The Exploratory Study on Antecedents of Online Medical Consultation Continuous Usage Intention

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Article Info

Abstract

The purpose of this study is to find and analyze factors that can affect the Intention to Recommend in the online medical consultation field. The research model was adapted from a previous study and then modified. Data were collected from women who were >17 years old and who had ever used the online medical consultation application, Halodoc. The research's method was a quantitative survey, with cross-sectional data. Respondents' data were taken by purposive sampling and questionnaires were distributed online. As many as 202 participants had fulfilled the requirements to be analyzed with PLS-SEM. The results showed that five antecedents had a significant influence on Intention to Recommend. Antecedents that were worth noting were Helpfulness Trust, Perceived Benefit, and Reliability Trust, where these factors showed a positive impact on Intention to Recommend. Factors were also found that could make users more considerate or careful in using online medical consultation applications such as Performance Risk and Privacy Risk factors. From the findings of this study, it can be concluded that there are factors that may need to be considered by online medical consultation service providers to maintain or even improve their quality of care.

Introduction

The development of Internet technology has altered business practices and services across all industries. Similar to what has been done in other industries, telemedicine technology has been proven to be advantageous to people in many ways (Chen *et al*., 2020; Fernandez, 2020). For instance, the usage of telemedicine services reduces the shortcomings in health services, saves time, and is cost-effective for the impoverished population (Albarrak *et al*., 2021; Hsu, 2019; Kaium *et al*., 2020; Pai & Alathur, 2019). According to certain research, if health services do not utilize information technology for further assistance, management will become inefficient, and patients will lose trust in them. Therefore, information technology must be applied to health services (Nurhayati *et al*., 2019).

Adequate quality of service via telemedicine is known to be associated with increased quality of care. The definition of telemedicine is the extent to which healthcare practitioners employ information and communication technology (ICTs) for diagnosis, health promotion, illness prevention, and transmission of telemedicine applications. Due to their quick services, telemedicine technologies have assisted communities during pandemics (Rahi, 2021). Telemedicine is the professional delivery of health services where a critical factor is distance, using information and communication technology to exchange information for the diagnosis, treatment, and prevention of illness and injury (Gutierrez *et al*., 2017). Indonesia ranked third globally

in utilizing health applications Telemedicine which is time and money-saving, makes healthcare more accessible, boosts patient participation, and encourages improved patient care (Pusparisa, 2020).

Online Medical Consultation (OMC) is not a new feature. But just since the pandemic, OMC usage has increased rapidly (Johnson *et al.*, 2021). However, a decrease in OMC satisfaction in 2021 from 2020 has been reported (Deloitte Indonesia *et al.*, 2019). A previous study indicated that patients still complain about limited services and inconsistent care with telemedicine (Gliadkovskaya, 2021). Patients are also less satisfied with telemedicine visits compared to in-person visits (Franco-Lara, 2023). Meanwhile, China faces serious problems in healthcare, such as high medical costs. Although the number of hospitals is sufficient, many patients still find it difficult to see a doctor, especially in tertiary hospitals (Zhang *et al.*, 2018), online medical consultation could be beneficial for the improvement of healthcare quality. However, online medical consultations will have little value if users do not use them appropriately.

The previous study by Yang *et al* (2021) argues that although OMC rapidly growing in popularity, there are still several issues that dampen the Continuum Usage of the OMC. The study exhibits several factors that may affect the people's Continuum Usage of the OMC and one of those factors is Trust. Another study indicates the lack of confidence that may cause hesitation in the Continuous Usage of OMC, which is a complex relationship that incorporates both technological and interpersonal aspects (Zhang *et al.*, 2018). In the field of online services, ratings and reviews play important roles in making a great service. Online ratings of services are thought to help consumers predict their future level of satisfaction with the product or service (Wulff *et al.*, 2014). If two online services have the same quality, customers will always choose the service that has a higher rating (de Langhe *et al.*, 2016a, 2016b).

Users' reviews shape readers' expectations about the quality and performance of the product (Han, 2020). From the studies mentioned it can be inferred that positive review

or Word-of-Mouth (or "Recommendation" as the term that the author will use in this writing) correlates positively with the Continuation of Usage in OMC. In other studies, trust is used as the mediating factor, to search whether certain factors affect the continuous usage of the telemedicine users (van Velsen *et al.*, 2016). In this study, the author wants to investigate which of the chosen factors affects Continuous Usage the most; trust will be used as an independent variable and not as a mediating factor. This study uses a unidimensional construct.

For telemedicine to thrive and improve itself, trust needs to be built as the foundation of telemedicine (Arfi *et al.*, 2021). While privacy concerns, security concerns, and regulatory issues are a big part of internet interactions, which also applies to telemedicine (Alhogail & Alshahrani, 2019; Martínez-Caro *et al.*, 2018). This is the reason why trust is a big field that still needs to be explored in the telemedicine field. In other studies, trust is more often assessed as a unidimensional variable, but in other studies, trust is suggested with a multidimensional approach because the components of trust differ based on the patient's perspective. Trust in health services is more likely benevolence. This research provides a new perspective from the aspect of the trust dimension which combines the perceptions of benefits and risks.

