

Changing Post-Adoptive Personal Healthcare IT Use during the COVID-19 Pandemic

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Abstract

We examine post-adoptive IT use of fitness tracking technologies longitudinally using three data sets gathered before, during, and after the COVID-19 lockdowns in the United States. Using adaptive structuration theory (AST) as a meta-theory, we model post-adoptive IT use as having two fundamental types (continued and novel), each having distinct psychological and sociological antecedents. Sociological antecedents are further broken down into those coming from society and those coming from the technology. Findings indicate there are strong correlations between antecedents and the two types of use in all three data sets. Post-hoc analysis indicates continued and novel use vary across time. These variations are not static and appear to be non-linear. Implications and future research directions are also discussed.

1. Introduction

The COVID-19 pandemic has led to a significant number of changes in behavior, especially in the way individuals use information systems [1]. We study the effect of the pandemic lockdowns on the use of digital diet and fitness trackers. Fitness trackers Fitbit trackers or Apple watches, measure an individual body movement and vital signs such as heart rate, as well as provide prompts for individuals to stay active. Diet applications track eating habits and weight loss. As individuals locked down at home due to the pandemic, market research showed a continuous rise in the sales of such devices and apps, with a \$2.8 billion increase in sales from 2019 to 2020[2].

Given the advent of these consumer devices around 2007, early research focused on the adoption of these devices [3, 4]; however, with over 15.7 million devices, it is also important to look at post-adoptive use of these devices, as post-adoptive use drives benefits [5]. This research examines the two types of post-adoptive use (continued use and novel use) in a single model and theoretically derives the antecedents for each use type.

Most studies on IT use collect data at one point in time. Given the cross-sectional nature of such research, scholars publishing extant studies assumed a static nature IT use. However, there exists evidence that such use patterns change over time [6]. This paper gives the results of a survey given at three time periods: just before the pandemic, at the height of the pandemic lockdowns, and after the lockdowns were lifted. The pandemic affords us the opportunity to examine the generalizability of model as well [7].

Overall, the paper examines three research questions: What are the key antecedents of different types use of personal fitness devices? Is the nomological model stable in light of the pandemic? And does use change over time? Each one of these questions has important academic and practitioner implications. Through these research questions the paper gives scholars a nomological network that can better explain individual behavior and use. For practitioners, the paper has implications regarding design and support of such devices.

2. Literature Review

2.1. Post-Adoption Use

Recent work in post-adoptive IT use has shown it to be made up of two distinct constructs- continued use and novel use [8]. Continued use is the use of an IT after the user has incorporated the technology into their work patterns. In continued use, the user seeks to achieve a goal in an efficient way, often without needing to put much effort into their use [5, 9, 10].

In novel use, the user's purpose is to be more effective at using a technology [11]. In novel use, interaction occurs when users try to achieve new goals using existing features of the technology [12, 13] or use existing features of the technology in new ways [5, 12-14].

Many papers studying post-adoption IT use have done so from a purely psychological perspective. Table 1 shows the antecedents identified in many psychology-based papers from leading IS journals. Together, these papers demonstrate the efficacy of studying psychology antecedents to understand post-adoption as all of the constructs listed in Table 1 have

supported relationships with IT use. For example, using the psychological theory of self-determination researchers studied how intrinsic motivation influences exploratory (novel) use [15].

The papers in Table 1, however, do not show what external factors caused the various psychological states in the users. The study of factors external to an individual are studied in sociology. While many psychological theories and antecedents have been employed to study post-adoptive IT use, comparatively few studies have employed sociological theories and antecedents.

Traditional sociological theories do not incorporate psychological constructs. With the large amount of research that shows the strong connection between psychological antecedents and post-adoptive IT use, we seek to add to this body of work by systematically incorporating sociological theories and antecedents that can also be modeled with psychology antecedents.

