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General Causality Orientations and the Adoption of Integrated Personal Health Records Systems: A Latent Class Analysis with Distal Outcomes

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Abstract

Integrated Personal Health Record (PHR) systems could potentially transform healthcare delivery and management by providing consumers with access to and control over their health information. Despite numerous suggested benefits in utilizing PHR systems, research shows that these systems are not widely adopted by consumers. For the full benefits of PHR systems to be realized, consumers need to accept a more active role in managing their own health. This study leverages Self-Determination Theory (SDT) to gain a better understanding of the PHR adoption behavior of individuals with different characteristics. Using latent class analysis with distal outcomes technique, a sample of 150 individuals was classified based on the three causality orientations of autonomy, control, and impersonal from SDT. Consequently, the influence of the extracted latent class variable on PHR system adoption was investigated. Results suggest five different classes across which perceptions of usefulness and complexity of PHR systems significantly differ.

1. Introduction

Information technology (IT) can potentially transform health care delivery and management [1, 2]. In particular, health care IT can pave the way for a shift towards consumer-based health care where patients are considered as partners in their own care process [3, 4]. PHR systems are positioned to support this transformative effect of IT in health care, by providing consumers with greater access to and control over their own health information [5, 6].

A PHR system refers to "an electronic application through which individuals can access, manage, and share their health information, and that of others for whom they are authorized, in a private, secure, and confidential environment" [7-9]. Such a system is composed of both data (e.g., history of major illnesses, allergies, medications, home monitoring data, etc.), and supporting tools and functionalities (e.g., allowing the individual to request prescription renewals and to communicate electronically with clinicians, etc.) [9]. Data contents of PHR systems are created, owned, updated, and controlled by the individual and/or others authorized by him/her. An *integrated* PHR system, which is the focus of this paper, gathers and presents data from multiple sources (e.g., patient, care provider, healthcare organizations, etc.) into a single view, generally through secure internet access [10]. It is widely agreed upon that successful implementation and proper use of integrated PHR systems would give rise to a change of the role of consumers from passive recipients of treatment to active partners (with health care providers) in the care process. Examples of such a partnership include becoming more involved in health care decision making [11]. As such, integrated PHR systems are thought to be capable of facilitating transformative advancements in consumers' health management [5].

In spite of all the potential benefits of PHR systems and despite expressed consumer interest [12], such systems are not yet widely adopted by consumers [13, 14]. Thus, research is needed to understand the adoption mechanisms of such systems. Existing PHR adoption studies have put forth numerous factors that bring about the lack of PHR system popularity and adoption. Of particular interest, behavioural and environmental factors are suggested to impact PHR system adoption [9]. They suggest that a PHR system can be useful for the individual owner only if he/she understands and accepts a more active role as well as new responsibilities related to his/her own health care. However, the interplay of such a role change and PHR system adoption is not empirically examined.

The overall objective of this research is to contribute to the body of literature on PHR system adoption by identifying types of consumers that would/would not be willing to take up a more active role in their health and wellness management, and by understanding the perceptions of the identified types of consumers regarding the adoption of integrated PHR systems. As such, the focus of this paper is on the pre-usage stage of the PHR system adoption process [15].

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2. Theoretical Background

The theoretical underpinnings of this study are rooted in both the psychology and information systems (IS) literatures. From the psychology literature, Self-Determination Theory (SDT) is a theory of motivation that sheds light on the mechanisms through which individuals become motivated to take more active (rather than passive) roles in performing different types of behaviours [16]. Since its introduction in the 1970's, SDT has been successfully applied [16, 17] in many research domains including health care which is the context of the current study (e.g., [18, 19]). From the IS literature, mainstream IS adoption models are reviewed to incorporate relevant perceptual and behavioural factors.

