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# Examination of the Factors Impacting the Interest of Residents in Semarang City in Mobile Health Applications: An UTAUT Analysis

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**Abstract.**
**Purpose:** The study aims is to examine the determinants that impact the level of public interest in utilizing mobile health (m-health) applications in Semarang City, Indonesia. Our specific objective is to identify the critical factors that facilitate or impede the public's adoption of these applications.
**Methods:** This study objective was pursued using a comprehensive approach. A study model was developed utilizing the Unified Theory of Acceptance and Use of Technology (UTAUT) as its foundation. This model encompasses essential variables including performance expectancy, effort expectancy, social influence, facilitating conditions, price value, and perceived trust. The process of data collecting was carried out by means of a survey that was disseminated across widely used social media channels. The study was conducted using a sample size of 257 participants who are residents of Semarang City. The data that was collected underwent a thorough analysis utilizing the Partial Least Squares - Structural Equation Model (PLS-SEM) approach.
**Results:** The research conducted in our study resulted in several significant findings. The study revealed that several factors, namely performance expectancy, social influence, price value, and perceived trust, had a notable and beneficial impact on users' inclination towards using m-health applications. On the other hand, the variables of effort expectancy and facilitating conditions did not exhibit a statistically significant influence on the level of public interest in these applications. Furthermore, a substantial correlation was found between the behavioral intention and the actual usage behavior of inhabitants of Semarang City in their adoption of m-health applications.
**Novelty:** The research presented in this study is distinguished by its comprehensive analysis of the various factors that impact the adoption of mobile health (m-health) applications in Semarang City. Through the incorporation and expansion of variables such as price value and perceived trust, our study provides a comprehensive and nuanced comprehension of this particular occurrence by adapting and extending the UTAUT model. Our work emphasizes the importance of performance expectancy and social influence, while also suggesting the need for additional investigation into the roles of effort expectancy and facilitating conditions. Additionally, our study offers valuable information regarding the influence of age and gender as moderators in these associations. The results of this study have significant practical implications for healthcare professionals and policymakers who are interested in promoting the use of mobile health (m-health) technologies among the public. Additionally, these findings can serve as a valuable guide for future research endeavors in this particular area of study.

**Keywords**: Mobile health, UTAUT model, Behavioral intention, Technology adoption, Electronic health
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## INTRODUCTION

In the context of the Covid-19 pandemic, there has been a notable proliferation of digital technology [1], [2], in the global health domain. In response to the increasing incidence of Covid-19 infections, nations across the globe are enacting diverse strategies aimed at curtailing the transmission of the virus and mitigating its potential exacserbation. Promoting the implementation of electronic health (e-health) solutions has become a crucial approach to facilitate persons' access to healthcare services, reducing the necessity for considerable physical mobility in public spaces [3].

E-health, an essential element of healthcare systems worldwide [4], has experienced substantial expansion in recent years, specifically in the realm of mobile health (m-health) applications [5]. The prevalence of mobile health applications is conspicuous, as estimated to have been around 325,000 m-health apps

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accessible through App Stores in 2017. Furthermore, an astounding 3.7 billion users downloaded these applications, representing a 16% increase compared to the previous year [6].

An escalating number of nations, Indonesia included, are adopting m-health technology due to the benefits and positive effects it provides. The digital health services in Indonesia have experienced notable advancements, notably in the context of the ongoing pandemic [7]. According to Frost and Sullivan [8], it is projected that the income of the digital health sector in Indonesia may potentially reach 726 million dollars by the year 2022. This projection signifies a notable increase of 62.2% over the span of the past six years. The rise mentioned above is additionally bolstered by Indonesia's substantial internet penetration rate, which stands at approximately 23%. It is noteworthy that more than 70% of the country's populace can access the internet via mobile devices [9], [10].

A number of m-health apps have garnered significant attention and usage among the community. Notable examples include Alodokter, Halodoc, Mobile JKN, and KlikDokter [10]. The popularity of these applications stems from their capacity to offer cost-efficient and user-friendly solutions to meet the growing need for healthcare services [7], [11]. In addition, the use of these devices can aid healthcare professionals in collecting data, performing surveillance, and making timely determinations on particular medical ailments, owing to their ability to retain individuals' medical records [12]. These elements have the potential to significantly enhance health services and overall health quality within the community.

