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Expanding The UTAUT 2 Framework: The Role of Occupational Background in Technology Adoption for Social Security Services in Indonesia

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ABSTRACT: The digital competence of Indonesian society in 2024 is quite good. However, adopting digital technology in social security services still faces various obstacles, especially in improving the JMO application's effectiveness, which BPJS Ketenagakerjaan participants still complain about. This study aims to investigate and evaluate user acceptance of the JMO application. The research employs the Unified Theory of Acceptance and Use of Technology 2 (UTAUT 2), along with Multi-Group Analysis (MGA) and Importance-Performance Map Analysis (IPMA), to obtain a thorough understanding of the factors affecting user acceptance of the JMO application. A quantitative approach was adopted, involving the distribution of online questionnaires to JMO users across various regions in Indonesia. The study employed a purposive sampling method to gather data from 153 respondents. The data was analyzed using the SmartPLS 3 software, which revealed that factors including Effort Expectancy, Performance Expectancy, and Social Influence significantly impact users' intentions to adopt the application. These factors also shape users' behavior when utilizing the JMO application. The findings underscore the importance of prioritizing key aspects such as user comfort and ease of access in the development and maintenance of the application. By addressing these critical factors, the implementation of the JMO has the potential to achieve long-term success and encourage the provision of fairer and more equitable social security protection for all Indonesian workers.

Keywords: JMO Application, Technology Acceptance, UTAUT 2, Multi-Group Analysis, Importance Performance Map Analysis

INTRODUCTION

Apart from simplifying administrative procedures, the digitalization of public services in Indonesia aims to make it easier for people to get faster services at more affordable costs (Hartanti et al., 2022). This is supported by people's preferences and behavior patterns in this modern era, switching to accessing instant and flexible digital services to make their various activities easier (Hadi et al., 2024). Additionally, digitalization enables better data integration between institutions, thereby increasing the accuracy and efficiency of public services to encourage transparency in service management (Junaidi et al., 2024).

In employment and social security, this condition prompted the government to create an application that can provide services easily and quickly to participants for various needs called "BPJSTK Mobile" launched in 2017. In 2021, this application was updated to become "Jamsostek Mobile (JMO)" with more comprehensive features, offering faster and more convenient services. The JMO application provides various services, including balance checking, retirement insurance claims, workplace accident insurance, life insurance, pension plans, unemployment insurance, and other benefits. It also features a data update option for easier access, a complaint service to assist National Social Security Agency for Employment (BPJS Ketenagakerjaan) participants with consultations, a simulation tool for calculating old-age insurance, and information about other National Social Security Agency for Employment (BPJS Ketenagakerjaan) programs that can be accessed anytime and anywhere (Kompas.id, 2021).

According to the Central Statistics Agency in 2024, the Indonesian working population reached 142.18 million people, with formal workers making up 40.83% and informal workers making up 59.17% (Aberth, 2024). This data shows that most Indonesian workers are in the informal sector, with limited access to social security services such as the National Social Security Agency for Employment (BPJS Ketenagakerjaan) and manage independently. Therefore, ensuring easy access to health and social security benefits is crucial. The convenience offered by the Jamsostek Mobile (JMO) application can help enhance social protection in Indonesia (Putri et al., 2024).

Although the JMO application has been improved to provide easy access to social security services, it is undeniable that there are still many complaints from BPJS Ketenagakerjaan participants about the problems they experience when using the JMO application. Based on reviews in the Google Play Store, there are many problems, especially related to data updates that keep failing, the input process of the application is considered too complicated, and there are still many participants who do not understand how to use the JMO application, especially workers in the informal sector (entrepreneurs, traders, and others) who take care of their social security independently. This must be a major concern for the government when creating a new technology that the community can easy adopt.

Figure 1. The Indonesian Digital Society Index 2024 (Source: Komdigi HR Development Agency)

The Indonesian Digital Society Index 2024, published by the Ministry of Communication and Digital Affairs of the Republic of Indonesia, reveals that while digital literacy is reasonably high (43,34 our of 100 points), optimal digital technology usage remains limited, particularly concerning the "Empowerment" pillar's contribution to improving quality of life(Budiarto et al., 2024). Within the concept of e-government, public acceptance of technology is crucial to ensure that digital services are used effectively and have a positive impact (Sulistyowati et al., 2020).

Various theories explain the process of technology adoption, such as the Diffusion of Innovations Theory (DOI), which examines how innovations spread in society; Social Cognitive Theory (SCT), which highlights the interaction of personal, behavioral, and environmental factors; and the Motivational Model (MM), which explores the influence of intrinsic and extrinsic motivation. The IS Success Model evaluates the success of information systems based on quality elements. At the same time, Task-Technology Fit (TTF) emphasizes the alignment between technology and user tasks, and Innovation Resistance Theory (IRT) identifies barriers to adoption. Furthermore, the Technology Acceptance Model (TAM), rooted in the Theory of Reasoned Action (TRA), focuses on the relationships among attitudes, intentions, and behavior. TRA was later expanded into the Theory of Planned Behavior (TPB), incorporating perceived behavioral control to provide a more comprehensive explanation of intentions and behavior in technology adoption (Nugraha, 2023).

