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Survival of the fittest: A meta-analysis of users’ mobile payment adoption

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Abstract: How to inspire, acquire and retain users efficiently has been a great problem for the development of mobile payment service providers. Given the differences in existing studies on many issues regarding users’ mobile payment adoption intention, this study selected 46 highly relevant empirical studies, used visual knowledge map to identify key factors and construct a conceptual model. Weight analysis and meta-analysis were applied to identify the key factors. Sub-group analysis was conducted to explore the moderating effect of age, use experience and location. The results show that young users are more influenced by usefulness and satisfaction. Current users care more about ease of use and trust. Different degrees of compatible expectations lead to the development gap between the East and the West. This study explored the interaction mechanism between user attributes and behavior intention, which consequently offer valuable suggestions for theoretical research and practical application in mobile payment.

Keywords: Mobile payment, Individual adoption behavior, Weight analysis, Meta-analysis, Subgroup analysis

1 INTRODUCTION

Mobile payment uses mobile devices and wireless communication technology to buy goods or services¹,². The deepening of the global information technology revolution provides a suitable environment for the development of mobile payment. According to the statistical report, the Digital Payments segment has a global transaction value of $5204 billion in 2020 and is the largest segment within FinTech³. With the increasingly fierce mobile payment market competition, fully understanding and deeply analyzing the differences of user groups, and then catering to users’ habits with personalized and humanized services is the key for mobile payment providers to improve market share and survive in the fierce competition.

The existing literatures on mobile payment adoption behavior is mainly related to two aspects. One focused on product-related concepts, such as perceived usefulness and perceived ease of use⁴,⁵. The other focused on user-related concepts, such as social image and subjective norms⁶,⁷. Some classical theories and models, such as TAM and UTAUT⁸, are frequently accepted to take a holistic view of the key factors which determine mobile payment adoption⁹,¹⁰. After in-depth analysis of the literature, it is found that there are several limitations in the existing studies which may lead some further research.

Firstly, some conclusions of existing literatures are quite different due to the different sample objects, sample size, and survey background. For instance, some studies show that mobile payment intention behavior is influenced by trust¹⁰, while some results show that it is not significant⁹. The inconsistent conclusions cause some decision-making difficulties.

Secondly, the role of some key influencing factors at micro level, such as age and use experience, have not been deeply investigated. For the age factor, the early composition of mobile payment users is mainly young people. With the promotion and popularization of mobile payment, mobile payment will cover more and more age groups in the future. However, the existing literature does not tell mobile payment providers how to provide personalized services for users of different ages. For the use experience factor, many scholars have paid attention to this point and study the current users¹¹ and potential users¹², respectively. However, due to the

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lack of comparative research, a comprehensive explanation has not been obtained.

Thirdly, the role of some key influencing factors at macro level, such as the development difference between the East and the West, is still a mystery. In the process of globalization, more and more payment platforms are trying to open up new markets very accurately and smoothly. Previous research mostly focused on mobile payment in a single country. Therefore, the industry needs more research to guide the market development decisions of multinational mobile payment providers.

Based on the above analysis and related problems, the research questions (RQs) are proposed as follows:
RQ1: What are the driving factors of mobile payment adoption?
RQ2: How do age, use experience and location affect users' adoption intention?

This study selected meta-analysis and subgroup analysis to solve the above problems. Meta-analysis is a comprehensive quantitative analysis method. It can objectively reflect the previous research results and explain the heterogeneity between different research results. A meta-analysis is conducted to analyze research results highly related to the research topic to explore RQ1. To explore RQ2, we use subgroup analysis to examine the moderating effect of age, use experience and location.

2 THEORETICAL BACKGROUND

2.1 Theories of technology acceptance

TAM is developed from the theory of reasoned action (TRA) model. TAM focuses on the relationship between perceived usefulness, perceived ease of use and users' behavior intention. Based on TAM, perceived usefulness is defined as the degree of an individual thinks it is helpful to use mobile payment. Perceived ease of use is defined as the degree of an individual thinks using mobile payment is not difficult. Recent research focused on the differences of individual acceptance behavior in emerging technologies. Mingxing et al. and Liu et al. used TAM models in mobile payment adoption and confirmed that TAM is a powerful model to predict user adoption intention. Based on the TAM, an extended technology acceptance model (TAM2) was proposed, emphasizing that social factors affect perceived usefulness and then influence users’ intention and behavior.

