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Predicting Therapists' Intentions to Use an Innovation: The Role of Innovation-Specific, Individual, and Organizational Factors

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PREDICTING THERAPISTS' INTENTIONS TO USE AN INNOVATION: THE ROLE OF INNOVATION-SPECIFIC, INDIVIDUAL, AND ORGANIZATIONAL FACTORS

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ABSTRACT

Understanding factors that contribute to an individual's decision to use an innovation can increase the public health impact of innovations in children's mental health services. **Objective.** This study examined whether and to what extent therapists' innovation-specific judgements (e.g., innovation is easy to use, socially desirable) were associated with intentions to use an innovation using constructs from one of the most robust theories of innovation use–the Unified Theory of Acceptance and Use of Technology (UTAUT). **Method.** Two aims were addressed using data collected from 95 therapists and 28 supervisors who participated in a multi-site cluster randomized trial. Therapists used either a coordinated set of knowledge resources or traditional knowledge resources. For aim one, a multiple regression analysis was conducted to explore the proportion of variance in use intentions explained by the UTAUT constructs. For aim two, a series of multilevel models were constructed to assess the predictive utility of the UTAUT relative to individual and organizational variables in the literature (e.g., attitudes towards evidence-based practice, organizational climate). **Results.** Innovation-specific judgements explained approximately 74% of the variance in therapist intentions to use their respective knowledge resources. Additionally, innovation-specific judgements explained more than twice the variance in use intentions relative to the individual and organizational variables, and remained statistically significant predictors of use intentions after controlling for individual and organizational variables. In contrast, the individual and organizational variables only explained an additional 3% of the variance in use intentions after accounting for the innovation-specific judgements and were no longer statistically significant. **Conclusions.** This study demonstrated that therapists' innovation-specific judgements can be strong indicators of intentions to use an innovation. Results are discussed within the context of implementation interventions.

TABLE OF CONTENTS

Abstract ... iii

Chapter 1: Introduction ... 1

Chapter 2: Method ... 9

Chapter 3: Results ... 15

Chapter 4: Discussion ... 20

References ... 27

CHAPTER 1

INTRODUCTION

The field of mental health has experienced a recent proliferation in innovative tools and technologies. Current mental health innovations include mobile mental health applications to guide diagnosis and treatment (Chandrashekar, 2018), digital communication platforms that connect therapists and clients in isolated geographic areas (Zhou et al., 2020), information sharing technologies to coordinate care across services (von Esenwein & Druss, 2014), transdiagnostic therapies for complex clinical problems (e.g., Barlow et al. 2016), machine learning algorithms that automate risk screening (Shatte et al., 2019), and decision support systems to organize and coordinate research evidence (Chorpita et al., 2014). The tools and technologies used in today's mental health services began as innovations at one point in time. Treatment manuals are one popular example of a previously novel method to train providers in psychotherapeutic techniques (Luborsky & DeRubeis, 1984) that are now the focus of multiple statewide quality improvement initiatives (e.g., Hoagwood et al., 2014). Despite their potential to improve service quality, many innovations struggle to transition into widespread clinical practice and cross the "stagnation chasm"–the period between an innovation's initial introduction to its use by individuals within a system (Deglmeier & Greco, 2018). Consequently, only a fraction of children and families who access services will benefit from advancements in mental health services research. Public health interests would be well served by learning more about what contributes to an individual's decision to use an innovation.

Controlled experimental studies have identified intentions to perform a behavior as the most robust determinant of actual behavior (Webb & Sheeran, 2006), and intentions are represented in nearly all popular theories of behavior change (Fishbein et al., 2001). By extension, an individual's intention to use an innovation (i.e., use intentions[1]), in part, determines their actual use of the innovation (i.e., use behavior). Multiple studies within mental health have studied use intentions and behavior as a function of individual (e.g., therapist, supervisor) and organizational factors (Lyon & Bruns, 2019). For example, attitudes towards evidence-based practice and self-efficacy are some of the most popular individual factors in studies examining use of mental health innovations (Aarons et al., 2010; Nelson & Steele, 2007). A clinician's service and training characteristics (e.g., caseload size, years of experience) are also represented in studies of evidence-based practice as clinician-level factors that predict use (Beidas et al., 2017). Both use intentions and behavior have been explored as a function of an organization's social structure and psychological climate (Camisón-Zornoza et al., 2004; Chaudoir et al., 2013; Powell et al., 2021). Individual and organizational factors can be informative–for instance, therapists with large caseloads may not have time to learn how to use a new innovation or doubt the applicability of the innovation for their wide range of clients. Organizational climates characterized by a collective resistance to change may have individuals who are similarly reluctant to embrace new innovations. Despite the conceptual utility of individual and organizational factors, their effects can be small or non-existent depending on the organizational setting or innovation under study (Aarons et