Amid the many theories focusing on psychological aspects and human behavior in evaluating the use of technology and the user's behavioral intentions, the Unified Theory of Acceptance and Use of Technology (UTAUT) developed by Venkatesh stands out as one the most relevant frameworks for evaluating modern technology adoption in both individual and organizational settings (Tamilmani et al., 2021). UTAUT combines elements from eight different prior theories into a unified framework. This integration allows the UTAUT model to provide more comprehensive insights into the application and utilization of technology (Akbar et al., 2023).

The four key elements that influence the use and intention to adopt information technology: are performance expectancy, effort expectancy, facilitating conditions, and social influence, were further developed, in response to rapid advancements in technology, leading to the expansion of UTAUT to UTAUT 2 with the addition of three constructs: hedonic motivation, price value, and habit (Abbad, 2021). The enhancements in UTAUT 2 resulted in significant improvements and greater predictive accuracy regarding the variance accounted for in behavioral intentions, which increased from 56% to 74%, and in the variance in technology use, which increased from 40% to 52%. These improved predictions show that UTAUT 2 provides a deeper understanding of user behavior influencing technology adoption (Nugraha, 2023).

This study makes a unique contribution by integrating occupational background as a moderating variable into the UTAUT 2 framework, which already includes moderating variables such as age, gender, and prior experience to understand differences in technology adoption (Lakhal & Khechine, 2021). By including an occupational background as a moderating variable, this study extends the UTAUT 2 framework by offering deeper insights into how individuals from different occupations such as salaried workers and self-employed workers have different expectations and constraints toward technology (Haer & Mulyaningsih, 2023). This approach allows a more thorough analysis of technology adoption patterns among various populations, especially about

JMO applications. Furthermore, the inclusion of occupational background as a moderating variable to evaluate users' intentions and behaviors in adopting the JMO application is supported by prior studies, which emphasize that occupational background significantly influences how users adapt to new technologies (Sudiantini et al., 2023).

The effectiveness of UTAUT 2 in describing user behavior reinforces its relevance for analyzing more intricate phenomena and identifying various factors, thanks to its comprehensive coverage (Al Halbusi et al., 2024). Due to its widespread use, ability to integrate with other theories, and proven applicability in technological environments, the UTAUT 2 framework was chosen for this research. Considering these benefits, the UTAUT 2 is the most appropriate framework for analyzing the acceptance of the Jamsostek Mobile (JMO) application. However, this study excludes the variables of hedonic motivation and facilitating conditions, as the mandatory nature of the JMO application does not significantly influence users' intentions and behaviors. Hedonic motivation, defined as the enjoyment derived from using technology, is less relevant for JMO users, who prioritize practical benefits over enjoyment (Nugraha, 2023). Similarly, facilitating conditions, which refer to the availability of resources and support for using technology, were found to have minimal impact on users' adoption behaviors, likely because users who are already familiar with technology tend to rely less on these conditions (Pakaya & Ladiku, 2024)

Numerous researchers have researched the adoption and usage of the Jamsostek Mobile (JMO) application. Examples include analyzing the sentiment of JMO application users on Google Play Store (Rizaldi, 2023), increasing BPJS Employment membership through the JMO application (Barat et al., 2023), evaluating the satisfaction of BPJS Employment participants with JMO technology (Setiawan et al., 2023), and studying user behavior related to the JMO application (Salwa et al., 2023). Similarly, studies examining the adoption of JMO applications using the UTAUT framework have been extensively conducted. However, no studies have utilized the UTAUT 2 framework to test moderating variables and evaluate the impact of each component through performance map analysis.

Several moderating variables, including age, gender, and experience, are included in the Unified Theory of Acceptance and Use of Technology 2 (UTAUT 2) to explain differences in technology adoption and use as each variable significantly influences how people react to technology (Lakhal & Khechine, 2021). Age impacts a person's ability to adapt to new technology, younger people tend to be more open to technological advances than older people (Neves & Mead, 2021). Gender can influence preferences and priorities in technology use (Rola-Rubzen et al., 2020). Meanwhile, experience influences users' confidence in technology systems (Chen et al., 2021).

In this research, the moderating variable was expanded by adding work background, as workers with different backgrounds may have unique needs, views, expectations, and constraints regarding the use of technology (Rauschnabel et al., 2022)The addition of occupational background variables also aims to understand more deeply how individuals adopt technology, which the moderating variables in UTAUT 2 do not fully explain. So, it is important to understand its influence on technology adoption in diverse populations in a broader and more relevant way in real life.

Besides that, Important Performance Map Analysis (IPMA) is also used in this research to identify the parts that have the most significant impact and evaluate the performance of these components.

IPMA is an analytical tool used to assess how much influence each part has on a phenomenon and how effective these parts are in real situations (Teeluckdharry et al., 2024). Through the IPMA approach, practical understanding can be gained about aspects that need greater attention and which can increase the effectiveness of interventions (Dewi & Akbar, 2023)Therefore, this method helps understand which areas need improvement to optimize results, thereby providing more specific and data-driven recommendations for the development of a technology.

Research on technology adoption in social security in Indonesia is important to understand how people use digital innovations to access public services. Therefore, this study aims to identify the UTAUT 2 factors that most influence the intention to use and actual use of technology for social security services in Indonesia, how the importance of these factors varies based on differences between groups, and this study also highlights the most important issues that matter to users and influence satisfaction with services and their effectiveness through an indepth analysis using an importance-performance map analysis approach. It is hoped that the results of this study can provide stakeholders with valuable insights and recommendations for optimizing the future implementation of the Jamsostek Mobile Application (JMO).

