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Patient Trust and Resistance towards Patient Portals

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Abstract: Health information technologies (HITs) as facilitators of chronic disease self-management remains an ongoing topic for information system researchers. This research addresses a gap in knowledge surrounding patient trust and resistance towards using these technologies, specifically patient portals. The method used to accomplish this study is through the dispersion of a quantitative survey to participants in Ontario, Canada. This survey focused on questions related to the four variables that have been identified through the literature to be important in determining patient resistance of HITs. The results indicate the importance of patient trust in mitigating their resistance to using these technologies.

INTRODUCTION

Patient access to personal health information (PHI) results in numerous benefits. These benefits may include improved quality of care and safety, increased efficiency and consumer engagement, and decreased costs (Ancker, Edwards, Miller & Kaushal, 2012; Walker, Pan, Johnston, Adler-Milstein, Bates & Middleton, 2005). Despite this, resistance to the use of HITs is strongly prevalent for patients (Samhan, 2017; Samhan & Hauck, 2018). Additionally, there is a lack of literature addressing this trust as it pertains to the resistance of HITs (Li, James, & McKibben, 2016; Platt, Jacobson & Kardia, 2018). Trust is characterized as “a multidimensional dynamic between two parties defined by an expectation or willingness to impart authority and accept vulnerability to another in fulfilling a given set of tasks” (Platt, Jacobson & Kardia, 2018). Although trust has been determined as an important indicator in the reduction of uncertainty (Liang, Laoethakul, Lloyd, & Xue, 2005), the volume of literature on this topic is greatly lacking and should be explored further. To assist in mitigating these gaps in the literature this study will examine factors that contribute to patient resistance and more specifically focusing on trust concerns of patient portals. Patient portals are a HIT that allows patients to access PHI through a secure online website at any time as long as an internet connection is available (Kruse, Argueta, Lopez, & Nair, 2015). Therefore, this study seeks to address the research question of: *How does patient trust affect resistance behaviors towards the use of patient portals?*

BACKGROUND

Over the past several years the notion of patient portals has become a prevalent topic in literature (Kruse, Argueta, Lopez, & Nair, 2015). Patient portals enable patients to have 24-hour access to PHI via secure online websites; these websites may be accessed anywhere as long as an internet connection exists (Kruse, Argueta, Lopez, & Nair, 2015). These portals provide patients with the opportunity to better manage and understand their current health situations (Kruse, Argueta, Lopez, & Nair, 2015; Ammenwerth, Schnell-Inderst, & Hoerbst, 2012; Dohan & Tan, 2014). Patient portals differ from personal health records (PHR) in that data on the portals is updated whenever updates are made to the electronic health record (EHR), as opposed to PHRs, where data is only updated by patients (Kruse, Argueta, Lopez, & Nair, 2015). There are numerous different features that can be provided by patient portals including; access to information regarding recent office visits, summary of discharges, medications and lab results with more advanced options being prescription refill requests, scheduling of appointments, and communicating via secure messages with practitioners (Kruse, Argueta, Lopez, & Nair, 2015; Ammenwerth, Schnell-Inderst, & Hoerbst, 2012).

Although information sharing in healthcare is accomplished in various ways, the overall goal is to present patients as digital managers of their health data and information (Gordon & Catalini, 2018). The management of chronic diseases is essential to maintain a good quality of life and to mitigate health emergencies, complications and possibly even death (Dadgar, Majid, & Joshi, 2018), therefore information sharing could provide substantial benefits here. There are numerous self-management activities that patients with a chronic disease must manage in their everyday lives. These activities include communicating with healthcare providers, medication management, lifestyle management,

management of psychological consequences, use of social support systems and symptom management (Dadgar, Majid, & Joshi, 2018). Although most research on information sharing has focused on the provider perspective, research on Health Information Exchanges (HIEs) has investigated information sharing from the patient perspective (Esmailzadeh & Sambasivan, 2017). HIE technologies has shown great potential in improving safety and quality of care, increasing efficiency and consumer engagement, and reducing cost (Ancker et al., 2012; Walker et al., 2005). These benefits are not just acquired by individual groups such as providers, but all participants in the healthcare system including patients, providers, payers and the entire community (Murphy, 2013).