[1] Readers may be familiar with the term innovation adoption. Adoption is sometimes defined as behavioral use (e.g., RE-AIM framework; Glasgow et al., 1999), other times it is defined as a decision to accept or reject an innovation (see Wisdom et al. 2014 for summary). Intentions and behavior are used to minimize ambiguity between terms and remain congruent with the theoretical constructs examined in this study.

al., 2009; Beidas et al., 2017; Skriner et al., 2017). Moreover, one study estimated that individual factors accounted for only 7-20% of the variance in therapists' use of different treatment strategies, and organizational factors accounted for approximately 7-23% (Beidas et al., 2015). These studies suggest that individual and organizational conceptualizations alone do not provide a complete account of the factors that contribute to use of an innovation.

How an individual[2] perceives an innovation within their organizational context can advance our understanding of when an innovation is more or less likely to be used. Using evidence-based treatments as an example, previous research suggests therapists form specific attitudes about treatments over time, and that attitudes vary according to the characteristics of the treatment manual (Borntrager et al., 2009). Another study by Reding and colleagues (2014) found that providers did not rate all evidence-based treatments as uniformly appealing, and that interventions rated as more appealing were more likely to be used. While these studies were limited to perceptions about specific evidence-based treatments, multiple theories of behavior change support the broader notion that cognitive processes precede intentions to engage in a behavior and actual behavior (e.g., Theory of Planned Behavior, Theory of Reasoned Action; Ajzen, 1991; Fishbein, 1979). In the case of innovation use, individuals judge the value of an innovation before deciding to use the innovation or implementing it in practice. Innovation-specific judgements may be particularly informative because they are comprised of the individual making the judgement, the innovation being judged, and the surrounding organizational context (i.e., is this innovation valuable given my

[2] Many innovations are designed for providers, particularly where evidence-based practices are concerned. However, individual is used here to acknowledge there are multiple potential users of an innovation.

organizational context?). With some exceptions, previous research on innovation-specific judgements within mental health were limited in that they predominately studied one type of judgement, such as feasibility or acceptability, or did not include use intentions (see Chor et al., 2015; Damschroder et al., 2009; and Proctor et al., 2011 for review). A systematic review of measures of innovation characteristics by Lewis and colleagues (2021) found only nine measures of innovation-specific judgements, the majority of which were single use measures that were too specific to the innovation to be used broadly. To the author's knowledge, a theory that parsimoniously organizes multiple types of innovation-specific judgements and includes key constructs from the behavior change literature (i.e., intentions) has not been studied within the field of mental and behavioral health.

Several theoretical models of innovation use have evolved outside of mental and behavioral health to explain which innovation-specific judgements promote intentions and behavior. The Technology Acceptance Model developed by Davis (1989) first asserted that individuals' use intentions and behavior were determined by their judgements that the technology (1) benefits performance and (2) is easy to use. Venkatesh and colleagues (2003) extended this model by consolidating constructs from other theories and created The Unified Theory of Acceptance and Use of Technology (UTAUT), which added individual judgements that an innovation is (3) considered necessary by valued others and (4) feasible given the resources at their disposal. Most recently, the UTAUT was updated with three additional constructs that capture beliefs that an innovation is (5) enjoyable to use, (6) offers value above and beyond its price, and (7) used habitually (Venkatesh et al., 2012). The UTAUT has explained up to 74% of the variance in use intentions and 52% of the variance in use behavior, outperforming other models of technology use (e.g., Theory of Planned Behavior; Venkatesh et al., 2003; Venkatesh et al., 2012). The UTAUT's findings have been replicated with other organizational and non-organizational settings, technological innovations, types of users, and timepoints of adoption (Brown et al., 2010; Bourdon & Sandrine, 2009; Shibl et al., 2013; see Venkatesh et al., 2016 for review). Importantly, the UTAUT was not a complete reconceptualization, but rather incorporated select constructs from innovation and behavior change theories (e.g., Roger's Diffusion of Innovations, Theory of Planned Behavior, Theory of Reasoned Action) with the most empirical support and reconfigured them specifically to study technology use.