2.2. Longitudinal Post-Adoption Studies

Adoption has been seen as taking no more than six months to complete [16]. Post-adoption is generally understood to last from after adoption is complete to the end of the system's useful life, which may be many years. Given this comparatively long time frame and the knowledge that the benefits of the system are realized in post-adoption [5], it is imperative that researchers conduct longitudinal studies to further understand post-adoptive IT use. Longitudinal studies, however, have been scarce in the IT use literature. We identified only 7 longitudinal studies in the IS Senior Scholars' Basket of Journals published since 2011 [17-23] on post-adoptive IT use. Within these papers, there is no study on how post-adoptive IT use constructs change over time.

Table 1: Psychological and sociological antecedents

Construct	Studied In
Autonomy	Liang et al. [14], Ahuja and Thatcher [24], Rezvani et al. [25]
Intrinsic Motivation	Ke et al. [15]
Climate / situation	Sun [13], Liang et al. [14]
Cognitive Absorption	Burton-Jones and Straub [26]
Computer self-efficacy	Benlian [19]
Peer support, social norms	Zhang and Venkatesh [16]
Perceived usefulness	Bhattacharjee and Premkumar [27], Limayem et al. [9], Rezvani et al. [25]
Previous use / experience	Kim and Malhotra [28], Lankton et al. [29]
Satisfaction	Bhattacharjee [30], Bhattacharjee and Premkumar [27]
Task complexity/variety	Lankton et al. [29], Liang et al. [14]
Trust in technology	Tams et al. [31], Lankton et al. [18]

3. Overarching Model

We base our model of IT use on the theory of IT use [32]. This model uses adaptive structuration theory (AST) as a meta-theory to include both social and psychological constructs [33]. This model includes constructs from the environment as well as psychological constructs that influence the two types of post-adoptive IT use. The theoretical model for this research is presented in Figure 1.

3.1 Modalities

We include psychological antecedents given in Table 1 as first-order construct for two higher-order constructs of norms and facilities. Combining first-

order constructs into higher-order constructs has been done when there are many factors to consider. Prior research has also found that combining similar constructs into higher-order constructs has increased predictive power in models [34]. The first-order constructs are grouped according to their definitions and logical associations with one of the two higher-order constructs. Table 2 summarizes these groupings.

Table 2: Modalities of IT Use

Higher-Order Construct	First-Order Constructs
Norms Belief that structures provide efficiency toward achieving existing work goals	User Satisfaction [9, 30]
	Task-Technology Fit [35]
	Trust [18, 36, 37]
Facilities Perception of one's ability to influence and allocate resources	Autonomy [24, 25, 38]
	PIIT [12, 39]
	Computer self-efficacy [12, 40]

Norm modalities are based on beliefs that structures provide efficiency in achieving existing health goals [32]. A user who perceives norms is likely to heed the norm and engage in continued use behavior because norms indicate the efficient achievement of goals. For example, in the context of fitness tracking, the user must trust the technology to accurately track movements. Therefore, we

hypothesize:

- *H1: The more positive the perception of norm modalities, the more likely the user will exhibit continued use behavior compared with novel use.*

The modality of novel use, facilities, is the perception of one's ability to influence and allocate resources [41]. Resources include material resources such as an IT or immaterial resources such as a person's time [32]. Users who perceive that they have control over resources will try to reallocate them for their own benefit by engaging in novel use. An example of this is when a user feels they can innovate how they use existing fitness trackers by using additional features of the software. Therefore:

- *H2: The more positive the perception of facilities modalities, the more likely the user will exhibit novel use behavior compared with continued use.*

