford, 2006). A few studies also suggest that individuals' level of belief regarding the advantages of using computers influences their behavior (Renny et al., 2014). The philosophy of personal conduct is also related to students' educational attainment by using a particular educational strategy to improve their scholarly achievements (Huang & Liaw, 2018). According to researchers, the perceived usefulness of a technology is related to an individual's belief that it can help them improve their work performance (Salloum et al., 2019). Several studies have also shown that the perceived usefulness of a technology is related to the level of belief that it can help an individual improve their research and academic performance (Rezvani et al., 2022). Technology's perceived usefulness can also affect individuals' attitudes toward using information systems (Teo & Lee, 2010). The researchers noted that users can develop a positive outlook toward new technology if they are convinced it will meet their requirements and benefit them (Rosen et al., 2013). Thus, this study indicates that:

H4: Perceived usefulness has a significant influence on attitude.

2.4 Attitude

Researchers believe that an individual's subjective evaluation of an object can lead to a psychological tendency known as attitude (Eagly & Chaiken, 1993). Bashir and Madhavaiah (2015) stated that an individual's attitude toward using the Internet is influenced by their positive or negative experiences. According to Kuehn (2008), a study revealed that previous experiences influence an individual's attitude. Past experiences often trigger this tendency to respond negatively or positively to behavior. Recent studies have shown that ATT significantly influences user interest formation (Buabeng-Andoh, 2021). The degree to which an individual exhibits either a favorable or unfavorable outlook on e-learning is called attitude (Hussein, 2017). Other researchers also noted that attitude affects PEOU and PU users' intentions when accessing online services (Bashir & Madhavaiah, 2015). Thus, this study indicates that:

H6: Attitude has a significant influence on behavioral intention.

2.5 Task-Technology Fit

Task technology fit (TTF) refers to the degree to which a technology helps users complete their tasks (Goodhue & Thompson, 1995). Gebauer and Ginsburg (2009) defined the concept of task-technology fit as the requirement that a user only accepts a given tech if it fulfills their specific needs and enhances their performance. The extent to which a user is provided technical assistance to complete their tasks is referred to as TTF (Hsiao, 2017). Other researchers also discovered that TTF refers to the level at which a system matches the users' satisfaction (Al-Ammary et al., 2014). A study by Yuan et al. (2010) noted that the task-technology fit concept has been utilized in the mobile technology industry. Through the TTF model, various studies have been conducted on the effects of technology adoption and utilization (Wan et al., 2020). The study looked into the factors that influence students' MOOC adoption. The study's findings revealed that the TTF model had a favorable correlation with BI (Khan et al., 2018). Thus, this study indicates that:

H7: Task-technology fit has a significant influence on behavioral intention.

2.6 Information quality

The user determines the information quality. This is the degree to which they believe the information they receive is correct and timely (DeLone & McLean, 2003). Lin and Lu

(2000) noted that information quality could be used as a factor that helps predict the ease of use or usefulness of a given information. In studies, researchers have noted that the quality of information can be measured by the extent to which consumers get complete and accurate information from electronic interfaces (Liu et al., 2010). According to some studies, an information quality rating is determined by the degree to which users find the information to be complete, timely, accurate, and relevant (Kahn et al., 2002). The measurement criteria for information quality include the presentation format, accuracy, circulation, and consistency (Ahn et al., 2004). According to Lin (2011), the quality of information an e-commerce site provides will affect its effectiveness. Some researchers believe that the quality of information can be a key factor in the measurement process (DeLone & McLean, 2003). Ramayah et al. (2010) noted that a high-quality information system can increase the users' willingness to use the services offered. However, if the system's content needs to be clearer and complete, users might not trust the system and could start thinking it is unreliable, decreasing their intention to use it. Thus, this study indicates that:

H8: Information quality has a significant influence on behavioral intention.

2.7 Behavioural Intention

Some researchers have used behavioral intention to describe an individual's decision to accept a certain system's cognitive presentation (Asadi et al., 2017). A person's behavioral intention is determined by whether they intend to behave in a particular way in the future (Cigdem & Ozturk, 2016). According to Ho et al. (2015), use-based intent refers to an individual's eagerness to carry out a certain action. A positive correlation has been found between the effectiveness of online education and an individual's behavioral intention (Liaw, 2008). According to Soon and Kadir (2017), having a higher level of behavioral intention can improve the teaching effectiveness of online education. Huang et al. (2007) noted that perceived usefulness can benefit an individual's behavioral intentions. Further research also indicated that business intelligence can benefit the utilization of mobile learning (Alenezi et al., 2011).

3. Research Methods and Materials

3.1 Research Framework

The theory seeks to explain reality and aid researchers in identifying the link between different elements (Blaxter et al., 2010). Technology acceptance is widely used in the study of information systems. It is a well-understood and practical theoretical model(King & He, 2006). The paper presents a revised conceptual framework based on three primary theories: the technology acceptance model, the information ecology model, and the task technology adaptation model. This study aimed to develop a conceptual framework that can be used to investigate the various factors that influence the behavioral intention of non-Japanese language learners when it comes to using Japanese learning apps.