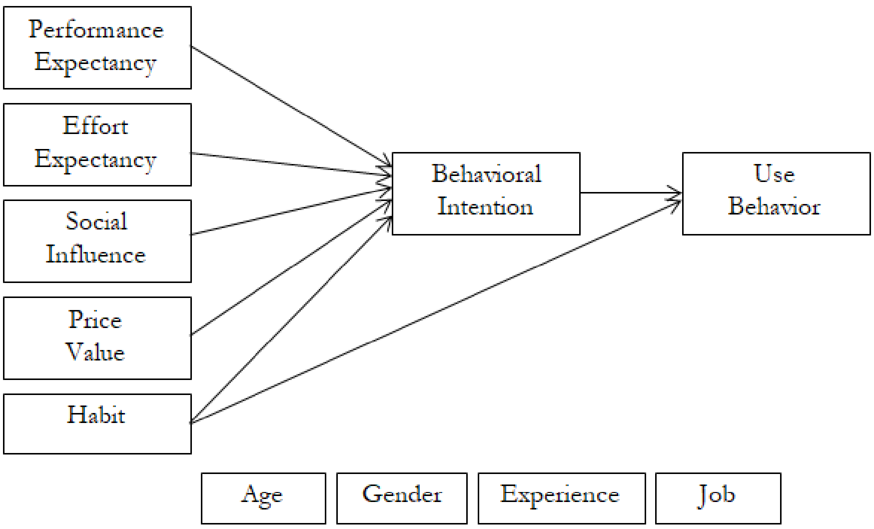

Figure 2. Diagram Structural Model UTAUT 2

Hypotheses must be formulated clearly to ensure that research findings are measurable and can be accounted for (Betts et al., 2021). Based on the structure of the UTAUT 2 model, this research's hypothesis is outlined as follows.

H1: Behavioral Intention affects Use Behavior

H2: Effort Expectancy affects Behavioral Intention

H3: Habit affects Behavioral Intention

H4: Habit affects Use Behavior

H5: Performance Expectancy affects Behavioral Intention

H6: Price Value affects Behavioral Intention

H7: Social Influence affects Behavioral Intention

H8: Group differences affect the path coefficient

METHOD

This research employs a quantitative approach to provide systematic and objective results on the constructs in the UTAUT 2 model, and the relationship between these constructs, and supports the expansion of the UTAUT 2 model by including work background as a moderating variable to produce strong statistical evidence to support or reject the hypothesis proposed (Tamilmani et al., 2021).

Samples were selected using a purposive sampling method to ensure that respondents had the relevant characteristics to assess the components of the UTAUT 2 model in the use of the Jamsostek Mobile (JMO) application. The sample collected was 153 respondents, which were analyzed using G*Power software with a statistical power of 0,95 to ensure the sample was used (Al-okaily et al., 2023). Respondents were classified based on several qualification indicators: age, gender, experience, and occupation. Gender qualifications include male and female categories. The age classification is divided into two nominal scale groups: 1 for 17-30 and 2 for 31-56. Employment classification is categorized into two main groups: permanent salaried and independent workers. Permanent salaried workers include private sector workers/employees, while independent workers include entrepreneurs and other jobs. The experience of using the JMO app was divided into two groups: group 1, new users, which is for users with less than 1 year or 1-3 years of experience, and group 2, experienced users, which is for users with more than 3 years of experience.

Based on the structural diagram of the model in figure 2, the seven fundamental variables that make up the UTAUT 2 model used in this research include performance experience "the extent to which the use of a technology will provide benefits for the user", effort expectancy "the level of ease associated with the use of the technology by the user", social influence "the extent to which users perceive that important others believe that they should use technology", habit "the extent to which people tend to carry out a behavior automatically due to learning", price value "the user's thinking that compares the benefits obtained with the costs incurred to use the application", behavior intention "individual behavior and attitudes to repeat or recommend to others", and use behavior "the level of variation and frequency of technology use by users" in understanding user behavior (Nugraha, 2023). A structured questionnaire measures these variables developed using a five-point Likert scale data measurement instrument, where a value of 1 indicates "strongly disagree" and a value of 5 indicates "strongly agree" (Al-okaily et al., 2023)To measure user readiness to use the JMO application, the Behavioral Intention variable is constructed by 3 indicator items: Use Behavior 2 indicators, Performance Expectancy, Social Influence, and Habit each having 3 indicators, Price Value 4 indicators, and Effort Expectancy 2 indicators.