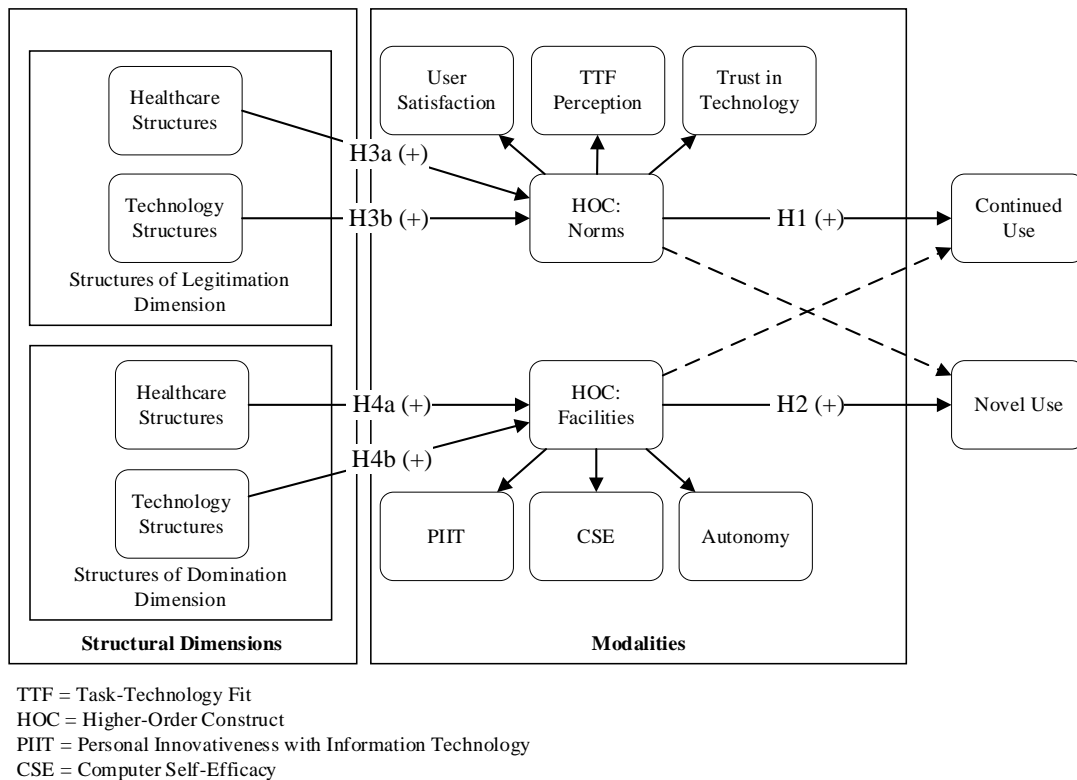


Figure 1: Theoretical Model

3.2 Structural Dimensions

In the context of personal healthcare during the COVID-19 pandemic, we contextualize the base

model in Figure 1 using relevant societal constructs. In alignment with AST, we collectively call these factors “structures,” which are the formal and informal rules and resources that are external to the user. These context-specific structure constructs take

two forms: legitimation and domination. Each of these two forms have structures that originate either from society or from the technology (see Figure 1). According to AST, each structural construct influences psychological constructs.

The structural dimension of legitimation is the extent to which rules regarding IT use allow for sanctions. These rules establish the importance of a technology in achieving healthcare goals [43]. Legitimation structures reduce information asymmetries, such as when a user talks with their physician. Legitimation also provides incentives and tools for efficiency [5]. Rezvani et al. [25] demonstrated the relationship between external regulation (a structure of legitimation) and satisfaction (a modality of continued use). The correlation between a continued use structure and a modality implies the broader hypothesis:

- *H3a: The greater the extent to which organizational structures exhibit the legitimation dimension, the more likely it is that the user will experience norm modalities.*

Technology structures are features of the technology that impart social meaning to users. These structures exist as part of the technology and are seen as unchanging to users. Technology features that limit the use of technology or impose sanctions on users are structures of legitimation. Such limitations occur when the user must log into the fitness tracker. The technology can also impose sanctions by reporting fitness habits to employers or insurance companies. Users will interpret these structures as restrictions and produce norm modalities. Therefore:

- *H3b: The greater the extent to which technological structures exhibit the legitimation dimension, the more likely it is that the user will experience norms modalities.*

The societal structural dimension of domination is the extent to which resources allow the conduct of IT use [32]. In fitness tracking applications, resources may be considered to be time to exercise and having access to healthy foods that can be positively logged in the application. Users who have more resources are more likely to perceive that they have control over those and other resources. Therefore:

- *H4a: The greater the extent to which organizational structures exhibit the domination dimension, the more likely it is that the user will experience facilities modalities.*

Technology domination structures, such as malleable IT [12], allow users to perceive that the IT is flexible and that they control how the IT may be used. Such features often appear as contextual help functions or emails from the application publisher sharing new features of the application. Therefore:

- *H4b: The greater the extent to which technological structures exhibit the domination dimension, the more likely it is that the user will experience facilities modalities.*

4. Research Method

Data was collected through three Qualtrics (Qualtrics.com) panels of people over 18 living in the United States. Using panel data allowed the data to not be constrained by traditional snowballing or convenience sampling techniques. The first sample was collected in December 2019, before the COVID-19 pandemic. The second was collected in May 2020, during the height of the COVID-19 lockdowns in the US, and the third sample was collected in October 2020, after the lockdowns had concluded. Descriptive statistics for the three rounds are given in Table 3. The data in this table shows there is a good distribution for gender and age in all the rounds. The sample was also constrained to ensure that the users had been using their chosen fitness tracker for at least six months [16]. Therefore, we believe we have adequate distribution of samples to be representative of the larger population.

Table 3: Descriptive statistics

Round	N	Gender %	Age Band %
1	319	Male: 34 Female: 66	18-24: 6 25-34: 29 35-44: 31 45-54: 16 55-64: 12 65-74: 6 75-84: 1
2	310	Male: 54 Female: 45	18-24: 6 25-34: 28 35-44: 30 45-54: 16 55-64: 13 65-74: 7 75-84: 1
3	316	Male: 49 Female: 51	18-24: 5 25-34: 15 35-44: 32 45-54: 15 55-64: 12 65-74: 19 75-84: 3

The technology structural dimension items are given in Table 4. Technology structures are modeled as reflective constructs. The word “[Technology]” in Table 4 was replaced in the survey by the name of the user’s technology of choice for personal healthcare.

Table 4: Technology structural items

Legitimation	Domination
[Technology] has rules embedded in it.	[Technology] has various help resources linked to it.
[Technology] reports what I do.	[Technology] prompts for ways I can use it better.
[Technology] provides evidence for sanctions in case of misuse.	[Technology] notifies me about new features as they get launched.
[Technology] restricts what I can do.	[Technology] has useful features built into it.
	[Technology] is flexible.

5. Data Analysis

The first step to comparing data across time is to confirm the measurement invariance across time. Similar to the measurement invariance across composite models (MICOM) process [44], the longitudinal invariance involves three steps. The first step deals with configural invariance or ensuring that the each of the constructs across the time are measured in a similar way. An independent confirmatory factor analysis of each of the factors showed that all items loaded on the constructs.

Table 5: Construct composition invariance

Correlation	1 vs 2	2 vs 3	1 vs 3
Cont. Use	0.9990	1.000	0.999
DomHlth	0.9970	0.998	0.998
DomTech	1.0000	0.999	0.999
Facilities	0.9940	1.000	0.995
LegHlth	0.9930	0.997	0.991
LegTech	0.9730	0.957	0.861
Norms	1.0000	1.000	1.000
Novel Use	1.0000	0.994	0.993

Step 2 is to look at the composition invariance, or if the construct correlations are significantly different across groups. Given the limitations of Smart-PLS v3, we compared two groups at a time. Table 5 presents results of a test for differences in composition for each construct and each time set. The results show partial invariance with only “LegTech” showing significant difference between time 1 and time 3.

Step 3 involves evaluation of means and variance invariance for a multi-group data. However, for this data, since we already expect means to change over time, we present a test of variance invariance test in Table 6. The table shows invariance across time 1 with time 2, and time 2 with time 3. However, invariance tests for use, domination health structures, and legitimation technology constructs do show significant variance over time. This establishes a partial invariance in the data. Thus, while a limitation of the data, still allows us to proceed towards further analysis [44].

Table 6: Construct invariance across time

Variance	1 vs 2	2 vs 3	1 vs 3
Cont. Use	0.189	0.104	0.294
DomHlth	-0.134	-0.125	-0.269
DomTech	-0.021	-0.071	-0.095
Facilities	-0.149	0.012	-0.132
LegHlth	-0.102	-0.108	-0.212
LegTech	-0.124	-0.108	-0.250
Norms	0.188	0.003	0.191
Novel Use	-0.121	-0.191	-0.328

Having established partial invariance, we now move on to the evaluation of the combined measurement model. In this regard, Table 7 presents the convergent and discriminant liability. The table, based on the combined data across time, shows reliability measures, as well as Fornell-Lacker matrix. Taken together, this shows sufficient convergent and discriminant validity for the model. The overall structural model is presented in Figure 2. The overall model shows that all paths are significant, except the path between LegTech and norms and norms and novel use.