The study model consists of 7 independent variables (Helpfulness trust, Reliability trust, Performance risk, Privacy risk, Perceived benefit, Perceived centeredness, and Benevolence trust) which have a relationship with Online Medical consultation services. This model will be tested empirically on a female population. Generally, women tend to be on their smartphones longer than men (women on average 166.78 minutes/day compared to men 154.26 minutes/day) (Andone *et al.*, 2016). Women were also reported to have significantly higher use of health applications than males (29.0% vs. 19.0%) (Escoffery, 2018). From the previous study, research based on trust and patient perceptions has an impact on intention to recommend which is mediated by the patient's evaluation of OMCS. In this research model, 8 hypotheses will be studied further.
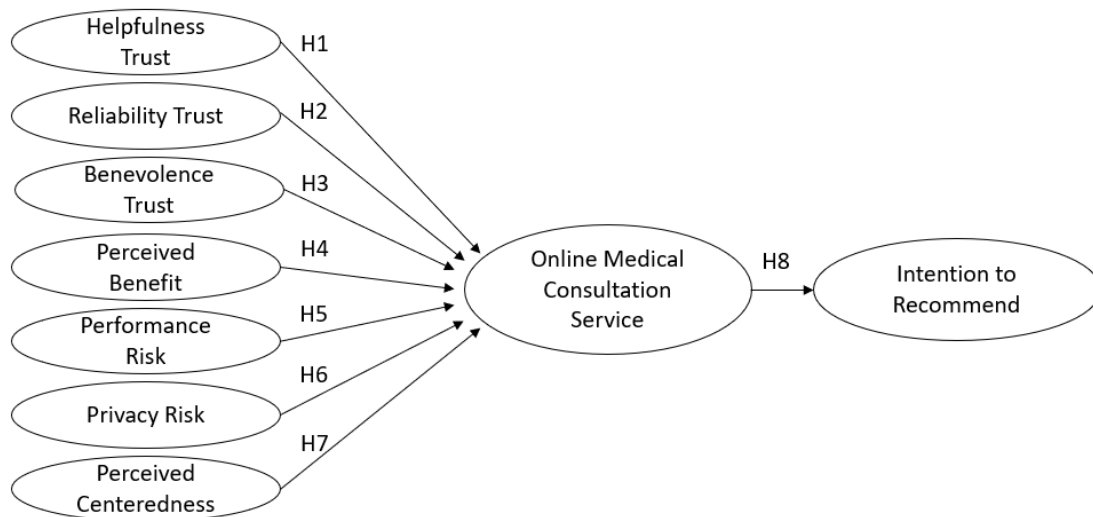
Figure 1. Conceptual Work

Method

This study was a cross-sectional study using a survey in the form of a Google with purposive sampling as a sample collection technique. The research sample is patients who have used the online consultation service of the Halodoc health application, a total of 202 people. The inclusion criteria of this study were women who had used the online consultation service of the Halodoc health application, aged between 17-65 years old. The sample in this study is women, because women bear significant responsibility for their children, families, houses, and even themselves (Sufyan *et al.*, 2022). The exclusion criteria were men, people who have never used Halodoc before, and those below 17 years old.

Halodoc is the number one mobile health platform that combines patients, doctors, laboratory tests, insurance, pharmacies, and prescription reminders into a single health application. Halodoc collaborates with more than 20,000 doctors and 1,000 reputable pharmacies to provide consumers with one-hour medication delivery and sell over-the-counter medications, vitamins, consumer goods, and prescription medications (Halodoc, n.d.). Halodoc internet searches have also significantly increased (*Google Trends*, n.d.). The survey was conducted by distributing a questionnaire in the form of an online Google form to women who have used Halodoc and met the inclusion criteria.

The number of samples in this study was calculated according to recommendations (Sarstedt *et al.*, 2022), that in a PLS-SEM study, the minimum sample should be calculated by power analysis. The sample size in this study was based on power analysis with G*Power 3.1 where f^2 was determined at 0.15, alpha 0.09 and power was 95%, while the number of predictors was 8. From the calculation, the minimum number of samples required was 160 and the denominator degree of freedom was 151. From the distributed questionnaires, it was found that 202 responses met the criteria and became the sample in this study.

After elimination and excluding invalid answers, 202 samples were eligible and sufficient for a minimum requirement from partial least squares structural equation modeling (PLS-SEM) analysis guidance (Kock & Hadaya, 2016). The questionnaire is adapted from Yang *et al* (2021); for variables HT, RT, BEV, PBE, PER, PVR, and PCT, and variable ITR is adapted from Octavius and Antonio (2021) and then modified to novelty concepts. The preparation of the questionnaire has been through a validity process and reviewed by an academic expert panel. Before distribution, the completed questionnaire was then translated into the standard local language (Bahasa) and reviewed by a translator. Data collection was carried out from September 22nd to October 3rd. All items from the survey were arranged as questions with a 6-point Likert as recommended by (Chomeya, 2010).

