Determinants factor affecting user continuance usage and intention to recommend of mobile telemedicine

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Abstract. This study analyses mobile telemedicine application’s users in Jakarta towards their behaviours intention to recommend the applications to others. Using Unified Theory Acceptance and Use of Technology 2 (UTAUT2), Diffusion of Innovation, and Perceived Technology Security (PTS) would eventually explain their continuance usage and intention to recommend. This study targeted 384 respondents as samples and used random sampling to collect data using online questionnaires. The study used Structural Equation Modelling (SEM) Partial Least Square (PLS) with WarpPLS 7.0 for analysing data. Determinant factors that affect Mobile Telemedicine Application’s users’ behaviours will eventually help the health care workers and the application system providers to deliver a better patient centric, convenience and reliable applications especially during COVID-19 pandemic. This study revealed performance expectancy, price value, compatibility, and perceived technology security as significant factors influencing continuance usage, and continuance usage as a significant factor influencing intention to recommend mobile telemedicine.

Keywords: mobile health, telemedicine, UTAUT2, DOI, technology security

1. Introduction
The industrial world is entering a new era, the industrial revolution 4.0 [1]. Evidence of fast-moving technology and urging evolution, together with increasing government efforts around the world, is leading to the conclusion that the health sector is already facing the impacts of industry 4.0, effectively moving e-health towards healthcare 4.0 [2]. E-health has grown from web-based services to mobile-based telemedicine applications, online video services, social media, as well as new services and technologies that continue to be presented. [3]. The terms of electronic health (e-health) is defined as electronic systems that can provide health services and information education to patients and health workers by means of electronic channels [4,5].

In a more specific and smaller scope, mobile health (m-health) is part of the e-health scope [6]. M-health is defined as provision of health services to consumers through application channels on mobile devices which can be used remotely by utilizing mobile device technology [7,8].The m-health application has now moved towards consumer health informatics by providing care, making diagnoses, disease monitoring, self-management, or promoting healthy lifestyle behaviors. [9]. M-health services include remote monitoring, remote consultation, and personal health care digital services, which can help save time and money on diagnosis [9,10].

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Telemedicine is a health service system in the form of remote consultation, treatment and diagnosis using any communication devices [11,12]. Telemedicine technology is a key element in future healthcare delivery [13]. Combination between telemedicine and mobile health is mobile telemedicine. Based on their respective definitions of mobile health and telemedicine, then we define mobile telemedicine as a system for providing health services to consumers, in the form of consulting, treatment, and diagnosis services remotely using application channels on mobile devices through the internet network.

With this paradigm, many telemedicine applications have sprung up in the last few years. Since 2016, 78,000 new mobile phone applications have been added to the application sales center (Pohl, 2017). Strong growth of 25% year over year shows the market has a great demand for mobile telemedicine applications, however, even though the high growth rate of the number of mobile telemedicine applications, overall, it is slowing down. The growth rate of the new m-health application was added to the application sales centre last year was 57%, this growth rate in 2017 has decreased to 25%. In 2017, 158,000 mobile telemedicine apps were added to Google Play Store - a 50% increase over last year and the highest growth rate for major app sales centers occurred in 2017. Meanwhile, a growth rate of 20% has been recorded to the iOS. Overall, in 2017 there were around 325,000 registered mobile telemedicine applications [14].

As the growth continue, there are major problems for the mobile telemedicine application. One of the problems is people stop using it after just several uses. Based on research conducted in the United States on 934 users of mobile telemedicine applications, 427 people or 45.7% of users stopped using some of these mobile telemedicine applications, primarily due to high data entry burden, loss of interest, and hidden costs[15]. This is a serious problem for health applications that are developing today. But now an anomaly occurs in the previous phenomenon, that is the emergence of the COVID-19 pandemic. In a study conducted in New York, United States, between March 2 to April 14, 2020, health services by means of telemedicine increased from 369.1 per day to 866.8 per day (135% increase) in urgent care after the system-wide expansion of virtual health visits in response to COVID-19, and in non-urgent cases an increase of 4345%, from 94.7 per day to 4209.3 per day [16].

From these data and theories, it can be said that there is a contradiction phenomenon that occurred in the use of mobile telemedicine applications during the COVID-19 pandemic. From the beginning, the mobile telemedicine application had experienced a decline and stagnation, but with the COVID-19 pandemic, the traffic using the mobile telemedicine application has increased quite drastically.

