Mind the Theoretical Gap: Interpreting, Using, and Developing Behavioral Theory in HCI Research

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ABSTRACT
Researchers in HCI and behavioral science are increasingly exploring the use of technology to support behavior change in domains such as health and sustainability. This work, however, remain largely siloed within the two communities. We begin to address this silo problem by attempting to build a bridge between the two disciplines at the level of behavioral theory. Specifically, we define core theoretical terms to create shared understanding about what theory is, discuss ways in which behavioral theory can be used to inform research on behavior change technologies, identify shortcomings in current behavioral theories, and outline ways in which HCI researchers can not only interpret and utilize behavioral science theories but also contribute to improving them.

Author Keywords
Behavior change; behavioral science; theory; persuasive technology; health; sustainability; behavior change technologies

ACM Classification Keywords
H5.2 User Interfaces: User Design; Theory & Methods

INTRODUCTION
HCI researchers are increasingly designing technologies to promote behavior change. A review of the last 10 years of CHI proceedings in the ACM Digital Library found 136 papers that mentioned "behavior change" with 76% of these from the last four years (Figure 1). Although this work has focused on diverse behaviors from diet [32] and exercise [16] to sustainable water usage [27], a common strategy underlies much of this work: to inform design, HCI researchers draw on theories from behavioral sciences.

For example, He and Greenberg [32] used the transtheoretical model of behavior change as an organizing framework for persuasive eco-feedback design. Consolvo *et al.* integrated multiple constructs from several behavioral theories to guide development and evaluations of UbiFit, a mobile-phone application for physical activity [16]. As HCI research on behavior change technologies matures, questions emerge about how best to utilize behavioral theory to inform design and evaluation, and what constitutes appropriate use of behavioral theory in HCI. Moreover, as these two research communities continue to explore intersecting topics, are there ways in which HCI research may contribute back to behavioral theory?

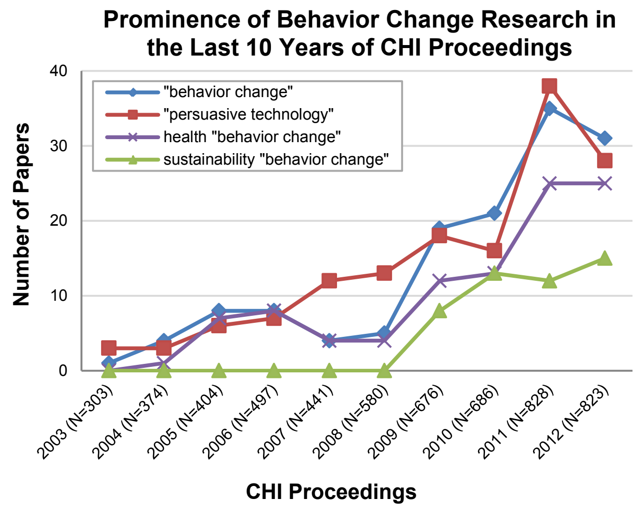

Figure 1: The prominence of behavior change related research in the last 10 years of CHI proceedings. Specific search terms (including quotes) are shown in the legend.

In this paper, we aim to provide HCI researchers with guidance on interpreting, using, and developing behavioral theories. We first provide an overview of different forms of behavioral theory across levels of generality—from *meta-models* to *empirical findings*. We then use these distinctions to discuss the current uses of behavioral theory in HCI and to highlight areas that, as yet, have received little attention. We then enumerate a series of shortcomings of behavioral theories as articulated within behavioral science itself, which are likely to be non-obvious to those outside this discipline. Finally, we conclude by suggesting ways HCI researchers can contribute to the development and refinement of behavioral theories. Our paper has implications for the growing body of research in the design and evaluation of behavior change technologies and for HCI researchers interested in utilizing behavioral theory.

A Note on Terminology
As this paper bridges two historically distinct research communities, it is worthwhile to define the terms. Within

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behavioral science, a common definition of behavioral theory proposed by Glanz and Rimer is ([30], p. 4): *"...a systematic way of understanding events or situations. It is a set of concepts, definitions, and propositions that explain or predict these events or situations by illustrating the relationships between variables."* When we refer to behavioral theory, this is the definition we are using.

In addition, we also borrow from other terms from behavioral science including: *constructs*, which are the fundamental components or "building blocks" of a behavioral theory, (*e.g.,* two key constructs from social cognitive theory are *self-efficacy* and *outcome expectations* [5]); and *variables,* which are the operational definitions of the constructs, particularly as they are defined in context (*e.g.,* specific measures used to assess self-efficacy or strategies used within an application to influence self-efficacy). We will use the term *design guidelines* to refer to the principles formulated by HCI researchers to make behavioral theory and empirical findings actionable for designing behavior change technologies (*e.g.,* [12, 15]).