Scale answers consisting of strongly

disagree, disagree, slightly disagree, somewhat agree, agree, and strongly agree. This study uses a data analysis method with a multivariate analysis approach due to its complexity. In the conceptual framework, there are seven independent variables (Helpfulness Trust, Reliability Trust, Benevolence Trust, Perceived Benefit, Performance Risk, Privacy Risk, Perceived Centeredness) as the antecedents of OMCS were tested to observe the impact of the dependent variable (Intention to Recommend). The instrument of this study includes the construct: Helpfulness Trust (two items), Reliability Trust (three items), Benevolence Trust (three items), Perceived Benefit (two items), Performance Risk (two items), Privacy Risk (three items), Perceived Centeredness (three items).

This conceptual framework makes up eight hypothetical paths marked with arrows and is regarded as a difficult research model; so, the PLS-SEM approach was used since it could assess complex models in exploratory research. When the emphasis of the investigation is on the model's explanatory and predictive qualities, PLS-SEM techniques are preferred (Hair *et al.*, 2019). This research has passed the ethical test of the Health Research Ethics Commission, Faculty of Medicine, University of Pelita Harapan No: 007M/EC-Apr/IV/2023.

Results And Discussions

There are 202 respondents, and the demographic data are presented in Table 1. The respondents were all females. Based on age group, most were from the group age of 25 - 34 years old (56.4%). Most were single (58.3%). As many as 57 women (28.2%) have been pregnant before and the number of times they get pregnant is mostly 1 or 2 times (25.7%). Most of the respondents work as employees (33.7%) and there are only 2 people who are not working (0.9%), and most of them have used Halodoc for more than 12 months (33.2%) and 69.8% live around the Jabodetabek area (Jakarta-Bogor-Depok-Tangerang-Bekasi). In terms of health insurance, most do not have private health insurance (54%).

Table 1. Respondent Profile.

Demographic Variables		Sample	Percentage (%)
Age	17 - 24	46	22.8
	25 - 34	114	56.4
	35 - 44	36	17.8
	45 - 54	4	2.0
	>55	2	1.0
Marital Status	Married	85	41.7
	Single	117	58.3
Pregnant	Never	145	71.8
	Ever	57	28.2
Number of Pregnancy	Never	145	71.8
	1 - 2	52	25.7
	2 - 4	5	2.5
	>4	0	0.0
Job	Housewife	22	10.9
	Self-Employed	32	15.8
	Professional	22	10.9
	Part Timer	20	9.9
	Government Employee	22	10.9
	Employee	68	33.7
	Unemployed	2	0.9
	Student	14	6.9
Duration of using Halodoc	1 - 3 Months	34	16.8
	4 - 6 Months	59	29.2
	7 - 12 Months	42	20.8
	>12 Months	67	33.2
Residency	Jabodetabek	141	69.8
	Non-Jabodetabek	61	30.2
Health Insurance beside BPJS	Have	93	46.0
	Don't Have	109	54.0

To assess the indicator of reliability, the outer loading was measured, and several indicators were eliminated that did not follow the recommended value limit set, which is 0.708. If the value of the indicators is greater than 0.708, then the indicators are considered reliable for measuring each research item (Hair *et al.*, 2019). There were 24 research indicators that met the outer loading criteria. From the internal consistency test, all constructs showed Cronbach's alpha greater than 0.7 and composite reliability ranging between 0.7 and 0.95, indicating that the constructs' reliability of the respective models is reliable (Hair *et al.*, 2019). Convergent validity is determined by measuring the Average Variance

Extracted (AVE). This validity check shows that each construct has an AVE ≥ 0.50, which indicates that all constructs can explain at least 50% of the item variance in the model, thus establishing a convergent validity (Hair *et al.*, 2019). The results of the reliability and validity tests can be seen in Table 2.

Table 2. Reliability and Validity Analysis.

Variables	Indicators	Outer Loading	CA	CR	AVE
HT	HT1	0.915	0.764	0.894	0.809
	HT2	0.883			
RT	RT1	0.909	0.822	0.894	0.738
	RT2	0.876			
	RT3	0.787			
BEV	BEV 1	0.877	0.888	0.931	0.817
	BEV 2	0.913			
	BEV 3	0.921			
PBE	PBE2	0.903	0.843	0.925	0.861
	PBE3	0.953			
PER	PER1	0.872	0.728	0.880	0.786
	PER2	0.901			
PVR	PVR1	0.803	0.855	0.913	0.779
	PVR2	0.935			
	PVR6	0.904			
PCT	PCT1	0.887	0.718	0.837	0.634
	PCT2	0.721			
	PCT3	0.771			
OMCS	OMCS1	0.850	0.824	0.895	0.740
	OMCS2	0.871			
	OMCS3	0.859			
ITR	ITR1	0.841	0.827	0.897	0.743
	ITR2	0.867			
	ITR3	0.878			

Cronbach's Alpha; CR, Composite Reliability; AVEl, Average Variance Extracted; HT–MT, Heterotrait-Monotrait. Var, Variables; HT, Helpfulness Trust; RT, Reliability Trust; BElV, Benevolence Trust; PBEl, Perceived Benefit; PElR, Performance Risk; PVR, Privacy Risk; PCT, Perceived Centeredness; OMCS, Online Medical Consultation Service; IlTR, Intention to Recommend.