UTAUT is used to explore the factors that affect user cognition and related issues. It contains four core factors, including performance expectation, effort expectation, social influence and facilitating conditions. Performance expectation can be understand as “the individual expects that using m-payment will enable him or her to achieve results”. Effort expected can be defined as “the individual expects that using m-payment will enable him or her to achieve results”. Behavior intention and facilitating conditions jointly affect the users’ behavior, and other three factors affect the consumer’s use intention directly. UTAUT also points out that gender, age, experience, and voluntariness significantly affect the above core dimensions. Kalinić et al. developed a model based on UTAUT and investigated the willingness of users of different genders to adopt mobile payment.

IDT is discussed in the book "Diffusion of Innovation" in 1962 and widely used after 1983. IDT suggests that the number of adopted innovators shows an S-shaped change track with time. IDT is used to study and classify all kinds of innovation subjects and its main influencing factors include relative advantage, personal innovativeness and compatibility. Compatibility is regard as “the degree of consistency of the product or function with the users’ needs and usage habits”. Innovativeness is regard as “the degree to which users are willing to accept new technologies”. Schmidhuber et al. proved that innovativeness has a positive effect on behavior intention. Research shows that compatibility is an important predictor of mobile payment use intention.

2.2 Moderator identification

In most cases, demographic differences can lead to individuals’ different behavioral intentions. It is found that age play a special role in the acceptance process of mobile payment and some scholars have explored the
factors that influence young users’ adoption of mobile payment [5].

Use experience has been observed to have a certain impact on mobile payment adoption. Some researches have testified the positive correlation between perceived ease of use and behavioral intention [19]. While some other researches have reported the nonsignificant and even negative relationships [26]. This kind of contradiction means the unstable relationship may be moderated by hidden factors.

User behavior is often affected by key factors such as traditional customs, consumption habits, laws and regulations, customer education and so on. All these key factors are usually closely related to location. In terms of mobile payment, scholars have paid active attention to the differences of users’ behavior caused by location.

2.3 Research sample selection

Research sample selection was divided into four steps as Fig. 1 shows.

![Figure 1. Paper selection procedure for the meta-analysis](image)

The first step is identification. Published journal papers, conference papers, degree theses, working papers and academic reports were all covered. Keywords with high correlation with mobile payment, such as mobile payment, mobile wallet, online payment, have been adopted to search in several major databases, including Science.net, Elsevier, SpringerLink, etc. At last, a total of 433 papers were obtained. The second step is to eliminate the duplication, after which 288 articles were left. The third step is to browse the title and full text and 85 papers were selected to meet the content-related requirements. We cleaned the research samples by using the following following criteria: a) must be an empirical study that investigates users’ mobile payment adoption intention, b) must report quantitative information about factors, including sample sizes, correlation coefficients, or other statistical data; and c) the investigated subject must be an individual mobile payment users. At last, 46 papers were included in this research.

2.4 Conceptual model construction

In this section, we tried to analyze the 46 papers, which were confirmed in Section 2.3, by means of visual knowledge map. We visualized these factors through Gephi2.0 and retained the ties with more occurrences (as shown in Fig. 2).

![Figure 2. Hot word network diagram of mobile payment adoption intention research](image)

From Fig. 2, we can extract the critical factors affecting users’ mobile payment behavior. They are perceived ease of use, attitude, satisfaction, perceived usefulness, trust, social impact, effort expectancy,
compatibility, innovativeness, performance expectancy and perceived risk. There are two reasons for excluding other factors. Firstly, some factors lack sufficient data to support the meta-analysis process. Secondly, some factors can be replaced by other more representative factors. We added three moderators to the proposed framework. Fig.3 shows the composite model.

![Figure 3. The conceptual model of mobile payment adoption intention.](image)

3. METHODOLOGIES

3.1 Coding procedure

To extract the data for meta-analysis, we read through each article and then coded the data. The coding process collected author information, publication date and other information. If two or more samples are given in one article, and the sample size and research results are reported separately, they are coded as independent studies. Finally, 51 studies are identified from all the 46 articles. The period of adopted articles is from 2007 to 2020.