Data was collected through a survey method by distributing online questionnaires for two weeks, from December 2-15, 2024. This method was chosen due to its efficiency in collecting data from a relatively large sample, covering users of the JMO application in various parts of Indonesia with diverse demographic groups and types of employment to answer the research questions (Shortt et al., 2023). After collecting the data, they were analyzed using PLS-SEM with the statistical analysis tool SmartPLS 3. PLS-SEM is a multivariate statistical method that enables the analysis of interactions between variables within a comprehensive conceptual model (Dash & Paul, 2021). This method involves testing both measurement and structural components simultaneously. To assess the structural model, the R Square value is evaluated to show the extent to which the independent variable explains the dependent variable, F Square to measure the influence of variables at the structural level, Q Square to assess the model's predictive power, and path coefficient to indicate the strength of the relationship between variables. In evaluating the measurement model, the factor loading value <0.70, convergent validity (composite reliability >0.70 and AVE value >0.50), and discriminant validity are assessed using the Fornell-Larcker Criterion and Heterotrait Monotrait Ratio (<90), which ensures that the variable has good discriminant validity (Hair et al., 2021). This study employed Multi-Group Analysis to compare the relationship paths between variables across different groups. In addition, importance-performance map analysis is used to identify and evaluate the performance of each variable based on the average value of rescaling results that change the value scale into a range of 0-100, where 0 indicates the lowest performance and 100 indicates the highest performance (Hair et al., 2021).

RESULT AND DISCUSSION

Evaluation of Measurement Models

Table 1. Convergent Validity Results

Construct	Outer Loading	Cronbach Alpha	rho_A	Composite Reliability	AVE
Performance Expectancy		0,831	0,836	0,901	0,752
The JMO application is useful in everyday life	0,926				
The JMO application makes it easier for me to access social security information and services	0,895				
The JMO application makes my activities easier than before using the application	0,773				
Effort Expectancy		0,870	0,939	0,937	0,882
I found the JMO app easy to use	0,919				
The features of the JMO application are simple and easy to understand	0,959				

Social Influence		0,892	0,913	0,932	0,820
My boss encouraged me to use the JMO app	0,913				
I use the JMO application because of the influence of the organization where I work	0,879				
I use the JMO application because my coworkers also use it	0,924				
Price Value		0,873	0,890	0,913	0,724
I feel very satisfied with the various features and services in the JMO application	0,815				
I feel like I get a lot of benefits from the features of the JMO application	0,791				
The JMO application is very valuable because it makes it easy to access Jamsostek information and services	0,892				
I find the JMO application very helpful in managing my time as a busy worker	0,900				
Habit		0,858	0,859	0,913	0,778
I feel the need to use the JMO application	0,874				
I always use the JMO application to access social security services	0,887				
I use the JMO app as part of my routine	0,885				
Behavioral Intention		0,808	0,813	0,874	0,635
I plan to continue using the JMO app as long as it is active	0,751				
The good quality of service from the JMO application makes me intend to continue using it	0,806				
I always provide reviews of the JMO application on social media	0,795				
The ease of use of the JMO application encourages me to continue using it	0,834				
Use Behavior		0,928	0,928	0,965	0,933
I find the JMO app very user-friendly	0,967				

I highly recommend the JMO app to others	0,965

The results of the measurement model analysis indicate that all constructs exhibit good convergent validity. This is supported by the outer loading value of most indicators being above 0.70. Additionally, the Average Variance Extracted (AVE) values for all constructs ranged from 0.635 to 0.933, exceeding the threshold of 0.50. These results demonstrate that the construct successfully explains more than half of the variance in the indicators, thereby meeting the criteria for convergent validity.

Table 2. Discriminant Validity Results

		BI	EE	HB	PE	PV	SI	UB
Fornell-Larcker Criterion	BI	0.797						
	EE	0.559	0.939					
	HB	0.039	0.204	0.882				
	PE	0.609	0.505	0.169	0.867			
	PV	0.317	0.156	-0.056	0.256	0.851		
	SI	0.568	0.260	-0.072	0.473	0.481	0.906	
	UB	0.774	0.476	0.113	0.470	0.286	0.401	0.966
Heterotrait-Monotrait (HTMT) Ratio	BI							
	EE	0,651						
	HB	0,078	0,242					
	PE	0,746	0,587	0,200				
	PV	0,365	0,170	0,083	0,294			
	SI	0,660	0,274	0,088	0,546	0,529		
	UB	0,886	0,519	0,126	0,536	0,309	0,429	

Discriminant validity has also been verified using two main methods, Fornell-Larcker criteria, and Heterotrait-Monotrait Ratio (HTMT). According to the Fornell-Larcker Criterion, the square root of each construct AVE exceeds its correlation with other constructs, demonstrating that each construct in the model is distinct and unique. Furthermore, the HTMT values for all construct pairs are below the threshold of 0.90, suggesting that the relationship between constructs is not overly strong, thereby maintaining good discriminant validity. Thus, these results confirm that the constructs in this study possess adequate discriminant validity.

Structural Model Evaluation

Table 3. Structural Model Results

Connection	β	T Value	Variance Explained (R2)	R2 Adjusted	Predictive Relevance (Q2)	Effect Size (F2)	VIF
Behavioral Intention -> Use Behavior	0,777	16,981	0,594	0,574	0,363	1,422	1,080
Effort Expectancy -> Behavioral Intention	0,354	6,046				0,220	1,399
Habit -> Behavioral Intention	-0,049	0,815				0,005	1,100
Habit -> Use Behavior	0,081	1,399	0,607	0,599	0,553	0,017	1,010
Performance Expectancy -> Behavioral Intention	0,267	3,776				0,105	1,664
Price Value -> Behavioral Intention	0,009	0,148				0,000	1,325
Social Influence -> Behavioral Intention	0,305	4,267				0,141	1,620

Based on the structural model analysis results, the relationship between Behavioral Intention and Use Behavior demonstrates a significant influence, with a path coefficient of 0.777 and a very high T-value (16.981). This relationship explains 59.4% of the variance in Use Behavior (R^2 = 0.594). Additionally, the model exhibits strong predictive ability (Q^2 = 0.363) and indicates a substantial effect of Behavioral Intention on Use Behavior (F^2 = 1.422).

