Refining and Extending Task–Technology Fit Theory: Creation of Two Task–Technology Fit Scales and Empirical Clarification of the Construct

Article *in* Information & Management · December 2018

DOI: 10.1016/j.im.2018.12.002

Matt C. Howard
University of South Alabama

ARTICLE IN PRESS

Information & Management xxx (xxxx) xxx–xxx

Contents lists available at ScienceDirect

Information & Management

journal homepage: www.elsevier.com/locate/im

Refining and extending task–technology fit theory: Creation of two task–technology fit scales and empirical clarification of the construct

Matt C. Howard[a,*], Julia C. Rose[b]

[a] University of South Alabama, Mitchell College of Business, United States
[b] Pennsylvania State University, Labor and Employment Relations, United States

ARTICLE INFO

Keywords:
Task-technology fit
Task-technology misfit
Scale development
Theory development

ABSTRACT

Research on task–technology fit (TTF) theory is in need of refinement that is centered around (1) conceptualizations of TTF, (2) operationalizations of TTF, (3) an oversight of "misfit," and (4) an overemphasis on direct effects. We review TTF to place it in the broader nomological net of related constructs. We differentiate task–technology misfit (TTM) from TTF, and we distinguish two types of TTM, "Too Little" and "Too Much." Then, we undergo a four-study process to create two satisfactory scales. Finally, we perform two empirical studies to confirm our three-dimensional conceptualization of TTF and TTM in the larger TTF theory framework.

In the past several decades, the rapid innovation and application of new technologies in the workplace has changed the manner in which even the simplest jobs function, causing the link between workplace technologies and employee performance to grow even stronger [1–3]. Of the theories applied to understand this link, task–technology fit (TTF) theory is among the most popular [4–6]. TTF theory proposes that technologies positively impact performance outcomes when they are *utilized* and *match* a task [7–9]. As such, the construct of TTF refers to the match between a task and a technology. Since its creation, TTF theory has been applied across an array of contexts to understand the relation between tasks, technologies, utilization, user reactions, and performance [4,6,10–12]. Although the theory is succinct and popular, we argue that TTF theory needs to be refined and extended. Over time, many authors have gradually altered the original tenants of the theory, resulting in disparate investigations into TTF and possible inappropriate inferences about TTF theory itself. Likewise, the narrow scope of TTF theory may be the cause of these gradual alterations and inappropriate inferences, which may be rectified by extending TTF theory to better fit a wide range of settings. As such, we discuss three aspects to refine, one aspect to extend, and several recommendations for the application of TTF theory moving forward.

We focus on three aspects when refining TTF theory. First, many applications of TTF theory do not conceptualize TTF in a manner that is consistent with the theory itself [13,81,2,6,14–20][1]. Instead, TTF is often conceptualized similar to the construct of utility, and these conceptualizations fail to any aspects of fit or matching. Second, TTF is often inappropriately operationalized due to confounds in conceptualizations, resulting in the application of inaccurate scales to gauge TTF ([13,97,6,21–23];). These scales include items that represent outcomes, such as utility, which causes construct contamination and inaccurate observed relationships. Third, TTF theory proposes specific moderating and mediating effects, but studies often limit analyses to direct effects [2,5,18,24–28]. Many such analyses are not relevant to TTF theory, thereby facilitating an unclear view of TTF.

Further, we focus on one aspect when extending TTF theory. An overwhelming focus is placed on "good" TTF in research [4,7,29,98] Studies are largely limited to investigations of positive work scenarios, and relevant discussions do not consider that task–technology misfit (TTM) may not solely produce the opposite of TTF. Distinguishing types of TTM, such as the technology including too few *or* too many features, can provide novel insights into the construct and theory.

Using these points as a guide, we review TTF theory to position TTF in the nomological net of related constructs, including performance, utility, perceived utility, user reactions, and utilization. Our review also differentiates TTF from TTM to suggest that each produces different outcomes. Afterwards, we introduce two scales created in a four-study process. The first is the 8-item one-dimensional TTF scale. The second is the 18-item, three-dimensional TTF and TTM (TTF/M) scale, which distinguishes two forms of TTM ("Too Little" and "Too Much"). This effort also provides evidence that TTF and TTM indeed produce

* Corresponding author at: 5811 USA Drive S., Rm. 346, Mitchell College of Business, University of South Alabama, Mobile, AL, 36688, United States.
E-mail address: mhoward@SouthAlabama.edu (M.C. Howard).