Considering the effective literature reports, the correlation coefficient is selected to reflect the effect size. We completed the effect value statistics by transforming regression coefficient, path coefficient, or t value for a few studies that did not report correlation coefficient. Suppose the study reported the standardized regression coefficient β obtained by regression analysis, according to the calculation method of meta-analysis effect quantity. In that case, β is equal to r, and Fisher's z transformation is carried out. If the result of a valid literature report is the standard path coefficient obtained using the structural equation model with latent factors. We need to compute unadjusted coefficient to correct the latent variable error, then use it as effect value. The adjustment formula is as follows:

$$\beta_{\text{unadj}} = \beta_{\text{adj}} \times \sqrt{\alpha_{xx} \times \alpha_{yy}}$$

where $\beta_{\text{unadj}}$ is the unadjusted beta coefficient, $\beta_{\text{adj}}$ is the path coefficient, $\alpha_{xx}$ and $\alpha_{yy}$ is the internal reliability of the related independent variable and dependent variable. In addition, if the study only reports the t value of the path, we converted t value to effect value by using the formula:

$$\Gamma = \frac{t^2}{\frac{t^2}{df}}$$

where $t$ represents t value of the path, df represents the degree of freedom.

3.2 Analysis procedure

First, according to the relationships in 46 selected articles, this study made a weight analysis to test the significant rate of each pair-wise relationship and explanatory power of each variable in the relationship. Then the descriptive statistic reports basic information of correlation coefficient and sample size of each path...
relationship, including minimum value, maximum value, average value, etc. At the same time, the complete reliability of each structure is calculated.

Next, our study used Excel to adjust the correlation coefficients of each pairwise relationship and calculate a simple average of the effect sizes for each connection. The following formula is used to calculate the adjusted average of the sample size:

\[ r' = \frac{\sum_i N_i r_i}{\sum N_i} \]  \hspace{1cm} (3)

Where \( r_i \) represents the correlation observed in study \( i \) and \( N_i \) represents number of samples per study. Then, use the following formula to perform the Fisher \( r \) to \( z \) transformation:

\[ z = 0.5 \times \ln \left( \frac{1+r}{1-r} \right) \]  \hspace{1cm} (4)

\[ z_+ = \frac{\sum_i N_i z_i}{\sum N_i} \]  \hspace{1cm} (5)

\[ r'_z = \frac{\exp(z_+ - 1)}{\exp(z_+ + 1)} \]  \hspace{1cm} (6)

Where \( r \) represents correlations and \( N_i \) means the sample size. Besides, we calculated 95% confidence interval, heterogeneity statistic Q-value, heterogeneity index I², and conducted Egger’s test and z-test, for each relationship by using the function "metacor" and "metabias" from package "meta" in R. To evaluate and explain the significance of each relationship’s effect size, the Z-test and the 95% confidence interval were conducted. If 0 is excluded, it means the average effect size is significant at the level of \( P < 0.05 \). The z-test was used to evaluate the significance of each relationship’s effect size. To avoid the bias that authors tend to report good results when publishing articles, fail-safe N test is used to test the existence of publication bias. A higher fail-safe N value means a more reliable relationship. The fail-safe N was calculated using the formula:

\[ N_{fs, 0.05} = \left( \frac{\sum z}{1.645} \right)^2 - N \]  \hspace{1cm} (7)

where \( \sum z \) is the sum of Z values of all effect sizes and \( N \) is the number of effect sizes.

We used heterogeneity test to choose a suitable effect model to conduct a meta-analysis. According to the actual situation of this study, this study chose the random effect model. Finally, we filtered the moderating variables through weight analysis and article reading. The subgroup analysis divided samples into subgroups according to categorical moderator factor and calculate the heterogeneity between subgroups. When the \( p \)-value of Q-test less than 0.05, it suggests the existence of high heterogeneity and moderator effects.