Despite the growing advancements in digital health technology, specifically m-health, in Indonesia and its numerous advantages, there persists a relatively low level of public interest in embracing this technology. The current rate of adoption of mobile health (m-health) applications within the community is reported to be 21.56% of the entire population in Indonesia [13]. Furthermore, there exists an unequal distribution of adoption levels, with a predominant concentration in larger urban areas, whereas smaller regions have a slower pace of adoption. The adoption rate of m-health technology in these urban regions has been considerably influenced by the high incidence of Covid-19 cases and community mobilizations [14].

Central Java, a province that has been significantly affected by the epidemic, has recorded a total of 637,982 confirmed cases of Covid-19 and 33,543 deaths [15]. Semarang City is currently classified as a red zone due to the significant and quick spread of Covid-19-related information [14]. The study conducted by Warsito et al. [16] in Semarang City demonstrated that individuals exhibit a tendency to neglect the verification of news and health-related material obtained from the internet, particularly with regards to Covid-19. The reluctance to validate information is influenced by the intricate nature of the validation process, which is further compounded by the vast volume of data in circulation. The potential resolution of this matter may be achieved by the proper utilization of technology like as m-health, which enables individuals to acquire reliable information and news pertaining to the Covid-19 pandemic [17], [18].

Dewi et al. [19] conducted a study which provided evidence for the efficacy of m-health in augmenting pregnant women's knowledge and awareness pertaining to exclusive lactation. The m-health application was utilized to educate expectant women regarding the advantages of exclusive breastfeeding, leading to an increased consciousness regarding its critical role in safeguarding the health of infants. In a similar vein, Jannah et al. [20] investigated the effects of mobile health on student conduct and discovered favorable results. The m-health application empowered students to perform self-diagnosis and self-treatment, as well as filter and verify medical information, thereby contributing to the reduction of treatment errors.

Despite the fact that a number of studies have emphasized the beneficial effects of m-health applications, additional research is required, specifically from the user's standpoint. Previous research has predominantly concentrated on the advantages that m-health applications offer to their consumers. Nevertheless, there is a dearth of comprehensive research on the determinants that impact the community's approval of these applications [21], [22]. Insufficient community acceptability or interest could potentially impede the maximum potential of m-health applications [23], [24]. Hence, it is imperative to conduct research on the determinants that impact public interest in utilizing m-health applications in order to optimize health system efficacy, enhance the quality of public health, and enable mobile-based health service providers and government regulators to better meet the demands of their users [25]–[27].

Venkatesh et al.'s [28] Unified Theory of Acceptance and Use of Technology (UTAUT) model is a dependable method for assessing interest in adopting a technology. The variables comprising this model—

effort expectancy, performance expectancy, social influence, and facilitating conditions—are hypothesized to have an impact on behavioral intention and use behavior. Prior research has made extensive use of the UTAUT model and demonstrated its validity in comparison to other models of a similar nature [29]–[31]. Furthermore, its efficacy in health sector research pertaining to mobile technology has been demonstrated [32].

Prior studies that utilized the UTAUT model to examine the implementation of m-health in developing nations, including the one conducted by Alam et al. [33], established that the model accounts for as much as 62% of user behavioral intention. This was accomplished through the application of constructs including performance expectancy, effort expectancy, social influence, facilitating conditions, perceived reliability, and price value. In a similar vein, Semiz and Semiz [34] discovered that the UTAUT model, which included constructs such as perceived trust, hedonic motivation, habit, performance expectancy, and effort expectancy, accounted for approximately 54% of users' intention to utilize m-health applications. The UTAUT model has been effectively utilized in Indonesia to examine the various elements that impact user inclination towards utilizing m-health applications [7], [35].

Expanding upon prior research and the UTAUT model's efficacy, the objective of this study is to modify the UTAUT model proposed by Venkatesh et al. [28] in order to investigate the variables that might influence the inclination of Semarang City residents to utilize m-health applications.

## METHODS

The current study used a quantitative methodology in order to collect an exhaustive amount of data pertaining to the identified issue. Emzir [36] posits that a quantitative approach is grounded in positivism and collects statistical data through the implementation of research strategies such as surveys and experiments. The objective is to impartially ascertain facts or causes underlying social phenomena by employing a deductive methodology that evaluates hypotheses, thereby instigating the research process [37].