Although the term *persuasive technology* [25] is common within HCI, it has become somewhat controversial and can bring up negative associations (*e.g.,* while Fogg's original definition explicitly rebuked coercion as a component of persuasive technology [25], more recent papers have questioned if it is possible to avoid coercion within persuasion, partially by forcing an implicit value-system—see [60]). For this reason, we do not use the term in this paper (except as an author keyword). Instead, we refer to the broad array of systems and artifacts developed to foster and assist behavior change and sustainment as *behavior change technologies*. This term more adequately reflects the diversity of behavioral theories and goals beyond persuasion that can be encoded in technical artifacts.

Finally, based on our own areas of expertise, we primarily focus on behavioral theories from psychology that have been commonly applied in the health domain.

FORMS OF BEHAVIORAL THEORY

Behavioral theories vary widely in *which* behaviors they describe and *how* these behaviors are described. Some theories focus on one behavior (*e.g.,* smoking), others describe the specific process (*e.g.,* relapse prevention), and still others describe dynamics between behaviors and other constructs (*e.g.,* theory of planned behavior [2]). As a consequence, behavioral theories can be categorized in a variety of ways. One common distinction, for instance, is between behavioral theories that describe determinants of *behavior* (*e.g.,* the health belief model [8]) versus the *process of change* (*e.g.,* transtheoretical model [59]; see [66] for a discussion on this distinction).

For the purposes of this paper, we classify behavioral theories based on their generality/specificity: from *meta-models*, which incorporate multiple levels of influence (*e.g.,* individual to societal), to specific and often atheoretical *empirical findings* used to generate ideas, constructs, and design guidelines (see Figure 1). While we recognize that these levels of specificity exist on a continuum, we delineate discrete markers to anchor our discussion. To enhance understanding, we provide examples at each level drawn primarily from the behavioral science literature.

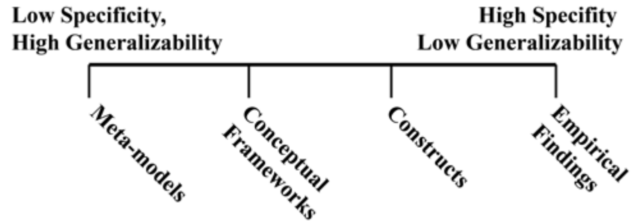

Figure 2: Spectrum of Specificity of Behavioral Theories

Meta-Models

At the highest level of generality are *meta-models*, which are organizational structures of multiple levels of influence on individual behavior. For example, an increasingly popular meta-model in health-related behavioral science is the social ecological model [63], which identifies broad "levels" of inter-related associations and factors of influence on a behavior of interest, from micro-level factors such as genetics and biology to meso-level factors such as interpersonal relationships and, finally, to macro-level factors such as urban design, public policy, and culture.

Like Erickson's model [24], meta-models are valuable for identifying the "lens" a researcher is using and other "lenses" not currently emphasized by the researcher or community at large. In this way, a meta-model can help identify new levels of inquiry. For example, the majority of behavior change-oriented research in HCI has thus far focused on the individual level (*e.g.,* goal-setting, self-monitoring) or the interpersonal level (*e.g.,* social support, social networks), with less emphasis placed on understanding the context with which these individual or interpersonal-level interventions are created and tested [21].

Examining prior work through the perspective of a meta-model can uncover previously under-explored research. For example, King *et al.* [41] used the social ecological model to emphasize important gaps and opportunities for improving population-level physical activity based on, at the time, relatively ignored levels of the social ecological model, such as policy or the built environment. This led to new research and partnerships, such as increased interaction between behavioral scientists and urban planners (*e.g.,* [39,64]). By virtue of their generality, however, meta-models are typically short on specifics about determinants of behavior that could be used to directly inform the design of technical systems. In addition, too often meta-models have too many levels of influence to adequately evaluate. As such, the use of meta-models in design requires a great deal of conceptual and formative work to translate into pragmatic design guidelines and system features.

Conceptual Frameworks

Whereas meta-models describe multiple models within a single frame, *conceptual frameworks* tend to focus on one or two levels of influence. Conceptual frameworks describe relationships among the fundamental building blocks of a behavioral theory, *constructs*, and provide a more specific account of how constructs are inter-related. Conceptual frameworks encompass several commonly used theories including the transtheoretical model [59], self-efficacy theory [5], theory of planned behavior [2], health belief model [8], and self-determination theory [18].

From an HCI perspective, conceptual frameworks provide more specific guidance to the design and implementation of behavior change technologies (and help guide the evaluation process). For example, goal-setting theory [47] describes the effect of different types of goals on performance, enabling HCI researchers to implement effective goals in their interventions (see, for instance, [13]). However, because of their emphasis on only one or two levels of analysis, conceptual frameworks have the potential to disregard key factors that may be influencing a behavior. For example, recent physical activity promotion research found that "walkability" of a person's neighborhood influenced physical activity intervention effectiveness, such that the interventions tested were only effective for those who lived in walkable neighborhoods [42]. Although conceptual frameworks were used to design the interventions (*i.e.,* the transtheoretical model and social cognitive theory), the key finding emerged from situating these models within the broader context of a meta-model.