SDT represents a broad framework for the study of human motivation and personality. SDT assumes that human beings are, by nature, active organisms with evolved tendencies toward growing, mastering new skills, applying their talents responsibly, and learning [16]. Such tendencies, however, do not work automatically, and they require ongoing supports from the social environment. Without such ongoing support, individuals might reject growth and responsibility [16]. SDT argues that the varying extent of such ongoing support partially explains the varying degrees of self-motivation in individuals, from active and motivated to passive and amotivated [16]. SDT is concerned with understanding the conditions and social contexts that cause these differences in motivation, both within and between individuals [16].

SDT is a macro-theory that comprises five formal mini-theories each of which is developed to explain and address various facets of motivation such as its properties, determinants, and consequences [20]. Of particular interest to this research, the causality orientations theory (COT) concerns individual differences in causality orientations. An individual's causality orientations refer to motivational orientations that are relatively stable over time and in different domains [16, 20]. COT describes and assesses three types of causality orientations: the autonomy orientation (ACO), the control orientation (CCO), and the impersonal or amotivated orientation (ICO) [20-22]. ACO refers to a person's tendency toward being autonomous and intrinsically motivated in general, and across different domains and times. CCO refers to a person's general tendency toward being controlled (vs. autonomous) and extrinsically motivated. Finally, the ICO refers to a person being amotivated. According to COT, each individual demonstrates each of these three causality orientations to some extent.

Since PHR systems are information systems, mainstream IS adoption models were reviewed in order to identify the core determining factors of adoption to utilize in this research. The extensive body of research devoted to IS adoption (e.g., [23, 24]), mainly guided by the technology acceptance model (TAM) [25] has revealed that perceptions of usefulness (perceived usefulness or PU) and effort associated with using a system are major determinants of behavioural intention (BI) to use such technology. PU in the context of this study is defined as the extent to which an individual believes that an integrated PHR system is capable of being used advantageously in managing his/her health [25]. BI is defined as a measure of the strength of an individual's intention to use an integrated PHR system for managing his/her health [26]. Existing research in the IS and its reference disciplines has shown the role of BI as a strong predictor of actual system use (e.g., [24]).

In terms of perceptions of effort associated with using an IS, most TAM-driven studies employ the construct of perceived ease of use (PEOU). The concept and measurement of PEOU relates mainly to the effort associated with learning how to use a system [25]. However, using a PHR system can entail efforts beyond just learning to operate the system. A PHR system owner/user must expend an ongoing and significant maintenance effort to keep his/her account up-to-date. Otherwise, the presence of outdated, inaccurate, or incomplete information in the PHR account could potentially result in the wrong healthcare decisions being made to the detriment of the user [9]. Therefore, for the purpose of the current paper, a construct and associated measurement scale that captures such ongoing effort is more appropriate. The complexity (CPLX) construct [27] captures such ongoing effort. CPLX is defined as the degree to which an integrated PHR system is perceived as relatively difficult to understand and use. An example item from the measurement scale for CPLX is "Using the system involves too much time doing mechanical operations (e.g., data input)" [27]. The measurement scale for CPLX also captures the effort required to learn how to operate the system as evidence by the following example measurement item: "It takes too long to learn how to use the system to make it worth the effort". Therefore, CPLX is incorporated in the current study.

The ultimate research question of this study is whether individuals with various degrees of causality orientations differ in their perceptions (PU and CPLX) regarding their BI to use integrated PHR systems. As such, individual profiles regarding autonomy, control, and impersonal orientations are investigated, and the differences in the outcome variables (PU, CPLX, and

BI) are examined for various extracted profiles as described later in this paper.

As mentioned earlier, for a PHR system to be useful, the individual owner should understand and accept a more active role in his/her health management. We argue that individuals with varying levels of self-determination in health management (resulting in part from varying levels of causality orientation), would exhibit different perceptions regarding the use of integrated PHR systems. This argument is made on the grounds that PHR systems are suggested to support individuals' self-determination in managing their health (e.g., [28-30]). Hence, it is reasonable to expect that individuals with varying degrees of causality orientations would demonstrate different perceptions regarding the use of a technology that supports self-determination in health.