To examine the direct impact of variables including performance expectancy, effort expectancy, social influence, facilitating conditions, price value, and perceived trust on the public's inclination to utilize m-health applications in Semarang City, the research design is founded upon an adapted version of the UTAUT model. Furthermore, the research investigated the moderating impact of gender and age on the independent variables, as these factors were identified as having a substantial effect on the model variables.

### Sampling

The study utilized purposive sampling, a form of non-probability sampling, to pick participants based on predetermined criteria. The participants in this research were chosen through purposive sampling, employing specific criteria. These criteria included being within the age range of 18 to 45 years, residing in Semarang City, and having utilized features or services in at least one of the m-health applications (such as Alodokter, Halodoc, Mobile JKN, KlikDokter, or SATUSEHAT Mobile) on at least one occasion.

Given the lack of precise knowledge regarding the population size, the sample size was determined by employing the rule of thumb, which involves multiplying the total number of indicators utilized by a factor of 5. The study encompasses a total of 32 variables, with each indicator consisting of four sub-indicators that pertain to performance expectancy, effort expectancy, social impact, facilitating conditions, pricing value, perceived trust, behavioral intention, and actual usage behavior. The minimal sample size for this study was estimated to be 160 respondents based on a calculation utilizing the rule of thumb. The size of the sample in question adheres to the specified range of 30 to 500 samples, as proposed by Roscoe [38].

The duration of data collecting spanned a period of approximately four weeks, commencing on April 5 and concluding on May 2, 2023. Based on the conducted data collection method, a total of 293 participants have completed online questionnaires. Subsequently, a process of data screening is conducted, resulting in a selection of 257 data points for further analysis.

### Research instruments

The data for this study was gathered through the utilization of a closed questionnaire, which was disseminated over several platforms such as WhatsApp, Telegram, and Instagram. Participants were presented with a Likert scale consisting of five points, which encompassed the response options of

"Strongly Disagree" to "Strongly Agree," in order to respond to the series of questions. The selection of this scale was based on its simplicity and the ease with which respondents could comprehend it [39], [40].

### Data analysis

The current study incorporates two primary components for data analysis: descriptive statistical analysis and inferential statistical analysis. The demographic profile of the respondents was analyzed using descriptive statistical analysis, which involved categorizing them according to their gender, age, and the m-health application they used.

The inferential statistical study employed the partial least squares - structural equation modelling (PLS-SEM). PLS-SEM is a research methodology that allows for the concurrent evaluation of both the measurement model (outer model) and the structural model (inner model) [41]. The objective of this methodology is to examine the associations between variables in the research framework [42]. In order to utilize PLS-SEM, two fundamental assessments were performed: the outer model assessment to evaluate the validity and reliability of the collected data, and the inner model assessment to examine the model's capacity to elucidate the links among the variables employed in the study.

## RESULTS AND DISCUSSIONS

The current study obtained a total of 257 genuine responses from the participants. Among the entire sample of respondents, 168 (65%) were female and 89 (35%) identified as male. A significant proportion of participants, 176 (68%), identified as being between the ages of 18 and 24. In relation to the m-health application utilized, Halodoc emerged as the favored option among the participants, boasting 141 (54.9%) users. SATUSEHAT Mobile, on the other hand, garnered 66 (25.7%) users.

### Outer model

The assessment of the validity and reliability of the research instruments was conducted in this study using the outer model measurement. The study encompassed the administration of many assessments, such as tests for convergent validity, discriminant validity, and composite reliability. The utilization of these tests is imperative in order to guarantee the precision and uniformity of the measurement tools employed in the research.

The initial assessment pertains to the concept of convergent validity. A criterion for determining the validity of an indicator is met when the external loading of each indication surpasses a minimum threshold of 0.5 [43]. From Table 1, all 28 indicators demonstrate validity, as indicated by their factor loading values exceeding 0.5.