Constructs

Constructs are the basic determinants or mechanisms that a theory postulates to influence behavior. For instance, social cognitive theory defines the notion of self-efficacy—a person's assessment of his/her ability to perform certain behaviors in a particular context [6]. The theory identifies this construct, along with other constructs such as outcome expectancies, as a key determinant of behavior.

In lieu of utilizing all of the constructs defined within a conceptual framework, a common practice in the development of behavior change interventions is to selectively use constructs from one or more theories. For example, many researchers both from behavioral science and HCI who utilize the transtheoretical model incorporate only the stages of change construct, leaving out other constructs such as the twelve processes of change or decisional balance (*e.g.,* [10,46]). Although common, this practice makes it difficult to evaluate the utility of the entire conceptual framework as the entire framework was not tested. This can lead to methodological flaws in interpreting the validity of behavioral theories. We return to this point in the *Shortcomings of Behavioral Theory* sections.

By virtue of their focus on a much smaller level of analysis, *constructs* translate more easily into features of a behavior change technology. By focusing on individual constructs rather than whole frameworks, however, an HCI researcher might inadvertently design a system based on constructs that do not work independently but only in tandem with other constructs. To continue with the self-efficacy example, a behavior change technology that supports self-efficacy might be effective for individuals who already have high outcome expectancies but might not work well for individuals with low outcome expectancies. Insofar as the other construct was not assessed or integrated in the system, it would be difficult to understand why the system may work for some individuals but not others.

Empirical Findings

Finally, in some cases, previously developed theories are insufficient to guide HCI research. In such cases, additional empirical work—often in the form of ethnographic and other qualitative approaches—can generate knowledge necessary to establish a starting point for design. Such empirical work can yield concrete and contextually-specific *findings*, which can be applied to ground specific designs and to create design guidelines. For instance, in their work with stroke patients, Balaam *et al.* found that household dynamics acted either as barriers or facilitators for patients' rehabilitation activities [4]. Based on this finding, Balaam *et al.* created personalized interventions to motivate regular performance of exercises needed to increase the range of motion in their affected limbs. Its high level of applicability to design makes such empirical work an essential component of HCI research (*e.g.,* [27, 50].

The level of specificity of empirical findings comes at the cost of generalizability, however. Empirical findings, by virtue of being observed in a given context, must be abstracted in some way to create generalized knowledge. Although it is tempting to directly generalize specific findings from empirical work, such generalizations should be tempered by factors such as the target participant group, study length and size, and other relevant contexts. That said, empirical findings are an invaluable starting point for the creation of new constructs and theories, as well as for informing the design of new technologies.

USES OF BEHAVIORAL THEORIES IN HCI

In our review of HCI literature on behavior change technologies, we have identified three broad uses of behavioral theory. HCI researchers use theory: (i) to inform the design of technical systems, (ii) to guide evaluation strategies, and (iii) to define target users. Here, we discuss how theory has been used for these purposes thus far and how theory can support HCI research going forward.

Informing design

HCI researchers often draw on theory to make design decisions about a technical system. Theory can be used both to make decisions about *which* functionality to support and *how* to implement such functionality. For example, Consolvo *et al.* [15] drew heavily on theory to design UbiFit, a mobile-phone application for encouraging physical activity. UbiFit supported weekly activity goals based on goal-setting theory [47], rewards for performed behavior based on the transtheoretical model [59], and a stylized display of performance information, based on

Goffman's theory of presentation of self in everyday life [31]. Theory also informed *how* this functionality was implemented. For instance, UbiFit required users to specify the number of strength training, cardiovascular, and walking sessions they would do each week. This design decision was informed by goal-setting theory, which postulates that performance is highest when goals are specific and created by the user (see [47]).

Similarly, Mamykina and colleagues [49] drew upon the construct of breakdown from the theory of sensemaking [19] to design MAHI, an application for patients with diabetes that supports reflection and problem-solving. The theory of sensemaking postulates that individuals constantly engage in drafting and redrafting of a story to understand their experiences. In sensemaking, breakdown refers to the times when everyday routines are interrupted by an unexpected or undesirable event that forces the individual to make sense of what happened and to create a new story that explains the experience. To help users reflect on breakdowns, MAHI enables: (i) flexible journaling through photos and audio recording on a mobile phone; (ii) collecting information about context for measuring glucose via experience sampling; and (iii) discussing captured data with a diabetes educator. By providing patients with the flexibility to capture, document, and discuss breakdowns when they occur, MAHI supports the reflection that sensemaking theory argues is essential to effective problem-solving.