A comparison of path co-efficient differences across time in Table 8 shows that most of the paths are invariant, except for an increase in path coefficient in time 2 when compared with time 1 for norms to continued use.

As a post-hoc analysis, we also compared the means of uses across time. The graph shows that both continued use and novel use have increased over the time of the pandemic. However, the results also shows that novel use starts to taper off over time, while continued use shows a constant increase over time (see Figure 3).

Table 7: Construct reliability and discriminate validity

	Alpha	CR	AVE	1	2	3	4	5	6	7	8
Continued Use (1)	0.892	0.917	0.649	0.806							
Domination Health (2)	0.775	0.838	0.429	0.448	0.655						
Domination Tech (3)	0.825	0.877	0.588	0.572	0.704	0.767					
Facilities (4)	0.626	0.799	0.571	0.592	0.599	0.595	0.756				
Legitimation Health (5)	0.786	0.839	0.381	0.363	0.660	0.575	0.561	0.617			
Legitimation Tech (6)	0.563	0.767	0.524	0.199	0.422	0.371	0.356	0.541	0.724		
Norms (7)	0.941	0.962	0.895	0.722	0.572	0.686	0.665	0.489	0.285	0.946	
Novel Use (8)	0.786	0.855	0.597	0.319	0.512	0.468	0.488	0.516	0.457	0.366	0.773