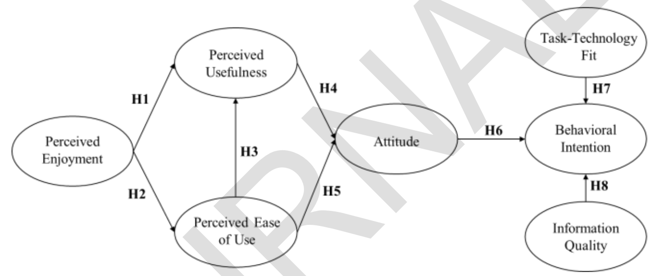

Figure 1: Conceptual Framework

H1: Perceived enjoyment has a significant influence on perceived usefulness.
H2: Perceived enjoyment has a significant influence on perceived ease of use.
H3: Perceived ease of use has a significant influence on perceived usefulness.
H4: Perceived usefulness has a significant influence on attitude.
H5: Perceived ease of use has a significant influence on attitude.
H6: Attitude has a significant influence on behavioral intention.
H7: Task-technology fit has a significant influence on behavioral intention.
H8: Information quality has a significant influence on behavioral intention.

3.2 Research Methodology

Using the quantitative method of non-probability sampling, the researchers designed questionnaires and collected quantitative data from 8 universities in Chengdu with a sample size of about 600. Standardized questionnaires are used to measure specific concepts, statistical methods are used to analyze and interpret the collected data, and a variety of methods are used to verify and confirm the findings and determine the credibility and validity of the study.

The questionnaire consists of three parts: first, demographic questions, including age and gender; second part is the screening question, whether they are non-Japanese major students and whether they have used Japanese learning apps. Motl et al. (2007) argue that Likert scales are a good tool for assessing attitudes because they enable respondents to express how much they agree or disagree with a certain statement or set of assertions. Therefore, a Likert 5-scale question was used to measure seven variables, ranging from strongly disagree (1) to strongly agree (5), to analyze all eight hypotheses.

Prior to commencing data collection and distributing the questionnaires, the content validity of the questionnaire was rigorously evaluated by enlisting the expertise of three experts who conducted the Item-Objective Congruence (IOC) assessment. Additionally, a pilot test using Cronbach's Alpha was employed to confirm the content validity of the questionnaire. All items in the IOC evaluation surpassed the 0.6 threshold, demonstrating strong content validity. According to the criteria established by George and Mallery (2003), an acceptable level of reliability is indicated when Cronbach's Alpha exceeds 0.7. In this context, the pilot test, which included a sample of 50 participants, yielded Cronbach's Alpha values of 0.7 or higher for all constructs, thus affirming the questionnaire's reliability.

After validity and reliability tests. the researchers used statistical software to analyze the collected data. Firstly, the model's fitting degree, convergence validity, and discrimination validity were verified by confirmatory factor analysis (CFA) to ensure the validity and reliability of the model. Finally, the structural equation model (SEM) was used to test the path coefficients and direct, indirect, and total effects among the variables to verify the hypothesis.

3.3 Population and Sample Size

The target population is 3820 non-Japanese major students from eight universities situated in Chengdu. The minimum sample size should be around 200 samples. Thus, the researcher aims to collect 550 samples for the data analysis.

3.4 Sampling Technique

A purposive sampling was employed to survey a sample of non-Japanese major students from eight universities situated in Chengdu. Due to the pandemic's impact, the researchers contacted the member schools of the Southwest Branch of the Chinese Association of Japanese Language Teaching and Learning after completing the questionnaire design. For convenience sampling, the participants response to the teachers of Japanese language courses in the schools listed through WeChat and QQ. For quota sampling, the proportional sample size is determined to 550. From the total population of 3820, and 573 valid questionnaires were obtained after sorting.

Table 1: Sample Units and Sample Size

University	Population Size	Proportional Sample Size
Sichuan University	240	40
University of Electronic Science and Technology of China	260	40
Southwest Jiaotong University	220	40
Southwest University for Nationalities	400	80
Sichuan Normal University	240	40
Chengdu University of Technology	380	80
Xihua University	400	80
Chengdu College, Sichuan International Studies University, Sichuan	1680	150
Total	**3820**	**550**

Source: Constructed by author

4. Results and Discussion

4.1 Demographic Information

Among the 573 questionnaires, 516 students have used Japanese learning apps, accounting for 90.1% of the total. The highest age group is 18-20 years old, with 359 students, 62.7%, indicating that most students study college Japanese courses, mainly distributed in the first and second years. Students aged 20-22 also account for a relatively high proportion, with 196 students (34.2%). This part should be students learning Japanese as a second foreign language, mainly distributed in the junior and senior years. Since the second foreign language Japanese course is mainly aimed at non-Japanese majors, this is also reflected in the gender distribution. There are 397 female respondents, 69.3%, and 176 male students, accounting for 30.7%.

Table 2: Demographic Profile

Demographic and General Data (N=573)		Frequency	Percentage
Used Japanese learning APP	Yes	516	90.1%
	No	57	9.9%
Age	Under 18 years old	4	0.7%
	18-20 years old	359	62.7%
	20-22 years old	196	34.2%
	Over 22 years old	14	2.4%
Gender	Male	176	30.7%
	Female	397	69.3%

Source: Constructed by author

4.2 Confirmatory Factor Analysis (CFA)

In this study, the statistical software was used to construct a suitable CFA matrix according to the research purpose and research model, and the fit degree test verified the fit degree of the model to determine whether the model conforms to the actual data. Table 3 shows the factor load, AVE, and CR values of the data. Hair et al. (2010) believed the factor load value should be greater than or equal to 0.5. The composite reliability (CR) with an absolute value greater than or equal to 0.7 is considered significant. The observed variable with a high load value strongly correlates with the potential factor. In addition, Cronbach's Alpha exceeds 0.7 (George & Mallery, 2003). At the same time, Hair et al. (2013) believed that the average variance extracted value should range from 0 to 1, and greater than 0.5 is a sufficient degree of convergence validity.