Despite these benefits, the success of information sharing depends on the degree of trust users feel towards the experience (Platt, Jacobson & Kardia, 2018). Trust as it relates to HITs has been determined to increase patients' improved decision making and use of HIE systems (Kisekka & Giboney, 2018). When individuals trust that the system will provide them with quality information, the chances of continued use are increased (Kisekka & Giboney, 2018). Further, it was found by (Kisekka & Giboney, 2018), that there is a positive relationship between information trust and optimistic attitudes towards using HIE technologies among providers. Trust entails that the implementer of a technology will deal with any related issues that emerge (Rivard & Lapointe, 2012). With regards to trust and patient portals, a patient must establish trust with both the organizations providing the information as well as trust with their physicians (Li, James, & McKibben, 2016; Platt, Jacobson & Kardia, 2018).

Given that these patient portals amount to some sort of investment, and that they have the potential to be an important part of normal care routines, it is imperative that patients' attitudes and behaviours related to resisting use of the technology be addressed. Resistance is an important factor here to take into account, as it captures the potential users consideration and subsequent rejection of a technology (Bhattacharjee & Hikmet, 2007). This can potentially lead to resistance behaviours beyond simple non-adoption, such as sabotaging change processes or open hostility towards change agents (Bhattacharjee & Hikmet, 2007), for examples.

Gaps in Research

Given the obstacles associated with the adoption of HITs to facilitate interoperability and manage chronic disease, as well as the benefits that may be attained with the implementation of these technologies, there are still several gaps in the literature that should be explored. The first gap identified concerns the lack of literature on patient resistance behaviors of HITs and more specifically patient portals (Samhan & Hauck, 2018). Within the healthcare industry, the resistance of users is considered a major contributor to the failure of systems. Given the importance of mitigating patient-user resistance, there is a lack of literature addressing the resistance of patients toward HITs (Samhan, 2017; Samhan & Hauck, 2018; Kim & Kankanhalli, 2009). For this gap to be addressed, patients perceived awareness and knowledge must be examined to initiate successful technological change directed towards patients. Second, there is a lack of literature addressing trust as it pertains to the resistance of HITs and more specifically patient portals (eg. Li, James, & McKibben, 2016; Platt, Jacobson & Kardia, 2018). Trust has been identified as an important factor in the reduction of uncertainty (Liang, Laosethakul, Lloyd, & Xue, 2005), but the volume of literature on this topic is lacking and should be explored further to find out how patient trust affects the resistance behaviors towards HITs such as patient portals.

THEORETICAL BACKGROUND

To address the aforementioned gaps in research, several theoretical approaches will be integrated into a model. First, constructs from Commitment-Trust Theory (Wang, Wang & Liu, 2016) will be employed in order to capture trust-related constructs. Second, Unified Theory of Acceptance and Use of Technology (UTAUT; Venkatesh & Davis, 2000) will be used to capture traditional variables related to personal use of technology and the context of its use.

Commitment-Trust Theory

The commitment-trust theory is a theory fixated on explaining the growth of long-term relationships among exchange parties (Wang, Wang & Liu, 2016). Specifically, this theory focuses on the concurrent adoption of relationship commitment and trust as critical indivisible factors for the formation and maintenance of business relationships between exchange parties (Wang, Wang & Liu, 2016). This theory thus proposes that the trust between exchange parties can aid in the reduction of the vulnerability of relationships, ultimately resulting in enhanced relationship

commitment (Wang, Wang & Liu, 2016; Yuan, Lai, & Chu, 2019). Although, this theory is generally used in the context of relational exchanges within the relationship marketing field (Morgan & Hunt, 1994), it similarly offers a powerful theoretical basis for the explanation of online service usage such as the use of patient portals within the healthcare field (Yuan, Lai, & Chu, 2019).