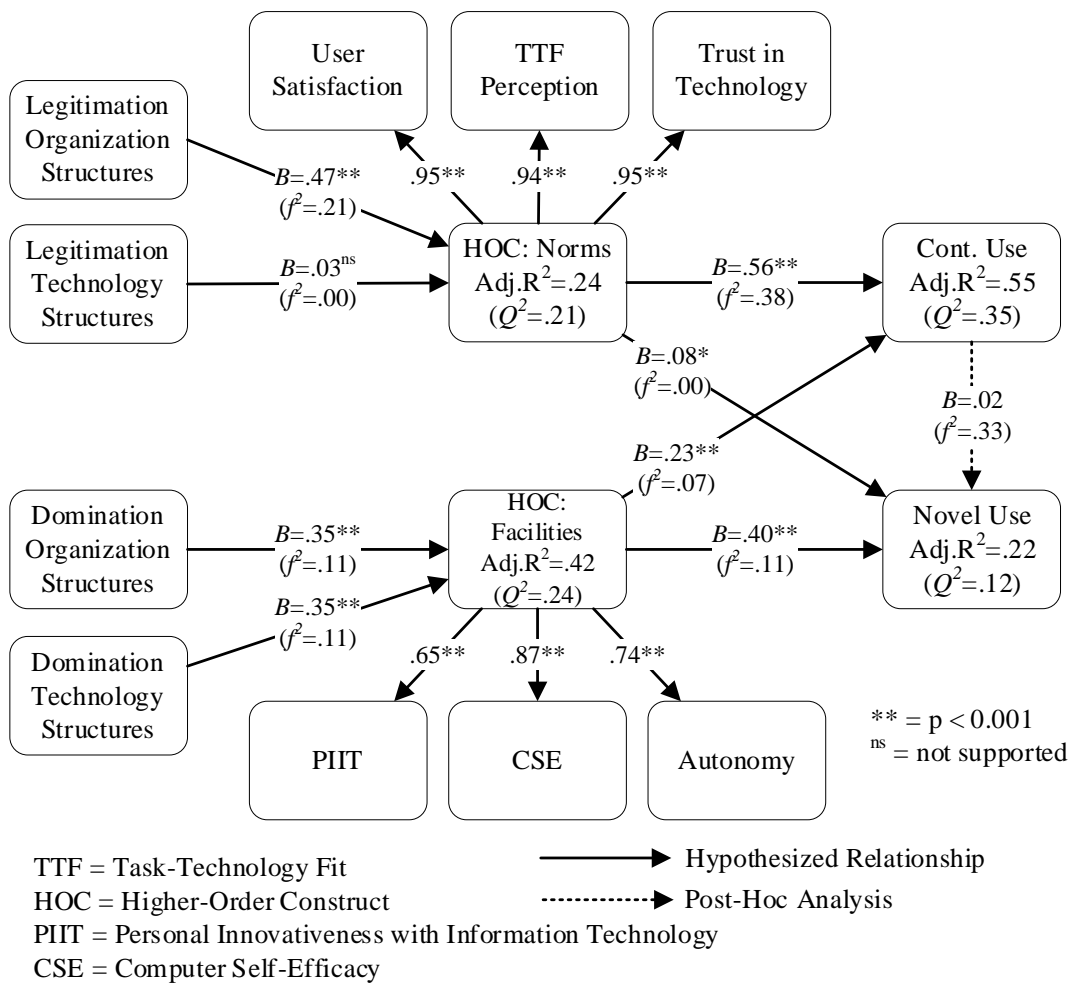


Figure 2: Structural results

Table 8: Path invariance

Path	1 vs 2	2 vs 3	3 vs 1
DomHlth → Facilities	0.005	-0.002	0.003
DomTech → Facilities	-0.127	0.016	-0.112
Facilities → Novel Use	-0.070	-0.078	-0.147
LegHlth → Norms	-0.142	0.031	-0.110
LegTech → Norms	0.024	0.092	0.116
Norms → Cont. Use	-0.133	0.096	-0.037
Norms → Novel Use	0.055	0.001	0.057

5.1 Limitations

Like all research, this research is subject to limitations. The first such limitation is from the survey data collection method. This survey collected both independent and dependent variables at the same time, spawning the possibility of common method bias [45]. This was mitigated by the collection of data over three time periods and through the design of the survey using a marker variable [46, 47]. We also

conducted Harman’s one-factor test of method bias. This method calculated that a single factor accounts for 29.8% of the variance. Since the cutoff for Harman’s one-factor test is 50%, this indicated bias did not affect the model [46, 48].

Figure 3 shows the standardized means of continued use and novel use for each data collection time. This figure shows close associations between the two constructs at time 1. However, at time 2 these associations widen. And at time 3 they further widen and cross. We believe these constructs may be moving nonlinearly across time with continued use in a U-shape and novel use in an inverted U-shape. To substantiate these notions an additional round or rounds of data would be needed.

Another limitation of this research concerns the differences in applications and devices used for fitness/health tracking. These take many forms from mobile apps, websites, smart watches, and more. There may be underlying differences in these devices that influence the results of this study. This limitation may explain why hypothesis H3b failed.