A second way of informing design is the development of design guidelines. For example, drawing on behavioral theory and their own empirical work, Consolvo *et al.* [15] derived eight guidelines for designing technologies for lifestyle change. Such technologies, Consolvo *et al.* argue, need to be *abstract* and *reflective*, *unobtrusive*, *public*, *aesthetic*, *positive*, *controllable*, *comprehensible* to users, and *include historical data*. Similarly, He *et al.* [34] used the transtheoretical model to develop guidelines for technologies for encouraging sustainable energy behavior. He *et al.* write, for instance, that technologies targeting individuals in the pre-contemplation stage "*plant the seed for individuals to acknowledge their current (energy) behavior as problematic*," while technologies targeting individuals in the preparation stage should support creating "*acceptable, accessible and effective*" plans (p. 5).

Moving forward

Behavioral theory can be a rich source of ideas for behavior change technologies. However, the translation of behavioral theory into effective behavior change technologies is by no means a trivial process. As Balaam *et al.* [4] note, "*Motivation theories…place more emphasis on concepts such as self-efficacy, goals, or the level of competence engendered by a task, rather than the nature of the task itself or what specifically will motivate an individual*" (p. 3079). Indeed, instantiating theory is a difficult task as theoretical constructs lack specificity for concrete design situations. This gap between theory and a concrete design has to be bridged for every new technology.

The design guidelines such as those described above can help, but researchers need to be mindful about their epistemic status. While we believe strongly in the value of empirical data for generating design guidelines, given the relatively limited amount of empirical data behind many proposed design guidelines (*e.g.,* [15,34,38]), we suggest that the guidelines are more akin to "design hypotheses," which require additional testing. Behind each guideline is a set of assumptions about how a technology that embodies the guideline should affect users' behavior. Testing these assumptions explicitly in user studies, along with exploring the design space for guidelines, can enable HCI researchers to build generalizable knowledge about ways in which behavioral theories can be translated into better designs.

In addition, new strategies for balancing abstraction with contextual relevance are needed. HCI researchers who translate theory into systems should pay close attention to issues such as the specific behavior in question (*e.g.,* physical activity, diet, sustainability), user characteristics (*e.g.,* age, education, values), and the sociocultural context (*e.g.,* Latino diabetic high schoolers). By investigating how technologies with similar theoretical grounding fare in different cultural contexts, the field can begin to develop both more nuanced design guidelines and to inform the development of better behavioral theories.

Guiding evaluation strategies

In addition to informing design, behavioral theories are also relevant to guiding evaluations of behavior change technologies. Although examples of this are less prevalent in HCI literature, behavioral theory has been used both to inform study design and to help interpret findings from technology evaluations.

In a recent paper, Lee *et al.* [45] explored the use of behavioral economics to design technologies to encourage healthy eating. Lee *et al.* developed a webpage for buying snacks at the office based on the behavioral economics construct of default bias (*i.e.,* a person tends to pick the first available option). This construct, however, did not only influence the design of the system but also the design of the evaluation. Specifically, the control condition was a webpage with all food options available on one screen whereas the intervention condition showed only two food options at a time and required participants to click to another page to explore other snack options. This study design was informed by the behavioral theory because the control condition (*i.e.,* having all options available without an explicit default) was a direct complement of the webpage that embodied the default option construct (*i.e.,* having two options as the default and requiring additional action to see more). This is an exciting use of theory to guide technology evaluation through a theoretically-informed delineation of the control condition. More common is the use of behavioral theory to identify measures. For example, in their evaluations of MAHI and UbiFit, Mamykina *et al.* and Consolvo *et al.* drew on theory for their studies by including a variety of measures related to the hypothesized core constructs of interest.

Theory can also help with the interpretation of study results. For example, to understand whether their game OrderUP! contributed to healthy eating behaviors, Grimes *et al.* structured their analysis of interview data from their user study according to the transtheoretical model's processes of change [33]. Grimes *et al.* argue that the themes emergent from these interviews were examples of the four processes that, according to the transtheoretical model, mediate the progression through the stages of change: *consciousness-raising*, *self-re-evaluation*, *helping relationships*, and *counter-conditioning*. For instance, Grimes *et al.* cite data that OrderUP! helped users correct their incorrect assumptions about which foods were healthy, and that it gave them culturally-relevant suggestions for healthy foods. Both of these effects are examples of consciousness-raising. By using theory in this way, Grimes *et al.* suggested that their application was supporting the right kinds of change processes expected by the theory. While not without potential methodological shortcomings, which we delineate in the next section, this is an innovative strategy for using theory in tandem with qualitative data to explore theoretical fidelity [62] within user testing.