4. DATA ANALYSIS
4.1 Weight analysis

Weights are used to express the explanatory strength of independent variables. Considering research situation, we only extracted variable relationships that occur more than 3 times in all original studies and incorporated them into weight analysis. The division basis of variable types of weight analysis in this study is shown in Table 1.

<table>
<thead>
<tr>
<th>Number of inspections</th>
<th>Type</th>
<th>Weight</th>
<th>Type</th>
</tr>
</thead>
<tbody>
<tr>
<td>≥ 3</td>
<td>Well-utilized predictor</td>
<td>≥0.8</td>
<td>Best predictor</td>
</tr>
<tr>
<td>&lt; 3</td>
<td>Experimental predictor</td>
<td>=1</td>
<td>Promising predictor</td>
</tr>
</tbody>
</table>

From 302 pairs of correlations, a total of 30 groups of variable relations that appeared more than 3 times were extracted. Among them, there are 15 groups of well-utilized variable relationships and 15 groups of experimental variables. Among the 15 groups of well-utilized variable relationships, only PC-BI and PR-BI showed research results in opposite directions. The relationship between these 30 groups of variables has a certain degree of stability.
9 groups of "best predictors", 9 groups of "promising predictors", and 1 group of "worst predictor" were identified from the 30 groups of variable relationships. Weight analysis can only simply characterize the significance of variable relationships based on the "vote counting method" and cannot judge the strength of variable relationships. In addition, the "best predictors" and "promising predictors" obtained by weight analysis need to be meta-analyzed to calculate the average effect value, determine the significance level and relationship strength, and make a more accurate estimation of the relationship between the variables. In addition, the emergence of a "worst predictor variable" requires follow-up discussion.

4.2 Descriptive statistic

As shown in Table 2, the average sample size of almost all paths is over 200. Perceived risk is the core factor of this research model, which has been widely studied in descriptive analysis, with 15 significant correlation coefficients and eight insignificant correlation coefficients. At the same time, PU-BI (21 studies) and SI-BI (20 studies) were widely investigated, with significant rates of 90.0% and 80.0%, respectively. Compared with continuance intention, behavior intention gets more attention. There are more researches on behavioral intention than on continuance intention. There is only one report correlation coefficient of ATT-CUSE and EE-CUSE, so these two relationships aren't studied in the later correlation analysis.

Table 2. Descriptive statistics

<table>
<thead>
<tr>
<th>Pair-wise relationship</th>
<th>K</th>
<th>Correlations.</th>
<th>Range of sample sizes</th>
<th>Range of correlations</th>
<th>N</th>
<th>Average sample size</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>NS</td>
<td>S</td>
<td>Sig.</td>
<td>Lower</td>
<td>Upper</td>
</tr>
<tr>
<td>ATT-BI</td>
<td>6</td>
<td>0</td>
<td>6</td>
<td>1.00</td>
<td>206</td>
<td>491</td>
</tr>
<tr>
<td>COM-BI</td>
<td>9</td>
<td>0</td>
<td>9</td>
<td>1.00</td>
<td>156</td>
<td>1256</td>
</tr>
<tr>
<td>INN-BI</td>
<td>9</td>
<td>0</td>
<td>9</td>
<td>1.00</td>
<td>156</td>
<td>670</td>
</tr>
<tr>
<td>PE-BI</td>
<td>8</td>
<td>0</td>
<td>8</td>
<td>1.00</td>
<td>225</td>
<td>1165</td>
</tr>
<tr>
<td>SAT-CUSE</td>
<td>7</td>
<td>0</td>
<td>7</td>
<td>1.00</td>
<td>149</td>
<td>336</td>
</tr>
<tr>
<td>PU-BI</td>
<td>21</td>
<td>19</td>
<td>2</td>
<td>0.90</td>
<td>119</td>
<td>922</td>
</tr>
<tr>
<td>SI-BI</td>
<td>20</td>
<td>16</td>
<td>4</td>
<td>0.80</td>
<td>119</td>
<td>670</td>
</tr>
<tr>
<td>TRU-BI</td>
<td>14</td>
<td>11</td>
<td>3</td>
<td>0.79</td>
<td>119</td>
<td>701</td>
</tr>
<tr>
<td>PR-BI</td>
<td>23</td>
<td>15</td>
<td>8</td>
<td>0.64</td>
<td>119</td>
<td>1165</td>
</tr>
<tr>
<td>EE-BI</td>
<td>8</td>
<td>4</td>
<td>5</td>
<td>0.50</td>
<td>225</td>
<td>1165</td>
</tr>
<tr>
<td>PEOU-BI</td>
<td>18</td>
<td>8</td>
<td>10</td>
<td>0.44</td>
<td>119</td>
<td>922</td>
</tr>
<tr>
<td>SAT-BI</td>
<td>3</td>
<td>3</td>
<td>0</td>
<td>1.00</td>
<td>206</td>
<td>1165</td>
</tr>
<tr>
<td>PU-CUSE</td>
<td>3</td>
<td>3</td>
<td>0</td>
<td>1.00</td>
<td>149</td>
<td>954</td>
</tr>
<tr>
<td>TRU-CUSE</td>
<td>3</td>
<td>2</td>
<td>1</td>
<td>0.67</td>
<td>195</td>
<td>276</td>
</tr>
<tr>
<td>ATT-CUSE</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td>1.00</td>
<td>336</td>
<td>336</td>
</tr>
<tr>
<td>PR-CUSE</td>
<td>2</td>
<td>1</td>
<td>1</td>
<td>0.50</td>
<td>180</td>
<td>243</td>
</tr>
<tr>
<td>EE-CUSE</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td>1.00</td>
<td>180</td>
<td>180</td>
</tr>
</tbody>
</table>