While the UTAUT has proved useful in other fields, it is unclear whether and to what extent the theory is applicable to innovation use in mental health settings. UTAUT studies of mobile mental health applications have found that Performance Expectancy, Effort Expectancy, and Social Influence explained 22% to 75% of the variance in use intentions (Damerau et al., 2021; Hennemann et al., 2018; Mitchell et al., 2021). However, these studies were limited in that they examined a small subset of UTAUT constructs. Furthermore, innovation-specific judgements may be more predictive of intentions to use consumer-facing mobile mental health applications compared to the innovations designed for providers in mental health systems. Indeed, mental health systems are complex contexts made up of multiple clinicians, work teams, and clinics that can vary substantially from the settings in previous studies. It is possible that under these circumstances innovation-specific judgements do not account for most of the variation in use intentions compared to provider and organizational factors. However, within the UTAUT literature, individual and organizational characteristics are found to be distally related to innovation use and therefore weaker predictors of use intentions and behavior (Brown et al., 2010). In contrast, innovation-specific judgements exhibit stronger relationships with innovation use and even account for some of the indirect effects of individual and organizational factors (e.g., Venkatesh & Bala, 2008). Thus, the UTAUT (and innovation-specific judgements more generally) may possess strong predictive value for innovation use because the theory captures information about the innovation, individual, and organization simultaneously.

1.1 THE CURRENT STUDY AND STUDY AIMS

This study examined the predictive utility of the UTAUT in a school-based mental health context. Data were collected during a multi-site cluster randomized trial that tested the effectiveness of a coordinated set of knowledge resources versus traditional knowledge resources for clinical decision making. Each set of resources was intended to help therapists and supervisors use research evidence across various treatment activities (e.g., assessing clinical problems, selecting interventions, monitoring outcomes). After concluding the study, therapists could choose to continue using their respective resources, which presented an opportunity to study use intentions after a brief trial with an innovation in a voluntary context. Therapists' perceptions of their resources and their subsequent use intentions were the focus of this study, whereas supervisors were conceptualized as part of the organizational structure and context (e.g., multiple therapists work with a single supervisor). Two aims were examined in this study:

Aim 1. Aim one assessed whether and to what extent the UTAUT constructs predicted therapists' intentions to use the knowledge resources.

H1. Consistent with findings from previous research, it was expected the UTAUT constructs (e.g., perceived performance benefit, perceived ease of use) would explain at least 50% of the variance in intentions (Venkatesh et al., 2003; Venkatesh et al., 2012).

Aim 2. Aim two explored the predictive value of the UTAUT constructs relative to other individual and organizational variables (e.g., climate, attitudes towards evidence) commonly studied in the literature.

H2. The UTAUT would account for substantial variance in use intentions even after controlling for individual and organizational variables. Furthermore, the UTAUT was expected to explain a greater proportion of variance in intentions than the individual and organizational variables.

Given that findings from the original UTAUT studies were conducted in business and consumer settings, there were no a priori hypotheses about the direction or magnitude of the relationship between the innovation-specific judgements and use intentions. However, if previous research is applicable to this mental health setting, then it would be expected that effort expectancy and social influence (i.e., easy to use, considered necessary by important others) would have a small, positive relationship with use intentions or no effect at all. A general finding from the UTAUT literature is that an innovation's perceived ease of use becomes less important as individuals gain experience with the innovation and can more accurately determine whether it is useful for the task (Venkatesh & Bala, 2008). Furthermore, social influence is presumably irrelevant when individuals can voluntarily choose to use a technology or not, and therapists were not under any organizational mandates to continue using their knowledge resources after the study concluded (Venkatesh & Davis, 2000).