Table 3: Confirmatory Factor Analysis Result, Composite Reliability (CR) and Average Variance Extracted (AVE)

Variables	Source of Questionnaire (Measurement Indicator)	No. of Item	Cronbach's Alpha	Factors Loading	CR	AVE
Perceived Usefulness (PU)	Davis et al. (1992)	3	0.848	0.726-0.953	0.869	0.692
Perceived Ease of Use (PEOU)	Davis (1989)	4	0.728	0.628-0.861	0.849	0.587
Perceived Enjoyment (PE)	Chao (2019)	4	0.715	0.703-0.887	0.881	0.652
Attitude (ATT)	Fishbein and Ajzen (1975)	3	0.810	0.701-0.909	0.835	0.631
Behavioral Intention (BI)	Fishbein and Ajzen (1975)	3	0.829	0.777-0.856	0.864	0.680
Information Quality (IQ)	DeLone and McLean (2003)	3	0.827	0.762-0.905	0.863	0.679
Task-technology Fit (TTF)	Gebauer and Ginsburg (2009)	4	0.757	0.618-0.841	0.842	0.574

Hair et al. (2007) pointed out that the confirmation factor analysis (CFA) matrix is the most effective method to determine and evaluate variables' performance. This study used seven criteria to evaluate and fit the model. It includes relative Chi-square (CMIN/df), Goodness of Fit Index (GFI), approximate root mean square error (RMSEA), Comparative Fit Index (CFI), structured fit index (NFI), Tuck-Lewis index (TLI), and Adjusted Goodness of Fit Index (AGFI).

Table 4: Goodness of Fit for Measurement Model

Fit Index	Acceptable Criteria	Statistical Values
CMIN/DF	<5.00（Al-Mamary & Shamsuddin, 2015; Awang, 2012）	2.971
GFI	≥0.85 (Sica & Ghisi, 2007)	0.908
AGFI	≥0.80 (Sica & Ghisi, 2007)	0.881
NFI	≥0.80 (Wu & Wang, 2006)	0.919
CFI	≥0.80 (Bentler, 1990)	0.944
TLI	≥0.80 (Pedroso et al., 2016)	0.933
RMSEA	<0.08 (Pedroso et al., 2016)	0.059
Model Summary		**In harmony with empirical data**

Remark: CMIN/DF = The ratio of the chi-square value to degree of freedom, GFI = Goodness-of-fit index, AGFI = Adjusted goodness-of-fit index, NFI = Normed fit index, CFI = Comparative fit index, NFI = Normed fit index, TLI = Tucker-Lewis index and RMSEA = Root mean square error of approximation

Discriminant Validity means that in statistical measurements, different constructs should be distinguished in the measurement tool rather than mixed (Zait & Bertea, 2011). Suppose there is a high correlation between the items of the measurement tool. In that case, it may lead to confusion between different isomorphisms, affecting the measurement results' accuracy and reliability. The AVE square roots of the variables in the discriminant value summary are enumerated diagonally, and the square root of AVE for each potential variable should be greater than the causal connection of the conceptual framework to any structure. For each potential variable, the AVE threshold needs to be at least 0.5 (Fornell & Larcker, 1981). As seen from the values in Table 5, each coefficient is smaller than the value of the square root of AVE on the diagonal, and AVE is greater than 0.5, so the differential validity of this study meets the standard requirements.

Table 5: Discriminant Validity

	PU	PEOU	PE	ATT	BI	IQ	TTF
PU	**0.834**						
PEOU	0.402	**0.766**					
PE	0.305	0.490	**0.807**				
ATT	0.307	0.373	0.476	**0.794**			
BI	0.358	0.642	0.714	0.468	**0.825**		
IQ	0.373	0.514	0.581	0.415	0.689	**0.824**	
TTF	0.053	0.096	0.152	0.047	0.150	0.153	**0.758**

Note: The diagonally listed value is the AVE square roots of the variables
Source: Created by the author.

4.3 Structural Equation Model (SEM)

After the analysis through the CFA matrix, it is evaluated in this section by a structural equation model to examine the correlation between exogenous and endogenous potential variables. Hair et al. (2010) believed that the reliability, convergence validity, and discriminant validity test results could be achieved through the structural model level after evaluating the two. This section used the following structural equation model evaluation indexes for fitting: CMIN/DF, GFI, AGFI, RMSEA, CFI, and TLI. The indexes evaluated the model's fitting degree, and the agreement between the model and the actual data was judged.

Table 6: Goodness of Fit for Structural Model

Index	Acceptable	Statistical Values
CMIN/DF	<5.00（Al-Mamary & Shamsuddin, 2015; Awang, 2012）	4.577
GFI	≥0.85 (Sica & Ghisi, 2007)	0.883
AGFI	≥0.80 (Sica & Ghisi, 2007)	0.850
NFI	≥0.80 (Wu & Wang, 2006)	0.872
CFI	≥0.80 (Bentler, 1990)	0.897
TLI	≥0.80 (Pedroso et al., 2016)	0.879
RMSEA	<0.08 (Pedroso et al., 2016)	0.079
Model Summary		**In harmony with Empirical data**

Remark: CMIN/DF = The ratio of the chi-square value to degree of freedom, GFI = Goodness-of-fit index, AGFI = Adjusted goodness-of-fit index, NFI = Normed fit index, CFI = Comparative fit index, NFI = Normed fit index, TLI = Tucker-Lewis index and RMSEA = Root mean square error of approximation

4.4 Research Hypothesis Testing Result

Khosrow-Pour (2008) pointed out that the structural model of SEM represents the causal link in the structure of the research framework. After the SEM model's running data, this study's hypothesis verification results were obtained, as shown in Table 7. As can be seen from the values in the table, the results show that all hypotheses are supported, and the standardized path coefficients and T-values are shown in Table 7.