Table 1. Results for the measurement model

| Variable | Indicator | Factor Loading | Average variance extracted | Cronbach's Alpha | Composite Reliability |
|---|---|---|---|---|---|
| Performance Expectancy (PE) | PE1 | 0.697 | 0.519 | 0.690 | 0.811 |
| | PE2 | 0.711 | | | |
| | PE3 | 0.778 | | | |
| | PE4 | 0.690 | | | |
| Effort Expectancy (EE) | EE1 | 0.744 | 0.501 | 0.674 | 0.797 |
| | EE2 | 0.835 | | | |
| | EE3 | 0.654 | | | |
| | EE4 | 0.570 | | | |
| Social Influence (SI) | SI1 | 0.825 | 0.552 | 0.571 | 0.768 |
| | SI2 | 0.791 | | | |
| | SI3 | 0.752 | | | |
| | SI4 | 0.581 | | | |
| Facilitating Conditions (FC) | FC1 | 0.670 | 0.527 | 0.723 | 0.829 |
| | FC2 | 0.683 | | | |
| | FC4 | 0.815 | | | |
| Price Value (PV) | PV2 | 0.720 | 0.535 | 0.565 | 0.775 |
| | PV3 | 0.712 | | | |
| | PV4 | 0.762 | | | |
| Perceived Trust (PT) | PT1 | 0.677 | 0.523 | 0.696 | 0.814 |
| | PT2 | 0.736 | | | |
| | PT3 | 0.711 | | | |
| | PT4 | 0.765 | | | |

| Variable | Indicator | Factor Loading | Average variance extracted | Cronbach's Alpha | Composite Reliability |
|---|---|---|---|---|---|
| Behavioral Intention (BI) | BI1 | 0.744 | 0.618 | 0.793 | 0.866 |
| | BI2 | 0.827 | | | |
| | BI3 | 0.793 | | | |
| | BI4 | 0.778 | | | |
| Actual Usage Behavior (UB) | UB1 | 0.727 | 0.602 | 0.342 | 0.751 |

The subsequent convergent validity test is conducted for each of these variables using the AVE criteria, which stipulates that a minimum value of 0.5 is required for a variable to be considered valid [42]. Valid results for the convergent validity test were obtained for the eight variables whose AVE values exceeded 0.5. The findings of the research, presented in Table 1, indicate that all variables within their respective categories possess an AVE value exceeding 0.5, thus establishing their validity.

The variables in this research were evaluated for reliability using two criteria: Cronbach's alpha and composite reliability. In order for either of these reliability measures to be deemed moderate, they must both satisfy a minimum threshold of 0.5 [43]. The variables utilized in this investigation exhibited moderate to high degrees of reliability, as indicated by Cronbach's alpha and composite reliability values surpassing 0.5, as presented in Table 1. This suggests that the measurement instruments employed in the research exhibit consistency and dependability when evaluating the variables being examined.

**Inner model**

The purpose of the inner model testing was to investigate the relationship between variables and determine the validity of the research model. The purpose of the model fit measurement was to assess the performance of the research model and to reduce specification errors. Standardized root mean square residual (SRMR), exact fit test (Euclidean and Geodesic values), and normed fit index (NFI) were the three criteria that comprised the model fit test. The SRMR value in the model was 0.062, which is below the threshold of 0.08, as shown in Table 2. Both the Geodesic (d_G value of 0.383) and Euclidean (d_ULS value of 1.586) values satisfied the requirements by being below 95. Nevertheless, the NFI value acquired was 0.792, which was marginally below the suggested cutoff value of 0.9 for a satisfactory fit. This indicated that the fit could potentially be enhanced further.

Table 2. Model fit result.

| Criteria | Minimum Value | Actual Value | Information |
|---|---|---|---|
| SRMR | < 0.8 | 0.062 | Good fit |
| d_ULS | < 95 | 1.586 | Good fit |
| d_G | < 95 | 0.383 | Good fit |
| NFI | > 0.9 | 0.792 | Acceptable fit |

The R-squared value assessed the predictive model's ability to adequately elucidate the association between the dependent and independent variables. The R-square values associated with the variables in the research model indicated a considerable degree of predictive capability for the model. As shown in Table 3, the variables PE, EE, FC, SI, PV, and PT accounted for 53.5% of the variance in BI, whereas BI accounted for 35.5% of the variance in UB.