CHAPTER 2

METHODS

2.1 PROCEDURE

Data were collected during a multi-site cluster randomized trial that tested the effectiveness of a coordinated set of knowledge resources versus traditional knowledge resources in an urban and rural school-based mental health setting. Therapists and supervisors were recruited from the Los Angeles Unified School District and South Carolina Department of Mental Health. Participants from Los Angeles were recruited from five service districts: Central, East, Northeast/Northwest, South, and West. South Carolina participants operated out of mental health clinics that served the Pee Dee and Santee-Wateree areas of South Carolina, respectively. Supervisor-therapist dyads across Los Angeles and South Carolina were randomly assigned to one of two experimental conditions, each with their respective set of knowledge resources (a full description of the resources provided in each condition can be found in Becker et al., 2019). Dyads in the Coordinated Knowledge System (CKS) condition were given a decision support system that consisted of resources for assessment, treatment selection, and treatment delivery. Dyads in the Traditional Resources (TR) condition were provided resources for assessment and treatment selection that were not part of a comprehensive decision support system. Supervisor-therapist dyads utilized their respective resources collaboratively for approximately 6-12 months before completing self-report measures about the resources (i.e., UTAUT), demographic/service characteristics, and their organization. All study procedures were approved by the institutional review boards of University of California Los Angeles and University of South Carolina.

2.2 PARTICIPANTS

Participants consisted of 95 therapists and 28 supervisors from seven mental health clinics across Los Angeles and South Carolina. The number of therapists working under each supervisor ranged from one to six, with an average of 3.39 therapists per supervisor. On average, providers were 42 years old (*SD* = 10.8) at the time of data collection, of which 92% were female. The majority of therapists identified as Latinx (41%), followed by Black (39%), White (16%), Asian (4.4%), and Middle Eastern (0.1%).

2.3 MEASURES

Innovation-specific judgements and use intentions. Therapists completed six of the eight subscales from the updated UTAUT model (Venkatesh et al., 2012). Because therapists did not need personal finances or supplementary resources to use the system, the two subscales measuring Price Value and Facilitating Conditions were omitted. The remaining six subscales were Performance Expectancy, Effort Expectancy, Social Influence, Hedonic Motivation, Habit, and Intentions. Each subscale, respectively, assessed participants' belief that the innovation (1) benefits performance (three items); (2) is easy to use (three items); (3) is considered necessary by valued others (one item); (4) is enjoyable (one item); (5) has become a habit to use (one item); (6) will be used in the future. The Intentions subscale served as the dependent variable for this study. The remaining five subscales represented the different innovation-specific judgements and were re-worded to reference the knowledge resources used by therapists (e.g., “I find the [resources] useful in my clinical work”). Items were rated on a 7-point Likert scale from 1 (“strongly disagree) to 7 (“strongly agree”).

Provider background and training. Therapists and supervisors completed a demographics and training background questionnaire prior to the study. All participants reported on their age, gender, ethnicity, years of clinical experience, number of clients, and highest level of education.

Provider attitudes towards evidence. Therapists reported general attitudes towards evidence-based practices using the Evidence-based Practice Attitude Scale 50-item (EBPAS-50; Aarons et al., 2010). The EBPAS-50 is divided into the Appeal, Requirements, Openness, and Divergence subscales. The four subscales represented the degree to which therapists (1) found evidence-based practices intuitively appealing, (2) were likely to adopt it if required, (3) were open to learning new practices, and (4) felt evidence-based practices deviated from current treatment practices. Participants rated their agreement with each item on a 5-point Likert scale from 0 (“not at all”) to 4 (“very great extent”).

Organizational climate. Therapists completed the 30-item Texas Christian University Organizational Climate Scales (Lehman et al., 2002), which was composed of six subscales: Mission, Cohesion, Autonomy, Communication, Stress, Change. Respectively, the six subscales assessed the degree to which therapists (1) were aware of the organization’s mission or goals, (2) cooperated and trusted each other, (3) were granted decision-making authority, (4) felt suggestions were heard and valued by management, (5) perceived excessive work strain or overload, and (6) believed management was interested in and adaptable to novel changes. All items were scored on a 5-point Likert scale ranging from 1 (“strongly disagree”) to 5 (“strongly agree”).

2.4 DATA ANALYTIC PLAN

Data preparation. All analyses utilized R version 4.1.0 (R Core Team, 2017). Prior to the primary analyses, data were inspected for impossible values and data entry errors. Additionally, univariate statistics and bivariate relationships were calculated and/or plotted to assess the characteristics and structure of the data.