Moving forward

Although the stated aim of most behavior change technology research is to design technology that effectively changes behavior, this is rarely robustly demonstrated in HCI research [25,43]. Indeed, very few HCI researchers have the resources to conduct large-scale randomized trials of their prototypes. And though randomized controlled trials (RCTs) remain the gold standard of efficacy research in behavioral science, there are a number of emerging theory-driven study designs and analytic strategies that we believe are highly relevant to the HCI community. These include: (i) mediational/path and moderation analyses, (ii) alternative experimental designs, and (iii) evaluations of qualitative data.

Mediation/path and moderation. Mediation describes *how* an intervention works whereas moderation describes *for whom* or *under what circumstances* an intervention is most efficient [41]. From a behavioral theory perspective, mediating variables are the constructs that drive behavioral change (*e.g.,* breakdown from the MAHI example), while moderating variables identify who responds best to different interventions (*e.g.,* young vs. old, men vs. women) and under what conditions outcomes are optimized (*e.g.,* living in a walkable *vs.* not walkable neighborhood). Understanding key mediator variables within a behavioral theory can allow HCI researchers to both support these constructs in their designs and to assess them in their evaluations instead of solely relying on more distal outcomes such as behaviors. For example, if theory suggests that an application for encouraging physical activity works in part by strengthening self-efficacy, an evaluation that finds improved self-efficacy would provide preliminary evidence that the application is functioning as intended, even if the study is not able to detect behavioral changes due resource constraints on the study.

Similarly, moderation analyses can be very valuable for defining for whom a system will work. For example, Hekler *et al.* [35] explored who responds better to a physical activity intervention with identical content but delivered either by an interactive voice response (IVR) system or a human advisor. Hekler *et al.* used moderation analysis to explore individual characteristics that self-determination theory suggested might play a role. They found that individuals who were high in amotivation (*i.e.,* who lacked interest in being active) required a human advisor to become more physically active whereas those who were low in amotivation (*i.e.,* were interested in being active) fared better with the IVR system. Such analyses can provide another way to gain knowledge about how technical interventions work for different groups of users.

Alternative experimental designs. There is a small but growing revolution in behavioral science related to the use of alternative experimental designs beyond the RCT to develop and test behavior-focused interventions. Some of these designs, such as single case experimental designs [37] and factorial designs [11], might prove to be useful in HCI research as well. Their emergence is at least partly due to the recent ease with which: (i) behaviors and important variables can be frequently assessed (*e.g.,* multiple times per day over a long time period), a requirement which is key for "in the wild" N-of-1 style experimental designs [37]; and (ii) a much wider range of small variations of experimental conditions can be easily created, which was previously a stumbling block for factorial study designs [11]. A full description of these methods is beyond the scope of this paper, but many were and still are used in lab-based psychological research [37]. Until now, however, such designs were not used in "free-living" situations due to resource constraints that have now largely been abated by new technologies.

Using theory to help evaluate qualitative data. Finally, Grimes *et al.*'s work points to new opportunities for using theory to understand how our technologies affect behavior. As we mentioned, Grimes *et al.* [33] used theory to guide the interpretation of their end-user testing interviews. Such theoretically-guided analyses of qualitative data are a promising form of evaluation for HCI research on behavior change technologies, and they fit well within the tradition of theory-driven qualitative methods such as ethnomethodology, conversation analysis, and other methodologies from anthropology and sociology.

Specifically, the Grimes *et al.* approach points to a way to use theory to test *theoretical fidelity* [62]—whether a technology is operating according to the theoretical mechanisms (*e.g.,* psychological, social, etc.) that were used to guide the design of that technology. To do this, researchers would formulate *a priori* expectations of likely responses in user feedback that would indicate that the technology was having or not having a theoretically postulated effect. For example, a statement like "*Using the application made me feel more confident about being active*" could be an indicator that the system influenced self-efficacy. Having a coding manual with such statements (along with a set of negative examples) would enable researchers to use qualitative data to rigorously assess if a behavior change technology is influencing the proposed constructs (*e.g.,* see [54] for a coding scheme developed for understanding therapist/client interactions based on motivational interviewing).

To decrease the risk of the confirmation bias [55], it would be important for such coding manuals to be established *a priori*, before user interviews begin. It is a well-known psychological fact that humans tend to perceive and interpret their observations to "confirm" their preconceived notions and theories [55]. As with other cognitive biases, confirmation bias operates unconsciously, without our being aware of its influence. This is a central reason why the lists of statements that would indicate that users' experiences with a technology are in line with or refute theoretical expectations should be established in advance. We discuss this idea further in the *HCI Contributions to Behavioral Theory* section.

Put together, these three theoretically-informed evaluation strategies—moderation and mediation analyses, alternative experimental designs beyond the RCT, and using qualitative data to assess theoretically-expected outcomes from user testing—can offer HCI researchers powerful new ways to assess technologies that they are developing.

Selecting target users

Theories like the transtheoretical model suggest that different user groups will have diverse needs and interventions that effectively support one group might be ineffective for another. He *et al.*'s taxonomy of guidelines for technologies that support sustainable energy behaviors is a good example of how theory can help researchers uncover differing needs across user groups. Individuals at different stages of change may require different types of support, even if the goal is to encourage the exact same behaviors (*e.g.,* using public transportation).