In addition to the above argument, prior research has revealed early signs that self-determination theory might explain differences in perceptions regarding the use of PHR systems. For example, Beckjord et al. [31], in a survey of consumers' perceptions regarding the use of PHR systems, found out that PHR functionalities that were rated highest among survey respondents were the ones that aligned with the consumers' levels of self-determination (e.g., viewing the same health records as the care provider can see, and keeping track of health information and appointments).

3. Methods

Data collection for this study was conducted using a cross-sectional online survey. Surveys are one of the most widely used methods in IS research [32]. Since the focus of this research is on understanding the "pre-usage" stage of the PHR adoption process, the online survey was administered to individuals with no prior experience in using PHR systems.

For the purpose of this study, integrated PHR systems were introduced to participants using a 12-minute online video clip. The purpose of the video clip was to provide participants with introductory information about PHR systems and to show them how a PHR system can be used through demonstrating the execution of a few real life scenarios in an HTML prototype of a fictitious PHR system with voice narration. Davis et al. [23] suggest that, in the absence of an actual system, video mockups can help introduce the system to the participants. The content of the video clip was created based on information gathered from multiple sources including published research papers, review websites, expert opinions, and a number of available PHR systems. Prior to starting the data collection, a link to the online video clip was sent to a number of experts in order to ensure the contents of the clip represented typical functionalities of an online integrated PHR system. Subsequently, the video clip was revised based on the feedback received from those experts. The video clip was shown to participants in full before they were asked to respond to related questions on the online survey. Examples of research showing the effectiveness of video clips are abundant for various educational purposes (e.g., [33, 34]) as well as for software skills training (e.g., [35, 36]).

The measurement instrument of this study contained closed-ended questions related to the three causality orientations, IS adoption factors (PU, CPLX, and BI), participants' demographics, and other control variables. In order to ensure content validity, measurement scales were selected from the extant literature, and in some cases, they were slightly adapted to reflect the context of this study.

The three causality orientations (autonomy, control, and impersonal) were measured using the General Causality Orientations Scale (GCOS) [22], 12 7-point Likert items per causality orientation. For each of the three orientations, one score is calculated for each individual by summing the values of the corresponding 12 items.

BI (3 items), PU (4 items), and CPLX (4 items) were measured using 7-point Likert scales adapted from [24], [37], and [27], respectively. For all the items for these scales, the name of the system was changed to "online PHR system"; and the purpose of the system was changed to "managing health". Since a fictitious PHR system rather than an actual available system was presented to participants, the phrase "If available to me" was added at the beginning of BI items. The participants were also clearly instructed to refer to the online PHR system presented in the video clip in answering the questions.

The survey of this study also included questions related to several control variables to be examined as part of the post-hoc analyses presented later in this paper. The control variables were age, gender, internet experience, household income, information privacy/security concerns, chronic illness, perceived health status, PHR self-efficacy, and prior collection of paper-based health records.

Participants were recruited in Canada, through a commercial market research firm with a paid consumer panel that includes over 400,000 Canadians. Invitations were sent out to achieve a balanced stratified sample based on participants' location, age, and gender, according to the 2011 Canadian Census Profile [38]. Invitations were sent via e-mail. E-mail recruitment helped overcome physical limitations in reaching a wider audience across the target population, thus enhancing the representativeness of the drawn sample. The market research firm conducts a random sampling of the Canadian population, and its panelists are recruited from various sources (TV ads, newspaper ads, etc.). Such random sampling is expected to enhance generalizability of the findings of the study [39]. At the end of data collection, a total of 150 completed usable surveys were collected. The recruitment of participants and the data collection for this study took place in August 2012. Prior to conducting data collection for the study, a pre-test of the instrument and a pilot study were conducted. Finally, an ethics application was submitted to and was approved by the ethics board at the authors' university before any data collection.