Table 7: Hypothesis Results of the Structural Equation Modeling

Hypothesis	(β)	t-Value	Result
H1: PE→PU	0.473	11.659*	Supported
H2: PE→PEOU	0.135	2.922*	Supported
H3: PEOU→PU	0.277	4.995*	Supported
H4: PU→ATT	0.544	9.762*	Supported
H5: PEOU→ATT	0.173	3.890*	Supported
H6: ATT→BI	0.431	9.928*	Supported
H7: TTF→BI	0.075	2.031*	Supported
H8: IQ→BI	0.600	15.429*	Supported

Note: * p<0.05
Source: Created by the author

The standardization coefficient between PE and PU is 0.473, and the T-value is 11.659, which indicates that PE has a significant positive effect on PU in this part of the data. Lu et al. (2021) confirmed that when students participate in e-learning, users are more likely to have a positive attitude toward perceived usefulness if the system is convenient.

The standardization coefficient between PE and PEOU is 0.135, and the T-value is 2.922. This indicates that PE significantly affects PEOU in this data part, and H2 is supported. Fagan et al. (2008) conducted some studies, and the results showed that PE positively impacted PEOU when evaluating intrinsic motivation through PE.

The normalization coefficient between PEOU and PU is 0.277, and the T-value is 4.995, which indicates that PEOU has a significant positive effect on PU in this part of the data. Holden and Rada (2011) found that perceived ease of use positively impacts perceived usefulness.

The standardization coefficient between PU and ATT is 0.544, and the t value is 9.762, which indicates that PU has a significant positive impact on ATT in this part of the data. The researchers（Hu et al.，2022）found that when students think the product is useful, they will form a positive attitude when adopting it, further affecting their behavioral intention.

The normalization coefficient between PEOU and ATT is 0.173, and the T-value is 3.890, which indicates that PEOU has a significant positive impact on ATT in this part of the data. In their research, Liu et al. (2009) found that PEOU is positively correlated with people's attitudes toward using e-learning systems and has a direct impact.

The standardization coefficient between ATT and BI is 0.431, and the t value is 9.928, which indicates that ATT has a significant positive impact on BI in this part of the data. In recent years, some studies have shown that in terms of acceptance and use of information technology, attitudes will further affect users' behavioral intentions, thus promoting users' adoption results (Yu et al., 2020).

The standardization coefficient between TTF and BI is 0.075, and the T-value is 2.031, which indicates that TTF has a significant positive impact on BI in this part of the data. Khan et al. (2018) studied the factors influencing students' adoption of mobile learning, and the results showed that TTF had a positive and positive impact on BI adoption.

The normalization coefficient between IQ and BI is 0.600, and the T-value is 15.429. This means that IQ has a significant positive effect on BI in this part of the data, and H8 is supported. Mohammadi (2015) believes that information quality is an important factor affecting user intent.

5. Conclusion and Recommendation

5.1 Conclusion and Discussion

The study aimed to investigate the factors influencing students' behavioral intention to use Japanese learning apps in Chengdu, China. To accomplish this, a comprehensive conceptual framework comprising three theoretical models and seven variables, namely perceived enjoyment, perceived usefulness, perceived ease of use, attitude, task-technology fit, information quality, and behavioral intention, was employed. The results of this study provide insights into the determinants that shape students' intentions to use these language learning apps.

The findings of the study revealed a significant positive relationship between perceived enjoyment and perceived ease of use. This connection suggests that students who find the use of Japanese learning apps enjoyable tend to perceive these apps as easy to use. This is a critical observation because perceived ease of use can significantly impact a user's overall experience and willingness to engage with the technology. When students derive pleasure from using these apps, it likely makes the learning process more enjoyable, enhancing their motivation to use them frequently.

Perceived enjoyment and perceived ease of use were also found to exert a substantial positive influence on perceived usefulness. This result suggests that when students derive enjoyment from the learning experience and perceive it as easy, they are more likely to find the apps useful for their Japanese language learning goals. This highlights the importance of designing learning apps that not only facilitate the learning process but also make it enjoyable for users.

The study further revealed that perceived usefulness and perceived ease of use significantly influence students' attitude towards their intention to use Japanese learning apps. This finding underscores the critical role of these factors in shaping a positive attitude among users. Students who perceive these apps as useful and easy to use are more likely to have a favorable attitude towards continued use, which can ultimately impact their intentions to use the apps.

In addition to the variables related to user experience, this study also demonstrated the significance of task-technology fit and information quality in influencing behavioral intention. A positive relationship was observed between task-technology fit and information quality with students' intention to use these apps. This finding underscores the importance of ensuring that these apps align with the specific learning tasks and objectives of the students and provide high-quality, reliable information.

In conclusion, this study offers valuable insights into the factors affecting students' behavioral intention to use Japanese learning apps in Chengdu, China. The conceptual framework, which incorporated perceived enjoyment, perceived usefulness, perceived ease of use, attitude, task-technology fit, information quality, and behavioral intention, served as a robust model for examining these factors. The quantitative approach involving a sample of 500 non-Japanese major students provided comprehensive data for analysis.