Table 3. Result of R-squared value

| Variable | R-Squared | R-Squared Adjusted |
|---|---|---|
| BI | 0.535 | 0.523 |
| UB | 0.355 | 0.352 |

The utilization of Q-squared testing was implemented in order to evaluate the model's predictive validity, which measures its ability to accurately forecast data that was not utilized in the estimation of the model's parameters. The Q-squared values for the two dependent variables, BI and UB, were 0.314 and 0.204, respectively, both indicating values above zero. Therefore, it can be inferred that the model utilized in the study exhibits strong predictive validity, as demonstrated in Table 4.

Table 4. Result of Q-squared value.

| Variable | Q Square |
|---|---|
| BI | 0.314 |
| UB | 0.204 |

Strengthening the relationships between latent variables in the research model was the objective of the path coefficient testing. As demonstrated in Table 5, the model employed in this investigation demonstrates an average positive correlation among its variables. Original sample value 0.595 indicated that the variable BI had the most robust correlation with UB. The relationship between PT and BI, which had an initial sample value of 0.472, was another variable that exhibited a robust correlation. With initial sample values of -0.048, the variables EE and FC exhibited a diminished correlation with BI.

Table 5. Path coefficient results

| Relation | Original Sample (O) |
|---|---|
| PE → BI | 0.199 |
| EE → BI | 0.027 |
| SI → BI | 0.132 |
| FC → BI | -0.048 |
| PV → BI | 0.114 |
| PT → BI | 0.472 |
| BI → UB | 0.595 |

Bootstrapping was employed in conjunction with SmartPLS 3 tools to verify hypotheses. The test outcomes are presented in Table 6. Upon conducting bootstrapping with a one-tailed test and a significance level of 0.05, it was determined that the majority of the study's formulated hypotheses were confirmed. The hypothesis is deemed accepted when the p-values are less than 0.05 and refuted when they exceed 0.05. Furthermore, the t-statistic value is employed; if it exceeds the critical value (1.64 for one-tailed), it indicates that the conducted measurements are statistically significant, subject to a specific margin of error.

Table 6. Hypothesis testing

| Hypothesis | Relation (Positive) | t-statistics | p-values | Information |
|---|---|---|---|---|
| H1 | PE → BI | 2.457 | 0.007 | Supported |
| H2 | EE → BI | 0.443 | 0.329* | Not Supported |
| H3 | SI → BI | 2.515 | 0.006 | Supported |
| H4 | FC → BI | 0.820 | 0.206* | Not Supported |
| H5 | PV → BI | 1.845 | 0.033 | Supported |
| H6 | PT → BI | 6.149 | 0.000 | Supported |
| H7 | BI → UB | 12.255 | 0.000 | Supported |

* p-values > 0.05.

The findings from the aforementioned hypothesis testing indicate that the two independent variables of the UTAUT model, PE and SI, have a statistically significant positive impact on BI (H1 and H3 are supported). This is consistent with the results reported in multiple other studies [7], [22], [31], [33], [44]–[46], which indicate that the PE and SI variables significantly influence user interest in utilizing m-health applications. Furthermore, this study incorporates two additional variables, PV and PT, which demonstrate a positive impact on user interest (BI) regarding the utilization of m-health applications (H5 and H6 are supported). These results are consistent with those of other studies [27], [34], [46]–[48] that conclude both PV and PT have a substantial impact on user adoption of technology.

In contrast, the results indicate that neither the EE nor FC variables significantly impact user interest in utilizing the m-health application (H2 and H4 are not supported). This is because both EE (0.329) and FC (0.206) have p-values greater than 0.05. The findings are consistent with those of a number of other studies

[7], [22], [27], [33], [48] that concluded the two variables, EE and FC, have no substantial impact on the public's interest in utilizing m-health applications.

The present study also examined the impact of moderator variables, namely age and gender, on the independent variables employed. Bootstrapping testing was replicated in order to examine this effect; however, this time, age and gender were included as moderator variables in order to observe the resultant moderation effect. The outcomes of the tests in which age was used as a moderator are presented in Table 7.

Table 7. Moderation by age.

| Relation (Moderated by Age) | Original Sample | p-values |
|---|---|---|
| PE → BI | -0.083 | 0.127* |
| EE → BI | 0.026 | 0.334* |
| SI → BI | -0.108 | 0.023 |
| FC → BI | -0.024 | 0.317* |
| PV → BI | -0.053 | 0.217* |
| PT → BI | 0.126 | 0.077* |

* p-values > 0.05.