For the purpose of identifying classes of participants based on their responses to the causality orientations scale and in order to investigate the differences among identified classes in terms of PHR system adoption, latent class analysis (LCA) with distal outcomes was conducted [40]. LCA is used to identify unobservable (latent) subgroups (classes) within a population, based on a set of observed variables (items) [41]. The identified classes are distinct from each other, and each class consists of individuals whose responses to the set of items are similar [40]. The development of LCA and similar methods has originated from the need to classify individuals based on similar personality traits and to provide support for the existence of theoretical personality constructs [42, 43]. LCA with distal outcome produces the conditional distribution of a distal outcome (such as PU, CPLX, and BI), given a latent class variable (such as the causality orientation classes identified in this study) [40]. The conditional distributions can then provide "etiological" information about how the items predict the outcome of interest [40]. A detailed discussion on LCA with distal outcomes can be found in [40]. Finally, this method was conducted using the SAS LCA procedure and SAS %LCA_distal macro as outlined in [40].

4. Results

In order to examine the possibility of non-response bias in the data set, respondents and non-respondents were compared based on their demographic and socioeconomic information (age, gender, education level, and household income) [32]. As such, the means of demographic and socioeconomic information for the two groups were compared using independent-samples t-tests [44]. Results of the comparisons showed no statistically significant difference between respondents and non-respondents. Hence, it was concluded that non-response bias was not a concern for generalizing the findings of this study. Table 1 summarizes the demographic and socioeconomic information for the respondents of this study.

Assessment of measurement reliability was conducted using Cronbach's Alpha [45], and the results are summarized in Table 2. The reliabilities of GCOS scales as well as IS adoption factor scales were all above the acceptable threshold of .70 [46]. The Cronbach's Alpha for the CCO variable was slightly below the threshold; however, this is consistent with previous studies in this context (e.g., [22, 47]). In addition, running a factor analysis on CCO revealed that there were multiple eigenvalues that exceeded 1

Table 1. Participant characteristics

Characteristic	Min	Max	Mean	Standard Deviation (SD)
Age (years)	19	82	48.11	16.06
Internet Experience (in years)	3	26	15.56	4.96
Time spent online (hours per day)	1	12	3.67	2.43

Characteristic		Frequency	Percentage %
Gender	Female	81	54
	Male	69	46
Education Level	Secondary School or Less	23	15.33
	Some University or College	35	23.33
	University or College Degree	63	42
	Some Graduate Work	4	2.67
	Graduate Degree	25	16.67
Annual Household Income	Less than 40,000	33	22
Values are in Canadian	$40,000 - $79,999	61	40.67
Dollars	$80,000 - $119,999	36	24
	$120,000 - $159,999	17	11.33
	More than $160,000	3	2

for this factor, and as a result this may have contributed to its low reliability [47].

Discriminant validity was examined by comparing the square root of the Average Variance Extracted (AVE) for each variable with the variable's correlations with all the other variables in the study [48]. As seen in Table 2, all the values along the diagonal (square root of AVE) are greater than the correlations on the respective rows and columns, thus confirming the discriminant validity of the measurement scales. Finally, the correlations among the three GCOS scores are consistent with previous studies (e.g., [22, 49]). Table 2 also provides the means and standard deviations for the variables in this study.

Table 2. Reliability and discriminant validity

Variable	Mean (SD)	Cronbach's Alpha	Correlations					
			ACO	CCO	ICO	BI	PU	CPLX
ACO	67.43 (8.53)	.80	**1**					
CCO	49.49 (7.07)	.65	.03$^{n.s.}$	**1**				
ICO	39.22 (9.76)	.76	-.25**	.46**	**1**			
BI	4.94 (1.45)	.98	.21**	-.05$^{n.s.}$	-.02$^{n.s.}$	**.98**		
PU	5.47 (1.09)	.96	.33**	-.07$^{n.s.}$	-.05$^{n.s.}$	.78**	**.95**	
CPLX	3.26 (1.32)	.93	-.30**	.17*	.18*	-.54**	-.53**	**.87**

Bold values represent the square root of AVE.
* *Significant at 0.05 level (2-tailed);* ** *significant at 0.01 level (2-tailed);* $^{n.s.}$ *non-significant; SD: standard deviation.*

The main analysis of this study consists of two parts. First, using LCA, the number of latent classes was identified based on a set of information criteria and interpretability of the latent model. Second, using the identified number of classes, the influence of the identified latent class variable on IS adoption factors was examined for the context of PHR system adoption.