Var, Variables; HT, Helpfulness Trust; RT, Reliability Trust; BEV, Benevolence Trust; PBE, Perceived Benefit; PER, Performance Risk; the second part of the analysis to evaluate the quality of the model in this research by predicting the relation between variables. Parameters in the inner model consist of R-square (R^2), Q-square (Q^2), and variance inflation factor (VIF). R^2 to measure predictive accuracy, Q^2 to measure predictive relevance and the significance and coefficient of the variables are to be decided whether the hypothesis can be supported or not.

Previously, common method bias arising from errors or biases in measurement methodology was evaluated using the inner variance inflation factor (VIF). Before proceeding, it is important to conduct an Inner Variance Inflation Factor (VIF) test to check multicollinearity issues. The findings showed all the constructs had inner VIF below 3 as suggested (Hair *et al.*, 2019; Sarstedt *et al.*, 2022); thus, it can be concluded that there is no multicollinearity issue found in this model. The R^2 value of Intention to Recommend = 0.541 which is categorized as moderate predictive accuracy Online Medical Consultation Service has R^2 = 0.761 which is categorized as strong predictive accuracy.

Thus, it can be said that the respective model has a strong explanatory capability to estimate the respective variable. OMCS has a large effect size on ITR with an F^2 value of 1.190. The out-of-sample redundancy value was applied from the blindfolding feature of PLS-SEM (Hair *et al.*, 2019). All the Q^2 are found > 0, whereas ITR shows Q^2 = 0.511 and was categorized as a large value (> 0.5). OMCS has Q^2 = 0.753. Therefore, it can be said that endogenous constructs in the out-of-sample model approach have sufficient cross-validated redundancy.

Based on the results of hypothesis testing with the bootstrapping feature (Table 4), it was shown that there were six accepted hypotheses ($p < 0.05$, CI 5%, and CI 95% following the direction of the hypotheses). However, hypotheses H1 and H4 did not meet the significant requirement, so they are not supported. Meanwhile, it is recommended to use the corrected p-value with the Bonferroni Correction Method approach where the p-value should be lower than the corrected p-value. In this study, there were 8 hypotheses, so the corrected p-value was 0.05/8= 0.006. From the results of the hypothesis test, it can be found that the variables that have the strongest effects on OMCS are the HT (β = 0.368) therefore Helpfulness trust could be a great predictor of OMCS, PBE (β = 0.264), and RT (β = 0.236). Then, OMCS has a predominant relationship with ITR (β = 0.737)

Table 3. Discriminant Validity with HT/MT Ratio.

Var	BEV	HT	ITR	OMCS	PEB	PCT	PER	PVR	RT
BEV	0.866 CI[0.794;0.928]								
HT	0.505 CI[0.388;0.618]	0.655 CI[0.546;0.758]							
ITR	0.762 CI[0.686;0.834]	0.905 CI[0.839;0.969]	0.883 CI.900[0.837;0.925]						
OMCS	0.636 CI.900[0.528;0.739]	0.563 CI.900[0.449;0.667]	0.646 CI.900[0.559;0.726]	0.815 CI.900[0.753;0.874]					
PEB	0.469 CI.900[0.334;0.609]	0.407 CI.900[0.267;0.551]	0.410 CI.900[0.292;0.530]	0.555 CI.900[0.416;0.697]	0.455 CI.900[0.330;0.580]				
PCT	0.459 CI.900[0.317;0.584]	0.556 CI.900[0.435;0.664]	0.675 CI.900[0.579;0.766]	0.702 CI.900[0.604;0.791]	0.484 CI.900[0.351;0.598]	0.298 CI.900[0.156;0.460]			
PER	0.540 CI[0.437;0.638]	0.610 CI[0.510;0.703]	0.710 CI[0.640;0.779]	0.758 CI[0.690;0.825]	0.597 CI[0.503;0.685]	0.450 CI[0.300;0.606]	0.623 CI[0.509;0.729]		
PVR	0.640 CI[0.519;0.764]	0.576 CI[0.464;0.687]	0.727 CI[0.652;0.802]	0.808 CI[0.752;0.866]	0.635 CI[0.545;0.718]	0.714 CI[0.581;0.849]	0.457 CI[0.304;0.595]	0.643 CI[0.545;0.739]	
RT									

Table 4. Hypothesis Test Results.

	Hypothesis	Standardized Coefficient	p-value	Confidence Interval 5%	Confidence Interval 95%	f^2	Result
H1	Helpfulness Trust → Online Medical Consultation Service	0.368	0.000**	0.277	0.460	0.264	Hypothesis Supported
H2	Reliability Trust → Online Medical Consultation Service	0.236	0.000**	0.166	0.308	0.112	Hypothesis Supported
H3	Benevolence Trust → Online Medical Consultation Service	0.001	0.491 NS	-0.079	0.076	0.000	Hypothesis not Supported
H4	Perceived Benefit → Online Medical Consultation Service	0.264	0.000**	0.187	0.339	0.164	Hypothesis Supported
H5	Performance Risk → Online Medical Consultation Service	-0.145	0.000**	-0.198	-0.086	0.064	Hypothesis Supported
H6	Privacy Risk → Online Medical Consultation Service	-0.104	0.010*	-0.177	-0.030	0.026	Hypothesis Supported
H7	Perceived Centeredness → Online Medical Consultation Service	0.028	0.231 NS	-0.036	0.086	0.002	Hypothesis not Supported
H8	Online Medical Consultation Service → Intention to Recommend	0.737	0.000**	0.690	0.773	1.190	Hypothesis Supported