To answer the problem described earlier, we do research to understand what factors that impact user’s continuance usage for this kind of healthcare technology. This study adopt model from acceptance mobile payment application [17] to continuance usage of mobile telemedicine application. A combination of Unified Theory of Acceptance and Use of Technology (UTAUT) [18], Diffusion of Innovation Theory (DOI) [19], and Perceived Technology Security [20]. The UTAUT method can offer in-depth analysis of critical factors and the possibilities that will occur in the user's behavior intention in using technology [18]. The use of the UTAUT research method in this study, which was developed into UTAUT2[21],used more to explain the acceptance of mobile telemedicine application users due to the social influence variable[22]. Meanwhile, the Diffusion of Innovation (DOI) theory put forward by Rogers[19], says that innovations that are in accordance with the suitable environment will be easier to adopt than those that are not suitable [19].

Even though mobile applications are the leading technology in today's computing technology, security issues pose a threat in the adoption and integration of these technologies. [23]. As previous research revealed that perceived technology security had a significant effect in explaining customer intentions [24]. Of course, this is a serious obstacle and needs to be looked at further, for that researchers include perceived technology security to complement this research.

This study also connects continuance usage with the intention to recommend with the explanation that social influence, or social support, is an important factor in technology acceptance [22]. Recommendations from others was strongly influence users intention to use and adopt technology in the context of health care information technology [17,25]. By targeting early adopters and continuance
usage, recommendations from other people will be one of the main drivers for increasing the diffusion of m-health technology [6].

2. Literature Review
Unified Theory Acceptance and Use of Technology (UTAUT) was first introduced by Venkatesh et al., in 2003 and then redeveloped into UTAUT2 by Venkatesh et al., in 2012. The combination of the UTAUT2 dimensions can explain m-Health adoption [26]. UTAUT has four key building blocks that influence behavioral intention to use technology and / or technology uses. Performance expectancy, effort expectancy, social influence, and facilitating conditions are the four key builders [27]. In UTAUT2, three building blocks were added as a complement to the theoretical perspective on the UTAUT mechanism. The three keys to building this complement are hedonic motivation, price value, and habit [18].

Diffusion is defined as a process by which an innovation communicates across multiple channels at a time in a member of the social system [19] which can be separated into four elements, (1) an innovation (2) communicates across multiple channels (3) at a time (4) in a member of the social system. This study focuses on the part of the first element, namely compatibility and part of the third element, namely innovativeness. Compatibility is the level where an innovation is deemed in accordance with existing values or habits, past experiences, and also the needs of potential users and innovativeness is the degree to which an individual or another unit adopts it easily and quickly adopts an innovation [19].

Perceived security mobile applications are defined as appropriate actions by application providers to protect user data, during transmission via cell phones or after the transmission, from security breaches [28–30].

Continuance usage is defined as a mental state that reflects a person’s decision to repeat his current behaviour and can be compared with the intention to make repeat purchases in marketing [31]. Continuance usage functions well in predicting the actual use of a technology or application, which affects behaviour acts as an indirect influence through continuance usage [32]. Adopters of new technology are more likely to occur with consumers with a higher intention to accept technology, and then often recommend the technology to others. It is very attractive to service providers for the adopters recommending technology to others as part of post-adoption behaviour [33].

3. Methodology
Based on the literature review, a research structure was developed to simultaneously study the relationship between UTAUT2, DOI, PTS, Continuance Usage, and Intention to Recommend. The framework is showed in Figure 1.
The research design used a quantitative approach to examine the individual behavior of mobile telemedicine application users. The unit analysis comprises users in Jakarta that uses mobile telemedicine applications at least one time. This study gathered data in the cross-sectional set of time. The data collection method in this study is by distributing online questionnaires, and the sampling technique used was probability sampling with random sampling. The Likert scale was used as a measurement of data extending from 1 = strongly disagree to 5 = strongly agree.

Population of this study is unknown, therefore, to determine sample size of this study we used Lemeshow method and the result is minimum sample of 384 is required. The argument for taking this procedure is that a study conveyed using a planned questionnaire can provide a record of topics to respondents to collect answers. Eventually, it started in July 2020 and until September 2020, 101 valid respondents were added. Even the sample is far below the requirement previous study stated that surveys with lower response rates (near 20%) yielded more accurate measurements than did surveys with higher response rates (near 60 or 70%) [34].

For measurement indicators, this research use Yi et al., (2006) for Innovativeness; D. Kim & Ammeter, (2014) and Mallat et al., (2009) for compatibility; items for UTAUT2 are from Venkatesh et al., (2012); and perceived technology security from Chellappa, (2008). This research applies SEM-PLS (structural equation model - partial least square) using WarpPLS 7 for data processing. Due to high complexity (many indicators and many construct) of research model, we chose to use SEM-PLS method that can help to shows statistically significant construct.PLS-SEM is a causal-predictive approach to SEM that emphasizes prediction in estimating statistical models, whose structures are designed to provide causal explanations[39,40]. The SEM-PLS method enables user to estimate complex models with many constructs, indicator variables and structural paths without imposing distributional assumptions on the data[41].