For other relationships, Effort Expectancy significantly influences Behavioral Intention, with a path coefficient of 0.354 and a T-value of 6.046, indicating a medium effect (F^2 = 0.220). Performance Expectancy also significantly influences Behavioral Intention, with a path coefficient of 0.267 and a T-value of 3.776, though it demonstrates a small effect (F^2 = 0.105). Social influence also significantly impacts behavioral intention, with a path coefficient of 0.305, a T-value of 4.267, and an F^2 value of 0.141 (> 0.02 and < 0.15), which is categorized as a small effect. Conversely, Habit and Price Values show weaker influences on Behavioral Intention, with negative path coefficients (-0.049 and 0.009), lower T-Value (0.815 and 0.148 < 1.96), and very small (F2 = 0.005 for Habit and 0.000 for Price Value), indicating that their impacts are not statistically significant.

Meanwhile, the relationship between Habit and Use Behavior demonstrates a very small effect with a path coefficient of 0.081 and a low T-value (1.399 < 1.96), indicating that Habit does not significantly influence Use Behavior. However, this model explains 60.7% of the variation in Use Behavior (R^2 = 0.607). The analysis shows that Behavioral Intention is the primary factor influencing Use Behavior. At the same time, Effort Expectancy, Performance Expectancy, and Social Influence significantly impact behavioral intention, albeit to a lesser extent. Additionally, some constructs show no significant influence.

Table 4. Hypothesis Testing

Connection	**β**	**T value**	**P Value**	**Hypothesis**
H1 : Behavioral Intention -> Use Behavior	0,777	16,981	0,000	Accepted
H2 : Effort Expectancy -> Behavioral Intention	0,354	6,046	0,000	Accepted
H3 : Habit -> Behavioral Intention	-0,049	0,815	0,416	Rejected
H4 : Habit -> Use Behavior	0,081	1,399	0,162	Rejected
H5 : Performance Expectancy -> Behavioral Intention	0,267	3,776	0,000	Accepted
H6 : Price Value -> Behavioral Intention	0,009	0,148	0,882	Rejected
H7: Social Influence -> Behavioral Intention	0,305	4,267	0,000	Accepted

The results of hypothesis testing show that H1 (behavioral intention towards use behavior) is accepted, with β = 0.777, T-Value = 16.891, and P Value = 0.000. Similarly, H2 (effort expectancy to behavioral intention, β = 0.354, T-Value = 6.046, and P Value = 0.000), H5 (performance expectancy to behavioral intention, β = 0.267, T-Value = 3.776, and P Value 0.000), and H7 (social influence to behavioral intention, β = 0.305, T-Value = 4.267, and P Value 0.000) are also accepted, showing a positive influence. On the other hand, Hypotheses H3 (habit) and H6 (price value) on behavioral intention were rejected as indicated by very small path coefficients (-0.049) for habit and (0.009) for price value, with the T-Value both being below the critical value of 1.96 (in a two-way test), as well as high probability values (0.416) for habit and (0.882) for price value causing these hypotheses to be rejected. In addition, Hypothesis H4 (Habit to Use Behavior) is also rejected, judging from the small path coefficient value (0.081), the T-value is below the critical value (1.399 < 1.96) and the high probability value (0.162).

Analysis of Group Differences

Table 5. Group Analysis

Path of Influence	**P**	**Standard Coefficient**	**P**	**Standard Coefficient**
Gender	**Man**		**Woman**	
Behavioral Intention -> Use Behavior	0,000	0,656	0,000	0,861
Effort Expectancy -> Behavioral Intention	0,019	0,281	0,000	0,395
Habit -> Behavioral Intention	0,273	0,115	0,808	-0,020
Habit -> Use Behavior	0,300	0,125	0,174	0,098
Performance Expectancy -> Behavioral Intention	0,044	0,239	0,005	0,238
Price Value -Behavioral Intention	0,578	-0,079	0,760	0,022
Social Influence -> Behavioral Intention	0,020	0,401	0,000	0,308
Age	**17-30**		**31-56**	
Behavioral Intention -> Use Behavior	0,000	0,853	0,000	0,764
Effort Expectancy -> Behavioral Intention	0,000	0,272	0,007	0,397
Habit -> Behavioral Intention	0,331	0,102	0,387	-0,080
Habit -> Use Behavior	0,397	0,116	0,180	0,052
Performance Expectancy -> Behavioral Intention	0,002	0,338	0,011	0,247
Price Value -> Behavioral Intention	0,761	-0,047	0,602	0,030
Social Influence -> Behavioral Intention	0,002	0,345	0,015	0,258
Experience	**<1 Year and 1-3 Years (New users)**		**>3 Years (Experienced User)**	
Behavioral Intention -> Use Behavior	0,000	0,782	0,000	0,731
Effort Expectancy -> Behavioral Intention	0,005	0,369	0,000	0,370
Habit -> Behavioral Intention	0,053	-0,299	0,593	0,059
Habit -> Use Behavior	0,241	0,136	0,982	-0,003