Based on the output presented in Table 7, it can be observed that the average p-values for the age-modified relationship between the independent variables and the dependent variable exceed 0.05. This indicates that age has no substantial moderating effect on the relationship between the variables BI and PE, EE, SI, FC, PV, and PT. Nevertheless, when age moderates the relationship between SI and BI variables, the resulting p-values are 0.023 or less than 0.05. Consequently, age only moderates the relationship between the SI and BI variables in a significant way.

In addition, the effect of another moderator variable, namely gender, was also assessed in this study. The outcomes of the measurements incorporating gender as a moderating factor are presented in Table 8.

Table 8. Moderation by gender.

| Relation (Moderated by Gender) | Original Sample | p-values |
|---|---|---|
| PE → BI | -0.060 | 0.236* |
| EE → BI | -0.029 | 0.335* |
| SI → BI | 0.018 | 0.367* |
| FC → BI | -0.046 | 0.246* |
| PV → BI | 0.056 | 0.228* |
| PT → BI | 0.021 | 0.412* |

* p-values > 0.05.

The results of the analysis presented in Table 8 indicate that the p-values associated with the influence of gender on the relationship between the variables PE, EE, SI, FC, PV, and PT are all greater than 0.05. Therefore, it can be concluded that gender does not exert a substantial moderating effect on the entirety of the association between the independent variables and the dependent variable that was incorporated into the model for this research.

Conclusions regarding the subsequent hypothesis can be derived from the outcomes of assessing the influence of age (Table 7) and gender (Table 8) as moderator variables in the model employed in this investigation. The findings are presented in Table 9.

Table 9. Hypothesis testing continuation

| Hypothesis | Relation | Information |
|---|---|---|
| H8 | Age moderates the relationship between the independent variable and the dependent variable | Partially Supported |
| H9 | Gender moderates the relationship between the independent variable and the dependent variable | Not Supported |

Age has no significant moderating effect on the relationship between the dependent variable and the independent variables PE, EE, SI, FC, PV, and PT, according to the outcomes of tests conducted concerning the influence of moderator variables on this relationship. On the contrary, age exerts a substantial moderating effect on the correlation between SI and BI, thus providing only partial support for hypothesis H8. With regard to H9, which posits that gender significantly moderates the relationship between the independent and dependent variables, it is possible to conclude that the hypothesis lacks support. This conclusion is reached on the basis that all p-values produced by gender-modified relationships between the independent and dependent variables are greater than 0.05.

**Multigroup analysis**

In order to ascertain whether the influence of moderator variables causes a significant difference in the calculation results within a particular group, multigroup analysis measurement is performed. Two demographic variables, specifically age and gender, are the subjects of this research.

The age variable is initially assessed, with the age range utilized in this research study being subdivided into the following categories: 25–34 years, 18–24 years, and 35–45 years. The age is additionally categorized into three distinct categories according to the measurement: young adults (ages 18 to 24), middle-aged adults (ages 25 to 34), and adults (ages 34 to 45). To determine whether there are significant differences between the results of calculations for different age categories, it is necessary to compare two groups. Table 10 presents the outcomes of the comparison between youthful adults and middle-aged adults.

Table 10. Multigroup analysis based on age: Comparison 1 (young adults vs. middle-aged adults).

| Relation | Young Adults | | Middle-aged Adults | | Path Coefficient Diff | p-values |
|---|---|---|---|---|---|---|
| | Path Coefficient | t-values | Path Coefficient | t-values | | |
| PE → BI | 0.234 | 2.992 | 0.112 | 0.623 | 0.122 | 0.271* |
| EE → BI | 0.030 | 0.410 | 0.071 | 0.455 | -0.041 | 0.383* |
| SI → BI | 0.169 | 2.744 | 0.169 | 1.163 | 0.001 | 0.459* |
| FC → BI | -0.007 | 0.094 | 0.023 | 0.136 | -0.030 | 0.413* |
| PV → BI | 0.146 | 2.224 | -0.014 | 0.082 | 0.161 | 0.183* |
| PT → BI | 0.407 | 5.112 | 0.480 | 2.653 | -0.073 | 0.325* |
| BI → UB | 0.615 | 11.820 | 0.510 | 5.705 | 0.106 | 0.161* |

* p-values > 0.05.