LCA works with categorical items, hence the scores of the 36 items of the three personality characteristics (ACO, CCO, and ICO) were re-coded so that a score of 4 or below on the 7-point Likert scale was re-coded to 1 (low), and a score of higher than 4 was re-coded to 2 (high). In addition, proper parameter restrictions were set in LCA in order to consider equal weights for the twelve items under each personality characteristic [22]. In summary, LCA was run using 36 items, each having two categories (low, high), and the weights of the 12 items under each personality characteristic were set to be equal in LCA estimation. In order to identify the "true" number of latent classes, LCA was conducted iteratively, each time with a different number of classes, starting with 2 classes [40], and until the method converged at the sixth (7 classes) iteration. In all the iterations, class sizes were set to be freely estimated (non-restricted).

Table 3 presents the fit statistics and information criteria for the six iterations of running LCA. The true model (number and composition of classes) can be selected using information criteria such as Akaike's Information Criterion (AIC [50]), Bayesian Information Criterion (BIC [51]), consistent AIC (CAIC [52]), and adjusted BIC (a-BIC [53]). The model with the minimum value for the information criteria is closest to the true model. The information criteria offer a relative estimate of the information lost when a given model (number and composition of classes) is used to represent the true latent classes. [41, 54]. However, the information criteria do not always agree, and in such a case the objectives and characteristics of the research as well as model interpretability would be the basis for selecting a model [55].

Table 3. Fit statistics for seven and fewer classes

N Class	AIC	BIC	CAIC	a- BIC
2	4635.28	4656.35	4663.35	4634.2
3	4556.51	4589.62	4600.62	4554.81
4	4540.25	**4585.41**	**4600.41**	4537.94
5	4528.88	4586.08	4605.08	4525.95
6	**4520.14**	4589.38	4612.38	**4516.59**
7	4521.01	4602.29	4629.29	4516.84

As shown in Table 3, two of the information criteria suggest a model with four classes, whereas two others suggest six classes. For a relatively small sample size (N=150), AIC tends to select too big a model, whereas BIC tends to select too small a model [54]. As a result, the composition of the models with 4, 5, and 6 classes were examined in terms of interpretability as suggested in [40, 55]. All the three variations shared the same 4 classes. The 5-class model had a class for which the probabilities of the three personality characteristics used in this study (ACO, CCO, and ICO) were all low. The 6-class model had all the classes of the 5-class variation; in addition, two of the classes were very similar to each other. Further, the results of the main analysis (LCA with distal outcomes) did not change by using 4, 5, or 6-class models. In summary, based on the above discussion and better class interpretability, it was decided to select the 5-class model.

The results of LCA with five classes are presented in Table 4 and Figure 1 (different representations of the same data). In the figure, the horizontal axes represent the three personality characteristics (ACO, CCO, and ICO), and the vertical axes represent the probabilities of each class of individuals responding high to the corresponding personality characteristic.

Table 4. Parameter estimates for the five-class model

	C 1	C 2	C 3	C 4	C5
Proportion	14%	02%	42%	06%	36%
Item	Response Probabilities (For a response of high)				
ACO	.86	.23	.92	.37	.74
CCO	.66	.12	.44	.43	.34
ICO	.52	.03	.17	.41	.19

As seen in Figure 1, Class 1 is composed of people who scored relatively high on all three orientations; Class 2 consists of individuals who scored low on all three orientations; Class 3 consists of individuals who scored high on autonomy, moderate on control, and low on impersonal orientations, Class 4 is composed of people who scored low on autonomy, moderate on control, and high on impersonal orientations; and Class 5 consists of individuals with relatively moderate autonomy, moderate control, and low impersonal orientations.