NS: Not Significant *Significant p-value <0.05; **Significant corrected p-value <0.006

The output of PLS's prediction can be used to assess predictive ability at the construct indicator level (Shmueli *et al.*, 2019) according to the requirements contained in the flow developed by (Hair *et al.*, 2019). In its development, a method that is considered more appropriate for measuring the predictive ability of a model is the cross-validated predictive ability test (CVPAT) developed by Liengaard *et al* (2021), and currently, CVPAT is recommended for measuring prediction-oriented model comparisons in PLS-SEM. From the findings of this study, we obtained CVPAT data compared to the average indicator (IA), both overall and at the indicator level. The results show a lower average loss value, which is indicated by a negative value. In accordance with the flowchart developed by (Sharma *et al.*, 2022), this model has predictive validity. Furthermore, a comparison was made with the linear model (LM), which obtained an average loss value greater than LM with positive results. Therefore, this model can only be said to have predictive validity, according to the naive benchmark stage. Three pathways have significant effects on Intention to Recommend, thus these three pathways are shown to be interconnected and show a link between the antecedents and Intention to Recommend as the dependent variable.

Importance-performance map analysis is a useful tool to identify indicators, providing input to managers to prioritize their improvement activities (Ringle & Sarstedt, 2016). This method is based on the importance that resulted from the total effect and performance based on the mean value. Importance-performance map analyses could be seen in four quadrants, whereas the focus is more on the quadrant with indicators that have more importance, whether the performance is sufficient or vice versa. For the research target construct, namely helpfulness trust in the upper right quadrant, the most important is HT1. These indicators are interpreted as important and have performed well in the eyes of consumers, so they need to be maintained by the management who manages Halodoc telemedicine. There are three indicators in the lower right quadrant which means that in the eyes of consumers, they are considered important but have below average performance. These indicators are HT2, PBE2 and PBE3.

This research model was conducted on telemedicine users, specifically Halodoc users, to reveal factors that influence telemedicine users to recommend the platform to potential users. The results of this study aligned with research that has been previously conducted by Yang *et al* (2021) and Octavius and Antonio (2021). What differentiates this study from previous studies is the sample. In this study, the author used women as the sample. According to (Sousa *et al.*, 2014) research, women spend more time on social media. It can be said that women are daily more dependent on their smartphones than men and by using women only as the gender of the sample, we expect that the result of this study will be more reliable.

The distribution of data obtained: based on age group, most were from the group age of 25 - 34 years old (56.4%), most were single (58.3%) and most of the respondents work as employees (33.7%). Based on the results of this distribution, the results show that women are quite busy due to work, thus many of them rely on telemedicine to seek treatments. It was found from 8 hypotheses that six hypotheses were supported and significant with a positive direction. The other 2 hypotheses did not support the hypotheses because they were found to have no significance in the matter. In this research model, 2 hypotheses have a negative direction, namely PER and PVR. This is because it is related to risk. Risk has become a concern for telemedicine users because the use of telemedicine has a close relationship to risk, such as privacy and performance in the application. The risk in this study is characterized by a negative coefficient, where consumers first form an initial expectation of a specific product or service before the transaction.

After their initial consumption, they form perceptions about its performance. Then, consumers compare their performance perceptions with their original expectations and determine the extent to which their expectations are confirmed. Interestingly, the predominant relation from independent variables was shown from helpfulness trust (0.368). The higher the users' trust in an application, the higher the

chances that users will choose that particular OMC. This finding is in line with previous research. Helpfulness trust in telemedicine in this study is not human to human but human to computer (Sousa *et al.*, 2014). Trust contributes to expectation formation and thus influences their satisfaction and intention to continue the service. Research suggests that it is important to note that a good user interface design is crucial to a mobile app's acceptance by its users, where women usually find it more difficult to understand difficult applications (especially in terms of the user interface) (Mohammadzadeh *et al.*, 2022).

Apart from that, an application can be said to be helpful if the application can be used as a "one-stop shopping application", where not only users can get their medical consultation but also can get medicine from cooperating pharmacies or laboratories to carry out supporting examinations. This implication is also reinforced by the IPMA results at the indicator level, which shows that the HT2 indicator is the most important thing, and its performance needs to be improved to support optimal OMCS. The second biggest relation is perceived benefit (0.264). Perceived benefit is a foundational aspect regarding consumers' decision-making and consumers tend to maximize the positive value, which this case the user's decision to use the Halodoc application to answer questions about their health (Gong *et al.*, 2019).

Based on previous evidence-based studies, it has shown that perceived benefits exerted a positive and significant effect on customers' behavioral intention (Gong *et al.*, 2019). This can be seen by the relationship between OMCS as one of many internet-based services that may bring about potential benefits for consumers, such as cost-effectiveness and time-saving which have been identified as relative benefits as compared with traditional offline services. This also follows the samples used in this study, while productive women have a lot of activities, so they choose to make the best use of their time and be as effective as possible.