The mean path coefficient difference between the young adult and middle-aged cohorts is presented in Table 10, which signifies a positive value. This implies that youthful adults, on average, possess a more pronounced capacity for exerting influence than middle-aged individuals. On the contrary, a number of variable relationships, including PT, EE, and FC with BI, demonstrate path coefficient differences that are negative or less than zero, indicating that the middle-aged group exerts a more pronounced influence in those particular instances. In order to ascertain the statistical significance of these effects, p-values were calculated. It is worth mentioning that all p-values associated with the comparison between young adults and middle-aged adults on all variables surpass 0.05. This suggests that there is no statistically significant distinction in the outcomes of the measurements when comparing the two age groups.

Furthermore, an analogous analysis was performed on the groups comprising young individuals and adults; the findings of this comparison are displayed in Table 11.

Table 11. Multigroup analysis based on age: Comparison 2 (young adults vs. adults).

| Relation | Young Adults | | Adults | | Path Coefficient Diff | p-values |
|---|---|---|---|---|---|---|
| | Path Coefficient | t-values | Path Coefficient | t-values | | |
| PE → BI | 0.234 | 2.992 | -0.073 | 0.308 | 0.307 | 0.130* |
| EE → BI | 0.030 | 0.410 | 0.128 | 0.744 | -0.098 | 0.277* |
| SI → BI | 0.169 | 2.744 | 0.072 | 0.360 | 0.097 | 0.321* |
| FC → BI | -0.007 | 0.094 | 0.046 | 0.274 | -0.053 | 0.373* |

| Relation | Young Adults | | Adults | | Path Coefficient Diff | p-values |
|---|---|---|---|---|---|---|
| | Path Coefficient | t-values | Path Coefficient | t-values | | |
| PV → BI | 0.146 | 2.224 | 0.132 | 0.699 | 0.014 | 0.498* |
| PT →BI | 0.407 | 5.112 | 0.732 | 3.385 | -0.325 | 0.094* |
| BI →UB | 0.615 | 11.820 | 0.654 | 2.199 | -0.038 | 0.313* |

* p-values > 0.05.

The analysis of the young and adult groups demonstrates a statistically significant difference in the average path coefficients, indicating a negative relationship. This suggests that the adult group exerts a more pronounced influence compared to the young adult group across many variables, such as emotional engagement (EE), financial commitment (FC), and physical touch (PT) in connection to behavioral intention (BI), as well as the relationship between BI and ultimate behavior (UB). In order to assess the importance of this discrepancy, the p-values obtained were analyzed. Nevertheless, the p-values associated with each variable in Table 11 exceed the threshold of 0.05, suggesting that the observed disparities between the two groups lack statistical significance. Table 12 presents a comparison between the middle-aged adult and adult groups for further analysis.

Table 12. Multigroup analysis based on age: Comparison 3 (middle-aged adults vs. adults).

| Relation | Middle-aged Adults | | Adults | | Path Coefficient Diff | p-values |
|---|---|---|---|---|---|---|
| | Path Coefficient | t-values | Path Coefficient | t-values | | |
| PE →BI | 0.234 | 2.992 | -0.073 | 0.308 | 0.307 | 0.130* |
| EE → BI | 0.030 | 0.410 | 0.128 | 0.744 | -0.098 | 0.277* |
| SI → BI | 0.169 | 2.744 | 0.072 | 0.360 | 0.097 | 0.321* |
| FC →BI | -0.007 | 0.094 | 0.046 | 0.274 | -0.053 | 0.373* |
| PV → BI | 0.146 | 2.224 | 0.132 | 0.699 | 0.014 | 0.498* |
| PT →BI | 0.407 | 5.112 | 0.732 | 3.385 | -0.325 | 0.094* |
| BI →UB | 0.615 | 11.820 | 0.654 | 2.199 | -0.038 | 0.313* |

* p-values > 0.05.