After identifying the latent class model using LCA, the influence of the identified latent class variable on PHR system adoption factors was examined using LCA with distal outcomes as described earlier. Table 5 presents the results of this analysis. For each PHR system adoption factor (i.e., BI, PU, or CPLX), the means and modes of the standardized factor scores are shown for each latent class. In addition, for each PHR system adoption factor, two log-likelihood (LL) values were calculated for the association between the latent class variable and the adoption factor (latent class model), one with and one without the adoption factor. Log-likelihood (natural logarithm of a likelihood function) captures the likelihood of a latent class model to be the true model. The significance of the influence of the latent class variable on the respective adoption factor can be determined by comparing the difference in the log-likelihoods minus 2 to a chi-square table with degrees of freedom equal to the number of latent classes minus one [40].

For each adoption factor, an effect size can be calculated by investigating the change in the model (with/without the corresponding adoption factor) in terms of either mean or mode of the standardized factor scores [40]. The effect sizes indicate the strength of association between the latent class variable and the corresponding adoption factor. The effect sizes are also presented in Table 5. Values of .02, .15, and .36 correspond to weak, medium, and strong effect sizes, respectively [56].

Finally, the conditional densities of PU and CPLX are presented in Figure 2.

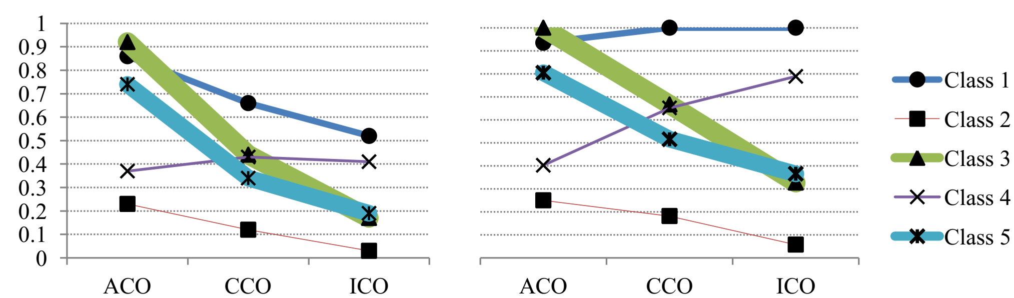

Figure 1. Parameter estimates for the five-class model

Left: LCA results with 5 classes; Right: normalized results for easier interpretation. The thickness of each line denotes the relative size of the corresponding class.

Table 5. Empirical results showing outcomes conditional on latent class membership

Distal Outcomes	Change in 2*LL	p-value		Class 1	Class 2	Class 3	Class 4	Class 5	Effect Size
Behavioural Intention	4.96	.292$^{n.s.}$	Std. Mean:	.15	-.19	-.53	-.31	-.10	N/A
			Std. Mode:	.20	.04	-.10	-.01	.07	N/A
Perceived Usefulness	11.37	0.023*	Std. Mean:	.26	-.41	-.30	-.56	-.15	.14 (Small)
			Std. Mode:	.49	-.43	-.43	-.44	.49	.17 (Medium)
Complexity	15.56	.004**	Std. Mean:	.23	.51	.59	-.36	.39	.12 (Small)
			Std. Mode:	.28	.88	1.01	-.92	.62	.23 (Medium)

* Significant at .05 level; ** Significant at .01 level; $^{n.s.}$ Not significant; Std. standardized.