The results of this study emphasized the significance of designing Japanese learning apps that prioritize the enjoyment and ease of use, as these factors positively influence perceived usefulness and attitude. Furthermore, ensuring that these apps align with students' specific learning tasks and provide high-quality information can enhance their behavioral intention to use them.

These findings have practical implications for the developers and educators in the field of language learning technology. To encourage the adoption and continued use of such apps, it is essential to focus on creating enjoyable and user-friendly experiences, emphasizing their usefulness, and tailoring them to meet the unique learning needs of the students. By addressing these factors, developers and educators can foster a more positive attitude among students and ultimately increase their intention to use Japanese learning apps for language acquisition.

5.2 Recommendation

The survey results involving students who are not majoring in Japanese studies indicate that all the hypotheses put forth in this study are supported. Consequently, the insights derived from this survey underscore the importance of comprehensively understanding user objectives, tailoring personalized learning experiences, and crafting features and content that cater to diverse user needs and interests when designing Japanese language learning applications.

To enhance the effectiveness of such applications, optimizing the interface, functionality, and overall usability is imperative to ensure a seamless and enjoyable learning experience for users. A straightforward, user-friendly interface, coupled with a robust user feedback mechanism, can significantly elevate user satisfaction levels. Moreover, it is crucial to provide content and features that are genuinely beneficial to users. Incorporating engaging and practical learning resources, exercises, and challenges can kindle user interest and drive more active app usage.

Effective feedback mechanisms should be integrated to provide users with timely insights into their learning progress, while the inclusion of reward systems can bolster user motivation. Building user trust in the application is essential by delivering accurate and reliable information and enhancing the quality of learning materials.

Ultimately, prioritizing the user experience is paramount to ensure that the Japanese language learning app's interface design, functional operation, and content presentation align with user expectations and needs, thus elevating overall user satisfaction.

5.3 Limitation and Further Study

Due to the epidemic's impact, the data collected in this study were all completed online, and there needed to be an on-the-spot explanation for the surveyed students, which inevitably resulted in certain deviations in the understanding of the questions. In the next step, through a detailed explanation and explanation of the survey questions, in-depth interviews with respondents can be conducted to understand the motivation, expectations, and experience behind users' use of apps and reveal more details.

Because the data for this study was collected between September 2022 and June 2023, it does not reflect the changes and attitudes of long-term users of the APP. The next step is a longitudinal study design that better tracks user changes to understand the evolution of their learning behaviors and attitudes. User behavior on the APP may be affected by various factors, and a single factor may not fully explain user behavior. At the same time, the user's motivation and experience of using an APP will also be affected by many external factors, such as personal interests, learning goals, etc., which may need to be fully considered. The next research needs to combine quantitative and qualitative data to analyze users' actual behaviors on the APP and explore their behavior patterns and habits.

References

Abbas, T. M. (2017). Human factors affecting university hospitality and tourism students' intention to use e-learning: A comparative study between Egypt and the UK. *Journal of Human Resources in Hospitality & Tourism, 16*(4), 349-366. https://doi.org/10.1080/15332845.2017.1266866

Abdullah, F., & Ward, R. (2016). Developing a General Extended Technology Acceptance Model for E-Learning (GETAMEL) by analysing commonly used external factors. *Computers in human behavior, 56,* 238-256. https://doi.org/10.1016/j.chb.2015.11.036

Ahn, T., Ryu, S., & Han, I. (2004). The impact of online and offline features on the user acceptance of Internet shopping malls. *Electronic Commerce Research and Applications, 3*(4), 405-420. https://doi.org/10.1016/j.elerap.2004.05.001

Al-Ammary, J. H., Al-Sherooqi, A. K., & Al-Sherooqi, H. K. (2014). The acceptance of social networking as a learning tool at University of Bahrain. *International Journal of Information and Education Technology, 4*(2), 208-214. https://doi.org/10.7763/ijiet.2014.v4.400

Alenezi, A. R., Karim, A. A., & Veloo, A. (2011). Institutional support and e-learning acceptance: An extension of the technology acceptance model. *International Journal of Instructional Technology and Distance Learning, 8*(2), 3-16.

Al-Mamary, Y. H., & Shamsuddin, A. (2015). Testing of The Technology Acceptance Model in Context of Yemen. *Mediterranean Journal of Social Sciences, 6*(4), 1-10. https://doi.org/10.5901/mjss.2015.v6n4s1p268

Asadi, S., Nilashi, M., Husin, A. R. C., & Yadegaridehkordi, E. (2017). Customers perspectives on adoption of cloud computing in banking sector. *Information Technology and Management, 18*(4), 305-330. https://doi.org/10.1007/s10799-016-0270-8

Awang, Z. (2012). *Structural equation modeling using AMOS graphic* (1st ed.). Penerbit Universiti Teknologi MARA.

Bashir, I., & Madhavaiah, C. (2015). Consumer Attitude and Behavioral Intention Towards Internet Banking Adoption in India. *Journal of Indian Business Research, 7*(1), 67-102. https://doi.org/10.1108/JIBR-02-2014-0013

Benmessaoud, C., Kharrazi, H., & MacDorman, K. (2011). Facilitators and Barriers to Adopting Robotic-Assisted Surgery: Contextualizing the Unified Theory of Acceptance and Use of Technology. *PloS one, 6,* e16395. http://doi.org/10.1371/journal.pone.0016395.