Performance Expectancy -> Behavioral Intention	0,263	0,174	0,009	0,254
Price Value -> Behavioral Intention	0,597	-0,103	0,162	0,122
Social Influence -> Behavioral Intention	0,018	0,429	0,030	0,261
Job	**Laborers/Private Employees (Permanent Salaried Workers)**		**Entrepreneurs and others (Independent Workers)**	
Behavioral Intention -> Use Behavior	0,000	0,736	0,000	0,792
Effort Expectancy -> Behavioral Intention	0,000	0,402	0,385	0,124
Habit -> Behavioral Intention	0,864	-0,016	0,521	0,120
Habit -> Use Behavior	0,776	0,042	0,892	-0,034
Performance Expectancy -> Behavioral Intention	0,009	0,289	0,006	0,525
Price Value -> Behavioral Intention	0,814	0,024	0,985	0,003
Social Influence -> Behavioral Intention	0,024	0,263	0,645	0,079

Based on Gender

Men and women exhibit significant differences in the influence of Behavioral Intention on Use Behavior. Among men, the path coefficient for Behavioral Intention influence on Use Behavior is 0.656, which is highly significant (P=0.000). In contrast, this influence is stronger among women, with a coefficient of 0.861 (P=0.000), indicating that Behavioral Intention has a greater impact on application usage behavior in women than in men, highlighting the difference in how both groups respond to intention to use application. Additionally, Performance Expectancy significantly affects behavioral intention in men (coefficient 0.239) and women (coefficient 0.238). The similarity in coefficient values suggests that both genders equally recognize the importance of the application's benefits. Social Influence, which reflects the impact of others' opinions, plays a larger role in shaping Behavioral Intention among men (coefficient 0.401) than women (coefficient 0.308). This indicates that men may be more influenced by the opinions or recommendations of others when deciding to use applications.

Based on Age

In the 17-30 age group, the influence of Behavioral Intention on Use Behavior is quite strong, with a coefficient of 0.853 (P=0.000), indicating that younger individuals are more likely to act on their intentions when using applications. The 31-56 age group also shows a significant influence, but with a lower coefficient of 0.764, suggesting a slightly weaker impact than the younger group. Then, Effort Expectancy plays a larger role in shaping Behavioral Intention among individuals aged 31-56 (coefficient 0.397) than those aged 17-30 (coefficient 0.272). This indicates that older individuals tend to prioritize ease of use when deciding to adopt an application. Performance Expectancy has a stronger effect on Behavioral Intention in the 17-30 age group, with a coefficient of 0.338 (P=0.002), compared to 0.247 (P=0.011) in the 31-56 group. This suggests that both age groups value the application's benefits or outcomes. Still, the impact is greater among younger individuals, who may prioritize efficiency and fast results when using technology. Furthermore, social influence has a greater influence on the younger age group (17-30 years, coefficient 0.345) than on the older group (31-56 years, coefficient 0.258). This indicates that younger individuals are more influenced by their social environment when using applications.

Based on Experience

In the group of novice users, the influence of Behavioral Intention on Use Behavior is quite large with a coefficient of 0.782 (P=0.000), meaning that new users are more influenced by their intention to use the application. In contrast, the effect is slightly lower for users with more than 3 years of experience with a coefficient of 0.731. Experienced users are more familiar with the application, so the influence of their intention to use it is somewhat smaller. Effort Expectancy influences Behavioral Intention in both groups, but the coefficient is slightly higher for experienced users (0.370) than for new users (0.369), although both are statistically significant. This may suggest that experienced users pay more attention to the application's ease of use than new users. The effect of Social Influence on Behavioral Intention is significant in both experience groups, with a coefficient of 0.429 (P=0.018) for new users and 0.261 (P=0.030) for experienced users. This implies that new users are more influenced by other people's opinions or recommendations of others when forming their intentions. In contrast, experienced users tend to be more independent in forming their intentions, although social influence still plays a significant role.

Based on Job

The influence of Behavioral Intention on Use Behavior is significant in both occupational groups. Among permanent salaried workers (laborers/private employees), the coefficient is 0.736 (P=0.000), whereas in the group of independent workers (entrepreneurs and others), the value is higher at 0.792 (P=0.000). This shows that behavioral intentions play a significant role in influencing application usage behavior in both groups. However, this effect is slightly stronger among self-employed workers, which may be attributed to their greater autonomy in making personal decisions about app usage.

The effect of Performance Expectancy on Behavioral Intention is also significant in both job groups. For permanent salaried workers, the coefficient is 0.289 (P=0.009), while for self-employed workers, the value is higher at 0.525 (P=0.006). This suggests that self-employed workers emphasize the benefits or expected outcomes of using the app when forming their intentions. This could be because they are more focused on the efficiency and productivity that applications provide, which aligns with their work's flexible and dynamic nature.