The findings shown in Table 12 demonstrate that, for the majority of variable relationships, the adult group consistently exerts a stronger influence compared to the middle-aged adult group. The presence of distinct path coefficient disparities may be noticed in many variable associations, including EE, FC, PV, and PT with BI, as well as the connection between BI and UB, wherein the resultant path coefficient values exhibit negativity. Upon doing an analysis of the p-values associated with the various variable associations, it becomes apparent that there is no statistically significant difference between the middle-aged and adult groups. This conclusion is drawn based on the fact that the resulting p-values exceed the threshold of 0.05.

This study not only evaluates the importance of the variations associated with the age variable but also investigates the significance of the disparities in the outcomes of the model that can be attributable to the gender variable. Gender is classified into two distinct categories, specifically male and female. The comparative findings pertaining to the two gender groups are displayed in Table 13.

Table 13. Multigroup analysis based on gender (male vs. female).

| Relation | Male | | Female | | Path Coefficient Diff | p-values |
|---|---|---|---|---|---|---|
| | Path Coefficient | t-values | Path Coefficient | t-values | | |
| PE →BI | 0.323 | 2.087 | 0.137 | 1.654 | 0.186 | 0.145* |
| EE → BI | 0.126 | 1.009 | 0.023 | 0.295 | 0.103 | 0.234* |
| SI → BI | 0.114 | 1.394 | 0.135 | 1.711 | -0.021 | 0.427* |
| FC →BI | 0.011 | 0.097 | -0.046 | 0.614 | 0.056 | 0.329* |
| PV → BI | -0.038 | 0.279 | 0.140 | 2.178 | -0.177 | 0.120* |
| PT →BI | 0.366 | 2.869 | 0.514 | 5.842 | -0.148 | 0.172* |

| Relation | Male | | Female | | Path Coefficient Diff | p-values |
|---|---|---|---|---|---|---|
| | Path Coefficient | t-values | Path Coefficient | t-values | | |
| BI →UB | 0.621 | 8.594 | 0.576 | 8.765 | 0.044 | 0.321* |

* p-values > 0.05.

According to the data provided in Table 15, it is apparent that males have a more pronounced impact than females on a number of relationships, including those involving BI and UB and PE, EE, and FC. Conversely, females exert a substantial impact on the correlation between BI and SI, PV, and PT. This comparison underscores the preponderance of males over females within the relationships in question.

Nevertheless, a closer examination of the p-values yields the conclusion that the disparity in influence between the sexes lacks statistical significance, as all values exceed 0.05. Therefore, it can be concluded that gender differences have no appreciable impact on the calculation results of the model utilized in this study.

## CONCLUSION

The objective of this study was to ascertain the factors that impact the level of community interest in utilizing mobile health (m-health) applications within Semarang City. Furthermore, the study examined the potential moderating effects of age and gender on the measurement outcomes. The acquired data was subjected to analysis utilizing the partial least squares - structural equation model (PLS-SEM) methodology, with the aid of SmartPLS 3 software. The analysis yielded numerous conclusions. Regarding the association between independent variables and the dependent variable, it was noted that a substantial positive impact on public interest in utilizing m-health applications was detected in four out of the six independent variables. Significantly, the variables that exhibited a substantial influence included performance expectancy, social influence, price value, and perceived trust. In contrast, the variables of effort expectancy and facilitating conditions did not have a statistically significant impact on the level of public interest in utilizing mobile health (m-health) applications. Additionally, the research revealed that the factor of behavioral intention exhibited a notable and favorable impact on the practical use behavior of the residents of Semarang City while embracing m-health applications. The research investigated the moderating influence of age and gender on the association between the independent variables and the dependent variable, namely behavioral intention. The results of the computations indicated that age played a moderating role specifically in the association between social influence and behavioral intention. Nevertheless, the variable of gender did not exhibit any significant moderating effect on the associations between the independent variables and the dependent variable. In order to conduct a more comprehensive analysis of the implications arising from variations in the computed outcomes, the investigators partitioned the age and gender variables into distinct subcategories. The age variable was divided into three distinct categories: 18 - 24 years, 25 - 34 years, and 35 - 45 years. The concept of gender was traditionally dichotomized into two distinct categories: male and female. Nevertheless, the multigroup analysis revealed that there were no statistically significant differences in the results across the various age and gender groups. Therefore, it can be inferred that there is a lack of variability in the assessment outcomes across various age or gender cohorts.

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