Bentler, P. M. (1990). Comparative fit indexes in structural models. *Psychological bulletin, 107*(2), 238-246. https://doi.org/10.1037/0033-2909.107.2.238

Bhattacherjee, A., & Sanford, C. (2006). Influence processes for information technology acceptance: An elaboration likelihood model. *MIS quarterly, 30*(4), 805-825. https://doi.org/10.2307/25148755

Blaxter, L., Hughes, C., & Tight, M. (2010). *EBOOK: How to Research* (1st ed.). McGraw-Hill Education (UK).

Buabeng-Andoh, C. (2021). Exploring University students' intention to use mobile learning: A research model approach. *Education and information technologies*, *26*(1), 241-256. https://doi.org/10.1007/s10639-020-10267-4

Chao, C. (2019). Factors Determining the Behavioral Intention to Use Mobile Learning: An Application and Extension of the UTAUT Model. *Frontiers in Psychology, 10,* 1-10. https://doi.org/10.3389/fpsyg.2019.01652.

Chawla, D., & Joshi, H. (2019). Consumer attitude and intention to adopt mobile wallet in IndiaA empirical study. International Journal of Bank Marketing, 37(7), 1590-1618. https://doi.org/10.1108/ijbm-09-2018-0256

Cigdem, H., & Ozturk, M. (2016). Factors affecting students' behavioral intention to use LMS at a Turkish post-secondary vocational school. *International Review of Research in Open and Distributed Learning, 17*(3), 276-295. https://doi.org/10.19173/irrodl.v17i3.2253

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, & user acceptance of information technology. *MIS Quarterly, 13*(3), 319-340. https://doi.org/10.2307/249008

Davis, F. D., Bagozzi, R. P., & Warshaw, P. R. (1992). Extrinsic & intrinsic motivation to use computers in the workplace 1. *Journal of Applied Social Psychology, 22*(14), 1111-1132. https://doi.org/10.1111/j.1559-1816.1992.tb00945.x

DeLone, W. H., & McLean, E. R. (2003). The DeLone and McLean model of information systems success: A ten-year update. *Journal of Management Information Systems, 19*(4), 9- 30.

Eagly, A. H., & Chaiken, S. (1993). *The psychology of attitudes* (1st ed.). Harcourt Brace Jovanovich College Publishers.

Fagan, M. H., Neill, S., & Wooldridge, B. R. (2008). Exploring the intention to use computers: An empirical investigation of the role of intrinsic motivation, extrinsic motivation, and perceived ease of use. *Journal of Computer Information Systems, 48*(3), 31-37.

Fishbein, M., & Ajzen, I. (1975). *Belief, attitude, intention, and behavior: An introduction to theory and research* (1st ed.). Addison-Wesley.

Fornell, C., & Larcker, D. F. (1981). Structural equation models with unobservable variables and measurement error: Algebra and statistics. *Journal of Marketing Research, 18*(3), 382-388. https://doi.org/10.1177/002224378101800313

Gebauer, J., & Ginsburg, M. (2009). Exploring the black box of task-technology fit. *Communication of the ACM, 52*(1), 130-135. https://doi.org/10.1145/1435417.1435447

George, D., & Mallery, P. (2003). *SPSS for Windows Step by Step: A Simple Guide and Reference. 11.0 Update* (4th ed.). Allyn & Bacon.

Goodhue, D. L., & Thompson, R. L. (1995). Task-technology fifit and individual performance. *MIS Quarterly, 19*(2), 213-236. https://doi.org/10.2307/249689

Guo, C., & Wan, B. (2022). The digital divide in online learning in China during the COVID-19 pandemic. *Technology in society*, *71*, 102122. https://doi.org/10.1016/j.techsoc.2022.102122

Hair, J. F., Anderson, R. E., Tatham, R. L., & Black, W. C. (2010). *Multivariate Data Analysis* (6th ed.). Prentice Hall.

Hair, J. F., Arthur, M. H., Samouel, P., & Page, M. (2007). *Research Methods for Business*. John Wiley and Sons

Hair, J. F., Ringle, C. M., & Sarstedt, M. (2013). Partial Least Squares Structural Equation Modeling: Rigorous Applications, Better Results and Higher Acceptance. *Long Range Planning, 46,* 1-12. https://doi.org/10.1016/j.lrp.2013.01.001

Hasan, H., Linger, H., Chen, A., Lu, Y., & Wang, B. (2016). Enhancing perceived enjoyment in social games through social and gaming factors. *Information Technology & People, 29*(1), 99-119. https://doi.org/10.1108/itp-07-2014-0156

Ho, C. K., Ke, W., & Liu, H. (2015). Choice decision of e-learning system: Implications from construal level theory. *Information & Management, 52*(2), 160-169. https://doi.org/10.1016/j.im.2014.07.003

Holden, H., & Rada, R. (2011). Understanding the influence of perceived usability and technology self-efficacy on teachers' technology acceptance. *Journal of Research on Technology in Education*, *43*(4), 343-367. https://doi.org/10.1080/15391523.2011.10782576

Hsiao, K. L. (2017). What drives smartwatch adoption intention? Comparing Apple and non-Apple watches. *Library Hi Tech*, *35*(1), 186-206. https://doi.org/10.1108/lht-09-2016-0105

Hu, X., Zhang, J., He, S., Zhu, R., Shen, S., & Liu, B. (2022). E-learning intention of students with anxiety: Evidence from the first wave of COVID-19 pandemic in China. *Journal of affective disorders*, *309*, 115-122. https://doi.org/10.1016/j.jad.2022.04.121

Hu, Y., & Li, J. (2020). *Statistic of Education* (1st ed.). China Renmin University Press.