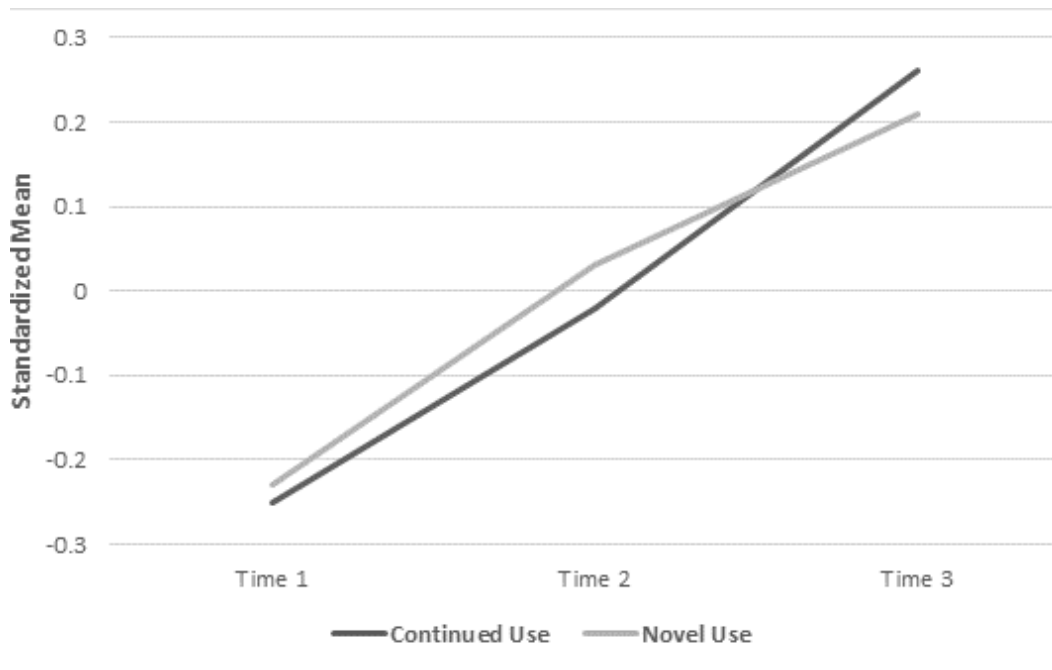


Figure 3: Standardized means of use types

6. Discussion and Future Research

6.1 Theory contribution

Theories are nets cast to catch what we call 'the world': to rationalize, to explain, and to master it [49].

The focus on theories when studying IT use has led to three concerns. First, the primary nature of theories has been in the form of using an existing well-established theory from a reference discipline to explain an IS phenomenon more clearly. The multitude of theories used in this regard has led to considerable number of antecedents and environmental or IT structures.

In response to this, the present study presents a comprehensive model that integrates the psychological and social antecedents that impact two different types of use, specifically for consumer health care devices. As shown in the model, we argued that an individual's perception of norms and facilities have a different impact of whether an individual is exploring new uses or new features of the device or they have settled into a routine of use. Additionally, the model also goes beyond analyzing traditional human-based structures to see if structures designed in the technology have an impact on use. We find that while domination technology structures (such as built-in help features and ways to discover unused functionality) indirectly influence novel use (H4b), whereas legitimation technology structures (such as activity logging and gaining access to a system by means of a username and password) do not influence continued use (H3b). Technology features do not play a significant role in routinization of behavior. Rather, they play a more significant role in change in behavior or opportunities for innovation. This finding helps inform affordance-based studies for these technologies [50].

The second concern about the theoretical study of IT use is most models have been cross-sectional in nature. While this fact remains true in the present study as well, we address this concern by testing the model at three time periods. Even with a pandemic and lockdowns in the second round of data collection, the model showed significant invariance across time. This reliability of the model to predict continued and novel use speaks to the robustness of the model.

The third concern is a limitation of variance models. Variance models require static dependent variables, but this is not the case with IT use [19]. In this study we go beyond a variance model to examine the changes in two use methods. Interestingly, while the magnitude of both IT use types increased over

time, there is a clear difference in the slopes of change over time. It sees that while continued use keeps increasing, novel use tends to decrease in its slope of change. This provides a promising new area of research with regard to change management. Theories such as theory U [51] argue that technology use is not a linear process, but goes through high levels of use initially, before reducing substantially and then settling into a new normal. While our research provides initial evidence of such a phenomenon, more search is needed in this area, especially given that personal healthcare devices are evolving at a high pace and the use is completely directly by an individual.

A final avenue for future research concerns the relationship between continued use and novel use across time. It has been suggested that practitioners may move between continued and novel use given the right set of circumstances [6, 8]. From the present study it appears that continued use is a baseline type of use. Therefore, events must occur to incite the user to move to novel use for a time. The mechanisms for this move are currently unclear and warrant further research. [8] advises longitudinal data may be able to help determine the causes of these moves.

7. Conclusion

This paper set forth a model of post-adoptive IT use for individual healthcare technology. The model was based on AST and recent work by [32]. The model was tested before, during, and after the COVID-19 pandemic lockdowns in the United States. The model was shown to be predictive of both continued and novel use for all three rounds of data. This implies the model is robust and may be employed in different contexts to study IT use. Findings indicated while the magnitude of both IT use types increased over time, there is a clear difference in the slopes of change over time. It sees that while continued use keeps increasing, novel use tends to decrease in its slope of change.

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