In HCI research on behavior change technologies, this insight is most strongly reflected in the use of theory to screen participants for evaluation studies. Among others, Consolvo *et al.* [12,14] have used the transtheoretical model to screen out pre-contemplation individuals from their studies of technologies for physical activity promotion under the assumption that such tools would not be helpful to someone who has no interest in becoming more physically active.

Moving forward

One corollary of this point is that researchers should be specific about the characteristics of users who are testing the behavior change technologies. If study participants do not match the target user group sufficiently closely, it becomes very difficult to make sense of study results, increasing the likelihood of type III error (*i.e.,* finding null results when the hypothesis was never tested in the first place [20]). Put differently, does the system not work or did it not work for these particular participants?

Theory can also help HCI researchers to better understand *who* the most appropriate target users are for a given technology. This is evidenced by King *et al.*'s work that suggests that some physical activity promotion interventions may only work for people living in walkable neighborhoods [42]. Using theory to define target users could lead to the design of tailored—and potentially more effective—interventions.

Related to this point, theory could be used *post hoc* to understand different patterns of use and outcomes among study participants. Similar to how Grimes *et al.* used theory to investigate effects of their system or Hekler *et al.*'s work on physical activity promotion via IVR or human counseling [35], theory could guide analyses of interview and demographic data to create hypotheses about the factors that shaped technology use. These factors could then be more rigorously assessed in follow-up studies, leading to a richer understanding of the individual, social, and cultural variables that influence the effectiveness of behavior change technologies. By extension, findings from such studies would also help delineate for which users a system is and, perhaps more importantly, is not appropriate.

Common pitfalls when using behavioral theories

Although we have argued that theory can be helpful to HCI researchers working on behavior change technologies, its use is not without pitfalls. We have alluded to several common pitfalls already, including: (i) ignoring the broader context in which a technology will be used (*e.g.,* not taking into account a person's neighborhood environment); (ii) picking only some constructs from a theory and thus losing the potency of the full conceptual framework for designing a system; (iii) treating design guidelines generated from one empirical study as "requirements" when they should be thought of as design hypotheses; (iv) using selective constructs from a theory but making claims that are related to the full theory (*e.g.,* stating that a system was based on the transtheoretical model but then only using the stages of change); (v) increasing the likelihood of confirmation bias in studies; (vi) falling prey to Type III error due to poor specification of the target audience (*i.e.,* concluding a hypothesis is false when it was never tested).

We want to emphasize that many of these pitfalls are shared by behavioral science as well. We explicitly enumerate them to help HCI researchers avoid them in their work.

Finally, some HCI researchers may think of behavioral theories as if they were in some way "truth" or "fact" with regard to understanding behavior and behavior change. While tempting, this view would be inappropriate. In the following section, we provide a brief summary of the shortcomings of current behavioral theories, both to inform HCI researchers of their limitations and to highlight that these shortcomings present opportunities for HCI researchers to contribute to the process of refinement and development of behavioral theories.

SHORTCOMINGS OF BEHAVIORAL THEORIES

Despite their prominence in HCI research, behavioral theories have many shortcomings which may not be well-known in the HCI community. These shortcomings include: (i) most behavioral theories explain only a small portion of variance in the outcomes they are trying to account for; (ii) many behavioral theories, in their current form, are not falsifiable; and (iii) there is a fragmentation and an over-abundance of different theories. We expand on each point in turn and summarize strategies behavioral scientists are using to combat each shortcoming. While other shortcomings and debates certainly exist (*e.g.,* the gap between *behavioral theory* and *social theory* [65] and other issues listed in our conclusion section), we see the three we mention above as most relevant to HCI.

Small variance explained

Most behavioral theories traditionally explain, at best, only 20-30% of the total variance in a given health behavior, particularly when the behavior is tested in an intervention (*e.g.,* [58]). In other words, approximately 75% of the variance is not accounted for by behavioral theory and thus can be attributed to unmeasured and unknown factors. There are highly efficacious exceptions (*e.g.,* cognitive behavioral interventions for sleep disturbances, which are based on behavioral theories such as operant conditioning, produce clinically significant improvements in 70-80% of adults [53]); however, the vast majority of behavioral theories explain only a small portion of variance, resulting in interventions that leave much to be desired. For example, Prochaska, the originator of the transtheoretical model recently noted: "*We are convinced that the glass ceiling that has kept efficacy at about 25 per cent for smoking cessation is due first and foremost to inadequate knowledge about the principles of change.*"([58], p. 584).