Note: K=number of studies; N= Cumulative sample size; S=significant; NS=non-significant; Sig.=significant rate; BI-Behavior Intention; PU-Perceived Usefulness; CUSE-Continuance Intention; ATT-Attitude; COM-Compatibility; INN-Innovativeness; PE-Performance Expectancy; SAT-Satisfaction; SI-Social Influence; TRU-Trust; PR-Perceived Risk; EE-Effort Expectancy; PEOU-Perceived Ease Of Use.

4.3 Reliability statistics

In reliability analysis, Cronbach’s α and composite reliability (CR) are calculated to test the consistency and stability of the model measurement results. Cronbach’s α is used to test the correlation of common factors among variables. In addition, CR is also a kind of reliability measurement. The difference between the two values is not significant. If Cronbach’s α is not reported in the literature, it is replaced by the CR value. In our study, the mean reliability of all variables exceeded 0.8, indicating that the reliability of variables is relatively high.

4.4 Correlation analysis

Among the three values of r +, r and r_s, r_s is the largest in most cases. Combining the three effect values, the strength of the effect value studied in this paper is high. The confidence intervals of PR-BI and PR-CUSE contain a value of 0, so they fail the whole test. In the relationship PEOU-BI, N values is favorable and relatively large, indicating that perceived ease of use plays a significant role in mobile payment adoption. Trust and perceived
usefulness have adverse effects on continuance intention but positive effects on behavior intention.

The FSN values of attitude and effort expectancy on continuance intention and behavioral intention are positive, indicating that attitude and effort expectancy play essential roles in mobile payment adoption. PR-CUSE and PR-BI did not pass FSN test, which shows that perceived risk has no significant impact on mobile payment adoption.