Aim 1. A multiple regression analysis was conducted to assess whether and to what extent the five innovation-specific judgements predicted therapists’ intentions to use the innovative decision support system. Specifically, aim one estimated the proportion of variance in therapists’ intentions to use the innovative decision-support tool that was accounted for by the UTAUT constructs (i.e., performance expectancy, effort expectancy, social influence, hedonic motivation, and habit). R^2 and adjusted-R^2 values were calculated as estimates of effect size.

Aim 2. A series of multilevel models were constructed to explore the predictive value of the innovation-specific judgements relative to other covariates (i.e., provider and organizational variables). These models were used to calculate the proportion of variance accounted for by the innovation-specific judgements and covariates, both individually and collectively. Multilevel modeling was utilized to account for the nesting of therapists within supervisors who were further nested in clinics in this study’s design (Raudenbush & Bryk, 2002). Marginal and conditional pseudo-R^2 estimates served as the measure of variance explained. Marginal R^2 estimates captured proportion of total variance explained by the fixed effects, while conditional R^2 estimates represented proportion of total variance explained by fixed and random effects (Nakagawa & Schielzeth, 2013). Pseudo-R^2 estimates were necessary in a multilevel modeling framework because there were multiple sources of variance (e.g., fixed components, random components) that precluded simple partitioning of variances. All predictors were entered as fixed effects, making marginal R^2 a useful metric to compare the relative predictive value of one set of predictors over another (i.e., innovation-specific judgements vs. individual and organizational variables). The use of fixed effects for all predictors was justified given that there was no strong theoretical rationale why the predictors should be entered as random slopes.

Before estimating the model for aim 2, a model building approach was employed to identify an appropriate random effects structure and set of covariates (i.e., individual and organizational variables) to be compared with the innovation-specific judgements. Table 1 outlines each step of the model building approach the full set of covariates that were considered. All multilevel models were estimated using the lme4 package and *p*-values calculated using the lmerTest package (Bates et al., 2014; Kuznetsova et al., 2017). All test statistics were based on the Kenward-Roger's correction of degrees of freedom and standard error estimates from the lmerTest package to adjust for the relatively small sample size (Kenward & Roger, 2009; Kusnetsova et al., 2015; McNeish, 2017). First, two unconditional models were estimated with random intercepts for supervisors, then supervisors and clinics. The random intercept for clinics was omitted from the final model because it accounted for less than 5% of the variance in the outcome variable and three-level models would not converge when additional predictors were added. Consequently, the organizational climate scales and site (Los Angeles or South Carolina) were entered at a lower level of analysis during the model building process described next.

A model building approach was utilized to identify covariates to be compared against the innovation-specific judgements in the final model. Separate models were estimated for sets of covariates (e.g., EBPAS scales, therapist background). Individual covariates with an associated *p*-value less than 0.10 were retained for the full model. After identifying relevant covariates, the MuMIn package was used to obtain marginal and conditional R^2 statistics for a (1) multilevel model with only the covariates, (2) model with only the innovation-specific judgements, and (3) full model with covariates and innovation-specific judgements. To assess the absolute and relative predictive value of each set of predictors for aim 2, R^2 statistics for individual models and change in R^2 statistics between subsequent models were calculated. Additionally, the magnitude, direction, and statistical significance of parameter estimates between the three models were evaluated.

CHAPTER 3

RESULTS

Aim 1. The multiple regression model with innovation-specific judgements as the only predictors of use intentions explained approximately 74.1% of the variance in use intentions, $F(5,89) = 50.97$, $p < .001$, $R^2_{adjusted} = .73$.

Aim 2. As seen in Table 2, there were large differences in variance explained between the covariates only, UTAUT only, and full multilevel model. Based on the marginal R^2 value, the model with only provider and organizational covariates explained roughly 34% of the variance in use intentions. In contrast, the model with only innovation-specific judgements explained 72% of the variance in intentions–more than double the variance explained by the individual and organizational variables. When the covariates and innovation-specific judgements were entered in a single model, this yielded a marginal R^2 value of 75%–a 3% increase from a model with innovation-specific judgements alone.

The difference between marginal and conditional R^2 values was calculated to estimate what percent of variation in the random effects remained after fixed effects were accounted for. These difference scores represented remaining variability between supervisors that was not explained by the covariates and/or innovation-specific judgements. A difference of zero would indicate that all of the random variability attributed to supervisors was explained by the fixed effects. As seen in Table 2, after accounting for the covariates, there was still roughly 16% of variability in use intentions that was explained by the random intercept for supervisors. In comparison, approximately 3% of the variability in use intentions was still accounted for by the random effects after innovation-specific judgements were added.