Implicitly, all initiatives within behavioral science are targeting this core problem. Behavioral scientists are continually refining their interventions, improving measurement of constructs, and striving to increase the efficacy of their interventions. For example, behavioral scientists are increasingly utilizing the social ecological model to better understand and represent multiple determinants of behavior, with the goal of explaining more variance [41]. Behavioral scientists are also increasingly relying upon alternative experimental designs (as discussed earlier) to improve evaluation. However, as evidenced here, there is still much to be done. Finally, behavioral scientists are critically evaluating and questioning central tenets of theories to allow for the models to be falsifiable and by extension testable, a point we address next.

Theories and evaluations that preclude falsification

As discussed in the common pitfalls section, there are important methodological shortcomings related to the evaluation of behavioral theories. A central reason, as pointed out by Ogden [57], is that many current behavioral theories do not generate or are not challenged by falsifiable hypotheses and therefore cannot be tested. For example, the theory of planned behavior [2] identifies subjective norms, perceived behavioral control, attitudes, and behavioral intentions as key predictors of behaviors, but in the evaluations of this conceptual framework reviewed by Ogden, a majority of studies did not find that all of these constructs predicted behavior [57]. However, rather than reject the theory, most papers reviewed by Ogden stated that the theory was good because *some* aspects of the theory were deemed relevant and important, thereby rendering it impossible to falsify the conceptual framework as a whole.

Behavioral theories can also lack falsification if the constructs and relationships are not well specified. For example, Adams et al [1] postulated that the construct of the decisional balance (*i.e.,* weighing the pros and cons for engaging in a behavior results in behavior change when the pros outweigh the cons) from the transtheoretical model was not fully specified. Adams et al argued that the possibility of weighing the pros and cons of competing behaviors (*e.g.,* the pros of sun exposure, such as tanning vs. the pros of sun screen, such as reduced skin cancer risk) was not articulated in the transtheoretical model but is central within other conceptual frameworks such as applied behavioral analysis. In their study, they explored if this poor specification made a difference in predictive models and found that the balance between the pros of the two competing behaviors (*i.e.,* using sunscreen or unprotected sun exposure) was a stronger mediator of the behavior than the pros and cons to just the health behavior (*i.e.,* using sunscreen). This type of work highlights an important area whereby constructs are critically evaluated to generate falsifiable predictions that can be tested.

As these examples illustrate, behavioral scientists are increasingly calling for concrete predictions that are falsifiable and for tests that support, reject, or alter full conceptual frameworks, or alternatively, for tests that focus on constructs or interactions of constructs only [*e.g.,* 51]. In addition, there is a growing interest in comparative studies [56], which could directly compare predictions of different theories within the same context (again, see [1]).

Fragmentation and Over-abundance of Theories

Poor evaluation and lack of falsification of theories has led to a plethora of different conceptual frameworks, competing research findings/conclusions, and redundant underlying constructs that are labeled differently depending on the theoretical camp of origination [3, 51, 57]. For example, confidence in one's ability to perform a given action is a popular construct in behavioral science that has been labeled *self-efficacy* in social cognitive theory but is called *perceived behavioral control* or *locus of control*. While the originating theories do define these constructs slightly differently, many behavioral scientists see the constructs as practically the same [3]. Despite this, the terms remain and are a source of confusion to non-behavioral scientists and behavioral scientists alike.

To resolve this issue, behavioral scientists have attempted to synthesize theories into broader frameworks and, more recently, to create a theory agnostic taxonomy of behavior change techniques. Indeed, the original intent of the transtheoretical model was to, "*reduce 300 theories of psychotherapy and behavior change down to the most common and robust processes of change*" ([58], p. 569). More recently, researchers in Europe have started to develop a taxonomy of behavior change techniques [67]. This work is currently progressing using consensus methodology, but there are already early versions of the taxonomy in the literature (*e.g.,* [51]).

HCI CONTRIBUTIONS TO BEHAVIORAL THEORY

Although HCI researchers have traditionally not engaged in the development of behavioral theory, we see HCI as being in a unique position to help mitigate the shortcomings in behavioral theory we discuss above. Here we outline three ways in which HCI could help improve behavioral theory: (i) improving measurement and, by extension, fostering better theories of behavior, (ii) enhancing early-stage theory fidelity, and (iii) using big data and A/B testing.

Improving Measurement

Many behavioral theories are based on studies that rely on self-report measures and assess key variables infrequently (*e.g.,* see [61] for a discussion about this). The small variance explained by such theories as well as the lack of rigorous testing is at least in part due to the poor fidelity of data on which the theories are based. HCI researchers can significantly contribute to solving both of these problems by improving measurement of theoretical constructs and behaviors.