Table 3. Correlation analysis

<table>
<thead>
<tr>
<th>Pairwise relationship</th>
<th>r_m</th>
<th>t+</th>
<th>t_</th>
<th>S.D.</th>
<th>Z-score</th>
<th>95% CI</th>
<th>P (Q)</th>
<th>P (Q)</th>
<th>Q-value</th>
<th>f²</th>
<th>N_{0.05}</th>
</tr>
</thead>
<tbody>
<tr>
<td>ATT-BI</td>
<td>0.726</td>
<td>0.737</td>
<td>0.734</td>
<td>0.064</td>
<td>15.63</td>
<td>(0.6751; 0.7838)</td>
<td>0.000</td>
<td>0.000</td>
<td>35.67</td>
<td>86.0</td>
<td>5.599</td>
</tr>
<tr>
<td>COM-BI</td>
<td>0.563</td>
<td>0.578</td>
<td>0.579</td>
<td>0.129</td>
<td>9.84</td>
<td>(0.4843; 0.6594)</td>
<td>0.000</td>
<td>0.000</td>
<td>133.26</td>
<td>94.7</td>
<td>2.238</td>
</tr>
<tr>
<td>INN-BI</td>
<td>0.518</td>
<td>0.506</td>
<td>0.518</td>
<td>0.065</td>
<td>16.65</td>
<td>(0.4665; 0.5652)</td>
<td>0.000</td>
<td>0.014</td>
<td>15.95</td>
<td>62.4</td>
<td>-0.974</td>
</tr>
<tr>
<td>SAT-CUSE</td>
<td>0.699</td>
<td>0.690</td>
<td>0.712</td>
<td>0.116</td>
<td>11.24</td>
<td>(0.6262; 0.7801)</td>
<td>0.000</td>
<td>0.000</td>
<td>57.83</td>
<td>89.6</td>
<td>7.427</td>
</tr>
<tr>
<td>PE-BI</td>
<td>0.683</td>
<td>0.688</td>
<td>0.699</td>
<td>0.108</td>
<td>9.09</td>
<td>(0.5908; 0.7827)</td>
<td>0.000</td>
<td>0.000</td>
<td>107.19</td>
<td>95.3</td>
<td>3.937</td>
</tr>
<tr>
<td>PU-BI</td>
<td>0.584</td>
<td>0.559</td>
<td>0.611</td>
<td>0.177</td>
<td>10.19</td>
<td>(0.5177; 0.6891)</td>
<td>0.000</td>
<td>0.000</td>
<td>384.86</td>
<td>96.1</td>
<td>16.210</td>
</tr>
<tr>
<td>SI-BI</td>
<td>0.477</td>
<td>0.471</td>
<td>0.499</td>
<td>0.166</td>
<td>8.35</td>
<td>(0.3960; 0.5890)</td>
<td>0.000</td>
<td>0.000</td>
<td>402.67</td>
<td>95.8</td>
<td>17.985</td>
</tr>
<tr>
<td>TRU-BI</td>
<td>0.562</td>
<td>0.568</td>
<td>0.588</td>
<td>0.160</td>
<td>6.89</td>
<td>(0.4483; 0.6996)</td>
<td>0.000</td>
<td>0.000</td>
<td>292.16</td>
<td>96.6</td>
<td>9.265</td>
</tr>
<tr>
<td>PR-BI</td>
<td>-0.014</td>
<td>-0.120</td>
<td>0.006</td>
<td>0.473</td>
<td>0.05</td>
<td>(-0.2258; 0.2365)</td>
<td>0.962</td>
<td>0.000</td>
<td>1654.69</td>
<td>99.0</td>
<td>-17.994</td>
</tr>
<tr>
<td>EE-BI</td>
<td>0.624</td>
<td>0.624</td>
<td>0.641</td>
<td>0.112</td>
<td>7.60</td>
<td>(0.5105; 0.7421)</td>
<td>0.000</td>
<td>0.000</td>
<td>118.13</td>
<td>95.8</td>
<td>1.648</td>
</tr>
<tr>
<td>PEOU-BI</td>
<td>0.562</td>
<td>0.498</td>
<td>0.588</td>
<td>0.192</td>
<td>9.98</td>
<td>(0.4943; 0.6677)</td>
<td>0.000</td>
<td>0.000</td>
<td>366.87</td>
<td>95.9</td>
<td>27.677</td>
</tr>
<tr>
<td>SAT-BI</td>
<td>0.622</td>
<td>0.690</td>
<td>0.635</td>
<td>0.116</td>
<td>6.20</td>
<td>(0.4724; 0.7563)</td>
<td>0.000</td>
<td>0.000</td>
<td>29.67</td>
<td>93.3</td>
<td>-1.158</td>
</tr>
<tr>
<td>PU-CUSE</td>
<td>0.463</td>
<td>0.395</td>
<td>0.469</td>
<td>0.170</td>
<td>4.55</td>
<td>(0.2820; 0.6222)</td>
<td>0.000</td>
<td>0.000</td>
<td>22.27</td>
<td>91.0</td>
<td>-2.103</td>
</tr>
<tr>
<td>TRU-CUSE</td>
<td>0.576</td>
<td>0.584</td>
<td>0.583</td>
<td>0.088</td>
<td>8.31</td>
<td>(0.4693; 0.6769)</td>
<td>0.000</td>
<td>0.013</td>
<td>8.64</td>
<td>76.9</td>
<td>-1.535</td>
</tr>
<tr>
<td>PR-CUSE</td>
<td>-0.232</td>
<td>-0.213</td>
<td>-0.233</td>
<td>0.172</td>
<td>-1.83</td>
<td>(-0.4542; 0.0164)</td>
<td>0.067</td>
<td>0.009</td>
<td>6.80</td>
<td>85.3</td>
<td>-1.915</td>
</tr>
</tbody>
</table>