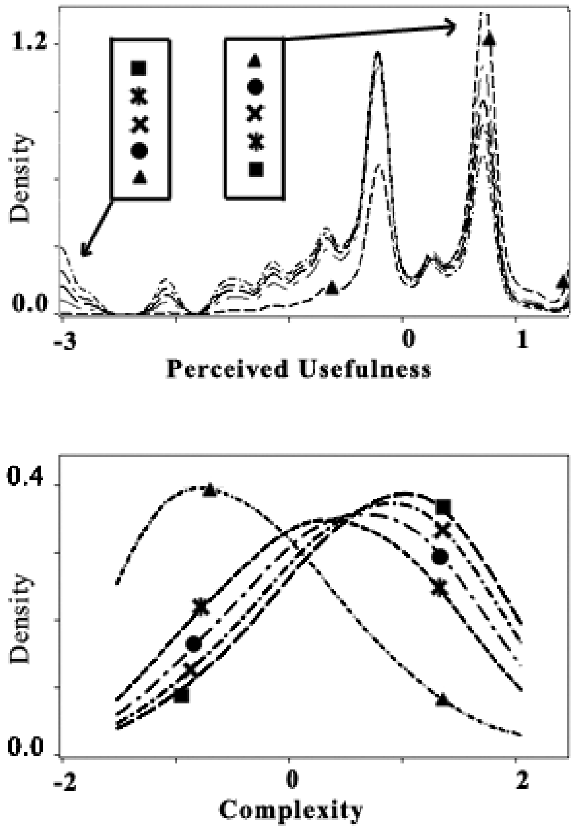

Figure 2. Estimated density for PHR adoption factors conditional on latent class membership

Each line represents a class; Line markers match those of Figure 1; horizontal axes represent standardizes scores of the adoption factors.

Conditional density refers to the density of a certain score for a distal variable (i.e., adoption factors in this paper) given membership in a certain latent class. BI was excluded in Figure 2, as it did not get a significant effect from the latent class variable (Table 5), and its conditional density graph would show no difference among the five classes.

In order to isolate the influence of the latent class variable on the distal variables, the following analysis conducted in order to rule out possible effects of a number of control variables which were outlined in Section 4. For each control variable and each of the causality orientations, a PLS (Partial Least Square) model was created (33 variations: 11 control variables x 3 causality orientations). The results were investigated to determine if, in any case, a control variable fully mediated the relationship between any causality orientation and either PU or CPLX. As a result, no such case was found, and it was concluded that influences of the latent class variable on PU and CPLX were not due to any of the control variables.

5. Discussion and Conclusions

The current study is unique and original in that it employs SDT for the purpose of explaining PHR adoption. In addition, it helps investigate a previously unexplored research area which is the influence of the changing role of consumers in the management of their health facilitated by consumer-based health care and the use of integrated PHR systems.

Results of this study suggest that SDT (particularly COT) is a viable theory in explaining PHR adoption behaviour, on the grounds that the extracted LCA class variable was shown to be significantly related to the individuals' perceptions regarding the use of PHR systems (Table 5). Prior research in IS adoption area has consistently shown the influence of individual perceptions on adoption [24].

Overall, results suggest that in the adoption of PHR systems, the autonomy causality orientation (ACO) plays a more important role than control and impersonal orientations. The evidence for this is twofold. First, Class 3 and 5 whose members scored relatively higher on ACO (Figure 1) had significantly different (better) perceptions regarding the use of PHR systems (Figure 2). Second, Class 2 and 4 whose members scored relatively lower on ACO (Figure 1) had significantly worse perceptions regarding the use of PHR systems. This is consistent with the literature that suggests that in an environment which supports autonomy, autonomy orientation matters the most in terms of motivating individuals to perform self-management behaviours [20]. As explained earlier, PHR systems are suggested to facilitate an autonomy supportive environment. Some exceptions, however, were found in this study (presented in the results section) that suggest that for some certain combinations of the three orientations, higher ACO does not necessarily result in more positive perceptions regarding PHR system use. A possible explanation is that certain features of a PHR system might be of interest to individuals with high CCO. Research guided by SDT shows that individuals with higher CCO are more likely to regulate their behaviours through external cues (e.g., rewards and punishments), whereas individuals with higher ACO are more likely to regulate their behaviours based on interest and inherent satisfaction [16, 20]. For example, being able to set deadlines on the system (e.g., a date to reach a certain body weight), or getting feedback from physicians/relatives might be of interest to these individuals who are mostly motivated by external cues, whereas monitoring and tracking features are more likely to be of interest to individuals with higher ACO. A PHR system may encompass various features, and each feature may appeal to a different persona, as explained in the above example.