Unified Theory of Acceptance and Use of Technology

The Unified Theory of Acceptance and Use of Technology (UTAUT) is a cognitive theory focused on understanding and predicting human behavior as it relates to the adoption and use of technology (Venkatesh et al., 2003; Venkatesh et al., 2016). It incorporates various cognitive theoretical foundations that focus on the intention of an individual to use technology (Venkatesh, Morris, Davis, & Davis, 2003; Venkatesh, Thong & Xu, 2016). Four main factors are posited to predict the intention to use a technology: performance expectancy, effort expectancy, social influence and facilitating conditions (Venkatesh et al., 2003; Venkatesh et al., 2016). This model is very popular, and has been applied to explain factors related to the technology and context of its use, and their effect on the intention to use technology. Previous studies have reported empirical evidence integrating the four UTAUT predictors along with resistance in investigations on patient use of cloud computing (Hsieh, 2016),

HYPOTHESIS DEVELOPMENT

As previously stated, the research question used to guide this study is: *How does patient trust affect resistance behaviors towards the use of patient portals.* Figure 1 (below) describes the theoretical model used in this research.

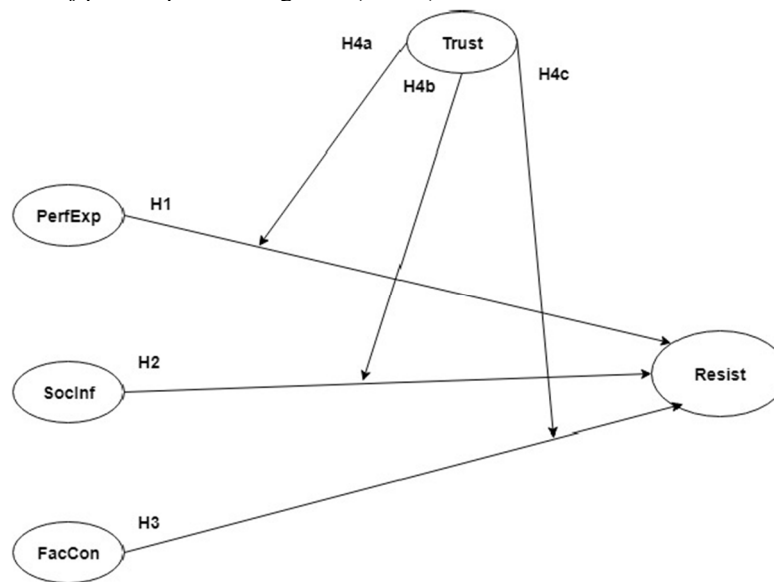


Figure 1: Theoretical Model Tested in this Research. PerfExp: Performance Expectancy. SocInf: Social Influence. FacCon: Facilitating Conditions. Resist: Resistance.

The first hypothesis refers to the ability of performance expectancy to positively impact user resistance behaviors towards patient portals. Performance expectancy is defined as the extent to which an individual believes the use of a system will provide them with their desired outcomes (Venkatesh & Davis, 2000; Venkatesh et al., 2003). There is a positive impact associated with a high degree of performance expectancy, which results in user acceptance or reduced resistance (Venkatesh & Davis, 2000; Venkatesh et al., 2003; Venkatesh et al., 2016). Here, the perception related to the ability of the patient portal to help the patients achieve their health goals will be a compelling argument for them to use the technology, thereby lowering their resistance-related attitudes towards it. Therefore, hypothesis 1 is:

H1: As the "Performance Expectancy" of patient portals increases, the overall resistance of the patient portals will decrease.

The next hypothesis refers to social influence and its impact on resistance behaviors toward patient portals. Social influences can be characterized as the degree to which an individual perceives that people significant to them believe in the use of the technology (Venkatesh et al., 2003). Positive or encouraging social influences would encourage an individual to perform or in this case be accepting of patient portals, and this has been hypothesized and supported in other contexts (Samhan, 2017; Oreg, 2006). The second hypothesis is:

H2: As the “Social Influence” towards patient portals becomes positive, the resistance to patient portals will decrease.