4.5 Moderator analysis

As shown in Table 4, we took age, use experience and as moderators. To examine the moderators, the subgroup analysis was adopted.

The first moderator is age. The study was divided into the young user group and all age groups. PU-BI and SAT-CUSE are significantly moderated by age. Young users are more sensitive to perceived usefulness when they choose to use mobile payment. In the SAT-CUSE relationship, the impact on young users is more significant than that on all age groups.

The second moderator is use experience. In this study, users are divided into current users and potential users. The subgroup analysis process is the same as above. The results show that compared with potential users, current users are more concerned about the ease of use and trustworthiness of mobile payment.

The third moderator is location. The region is divided into Asian region and western region for subgroup analysis. The result indicates that there are significant differences in subgroups caused by the geographical location of countries or areas in the four groups of path relationships of COM-BI.

Table 4. Brief results of moderator analysis

<table>
<thead>
<tr>
<th>Moderator 1: Age</th>
<th>Moderator groups</th>
<th>Number of studies</th>
<th>95% CI</th>
<th>Combined effect size</th>
<th>Between groups tests</th>
</tr>
</thead>
<tbody>
<tr>
<td>PU-BI</td>
<td>Young user</td>
<td>4</td>
<td>[0.5966; 0.8282]</td>
<td>0.7330</td>
<td>4.28</td>
</tr>
<tr>
<td></td>
<td>All age group</td>
<td>12</td>
<td>[0.4543; 0.6509]</td>
<td>0.5605</td>
<td></td>
</tr>
<tr>
<td>SAT-CUSE</td>
<td>Young user</td>
<td>2</td>
<td>[0.7432; 0.8235]</td>
<td>0.7866</td>
<td>4.85</td>
</tr>
<tr>
<td></td>
<td>All age group</td>
<td>5</td>
<td>[0.5672; 0.7651]</td>
<td>0.6782</td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Moderator 2: Use experience</th>
<th>Moderator groups</th>
<th>Number of studies</th>
<th>95% CI</th>
<th>Combined effect size</th>
<th>Between groups tests</th>
</tr>
</thead>
<tbody>
<tr>
<td>PEOU-BI</td>
<td>Current user</td>
<td>5</td>
<td>[0.4335; 0.6197]</td>
<td>0.5330</td>
<td>5.38</td>
</tr>
<tr>
<td></td>
<td>Potential user</td>
<td>2</td>
<td>[0.3442; 0.4517]</td>
<td>0.3993</td>
<td></td>
</tr>
<tr>
<td>TRU-BI</td>
<td>Current user</td>
<td>2</td>
<td>[0.4891; 0.7022]</td>
<td>0.6064</td>
<td>4.61</td>
</tr>
<tr>
<td></td>
<td>Potential user</td>
<td>2</td>
<td>[0.1911; 0.5504]</td>
<td>0.3852</td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Moderator 3: Location</th>
<th>Moderator groups</th>
<th>Number of studies</th>
<th>95% CI</th>
<th>Combined effect size</th>
<th>Between groups tests</th>
</tr>
</thead>
<tbody>
<tr>
<td>COM-BI</td>
<td>Asian region</td>
<td>6</td>
<td>[0.4263; 0.5859]</td>
<td>0.5105</td>
<td>22.24</td>
</tr>
<tr>
<td></td>
<td>Western region</td>
<td>2</td>
<td>[0.6814; 0.7898]</td>
<td>0.7404</td>
<td></td>
</tr>
</tbody>
</table>

Note: Q is the heterogeneity within subgroups; P is the heterogeneity between subgroups.