HCI researchers have ample experience with developing tools that take advantage of ubiquitous sensing, machine learning, and mobile computation to collect data on human behavior (*e.g.,* [7,28]). For example, mobile phones equipped with activity and location sensing [52] allow for data collection on user behavior not just with regards to application usage on the device but interactions and movements in the physical world as well (*e.g.,* [23]). HCI researchers can work with behavioral scientists to develop tools and techniques for precise and frequent measurement of key theoretical constructs and behaviors postulated by current and future behavior theories. Such tools could collect data both automatically (*e.g.,* through sensing) as well as through lightweight self-report at inferred moments of interest (*e.g.,* context-aware experience sampling, [22]). And, crucially, because many new data collection methods require little-to-no user attention, the data collection tools developed by HCI researchers would enable longer and larger user studies, improving not only the quality of the data but its quantity as well. Better and more frequent assessments, in turn, would enable behavioral theories to be more rigorously tested—and then refined—than behavioral scientists have been able to do in the past (*e.g.,* see [61]).

In addition, tools built by HCI researchers could enable the development of a different kind of theory: personalized, dynamic models of factors that influence behavior of a particular person. By collecting fine-grain data about behavior, context, physiological measures, and cognitive constructs, systems built by HCI researchers could use machine learning techniques to model how various elements in the user's life (*e.g.,* who the user spends time with, the user's daily routine) affect the behavior the user is trying to change (*e.g.,* physical activity or smoking). In addition, as the system is used over time, the model could be continuously tuned and improved. Such individualized models of behavior could be used to create highly effective behavior change interventions which take into account the precise factors that shape the behavior of a particular person. In addition, the models could be aggregated across individuals to create more general theories of behavior which are likely to be more precise than current theories.

Enhancing early-stage theory fidelity testing

Behavioral scientists have historically put great effort into reducing the likelihood of type I error (*finding* a result when that result does *not* exist) and type II error (*not* finding a result when the result *does* exist). Type III error (*i.e.,* concluding a finding does not exist when, in fact, the study was not designed properly and therefore never tested the hypothesis [20]) is becoming an increasing concern. Type III error can lead to erroneous conclusions with regard to the accuracy of a theory. To minimize this, some behavioral scientists are starting to explore *theoretical fidelity*—whether a theoretically-guided intervention actually functions according to the theory [52]. Mediation analyses and treatment fidelity methods [29] are the standard "checks" behavioral scientists use to determine theoretical fidelity. Current behavioral science methods for theoretical fidelity, however, are largely lacking for initial system development. As discussed in the *Uses of Behavioral Theory* section, HCI researchers could establish *a priori* expectations of words or phrases from user testing research to establish early-stage theoretical fidelity tests. To the best of our knowledge, this strategy has not been employed previously but may offer exciting new opportunities for early-stage theoretical fidelity testing.

Supporting and using big data and A/B testing

Finally, increasing opportunities in big data and A/B testing allow unique opportunities for improving behavioral theory. Much of this work is currently being conducted by large corporations (*e.g.,* Facebook) or start-ups with loyal followers (*e.g.,* Runkeeper) that have access to large databases of user interactions with their systems. The opportunities for testing, refining, and creating new theories about behavior are astounding when big data, improved measurement, and A/B experimental testing are combined.

Big data and A/B testing allow for research that goes beyond testing individual constructs or conceptual frameworks but full meta-models. Before big data, tests of meta-models were almost impossible; this, however, is rapidly changing with big data and improved multilevel measures and A/B testing is a particularly promising approach to testing meta-models. Using A/B tests, it becomes possible to explore the causal impact of constructs after controlling for other components identified in the meta-model. The closest example to this type of study that we are aware of is a recent study in which an A/B test of 61-million users of Facebook was conducted to test the effect of social influence on voting patterns [9]. This type of research, which HCI researchers are uniquely poised to conduct, could radically transform our ability to test and further develop behavioral theories.

CONCLUSIONS AND NEXT STEPS

Our goal in this paper was to provide HCI researchers and designers with guidance for interpreting, using, and contributing to behavioral theories. We explicitly sought to highlight the important place for a cross-pollination of ideas and methods between disciplines. That said, this paper only scratches the surface. Issues that require further explication are numerous such as: (i) best methods for evaluating behavior change technologies in HCI research (extending [43]); (ii) a full understanding of the requisite knowledge each field requires before engaging with the other (*e.g.,* how much knowledge does an HCI researcher need about behavioral theory to use and contribute to it?); (iii) the possibility of distortions that arise from poor translations of concepts between fields; and (iv) the impact of sociocultural differences related to the origin of theories on the interpretability, utility, and generalizability of different behavioral theories within an HCI context. Each of these points requires more careful thought and work from both fields. As such, our final goal is a call for behavioral scientists and HCI researchers to work more closely together both on the design of behavior change technologies and the development of better theories. This paper itself represents the collective effort of two behavioral scientists (one psychologist and one public health researcher), and two HCI researchers (a researcher in health informatics and a computer scientist). We believe that such collaborations and open exchanges of ideas across disciplines are fundamental to the development of better theories, better systems, better behavioral outcomes, and, ultimately, to positive societal impact.

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