The third hypothesis refers to the impact of facilitating conditions on intentions to resist patient portals. Facilitating conditions can be defined as the degree that an individual is convinced that an organization and information technology exists to support the use of the specified system (Venkatesh et al., 2003). In the case of patient portals, the patient’s physician may provide varying levels of support for the use of the patient portal. Thus, hypothesis 3 reflects this relationship:

H3: As the “Facilitating Conditions” towards patient portals increases, the resistance to patient portals will decrease.

The fourth hypothesis refers to the impact that trust has on patient portal resistance. An ongoing concern is the trust between physicians and patients; this degree of trust affects the development of this important relationship (Li, James, & McKibben, 2016). Technology changes the way patients and physicians interact, and the degree of trust can impact whether a patient is accepting of the technology or resistant toward the technology (Li, James, & McKibben, 2016). It is expected that trust will have a moderating effect on resistant behaviors. Thus, hypothesis 4 is broken into three separate hypotheses as follows for each of the aforementioned independent variables:

H4a: Increased “Trust” will moderate (amplify) performance expectancy behaviors to resist patient portals.

H4b: Increased “Trust” will moderate (amplify) social influence behaviors to resist patient portals.

H4c: Increased “Trust” will moderate (amplify) facilitating condition behaviors to resist patient portals.

METHODOLOGY

Data was collected between February and August 2019 in Ontario, Canada. Participants were recruited via posters dispersed amongst various locations in Ontario, Canada and through posts on social media. The survey was administered online, and participants were motivated with the chance to enter into a draw upon completion of the questionnaire. The survey was comprised of three sections; the first section provided a brief explanation of patient portals to ensure participants were aware of what was being talked about. This explanation was followed demographic questions on age, gender, education, voluntariness, access frequency, and chronic disease. The main component of the survey included questions regarding the performance expectancy, effort expectancy, social influence, and facilitating conditions adapted from Venkatesh et al (2003). The trust and resistance items were adapted from Aboobucker & Bao (2018) and Bhattacharjee & Hikmet (2007), respectively. The items for each of the constructs of the model were measured on a seven-point Likert scale (Strongly Disagree – Strongly Agree). To control for common method bias and to avoid impulsive and repetitive responses, the order of the questions was randomized for each participant. Lakehead University Research Ethics Board (REB) provided ethics approval.

Analyzing the data involved the following steps. First, the dataset was examined using both a visual assessment and SPSS software for any major concerns such as missing data, suspicious response patterns, and outliers. After screening and cleaning the data, descriptive analysis was then run in SPSS to determine what trends exist in the data, whether the data set was normally distributed and to be able to describe the data. From this, it was identified that the data was somewhat negatively skewed with some indications of non-normality. Due to the nature of the data being somewhat non-normally distributed, having a smaller sample size and most variables being continuously measured, the rest of the data analysis was conducted with WarpPLS (Kock, 2018). PLS makes little to no assumptions regarding the distribution of the data and is ideal for small sample sizes (Hair et al., 2016). The outer model was tested utilizing the PLS Mode M Basic algorithm in WarpPLS and from this, it was identified that there was a presence of non-linear

relationships. The inner model was analyzed using the Warp3 algorithm, which attempts to identify relationships among latent variables that follow a pattern similar to an “S”-shaped curve using a logarithmic function (Kock, 2018).

Descriptive Statistics

After screening and cleaning the data, descriptive analysis was then run in SPSS to determine trends in the data. From this analysis it was determined that there was a total of 91 usable samples within this data set; of these 21 are males (23.1%), 69 are females (75.8%) and one respondent preferred not to disclose this information. Most respondents were between the ages of 19-34 years old (about 64%). Regarding the highest level of education obtained, most respondents had achieved a level of education of College or University or higher (about 81%). For the responses on the management of a chronic disease, there were only 33 respondents (about 36%) who identified to manage a chronic disease for themselves or a family member/loved one. Most individuals in this study (about 70%) indicated that they felt the use of patient portals was voluntary, followed by 24 respondents who felt it was somewhat voluntary (about 26%) and 3 respondents felt it was not voluntary (about 3%). Lastly, of the respondents who use patient portals, 36 participants used patient portals yearly (about 40%), followed by 9 monthly users (about 10%) and 4 weekly users (about 4%). The results of these tests are summarized in Table 1 (below).