The third biggest relation is reliability trust (0.236). Trust can be referred to as perceived trust, which is the user's level of confidence that an application is trustworthy (Alexandro & Antonio, 2021; Schnall *et al.*, 2015). Trust is also one of the components that are considered the top five most frequent factors that affect the continuance usage intention of OMC applications. In this case, it is related to the trusting attitude by (Schnall *et al.* 2015) who define trusting attitude as a feeling of expression of a person towards evaluating an object, for example, "I feel that I would trust OMC platforms for reliable medical information services". As an indicator of how well the OMC platforms provide services, trust is critical because if patients trust the platform, both parties will build a mutual understanding, and the relationship will be more likely to continue (Matikiti *et al.*, 2018). Therefore, when OMC patients' trust keeps increasing, they are more likely to continue their relationship with the doctor and pay for the services continuously.

This study also found that there was no adequate evidence from a few antecedents of online medical consultation services, namely the BEV and PCT, although it had a positive effect. Benevolence is the extent to which a trustee is believed to want to do good to the trustor, aside from an egocentric profit motive (Mayer *et al.*, 1995). Those who are benevolent will use all their abilities and skills to help others to their utmost. Benevolence is described as the certainty that the other will not abuse someone's vulnerability or take unfair advantage of someone, even if the opportunity exists (Di Battista *et al.*, 2020). It is difficult to assess the benevolent attitude of physicians online as the medium because women put a value on something that they can sense (touch, feel, and hear). This benevolent trust will be felt more by the patient in a face-to-face consultation. Perceived centeredness is the extent to which the physicians' services are respectful of patients' preferences and needs (van Velsen *et al.*, 2016). The patient's perception that they feel respected for their preferences and needs is also difficult because in OMCS services there is no special touch that makes patients feel their needs are cared for.

In addition, the time-limited condition also makes the patient feel the same way. This study shows that the OMCS and its antecedents, from the HT to the PCT, might have a significant

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association with ITR (0.737; p 0.000). Similarly, the findings of this study support the hypothesis that the customer experience concept adopted in Online Medical Consultation Services may have a favorable impact on Intention to Recommend, which is a higher emotional state than contentment (Klaus & Maklan, 2013; Parasuraman *et al.*, 2020).

This study's novel contribution is to demonstrate a new method for estimating ITR using OMCS. The model has a moderate association strength ($R^2 = 0.541$) and a high effect size ($f^2 = 1190$). The cross-validated redundancy value provided by Q^2 was used to measure model quality in the out-of-sample prediction approach. The Q^2 value found in this study is 0.511, demonstrating the model's validity when parameters are changed. As a result, this model may be deemed acceptable for estimating ITR and should be duplicated and tested in future research with a bigger and more diversified population.

Conclusions

This research concludes that HT, PBE, PER, PVR, and RT have all been proven to have a significant and positive relation. The strongest relation comes from the components of technological trust, namely Helpfulness Trust, and Reliability Trust. In addition, Perceived Benefit is also a variable that has significant value for OMCS users. Furthermore, OMCS shows adequate evidence and a positive impact on ITR. PCT and BEV showed a negative connection that weakens the OMCS. With these findings, managerial implications can be drawn up. Logical from the findings, 2 elements of technological trust get the most value. Therefore, management needs to create an application that users can trust. Reliable information and a helpful interface can make users continue using the application and recommend it to other people. In addition, because the sample used is a woman and 33.7% are workers who incidentally are busy, therefore making an application that is cost and time-effective. Li et al. (1999) said there are 3 main things that consumers relate to online buying behavior, a price benefit; (2) a convenience benefit; and (3) a recreational benefit in terms of enjoyment which can be realized by being able to provide free vouchers

or attractive prizes. Concerning perceived benefits, OMCS users want to feel these three things when using the application. This research also noted some limitations and one of them was that this study was only conducted on one Online Medical Consultation. By using more than one application, it is hoped that we will get more diverse answers. In addition, the inclusion criteria do not include the frequency of users in a certain period, because it is related to continued usage intention, it is better if the frequency criteria are included in the questionnaire. In addition, this study did not classify patients based on the disease consulted. By knowing what diseases are consulted, it can be seen how far the application answers the user's needs.

References

Albarrak, A.I., Mohammed, R., Almarshoud, N., Almujalli, L., Aljaeed, R., Altuwaijiri, S., & Albohairy, T., 2021. Assessment of Physician's Knowledge, Perception and Willingness of Telemedicine in Riyadh Region, Saudi Arabia. *Journal of Infection and Public Health*, 14(1), pp.97–102.

Alexandro, R., & Antonio, F., 2021. Antesedent Dari Online Trust Serta Dampaknya Terhadap Willingness To Choose Konsultasi Online (Studi Empiris Pada Konsumen Aplikasi Layanan Kesehatan). *Jurnal Manajemen Dan Administrasi Rumah Sakit Indonesia (MARSI)*, 5, pp.128–150.

Alhogail, A., & Alshahrani, M., 2019. Building Consumer Trust to Improve Internet of Things (IoT) Technology Adoption. *Advances in Neuroergonomics and Cognitive Engineering*, 775, pp.325–334.