Importance Performance Analysis (IPMA)

Table 6. Impact – Performance Map

	Behavioral Intention		**Use Behavior**	
Construct	Importance	Performance	Importance	Performance
Effort Expectancy	0,336	59.437	0,259	59.437
Habit	-0,053	68.855	0,042	68.856
Performance Expectancy	0,287	76.678	0,221	76.679
Price Value	0,031	79.370	0,024	79.372
Social Influence	0,327	70.622	0,252	70.620
Behavioral Intention			0,771	75.415

The Importance-Performance Map Analysis (IPA) results provide important insights into the factors influencing Behavioral Intention and Use Behavior in adopting the application. For behavioral intention, effort expectation is highly important (0.336) but has low performance (59.437), indicating that developers should improve the application's ease of use to meet user expectations better. In contrast, Habit has low importance (-0.053) but moderate performance (68.855), which means it does not require immediate attention. Both Performance Expectancy (importance 0.287, performance 76.678) and Social Influence (importance 0.327, performance 70.622) are important and perform well, but can still be optimized to increase their influence on use behavior. In addition, price value is of relatively low importance (0.031). Still, it has an excellent performance (79.370), which indicates that users are satisfied with the benefits associated with cost, so no significant changes are needed in this area. For Use Behavior, Behavioral Intention is the most important factor, with the highest level of importance (0.771) and strong performance (75.415), it is important to maintain and strengthen the factors that drive user intention to ensure the application's long-term success. These findings are shown in Figure 3 and 4, illustrating the importance-performance relationship.

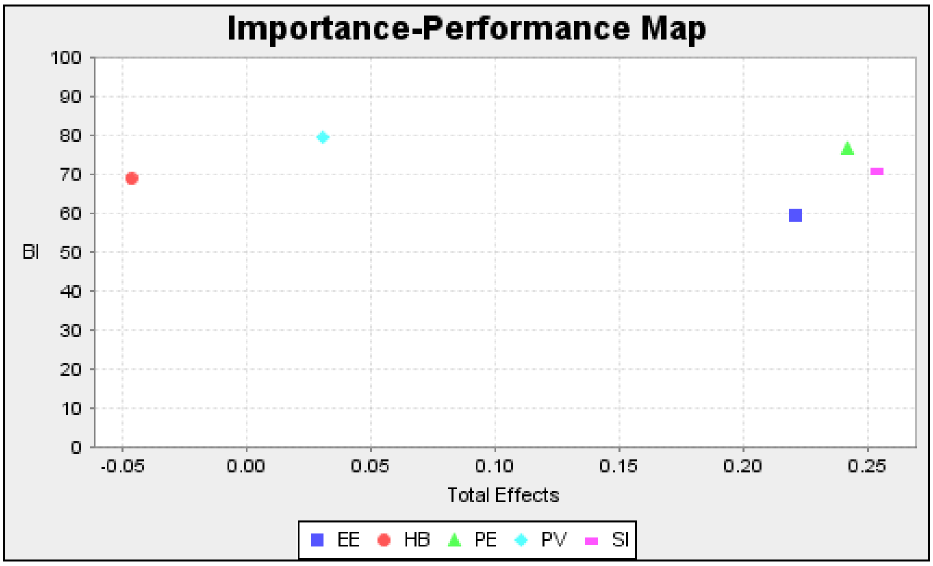

Figure 3. Behavioral Intention Impact-Performance Map

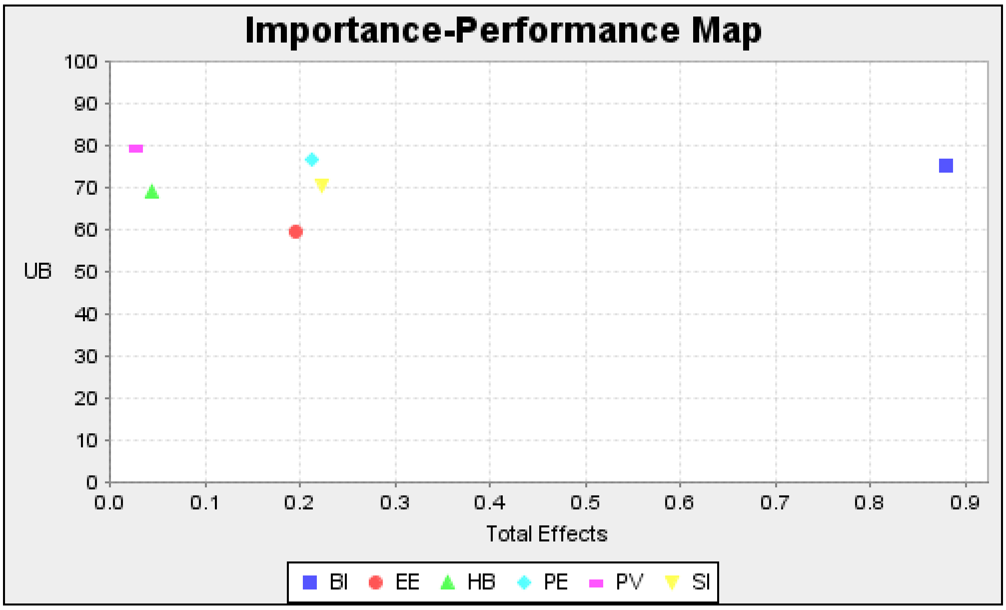

Figure 4. Use Behavior Impact-Performance Map

Effect of Behavioral Intention on Use Behavior

Behavioral intention directly measures the extent users want to use a system or application. This, in turn, affects how often and consistently the application is used in everyday life. In this study, user intention has a significant effect on usage behavior. This result is supported by Suroso & Sukmoro (2021), which indicates that the higher the intention to use the JMO application, the greater the possibility of using it.