Table 1: Descriptive Statistics for the sample

Total	n=91
Gender	Male (21; 23.1%) Female (69; 75.8%) Prefer not to Say (1; 1.1%)
Age	19-25 (36; 39.56%) 26-34 (22; 24.18%) 35-44 (9; 9.89%) 45-54 (6; 6.59%) 55-64 (12; 13.19%) 65-74 (6; 6.59%)
Highest Education	No High School (3; 3.30%) High School (14; 15.38%) College or University (66; 72.53%) Graduate Degree (8; 8.79%)
Manage a Chronic Disease	Yourself (23; 25.27%) Family Member or Loved One (10; 10.99%) No Chronic Disease (55; 60.44%) Prefer Not to Say (1; 1.10%) No Answer (2; 2.20%)
Voluntaryness	Daily (41; 45.05%) Weekly (4; 4.40%) Monthly (9; 9.89%) Yearly (36; 39.56%) Never (1; 1.10%)
Frequency of Use	Yes (64; 70.33%) No (3; 3.30%) Somewhat (24; 26.37%)

Reliability and Validity

Internal consistency reliability is usually the first criterion evaluated for the measurement model and it is evaluated using Cronbach’s alpha and composite reliability (Hair et al., 2016). Convergent validity can be described as the degree that an indicator positively correlates with other indicators from the same construct (Hair et al., 2016). Outer loadings between 0.4 and 0.7 will be deleted under the circumstance that deletion increases the AVE and composite reliability, while loadings below 0.4 will be deleted immediately (Hair et al., 2016). It is also noted that an acceptable AVE is any value above 0.5 (Hair et al., 2016). Discriminant validity will be assessed with the cross-loadings and the Fornell-Larker criterion. For this approach, the square root of the AVE should be greater than any inter factor correlations (Hair et al., 2016).

Structural Model Estimation

Following the confirmation of validity and reliability of the construct measures, the next phase assesses the structural model, also referred to as the inner model (Hair et al., 2016; Kock, 2018). The examination of the inner model involves both the model’s predictive capabilities and the relationships between constructs (Hair et al., 2016). Specifically, the procedure for assessing the structural model begins by assessing the model for any collinearity issues; collinearity is discussed further in the following section (Hair et al., 2016). The main criteria for assessing the inner model are displayed in table 3 (below) and include the assessment of the model’s structural paths, coefficient determination, effect size and predictive qualities (Hair et al., 2016; Kock, 2018). Also included in table 3 are the criteria for the analysis of the goodness of fit which includes several indices used to assess quality (Kock, 2018). Specifically, quality is assessed by the Average Path Coefficient (APC), Average R^2 (ARS), Average Adjusted R^2 (AARS), Average

Block VIF (ABVIF), and Average Full Collinearity VIF (AFCVIF), all of which should be below 5 or 3.3 (Kock, 2018). The VIFs below 5.0 are acceptable to assume collinearity is not present (Hair et al., 2016).

Alternative Model Evaluation

Several alternative models were compared using the goodness of fit tests as well as by examining the overall model fit and quality indices presented by WarpPLS. The model presented was the best one.

RESULTS

104 participants provided responses. After screening and cleaning the data, there were 91 usable samples. The data was screened and cleaned for any major concerns using SPSS software. With regards to missing data, four cases were removed due to a large percentage of unanswered questions. The threshold used for missing data was 15% (Hair et al., 2016). Upon examination, there were nine cases of straight-lining that were removed from the data set. There were no outliers identified in the data.