5. DISCUSSION
5.1 Results

Weight analysis shows that although there are many related theories and models in the empirical research, the variables with better explanatory effect are still relatively concentrated. The quantitative integration of weight analysis can clarify which variables are good predictors and which variables have greater explanatory power among many explanatory variables, which lays the foundation for the subsequent meta-analysis.

Meta-analysis points out that attitude and satisfaction are crucial to determine the use intention of mobile payment. ATT-BI and SAT-CUSE show a large effect size, both exceeding 0.7. Perceived usefulness and perceived ease of use are important elements of TAM. These results approve that TAM is still applicable in the field of mobile payment adoption. The variables in UTAUT are mostly supported by empirical research. Performance expectancy and social influence significantly influence users' behavior intention, and their effect size are above 0.35. Among the variables, effort expectancy plays a significant role in both behavior intention and continuance intention. Trust and compatibility do significantly influence user's behavior intention. It is worth noting that, existing researches do not support the effect of perceived risk, the possible reasons may be that when users choose mobile payments, the governance level of the platform and the development level of the legal can provide sufficient guarantee for payment security, or compared with the convenience obtained by using mobile payment, the risks problems are negligible.

Subgroup analysis confirms that user's age, experience and location have moderating effect on mobile payment adoption. The test results of age moderating effect show that, young users pay more attention to the usefulness of mobile payment, and their satisfaction has a more profound impact on continuous use intention. The test results of use experience moderating effect show that current users care more about perceived ease of use than potential users. What's more, we further discovered the effect of trust on current users. The test results of location moderating effect show that, western users care more about compatibility. This means that western users are more concerned about whether technologies such as mobile payment are suitable for their lifestyle. Compared with the western market, the Eastern market has a weak foundation in the diversification and convenience of traditional payment, which reduces the diffusion obstacles of innovative technologies such as mobile payment.

5.2 Implications

This study is that this study attempts to explore potential research areas by studying the factors that affect users’ adoption intention of mobile payment. In terms of theoretical research, we have mainly done the following three works. 1) this study identifies the key factors and proposes a systematic research framework by comprehensively using a variety of quantitative analysis methods. 2) this article verifies the moderating effects of age, use experience and location. 3) we find some interesting factors, such as compatibility, can play a significant role in users’ mobile payment adoption intention. Also, it is an important explanatory factor leading to the difference between eastern and Western markets. Secondly, this paper proves that age, use experience, and location can significantly impact users’ mobile payment adoption behavior, which means that the differences between user need to be paid enough attention. Product management should adopt the product development strategy of mass customization on the basis of personalization and differentiation. Thirdly, mobile payment providers should make planned dynamic adjustments according to the development stage of their own market to reduce the risk of being eliminated. Finally, customer management should improve the market research mechanism and pay more attention to customer education.

5.3 Limitations and future research directions

Although this paper provides meaningful discovery for users’ mobile payment adoption behavior, and due to some temporarily insurmountable difficulties, this study still has some limitations, but it also provides space for further research.
First, the sample data is incomplete. This study only collected research samples written in English, which means that some high-quality research literatures written in other language may be missed. Second, the age division of user groups can be more detailed. There will be more and more literatures focusing on middle-aged and elderly users in the future, and more detailed research can be carried out. Third, the moderating factors in cross regional research can be more abundant. Future research can further subdivide different countries according to other standards, such as culture, history, economic development level, etc.

6. CONCLUSIONS
This study uses multiple quantitative analysis methods to analyze 51 empirical studies in 46 articles high-related to mobile payment adoption intention. We analyze the relationship between factors to propose a comprehensive research framework. We also proved the moderating effects of age, use experience and location, and obtained some very interesting conclusions. This study is of great significance to both researchers and service providers. For researchers, our research model can help them quickly master the existing knowledge system of mobile payment adoption research, and also can help them find new scientific problems. For service providers, our research results can provide some valuable new ideas for product management, operation management and customer management, and also can help them realize product innovation and service innovation from some new practical perspectives.

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REFERENCES
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