4. Results and Discussion
The characteristics of the respondents are presented in table 1. The largest total of respondents of the research were female in 75.5% with the most age level is 21-25. Respondents used mobile telemedicine application mostly 2-5 times of user’s lifetime. The most respondents used the mobile
telemedicine application for the first time is last year. Based on how to find out about mobile telemedicine applications, where respondents may choose more than one answer, respondents mostly find out the mobile telemedicine application from social media.

Table 1. Respondent Characteristics

| Characteristics | Category | Frequency (n=101) | Percentage |
|-----------------|----------|------------------|------------|
| Gender          | Male     | 76               | 75.2%      |
|                 | Female   | 25               | 24.8%      |
| Age             | 16-20    | 2                | 2%         |
|                 | 21-25    | 49               | 48.5%      |
|                 | 26-30    | 32               | 31.7%      |
|                 | 31-35    | 15               | 14.9%      |
|                 | >36      | 3                | 3%         |
| Mobile telemedicine application usage in user’s lifetime | Just once | 33 | 32.7% |
|                 | 2-5 times | 55 | 54.5% |
|                 | More than 5 times | 15 | 12.9% |
| When was the first time you used the application? | ± 2 years ago | 10 | 9.9% |
|                 | ± 1 year ago | 48 | 47.5% |
|                 | During the COVID-19 pandemic | 43 | 42.6% |
| How did you find out about mobile telemedicine application? | Social Media (Facebook, Instagram, Twitter, etc.) | 81 | 80.2% |
|                 | Hospital | 5                | 5%         |
|                 | Family / Relatives / Friends | 40 | 39.6% |
|                 | Mobile telemedicine apps advertising | 34 | 33.7% |

Model fit and quality indices:
- Average path coefficient (APC)=0.236, P=0.003
- Average R-squared (ARS)=0.390, P=0.001
- Average adjusted R-squared (AARS)=0.374, P<0.001
- Average block VIF (AVIF)=1.770, acceptable if <= 5, ideally <= 3.3
- Average full collinearity VIF (AFVIF)=2.327, acceptable if <= 5, ideally <= 3.3
- TenenhausGoF (GoF)=0.554, small >= 0.1, medium >= 0.25, large >= 0.36
- Symponson’s paradox ratio (SPR)=0.813, acceptable if >= 0.7, ideally = 1
- R-squared contribution ratio (RSCR)=0.974, acceptable if >= 0.9, ideally = 1
- Statistical suppression ratio (SSR)=1.000, acceptable if >= 0.7
- Nonlinear bivariate causality direction ratio (NLBCDR)=1.000, acceptable if >= 0.7

General results indicate that the analysis can be preceded.

Table 2 describes loading factor, standard error (SE), and the p-values of the full SEM model. As the basis for determine that measurement model acceptable convergent validity, two criteria must be fulfilled. First, P values associated with the loadings equivalent less than 0.05, and second, the loadings be equivalent to or larger than 0.5 [42,43]. FC4 does not meet the criteria, so FC4 was dropped. Apart from FC4, other indicators meet the criteria of convergent validity.

Table 2. Validity Measurement

| Indicator | Loading Factor | SE  | P Values |
|-----------|----------------|-----|----------|
| Performance expectancy (PE) [18] | | | |
| PE1 – I find the mobile telemedicine application useful for everyday life | 0.786 | 0.092 | 0.001 |
| PE2 – Using the mobile telemedicine app increases the chance to get things done that are important to me. | **0.849** | 0.091 | <0.001 |
| PE3 – Using the mobile telemedicine application will allow me to do work much faster. | 0.822 | 0.092 | <0.001 |
| PE4 – Using the mobile telemedicine application increases my productivity. | 0.846 | 0.092 | <0.001 |
Cronbach’s alpha of PE, EE, SI, FC, HM, PV, IN, CO, and PTS were 0.844; 0.895; 0.898; 0.871; 0.875; 0.845; 0.777; 0.822 and 0.930. The composite reliabilities of PE, EE, SI, FC, HM, PV, IN, CO, and PTS were 0.896; 0.937; 0.936; 0.921; 0.923; 0.907; 0.871; 0.894 and 0.955, which surpass the suggested value of 0.70 [47,48].