Reliability and Validity

All Cronbach's alphas and composite reliabilities were greater than the 0.7 thresholds (Hair et al., 2016). In analyzing the data there were several indicators that were dropped due to high cross-loadings with regards to their component loadings: SocInfl and Trust4. There were few other indicators that were below the threshold of 0.708 that were examined further but due to their deletion not having any improved impact on the Adjusted R^2 , they were retained. The AVEs of most of the constructs are all larger than 0.5 suggesting an acceptable level of convergent validity (Hair et al., 2016). Two cases do not meet this criterion, they include trust as a moderator for social influence and facilitating conditions. The cross-loadings were confirmed for all independent variables, although some issues did arise with the moderating variables. This criterion was satisfied for the Fornell-Larcker criterion, although there were two violations for trust as a moderator for social influence and facilitating conditions. The reliability and validity analysis results are presented in Table 2 (below).

Table 2: Average Variance Extracted (AVE), Cronbach's Alpha (α), Composite Reliability, Latent Variable Correlations and Square Root of AVE (italicized on the intersections). The bolded numbers are the violations of the discriminant validity. PE: Performance Expectancy. SI: Social Influence. FC: Facilitating Conditions. T: Trust.

Variable	AVE	α	CR	1	2	3	4	5	6	7	8
1 PE	0.653	0.851	0.881	<i>0.808</i>							
2 SI	0.736	0.821	0.893	0.615	<i>0.858</i>						
3 FC	0.621	0.759	0.828	0.570	0.558	<i>0.788</i>					
4 Trust	0.674	0.754	0.860	0.695	0.553	0.425	<i>0.821</i>				
5 Resistance	0.627	0.724	0.833	-0.209	-0.137	-0.108	-0.090	<i>0.792</i>			
6 T*PE	0.551	0.944	0.935	-0.328	-0.250	-0.222	-0.372	-0.238	<i>0.742</i>		
7 T*SI	0.470	0.869	0.887	-0.296	-0.133	-0.260	-0.291	-0.243	0.740	<i>0.686</i>	
8 T*FC	0.491	0.880	0.896	-0.253	-0.206	-0.242	-0.264	-0.282	0.847	0.649	<i>0.701</i>

Structural Model

The final model using the PLS Mode M Basic Algorithm with the Warp3 algorithm meets most of the overall model fit criteria (APC=0.162, P= 0.027; ARS= 0.276, P= 0.001; AARS= 0.224, P= 0.006; AVIF= 1.827 < 3.3; AFVIF= 2.617, < 3.3) (Kock, 2018). Figure 3 (below) summarizes the structural model, as well as Table 6 (below), presents the full results of the significant relationships in the structural model. Additionally, the block VIFs are all below the

threshold of 5.0, thus it is assumed that collinearity is not a problem (Hair et al., 2016). The path coefficients, effect size (f^2), coefficient of determination (R^2) are all used to interpret the results (Hair et al., 2016).