Andone, I., Błaszkiewicz, K., Eibes, M., Trendafilov, B., Montag, C., & Markowetz, A., 2016. How Age and Gender Affect Smartphone Usage. *Proceedings of the 2016 ACM International Joint Conference on Pervasive and Ubiquitous Computing: Adjunct*, pp.9 – 12.

Arfi, W., Ben, N.I., Ben, K.G., & Hikkerova, L., 2021. The Role of Trust in Intention to Use the IoT in eHealth: Application of the Modified UTAUT in a Consumer Context. *Technological Forecasting and Social Change*, 167, pp.120688.

Chen, Y., Zhao, Y., & Wang, Z., 2020. Understanding Online Health Information Consumers' Search as a Learning Process: Search Platform Sequences, Query Reformulation

and Conceptual Changes. *Library Hi Tech*, 38(4), pp.859-881.

Chomeya, R., 2010. Quality of Psychology Test Between Likert Scale 5 and 6 Points. *Journal of Social Sciences*, 6(3), pp.399 – 403.

de Langhe, B., Fernbach, P.M., & Lichtenstein, D.R., 2016a. Navigating by the Stars: Investigating the Actual and Perceived Validity of Online User Ratings. *Journal of Consumer Research*, 42(6), pp.817–833.

de Langhe, B., Fernbach, P.M., & Lichtenstein, D.R., 2016b. Star Wars: Response to Simonson, Winer/Fader, and Kozinets. *Journal of Consumer Research*, 42(6), pp.850–857.

Deloitte Indonesia, Bahar Law Firm, & Chapters Indonesia., 2019. *21st Century Health Care Challenges: A Connected Health Approach*.

Di Battista, S., Pivetti, M., & Berti, C., 2020. Competence and Benevolence as Dimensions of Trust: Lecturers' Trustworthiness in the Words of Italian Students. *Behavioral Sciences*, 10.

Escoffery, C., 2018. Gender Similarities and Differences for e-Health Behaviors Among U.S. Adults. *Telemedicine and E-Health*, 24(5), pp.335–343.

Fernandez, P., 2020. Through the Looking Glass: Envisioning New Library Technologies Pandemic Response Technologies: Remote Working. *Library Hi Tech News*, 37(5), pp.21–23.

Franco-Lara, R., 2023. Comparing Patients' Satisfaction with Telemedicine Visits to In-person Visits at Central Washington Onsite Clinics: A Program Evaluation. *Doctor of Nursing Practice (DNP) Scholarly Projects*, 55.

Gliadkovskaya, A., 2021. *Telehealth Use is Surging but Patient Satisfaction with the Service has Declined, New Study Finds*.

Gong, Z., Han, Z., Li, X., Yu, C., & Reinhardt, J., 2019. Factors Influencing the Adoption of Online Health Consultation Services: The Role of Subjective Norm, Trust, Perceived Benefit, and Offline Habit. *Frontiers in Public Health*, 7, pp.286.

Google Trends., n.d. Retrieved May 15, 2023, from https://trends.google.co.id/trends/explore?date=today%205-y&geo=ID&q=halodoc

Gutierrez, M., Moreno, R., & Rebelo, M., 2017. Information and Communication Technologies and Global Health Challenges. *Global Health Informatics: How Information Technology Can Change Our Lives in a Globalized World*, pp.50–93.

Hair, J.F., Risher, J.J., Sarstedt, M., & Ringle, C.M., 2019. When to Use and How to Report the Results of PLS-SEM. *European Business Review*, 31(1), pp.2–24.

Halodoc., n.d. *Perlindungan Kesehatan Efisien dengan Halodoc Corporate Service*.

Han, W., 2020. Effects of User Reviews and Critic Rating on Online Healthcare Sales. *American Journal of Industrial and Business Management*, 10, pp.1902–1915.

Hsu, W.-Y., 2019. A Customer-Oriented Skin Detection and Care System in Telemedicine Applications. *The Electronic Library*, 37(6), pp.1007–1021.

Johnson, C., Dupuis, J.B., Goguen, P., & Grenier, G., 2021. Changes to Telehealth Practices in Primary Care in New Brunswick (Canada): A Comparative Study Pre and During the COVID-19 Pandemic. *PLOS ONE*, 16(11), pp.e0258839.

Kaium, M., Bao, Y., Alam, M., & Hoque, M., 2020. Understanding Continuance Usage Intention of mHealth in a Developing Country: An Empirical Investigation. *International Journal of Pharmaceutical and Healthcare Marketing*, 14(2), pp.251–272.

Klaus, P., & Maklan, S., 2013. Towards a Better Measure of Customer Experience. *International Journal of Market Research*, 55, pp.227–246.

Kock, N., & Hadaya, P., 2016. Minimum Sample Size Estimation in PLS-SEM: The Inverse Square Root and Gamma-Exponential Methods: Sample Size in PLS-based SEM. *Information Systems Journal*, 28.

Li, H., Kuo, C., & Russell, M., 1999. The Impact of Perceived Channel Utilities, Shopping Orientations, and Demographics on the Consumer's Online Buying Behavior. *J. Computer-Mediated Communication*, 5.

Liengaard, B., Sharma, P., Hult, G.T.M., Jensen, M., Sarstedt, M., Hair, J., & Ringle, C., 2021. Prediction: Coveted, Yet Forsaken? Introducing a Cross Validated Predictive Ability Test in Partial Least Squares Path Modeling. *Decision Sciences*, 52, pp.362–392.