Table 3 describes coefficients, Effect Sizes for Path Coefficients, and the p-values of the full SEM model. The value of path coefficients and p-values shows the effect, where the variables in the column are latent predictive variables, and the variables in the line indicate the criteria. While the value of the effect sizes shows how much the contribution of each latent variable to the observed variable. The f-squared effect size measured the effect sizes throughout the pathway [42]. The path coefficient has a weak impact if the recommended value is less than 0.02, it shows that even though the p-value of the calculation is significant, whereas if the coefficient value is higher than 0.02, but less than 0.15,
then the path coefficient has a moderate impact, and finally a strong influence happened if the value path coefficients greater than 0.15 to 0.35 [48].

| Construct | Path Coeff. | P Values | Standard Errors | Effect Sizes | Results |
|-----------|-------------|----------|-----------------|--------------|---------|
| H1        | PE – CU     | 0.235    | 0.007           | 0.093        | 0.142   | Supported |
| H2a       | EE – PE     | 0.284    | 0.001           | 0.092        | 0.144   | Supported |
| H2b       | EE – CU     | -0.037   | 0.353           | 0.099        | 0.016   | Not Supported |
| H3        | SI – CU     | 0.077    | 0.215           | 0.097        | 0.025   | Not Supported |
| H4        | FC – CU     | -0.009   | 0.465           | 0.099        | 0.003   | Not Supported |
| H5        | HM – CU     | 0.102    | 0.147           | 0.097        | 0.062   | Not Supported |
| H6        | PV – CU     | 0.175    | 0.034           | 0.095        | 0.106   | Supported |
| H7a       | IN – CO     | 0.449    | <0.001          | 0.088        | 0.202   | Supported |
| H7b       | IN – PE     | -0.105   | 0.141           | 0.097        | 0.034   | Not Supported |
| H7c       | IN – EE     | 0.208    | 0.014           | 0.094        | 0.081   | Supported |
| H7d       | IN – CU     | 0.080    | 0.206           | 0.097        | 0.016   | Not Supported |
| H8a       | CO – PE     | 0.393    | <0.001          | 0.089        | 0.222   | Supported |
| H8b       | CO – EE     | 0.402    | <0.001          | 0.089        | 0.199   | Supported |
| H8c       | CO – CU     | 0.323    | <0.001          | 0.091        | 0.224   | Supported |
| H9        | PTS – CU    | 0.201    | 0.018           | 0.094        | 0.103   | Supported |
| H10       | CU – IR     | 0.691    | <0.001          | 0.083        | 0.477   | Supported |

Note: IN-Innovativeness, CO-Compatibility, PE-Performance Expectancy, EE-Effort Expectancy, SI-Social Influence, FC-Facilitating Condition, HM-Hedonic Motivation, PV-Price Value, , CU-Continuance Usage, IR-Intention to Recommend

Figure 2 represents the complete SEM model as the outcomes of the examination, confirming the parameter values of all examined variables (indicator), including exogenous latent variables, also endogenous latent variables.

Our study reveals that most of the construct of UTAUT2 did not appeared to be significance in the sample analysed study. Effort expectancy (H2b) ($\beta = -0.04; p = 0.35$), social influence (H3) ($\beta = 0.08; p = 0.32$), facilitating condition (H4) ($\beta = 0.08; p = 0.32$) and hedonic motivation (H5) ($\beta = 0.10; p =$
0.15) was found statistically not significant influencing continuance usage of mobile telemedicine application. Previous study, in context of mobile health acceptance, reported similar result [6].

On the other hand, performance expectancy (H1), similar result with previous study [6] had significant influence on user continuance usage of mobile telemedicine application. Individual decisions to use mobile telemedicine applications are influenced by the price value of services in mobile telemedicine applications which are described as functional values. It is also shown in our results that the continuance usage of mobile telemedicine applications is significantly affected by the price value, which similar with previous study on continued usage intention of health application [49]. Other results show that compatibility (H7a) and effort expectancy (H7c) are validated by the influence of the innovation construct, but do not validate its effect on continuance usage (H7d), and performance expectancy (H7b). Previous study reported similar result on influence innovativeness to compatibility and effort expectancy [17].

In explaining the user continuance usage of mobile telemedicine, here are some of the significant constructs, compatibility is the most important construct (β = 0.32; p < 0.01), followed by performance expectancy (β = 0.24; p < 0.01) which similar to previous study [17]. Continuance usage statistically influence intention to recommend (β = 0.69; p < 0.01), this value shows that people are recommending technology if they already use the technology several times.

5. Conclusion
The study was held in Indonesia with sample of 101 respondent, and the model explained 66% of the variance of continuance usage intention, and 48% of behavioral intention to recommend. Performance expectancy and price value appeared as predictors of continuance usage. Compatibility had an important effect on the influence of performance expectancy to continuance usage and innovativeness had significant influence compatibility to continuance usage. This implies that the user wants a compatible application first, which suitable with their style and habits, then the user can continuously use the application. Perceived technology security also plays important role for user continuance usage, as the user feel safe about the application, then user tends to use the application continuously rather than feel unsecured for personal data or information every time user use the application.

At last, as the user continuously using the application then user tends to not hesitate for recommending technology to others. With the mobile telemedicine application, user do not need to bother anymore to goto hospital or nearby clinic, they can use mobile telemedicine application for help to do self-medication after consulting the doctor at the application. As the COVID-19 emerged in Indonesia at the time this research was written, mobile telemedicine application plays a vital role for help the pandemic to get through the rough time easier.

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