Huang, H., & Liaw, S. (2018). An Analysis of Learners' Intentions Toward Virtual Reality Learning Based on Constructivist & Technology Acceptance Approaches. *International Review of Research in Open & Distributed Learning, 19*(1), 91-115.

Huang, J. H., Lin, Y. R., & Chuang, S. T. (2007). Elucidating user behavior of mobile learning: A perspective of the extended technology acceptance model. *The electronic library. 25*(5), 586-599. https://doi.org/10.1108/02640470710829569

Hussein, Z. (2017). Leading to intention: The role of attitude in relation to technology acceptance model in e-learning. *Procedia Computer Science, 105,* 159-164.

Kahn, B. K., Strong, D. M., & Wang, R. Y. (2002). Information quality benchmarks: product and service performance. *Communications of the ACM*, *45*(4), 184-192. https://doi.org/10.1145/505999.506007

Khan, I. U., Hameed, Z., Yu, Y., Islam, T., Sheikh, Z., & Khan, S. U. (2018). Predicting the acceptance of MOOCs in a developing country: Application of task-technology fit model, social motivation, and self-determination theory. *Telematics and Informatics*, *35*(4), 964-978. https://doi.org/10.1016/j.tele.2017.09.009

Khosrow-Pour, M. (2008). *Encyclopedia of information science and technology* (1st ed.). Igi Global.

King, R., & He, J. (2006). A Meta-Analysis of The Technology Acceptance Model. *Information & Management, 43*(6), 740-755. https://doi.org/10.1016/j.im.2006.05.003

Kuehn, K. W. (2008). Entrepreneurial intentions research: implications for entrepreneurship education. *Journal of Entrepreneurship Education, 11*(1), 87-99.

Lee, C. C., Cheng, H. K., & Cheng, H. H. (2007). An empirical study of mobile commerce in insurance industry: task-technology fifit and individual differences. *Decision Support Systems, 43*(1), 95-110. https://doi.org/10.1016/j.dss.2005.05.008

Liaw, S. S. (2008). Investigating students' perceived satisfaction, behavioral intention, and effectiveness of e-learning: a case study of the blackboard system. *Computers & Education, 51*(2), 864-873. https://doi.org/10.1016/j.compedu.2007.09.005

Lin, H. F. (2011). An empirical investigation of mobile banking adoption: The effect of innovation attributes and knowledge-based trust. *International journal of information management, 31*(3), 252-260. https://doi.org/10.1016/j.ijinfomgt.2010.07.006

Lin, J. C. C., & Lu, H. (2000). Towards an understanding of the behavioural intention to use a web site. *International journal of information management, 20*(3), 197-208. https://doi.org/10.1016/s0268-4012(00)00005-0

Liu, I. F., Chen, M. C., Sun, Y. S., Wible, D., & Kuo, C. H. (2010). Extending the TAM model to explore the factors that affect intention to use an online learning community. *Computers & education, 54*(2), 600-610.

Liu, S. H., Liao, H. L., & Pratt, J. A. (2009). Impact of media richness and flow on e-learning technology acceptance. *Computers and Education, 52*(3), 599-607. https://doi.org/10.1016/j.compedu.2008.11.002

Lu, W., Mustapha, S. M., & Abdullah, N. (2021). Constructing and Validating University Students' Blended Learning Acceptance Scale. *Int. J. Interact. Mob. Technol.*, *15*(4), 101-108. https://doi.org/10.3991/ijim.v15i04.20195

Mohammadi, H. (2015). Investigating users' perspectives on e-learning: An integration of TAM and IS success model. *Computers in human behavior, 45,* 359-374. https://doi.org/10.1016/j.chb.2014.07.044

Motl, R. W., Dishman, R. K., Saunders, R. P., Dowda, M., & Pate, R. R. (2007). Perceptions of physical and social environment variables and self-efficacy as correlates of self-reported physical activity among adolescent girls. *Journal of pediatric psychology*, *32*(1), 6-12. https://doi.org/10.1093/jpepsy/jsl001

OECD. (2015). *Education Policy Outlook Japan.* https://www.oecd.org/education/Japan-country-profile.pdf

Park, Y., Son, H., & Kim, C. (2012). Investigating the determinants of construction professionals' acceptance of web-based training: An extension of the technology acceptance model. *Automation in construction, 22,* 377-386. https://doi.org/10.1016/j.autcon.2011.09.016

Pedroso, R., Zanetello, L., Guimarães, L., Pettenon, M., Gonçalves, V., Scherer, J., & Pechansky, F. (2016). Confirmatory factor analysis (CFA) of the crack use relapse scale (CURS). *Archives of Clinical Psychiatry (São Paulo)*, *43,* 37-40. https://doi.org/10.1590/0101-60830000000081

Qin, C., Liu, Y., Mou, J., & Chen, J. (2019). User adoption of a hybrid social tagging approach in an online knowledge community. *Aslib Journal of Information Management, 71*(2), 155-175. https://doi.org/10.1108/ajim-09-2018-0212

Ramayah, T., Ahmad, N. H., & Lo, M. C. (2010). The role of quality factors in intention to continue using an e-learning system in Malaysia. *Procedia-Social and Behavioral Sciences, 2*(2), 5422-5426. https://doi.org/10.1016/j.sbspro.2010.03.885

Renny, R., Chandra, R., Ruhama, S., & Sarjono, M. W. (2014). Exploring Indonesian web-based career center discrepancy of web popularity and type of services. *arXiv preprint arXiv, 1403,* 5401.