Table 3 contains parameter estimates for the covariates only, UTAUT only, and full multilevel model. In the covariates only model, all but one of the provider and organizational variables remained statistically significantly associated with use intentions. Performance Expectancy, Hedonic Motivation, and Habit were the only variables associated with use intentions in the UTAUT only model. Under the full multilevel model, only supervisors' Supervision Experience ($\beta = .06$, $t(19.5) = 2.15$, $p = .044$) and the Traditional Resources Condition ($\beta = -.72$, $t(18.7) = -3.86$, $p = .001$) remained associated with use intentions. In contrast, Performance Expectancy ($\beta = .37$, $t(71.9) = 3.66$, $p < .001$), Hedonic Motivation ($\beta = .44$, $t(66.4) = 3.66$, $p < .001$), and Habit ($\beta = .26$, $t(70.5) = 3.16$, $p = .002$) were still statistically significant in the full model. Effort Expectancy ($\beta = -.04$, $t(71.5) = -.4$, $p = .684$) and Social Influence ($\beta = -.09$, $t(69.6) = -1.18$, $p = .241$) were not associated with use intentions in the full model (or the UTAUT only model).

Table 3.1 Variables Considered And Retained In Full Model Using A Stepwise Modeling Approach

Potential variables	Step 1: Specify Random effects	Step 2: Identify covariates and estimate model	Step 3: Estimate UTAUT model	Step 4: Estimate combined model
Therapist level				
UTAUT				
Performance			X	X
Effort			X	X
Social influence			X	X
Hedonic motivation			X	X
Habit			X	X
Condition				
CKS		X		X
TR		X		X
Therapist background				
Clinical experience		-		
Client caseload		X		X
Burnout		-		
EBPAS				
Requirement		-		
Appeal		-		
Openness		-		
Divergence		-		
Supervisor level				X
Random intercept	X			
Supervisor background				
Clinical experience		X		X
Supervision experience		X		X
Supervision caseload		-		
Clinic level				
Random intercept	-			
Site				
LA		X*		X*
PD		X*		X*
SW		X*		X*
TCU-ORC				
Mission		X*		X*
Cohesion		-*		
Autonomy		-*		
Communication		-*		
Stress		-*		
Change		-*		

X indicates random effects or variables retained at that step and included in the combined model
- indicates random effects or variables omitted at that step and not included in the combined model
* indicates clinic level variables entered at the therapist level

Table 3.2 Marginal And Conditional R-Squared Estimates From Multilevel Models

Model	R^2_m	R^2_c	ΔR^2_m	ΔR^2_c	$R^2_c - R^2_m$
Unconditional	-	35.89	-	-	35.89
Covariates only	33.62	50.05	+33.62	+14.16	16.43
UTAUT only	72.05	75.51	+38.43	+25.46	3.46
Full	75.12	75.76	+3.06	+0.25	.64

R^2_m represents percent of total variance that is explained by the fixed effects
R^2_c indicates percent of total variance explained by fixed and random effects
ΔR^2_m and ΔR^2_c are the change in R^2 values from the previous model

Table 3.3 Parameter Estimates For Multilevel Covariate, UTAUT, And Full Model

	Model 1: Covariates only		Model 2: UTAUT only		Model 3: Full model	
Parameter	β	SE	β	SE	β	SE
Intercept	5.24***	.24	5.15***	.08	5.44***	.12
Therapist (level 1)						
UTAUT						
Performance			.39***	.09	.37***	.10
Effort			.06	.09	-.04	.10
Social influence			-.11	.08	-.09	.08
Hedonic motivation			.38***	.10	.44***	.12
Habit			.27***	.08	.26**	.08
Therapist background						
Client caseload	.02*	.01			.00	.01
Climate						
Mission	.57*	.22			.18	.15
Condition[a]						
CKS	-	-			-	-
TR	-.97*	.34			-.72**	.18
Site[a]						
LA	-	-			-	-
PD	1.2**	.37			.09	.20
SW	.61	.46			.10	.23
Supervisor (level 2)						
Supervisor background						
Clinical experience	-.06	.04			-.01	.02
Supervision experience	.13*	.05			.06*	.03
Model R^2 estimates						
Fixed effects	33.62%		72.05%		75.12%	
Fixed and random effects	50.05%		75.51%		75.76%	

**p < .05, **p < .01, ***p <.001*

[a]Dummy coded variable. Estimates based on grand mean centered continuous predictors.