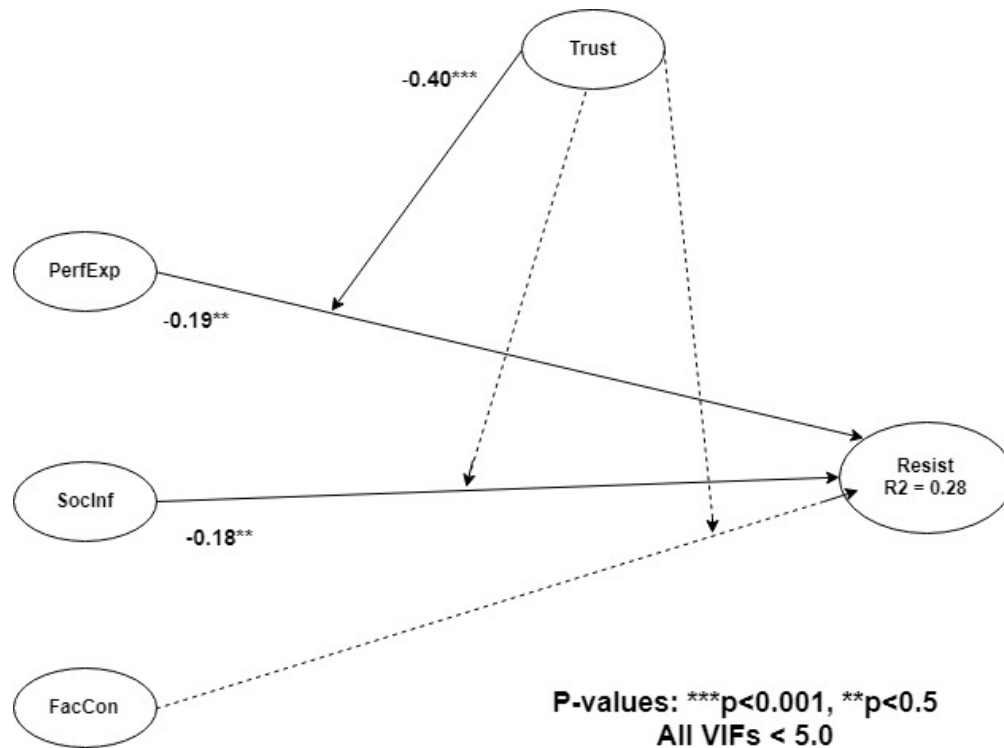


Figure 2: Structural Model Test Results. Significant relationships are denoted by bold lines, and non-significant relationships are denoted by dashed lines.

The R^2 for the dependent variable resistance is weak with a value of 0.28 (adjusted $R^2 = 0.22$) (Hair et al., 2016). Additionally, the supported hypotheses 1 and 2 have a small effect size, while hypothesis 4a, has a medium effect size (Hair et al., 2016). The confidence levels for each of the hypotheses were also assessed and are illustrated above in Table 6 for reference. The confidence levels for the supported hypotheses 1 and 2 are not significant, while hypothesis 4a yielded a significant confidence interval. Out of the six hypotheses included in the model, three are supported at the .05 level.

DISCUSSION

The purpose of this research was to determine the influence that trust has on the resistance behaviors towards the use of patient portals. From the results presented above, there was support for trust as a moderator of performance expectancy. Performance expectancy is characterized as the degree that a patient believes that the use of a system will contribute to the attainment of their desired outcome (Venkatesh et al., 2003). With higher degrees of trust, as performance expectancy increases, the resistance behaviors decrease. This result generally implies that trust is important for patients to adopt and use patient-focused HIT. More specifically, it implies that trust is important for patients to understand that the system will provide the intended benefits of the system. This result is in line with previous studies that suggest that trust plays an important role in the usage intentions of a system as well as having a positive effect on relationships (Yuan, Lai & Chu, 2019; Hashim & Tan, 2015). The effect of social influence on resistance was also significant. This result differs from that of previous studies (Samhan, 2017) although it uses a specific patient portal in a more tightly defined context. The moderation of trust on the relationship between social influence and resistance as well as facilitating conditions and resistance were both not supported (H4b and H4c). As this model yielded a small effect size for hypotheses 2 and hypothesis 3 was not supported, it is not surprising that hypothesis 4b and 4c were also not supported. Both of these results could imply that any action to increase trust in the

technology will not improve any resistance due to any social influences or perceptions regarding workloads necessary to use the HIT. Taken together, these results underline the importance of conducting more and larger-scale research on the role of trust in patient HIT adoption and use.

Limitations and Future Research

The chief limitation of this project pertains to its small sample size and the fact that participants self-selected. Being a small-scale research project, this limits its generalizability to any larger population. As well, the sample had a few shortcomings, such as the low proportion of participants who actually managed any chronic diseases. Finally, effort expectancy (Venkatesh et al., 2003) had to be dropped from the model, as the construct could not be found in the dataset. Future studies could focus more strongly on various aspects of the population, such as patients with certain chronic diseases. Future studies could also focus on certain interventions that are designed to address trust issues in a defined user base.

CONCLUSION

There has been a lack of literature focusing on the resistance behaviors toward HITs such as patient portals. The factors identified to be most important in reducing resistance include performance expectancy, social influence, and trust as a moderator to performance expectancy. These factors that identify to be most prevalent in contributing to resistant behaviors can thus be properly addressed in hopes of fully adopting patient portals as principal enablers of health management. Although many barriers exist in mitigating resistance behaviors such as trust concerns, this study is a step forward to not only contributing to the lacking literature but in facilitating change and complete adoption of patient portals.

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