Martínez-Caro, E., Cegarra, J., Garcia-Perez, A., & Fait, M., 2018. Healthcare Service Evolution Towards the Internet of Things: An End-User Perspective. *Technological Forecasting and Social Change*, 136.

Matikiti, R., Mpinganjira, M., & Roberts-Lombard, P., 2018. Application of the Technology Acceptance Model and the Technology–Organisation–Environment Model to Examine Social Media Marketing Use in the South African Tourism Industry. *SA Journal*

of Information Management, 20.

Mayer, R.C., Davis, J.H., & Schoorman, F.D., 1995. An Integrative Model of Organizational Trust. *The Academy of Management Review*, 20(3), pp.709.

Mohammadzadeh, Z., Eghtedar, S., Ayatollahi, H., & Jabraily, M., 2022. Effectiveness of a Self-Management Mobile App on the Quality of Life of Women with Breast Cancer: A Study in a Developing Country. *BMC Women's Health*, 22.

Nurhayati, S., Anandari, D., & Ekowati, W., 2019. Unified Theory of Acceptance and Usage of Technology (UTAUT) Model to Predict Health Information System Adoption. *Jurnal Kesehatan Masyarakat*, 15(1), pp.89–97.

Octavius, G.S., & Antonio, F., 2021. Antecedents of Intention to Adopt Mobile Health (mHealth) Application and Its Impact on Intention to Recommend: An Evidence from Indonesian Customers. *International Journal of Telemedicine and Applications*, 2021, pp.1–24.

Pai, R., & Alathur, S., 2019. Assessing Awareness and Use of Mobile Phone Technology for Health and Wellness: Insights from India. *Health Policy and Technology*, 8.

Parasuraman, A., Ball, J, Aksoy, L., Keiningham, T., & Zaki, M., 2020. More than a Feeling? Toward a Theory of Customer Delight. *Journal of Service Management*, 32(1), pp.1–26.

Pusparisa, Y., 2020. *Indonesia Peringkat ke-3 Global Memanfaatkan Aplikasi Kesehatan*.

Rahi, S., 2021. Assessing Individual Behavior Towards Adoption of Telemedicine Application During COVID-19 Pandemic: Evidence from Emerging Market. *Library Hi Tech*, 40(2), pp.394–420.

Ringle, C., & Sarstedt, M., 2016. Gain More Insight from Your PLS-SEM Results: The Importance-Performance Map Analysis. *Industrial Management & Data Systems*, 116.

Sarstedt, M., Hair, J, Pick, M., Liengaard, B., Radomir, L., & Ringle, C., 2022. Progress in Partial Least Squares Structural Equation Modeling Use in Marketing Research in the Last Decade. *Psychology & Marketing*, 39(5), 1035–1064.

Schnall, R., Higgins, T., Brown III, W., Carballo-Dieguez, A., & Bakken, S., 2015. Trust, Perceived Risk, Perceived Ease of Use and Perceived Usefulness as Factors Related to mHealth Technology Use. *Studies in Health Technology and Informatics*, 216, pp.467–471.

Sharma, P., Liengaard, B., Hair, J.F., Sarstedt, M., & Ringle, C., 2022. Predictive Model Assessment and Selection in Composite-Based Modeling Using PLS-SEM: Extensions and Guidelines for Using CVPAT. *European Journal of Marketing*, 57(6), pp.1662-1667.

Shmueli, G., Sarstedt, M., Hair, J., Hwa, C., Ting, H., Vaithilingam, S., & Ringle, C., 2019. Predictive Model Assessment in PLS-SEM: Guidelines for Using PLSpredict. *European Journal of Marketing*, 53(11), pp.2322–2347.

Sousa, S., Lamas, D., & Dias, P., 2014. A Model for Human-Computer Trust. *Learning and Collaboration Technologies. Designing and Developing Novel Learning Experiences*, 2014, pp. 128–137.

Sufyan, D.L., Syah, M.N.H., & Nurbaya, N., 2022. Impact of COVID-19 Outbreak on Women Quality of Life in Indonesia. *Jurnal Kesehatan Masyarakat*, 18(1), pp.67–73.

van Velsen, L., Tabak, M., & Hermens, H., 2016. Measuring Patient Trust in Telemedicine Services: Development of a Survey Instrument and its Validation for an Anticoagulation Web-Service. *International Journal of Medical Informatics*, 97.

Wulff, D., Hills, T., & Hertwig, R., 2014. Online Product Reviews and the Description–Experience Gap. *Journal of Behavioral Decision Making*, 28.

Yang, M., Jiang, J., Kiang, M., & Yuan, F., 2021. Re-Examining the Impact of Multidimensional Trust on Patients' Online Medical Consultation Service Continuance Decision. *Information Systems Frontiers*, 24.

Zhang, X., Yan, X., Cao, X., Sun, Y., Chen, H., & She, J., 2018. The Role of Perceived E-Health Literacy in Users' Continuance Intention to Use Mobile Healthcare Applications: an Exploratory Empirical Study in China. *Information Technology for Development*, 24(2), pp.198–223.