Rezvani, S., Heidari, S., Roustapisheh, N., & Dokhanian, S. (2022). The effectiveness of system quality, habit, and effort expectation on library application use intention: the mediating role of perceived usefulness, perceived ease of use, and user satisfaction. *International Journal of Business Information Systems*, *1*(1), 1. https://doi.org/10.1504/ijbis.2022.10049515

Rosen, L. D., Whaling, K., Carrier, L. M., Cheever, N. A., & Rokkum, J. (2013). The media and technology usage and attitudes scale: An empirical investigation. *Computers in human behavior*, *29*(6), 2501-2511. https://doi.org/10.1016/j.chb.2013.06.006

Ryan, R. M., & Deci, E. L. (2000). Self-determination theory and the facilitation of intrinsic motivation, social development, and well-being. *American psychologist, 55*(1), 68-78. https://doi.org/10.1037/0003-066x.55.1.68

Salloum, S. A., Alhamad, A. Q. M., Al-Emran, M., Monem, A. A., & Shaalan, K. (2019). Exploring students' acceptance of e-learning through the development of a comprehensive technology acceptance model. *IEEE access*, *7*, 128445-128462. https://doi.org/10.1109/access.2019.2939467

Shimauchi, S. (2018). English-Medium Instruction in the Internationalization of Higher Education in Japan: Rationales and Issues. *Educational Studies in Japan: International Yearbook, 12,* 77-90.

Sica, C., & Ghisi, M. (2007). The Italian versions of the Beck Anxiety Inventory and the Beck Depression Inventory-II: Psychometric properties and discriminant power. *Leading-edge psychological tests and testing research*, 27-50.

Siron, Y., Wibowo, A., & Narmaditya, B. S. (2020). Factors affecting the adoption of e-learning in Indonesia: Lesson from Covid-19. JOTSE: *Journal of Technology and Science Education, 10*(2), 282-295. https://doi.org/10.3926/jotse.1025

Soon, H. T., & Kadir, S. L. S. A. (2017). The drivers for cloud-based virtual learning environment: Examining the moderating effect of school category. *Internet Research, 7*(9), 942-973，

Suki, N. M. (2011). Factors affecting Third Generation (3G) mobile service acceptance: evidence from Malaysia. *Journal of Internet Banking and Commerce*, *16*(1), 1-12. https://doi.org/10.5897/ajbm11.281

Teo, T., & Lee, C. B. (2010). Examining the efficacy of the theory of planned behavior (TPB) to understand pre-service teachers' intention to use technology. *Campus-Wide Information System, 27*(2), 60-67. https://doi.org/10.1108/10650741111117798

Vahdat, A., Alizadeh, A., Quach, S., & Hamelin, N. (2021). Would you like to shop via mobile app technology? The technology acceptance model, social factors, and purchase intention. *Australasian Marketing Journal*, *29*(2), 187-197. https://doi.org/10.1016/j.ausmj.2020.01.002

Venkatesh, V. (2000). Determinants of perceived ease of use: Integrating control, intrinsic motivation, and emotion into the technology acceptance model. *Information systems research, 11*(4), 342-365. https://doi.org/10.1287/isre.11.4.342.11872

Veríssimo, J. M. C. (2016). Enablers and restrictors of mobile banking app use: A fuzzy set qualitative comparative analysis (fsQCA). *Journal of Business research*, *69*(11), 5456-5460. https://doi.org/10.1016/j.jbusres.2016.04.155

Wan, L., Xie, S., & Shu, A. (2020). Toward an understanding of university students' continued intention to use MOOCs: When UTAUT model meets TTF model. *Sage Open, 10*(3), 2158244020941858.

Wu, J. H., & Wang, Y. M. (2006). Measuring KMS success: A respecification of the DeLone and McLean's model. *Information & management, 43*(6), 728-739. https://doi.org/10.1016/j.im.2006.05.002

Yip, K. H. T., Lo, P., Ho, K. K., & Chiu, D. K. (2020). Adoption of mobile library apps as learning tools in higher education: a tale between Hong Kong and Japan. *Online Information Review, 1*(2), 1-10. https://doi.org/10.1108/oir-07-2020-0287

Yoshikawa, T. (n.d.). *China Becomes the World's Top-Ranking Nation of Japanese-language Learning.* Wochi Kochi. https://www.wochikochi.jp/english/special/2013/12/china-becomes-the-worlds-top-ranking-nation-of-japanese-language-learning.php

Yu, L., Huang, L., & Lei, W. (2020). Emotional responses and coping strategies in nurses and nursing students during Covid-19 outbreak: A comparative study. *PLoS One, 15*(8), e0237303. https://doi.org/10.1371/journal.pone.0237303

Yuan, Y., Archer, N., Connelly, C. E., & Zheng, W. (2010). Identifying the ideal fit between mobile work and mobile work support. *Information & management, 47*(3), 125-137. https://doi.org/10.1016/j.im.2009.12.004

Zait, A., & Bertea, P. S. P. E. (2011). Methods for testing discriminant validity. *Management & Marketing Journal*, *9*(2), 217-224.

Zhao, H. (2020). Chinese Japanese Education in World Foreign Language Education. *Northeast Asian Foreign Language Studies, 4,* 8-13.