Effect of Effort Expectancy on Behavioral Intention

Effort Expectancy, which has a significant impact, indicates that the ease of use of the JMO application is a very important aspect for users, supporting the findings of Venkatesh et al. (2016) In the UTAUT model. System improvements made to JMO Mobile, such as providing a clear interface, make it easy for users to access social security services in the application.

Effect of Habit on Behavioral Intention

Users ' adoption of the JMO app was not significantly influenced by habit. The limited functionality of the app, characterized by issues such as balance checking interruptions, data update failures, and complicated login processes, hindered the formation of positive habits in users. Thus, habit does not play an important role in predicting users' intention to use the JMO app. This finding is in line with the study by Kristi et al. (2024)Which states that habit does not predict user intention to adopt the Flip application.

Effect of Habit on Use Behavior

The insignificant effect of habit on use behavior in this study ($p > 0.05$, low path coefficient) indicates that users have not yet formed a pattern of regular use of the JMO application. This result is reinforced by the study of Talan et al. (2024), which also found that habit does not significantly affect use behavior.

Effect of Performance Expectancy on Behavioral Intention

Performance expectations confirm that the real benefits of the application, such as time efficiency and ease of access to services, play an important role in encouraging users to use the JMO application. This is supported by research by Rizkalla (2024) through the Technology Acceptance Model (TAM), which explains that the greater the benefits users feel from a technology, the greater their intention to use it. With the JMO application, BPJS Ketenagakerjaan can provide services quickly and minimize participant time because all services are already in one hand; there is no need to bother queuing at the branch office.

Effect of Price Value on Behavioral Intention

Price value is less relevant considering that the JMO application can be accessed at no cost, so it is not a major consideration in influencing user intentions and behavior. This finding is consistent with research by Kuarizmi & Padmalia (2024) In their research, “Behavioral Intention of Smart Home Users using UTAUT 2: Study in Citra Raya Tangerang,” they found that price value has no significant effect on behavioral intention.

Effect of Social Influence on Behavioral Intention

Social influence shows that recommendations from people around users, such as private workers/employees who get encouragement from superiors, organizations/companies, and colleagues, to use the JMO application further strengthen behavioral intentions. (Singh et al., 2020).

Multi-Group Analysis

Group differences show significant differences in UTAUT 2 factors related to behavioral intentions and usage behavior based on gender, age, experience, and occupation. Women are more influenced by ease of use (effort Expectancy) than men, while men are more influenced by social opinion (social influencers). Younger age groups (17-30 years) showed a stronger influence of behavioral intention on app use than older age groups (31-56 years), with social influence and app benefits being more dominant in younger age groups. New users pay more attention to ease of use and are more influenced by social recommendations than experienced users. Experienced users, on the other hand, are more likely to rely on relevant feature updates to meet their needs (Fernandes & Oliveira, 2021). Regarding occupation, self-employed workers influence behavioral intention and app usage more than salaried workers. This reflects the high need for efficiency and flexibility among self-employed workers, making applying JMO a practical solution in managing their social security independently.

Importance-Performance Map Analysis

The impact-performance map also extends the findings in this study by helping to identify priority areas of development and improvement of JMO applications based on user needs. Figures 3 and 4 and the analysis results show that the social influence and performance expectancy dimensions have the highest importance and performance values, making them key factors that should be prioritized to improve behavioral intention and usage behavior. On the other hand, effort expectancy shows the lowest performance, although the significance is relatively high, thus highlighting the need for improvement in the application's ease of use. Other dimensions, such as price value, showed excellent performance, but their importance for behavioral intention and usage behavior is low. Meanwhile, the habit dimension is at a moderate level of importance and performance, showing a relatively stable contribution but not as important as social influence and performance expectations. These findings emphasize the aspects of social influence and performance expectations while raising expectations of effort to maximize the adoption and effective use of the app.

CONCLUSION

This research highlights that effort expectancy, social influence, and performance expectancy are the primary factors influencing users' intentions and behavior in adopting applications. Social influence and performance expectancy are highly important, while effort expectancy needs improvements, given that application performance in this area is still low. The analysis also showed differences in the impact of app adoption based on user age, gender, and experience, with self-employed workers having a greater need for app flexibility.

Deploying the application with a simpler interface can enhance ease of use (effort expectancy). Strengthening social support through partnerships with companies or organizations, leveraging social media creatively, and introducing a reward system for users who consistently use (social influence). Additionally, developing features that provide tangible benefits for users, such as payment reminders and automatic claims, can improve performance expectancy. Policymakers and developers should also segment users by job type and age. This approach will help create a more relevant and flexible user experience.

Based on this study's findings, future research can explore technology acceptance factors using UTAUT 2 by expanding to other sectors or with different demographic groups. Given the importance of security in digital services, future research could also focus on how users' trust in personal data protection in the JMO app affects technology adoption intentions and behavior.

The findings of this study also offer important insights that can guide policymakers and app developers in formulating future strategies for implementing JMO apps. The development of features more responsive to the needs of various groups of workers, such as payment flexibility for informal workers, and periodic evaluation of application performance by quickly responding to complaints or complaints made by the public to improve the good experience for users. This is important to help maintain user engagement and ensure that the app remains relevant to the needs of the Indonesian workforce. Thus, technology adoption can increase and strengthen a fairer and more equitable social protection system.

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