This research makes several theoretical contributions in terms of PHR adoption. First, using LCA, a sample of individuals was classified into five distinct classes or personas in terms of causality orientation. Second, using LCA with distal outcomes, the influence of the latent class variable on PHR system adoption factors were examined and the results were presented. Third, in investigating the association between causality orientations and adoption factors, a person-based approach was taken rather than the usual variable-based approach. The person-based approach of this study helped investigate how a combination of causality orientations is associated with the adoption of PHR systems (rather than how each of the three causality orientation variables is associated with PHR system adoption). For example, an exception like the ones mentioned in the results section would not have been possible to identify using a variable-based approach, except through investigating interaction effects which would not have the simplicity of the approach undertaken in this paper. In addition investigating interaction effects (e.g., using regression) would not result in determining the number of individuals characterized by the same personas as presented in Table 4 [57]. Fourth, the incorporation of SDT allowed the understanding of PHR adoption with a focus on the changing role of consumers from passive recipients to active partners in care.

In terms of contributions to practice, the results of this study can guide the development, promotion, and facilitation of PHR system use as detailed below.

First, the LCA analysis as per Figure 1 above identifies five distinct classes in terms of the combination of the three causality orientations (i.e., ACO, CCO, and ICO). Further, PHR system developers can use this result to develop PHRs with these personas in mind such that users can personalize the system to best fit their persona. Healthcare practitioners can also tailor their support for users according to their personas. For example, individuals with higher ACO are more likely to be internally motivated [16]. Therefore, physicians should afford them more autonomy in monitoring their health information and acting on it (e.g. deciding when a physician visit it needed).

Second, Figure 1 and Table 4 reveal that the majority of Canadians fall in two classes (3 and 5). These two classes involve individuals with relatively high ACO, medium CCO, and low ICO. PHR system promoters should target individuals belonging to these two classes as potential early adopters of PHR systems. For example, PHR system functionalities that appeal to these two classes (e.g. monitoring and tracking) should be emphasized in advertising.

Third, as seen in Figure 2, these two main classes perceive higher usefulness and lower complexity compared to the other classes. This suggests that the majority of Canadians found PHR systems more useful and less complex which speaks to the high level of readiness to use PHR systems among Canadians. Thus Canadian health care administrators and practitioners should intensify their efforts in promoting PHR systems to Canadians especially chronic disease patients given the potential improvements in health outcomes and reduced associated costs [9].

Fourth, as seen in Figure 2, Class 4 members perceive higher complexity compared to other classes. In terms of causality orientation, members of class 4 demonstrate higher ICO relative to other classes. Individuals with high ICO are more likely to avoid change in their routine behaviours [20, 22]. Therefore, it is recommended that in personalizing PHR systems for this persona, the tasks and processes within the system be designed in a way which resembles how those tasks and processes used to be conducted without the use of PHR systems.

Fifth, in terms of PU, the higher the ACO for a class, the higher the score of PU for that class (top graph of Figure 2). An exception occurs for Class 5 (moderate ACO, moderate CCO, and low ICO) which has higher ACO than Class 4, yet lower PU. Further, in terms of CPLX, the higher the ACO for a certain class, the lower the score of CPLX for that class (bottom graph of Figure 2). An exception occurs for Class 1 (high on the three orientations) which has lower ACO than Class 5, yet higher CPLX. These exceptions in class perception indicate that the three causality orientation characteristics have to be considered in combination, in addition to individually, when designing, promoting and facilitating PHR systems to Canadians.

Finally, as with any research study in social sciences, generalizability is a limitation to this study which was conducted in one country with specific health care system and culture, and as such, the results may not be immediately transferrable to other countries. Hence, replications of this study in different countries with different cultures are needed.

6. References

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