CHAPTER 4

DISCUSSION

4.1 REVIEW OF FINDINGS

Aim one examined the proportion of variance in use intentions that was accounted for by innovation-specific judgements. In accordance with previous UTAUT findings, innovation-specific judgements explained approximately 74% of the variance in use intentions (Venkatesh et al., 2003; Venkatesh et al., 2012). This study did not examine the entire set of moderators (e.g., gender, age) defined under the original theory, and yet, innovation-specific judgements had similar explanatory power. Aim two compared the predictive value of innovation-specific judgements compared to individual and organizational variables. While individual and organizational variables accounted for roughly one-third of the variance in use intentions, innovation-specific judgements explained more than twice as much variance. Furthermore, the fact that almost all of the provider and organizational variables were no longer significant once innovation-specific judgements were entered simultaneously suggests that the UTAUT constructs accounted for their effects and also contributed unique information not captured by these variables. On the other hand, the provider and organizational variables only contributed an additional 3% of variance above and beyond the UTAUT constructs, which suggests innovation-specific judgements can be meaningful proxies for other aspects of an individual and their organizational context.

Findings related to the individual innovation-specific judgements were noteworthy. Hedonic motivation had the strongest association with use intentions relative to other innovation-specific judgements. That is, therapists reported greater intentions to continue using their resources the more they enjoyed using them. This is in contrast to previous UTAUT studies that routinely found performance and effort expectancies were the strongest predictors of use intentions (Venkatesh et al., 2016). Moreover, the fact that effort expectancies and social influence were not associated with use intentions was surprisingly consistent with the original UTAUT research. Previous studies have found that the effect of effort expectancies on intentions diminishes as individuals gain more experience with the system in as little as three months (Venkatesh & Bala, 2008). Across the two conditions, therapists in this study used their knowledge resources for 6 to 12 months, which may have been ample time for participants to down weight the importance of how easy the resources were to use in favor of the system's effectiveness (Davis, 1989; Davis, 1993). Additionally, whether valued others thought therapists should use the system was not related to use intentions, which is consistent with previous research on technology use in voluntary contexts (Venkatesh & Davis, 2000). One explanation is that this voluntary context did not create the same social pressures to use the resources that would be present in a mandatory context. Alternatively, it is possible that peers' opinions about the resources had an early effect on intentions, but that this effect diminished as therapists formed their own concrete evaluations of the resources through their own use.

Estimates of the individual and organizational variables' relationships with intentions were also noteworthy. Supervisors' supervision experience was positively associated with use intentions. Intuitively, this makes sense given the knowledge resources were meant to support collaborative decision making between therapists and supervisors in the context of supervision. Other organizational members' (e.g., supervisors) competencies may have consequences for an individual's intentions to use an innovation when the innovation requires participation from multiple people. In the context of this study, conceptualizing supervision experience as an "individual" factor may be an oversimplification because a supervisor's experience can also affect therapist-supervisor work activities (e.g., Boyd et al., 2021). Surprisingly, organizational climate and attitudes towards evidence-based practice were not associated with use intentions despite the popularity of these measures for studying use of innovations in mental health settings (Chaudoir et al., 2013). One interpretation is that the effect of organizational climate on use intentions may not have been detectable because it was too distal of a predictor. Relatedly, global attitudes towards evidence-based practice may not be strong predictors because the way that specific innovations package research evidence is more meaningful than attitudes towards evidence itself (e.g., Borntrager et al., 2009). This is not to say that organizational climate or attitudes towards evidence-based practice have no effect, but rather intermediary variables are needed to trace the effect of these distal predictors on more proximal outcomes (e.g., Brown et al., 2010). Lastly, differences in use intentions between the two experimental conditions is telling. Participants using the Traditional Resources were given materials with fewer features compared to those in the Coordinated Knowledge System condition. While the features of the Coordinated Knowledge System are only one explanation for why therapists who used those resources had greater intentions to continue utilizing them, this finding aligns with a qualitative study conducted among the same sample of providers that found different features of the system were rated as being more or less useful and easy to use (Chu et al., 2022). More generally, these results are congruent with a large body of research that objective characteristics of an innovation can shape people's subjective judgements about the innovation (Brown et al., 2010; Davis, 1993).

4.2 LIMITATIONS

The psychometric properties of the UTAUT, most notably its factor structure, could not be assessed in this study because four out of the six UTAUT constructs were assessed with a single item. Additionally, results were based on a single innovation and type of user in a mental health setting. It is unclear whether and to what extent these results would generalize across different innovations that are used by supervisors, administrators, or clients. However, these results are generally consistent with other studies that examined innovation-specific judgements for consumer mobile mental health apps (Damerau et al., 2021; Hennemann et al., 2018), which lends further support to the theory's generalizability with different innovations and individuals. Additionally, the dependent variable for this study was use intentions and it is unknown to what extent use intentions predicted use behavior. Follow-up surveys of use behavior were not possible since the mental health agencies in this study experienced significant staff turnover. Nonetheless, experimental studies have found that intentions lie along the causal pathway to behavior and are the strongest influence on behavior (Webb & Sheeran, 2006). Lastly, only a limited set of individual and organizational variables were available in these data. It is likely that there are other individual (e.g., general self-efficacy) and organizational (e.g., agency size, financial resources) factors not examined here that are meaningfully related to use intentions even after accounting for innovation-specific judgements.

4.3 FUTURE RESEARCH DIRECTIONS

A number of research directions can build on this study's findings and limitations. A large-scale, longitudinal study should be conducted to evaluate the UTAUT constructs in a mental health setting. The original UTAUT research was based on longitudinal field studies with organizations who were introducing new technologies into the work place (e.g., Venkatesh et al., 2003). The proliferation of innovative tools and technologies in children's mental health services presents natural opportunities to study multiple types of organizations, innovations, and individuals across time. Such studies could test the full causal pathway of when and how individuals move from judgments, to intentions, then behavior. Additionally, future research should examine what influences innovation-specific judgements to provide actionable guidance to innovation developers and implementation initiatives. This study provides clues that innovation-specific judgements may partially mediate the effect of individual and organizational characteristics, and future longitudinal studies could manipulate these variables to establish causal connections. Individual and organizational characteristics could be expanded to individual difference domains (e.g., motivation), organizational structure (e.g., agency size), and organizational processes (e.g., incentives, training). Finally, a natural extension of this work is examining what innovation characteristics influence which innovation-specific judgements and eventual use behavior. A preponderance of research in human factors, cognitive science, and user-centered design has studied design features and processes that increase the utility and usability of technologies (Norman, 2013; Stanton et al., 2017; Vaiana & McGlynn, 2002), some of which are already being applied in mental health (e.g., Lyon et al., 2019). Another important element of innovation design may be how the tool or technology is coordinated with other organizational resources and activities (Malone & Crowston, 1994). Studies that test whether and to what extent innovation-specific judgements mediate the effect of various design characteristics on use behavior will be an important step towards understanding how implementation strategies that target innovations affect implementation outcomes. Such mediational studies can provide a richer understanding of how innovations are best implemented in practice, particularly in mental health settings where mechanisms of change are poorly understood (Williams, 2016).

4.4 CONCLUSIONS

This study demonstrated that providers evaluate different aspects of an innovation and these innovation-specific judgements are meaningfully related to their intentions to use the innovation. These results support conceptualizations in the human factors literature that individuals do not passively implement technology (Bannon, 1995). Rather, individuals deliberately consider how an innovation fits their own beliefs, values, activities, and complex organizational ecology. Future research should explore how providers' judgements of a specific innovation reflect these complex interactions. A deeper understanding of these interactions can inform innovation design and implementation interventions that encourage greater use of innovations in mental health services. Psychology has studied and incorporated "user" perceptions into technology design for over 60 years, yet this knowledge has not been fully utilized within mental health services because of silos between branches of psychology and interdisciplinary studies (Proctor et al., 2021). Special attention should be paid to human-centered design in mental health, as well as understanding the user in context. Such work will advance our understanding of the causal processes behind the implementation of mental health innovations and expand the reach of psychological science (Wiltsey Stirman & Beidas, 2020).

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