[1] Not all of these citations (and the other citations within this paragraph and the following) are inappropriate applications of TTF theory. Instead, many of these citations are prior authors noting similar concerns.

https://doi.org/10.1016/j.im.2018.12.002
Received 25 October 2017; Received in revised form 29 November 2018; Accepted 9 December 2018
0378-7206/

differing outcomes that are more than the inverse of the other. Finally, using these scales, two empirical studies support our suggested positioning of the three dimensions in the larger TTF theory framework. These studies also provide a comprehensive analysis of the TTF framework, including moderating and mediating effects. Together, we refine and extend the conceptualization and operationalization of TTF; we clarify the theoretical foundation of TTF; and we further the validity and sophistication of research and practice involving the applications of technologies for work purposes.

While these efforts provide many theoretical and practical implications, we highlight two here. First, prior research has either implied or directly suggested that TTM simply produces the opposite effect of TTF, and TTM is often operationalized as the absence of TTF. The present article theoretically proposes and empirically supports that TTM is not simply the absence of TTF, and TTM produces more than the opposite effect of TTF. This discovery increases the sophistication of TTF theory, and future research can discover novel effects of TTM that may be largely independent of TTF. Second, the present article refines TTF theory to enable future research to progress more easily, but it also makes the theory more complex by integrating TTM. As such, a greater number of effects can be investigated when applying TTF theory, and these relationships can be explored by integrating TTF theory with other theoretical perspectives. As further discussed below, studying TTF and TTM together may naturally lend itself to the integration of TTF theory alongside expectancy disconfirmation theory [30], media synchronicity theory (MST) [1], and media richness theory [31]. While only two of the implications of the present article, these nevertheless highlight that the current series of studies may benefit our understanding of TTF, TTF theory, and beyond.

1. Task–technology fit theory background

Goodhue and Thompson [29] originally coined the construct of TTF, and they defined it as "the degree to which a technology assists an individual in performing his or her portfolio of tasks" (p. 216). The creation of this construct led to the subsequent creation of TTF theory [7–9], which suggests that technologies positively impact outcomes when they are *utilized* and *match* a task. From this theory, the conceptualization of TTF has gradually evolved to refer to the match between a task and technology. Although the theory may seem simple, its premise has been used to explain many dynamics of workplace technologies [4,5,7]. As such, it is useful to review key elements of TTF theory, as depicted in Fig. 1. These five key elements are summarized below; they do *not* represent gaps or concerns, but rather are meant to provide a basic understanding of TTF theory for those that may not be familiar with it.

First, TTF theory suggests tasks and technologies may interact to produce effects that are greater than the sum of their parts. Many other

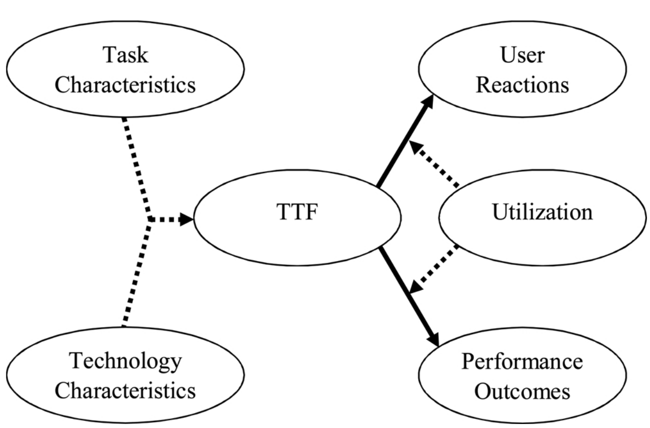

Fig. 1. Visual Representation of Task–Technology Fit Theory.

theories and models related to technological applications, such as MST and the technology acceptance model (TAM), denote properties of technologies that directly influence performance or utilization, such as processing capabilities, transmission capabilities, and media capabilities [1,2,32,33]. TTF theory, on the other hand, does not pertain to particular characteristics or direct effects. Instead, TTF theory draws attention to the general reliance of technologies on the context in which they are applied, and it does not propose any task or technology pairings that produce a particularly strong interactive effect.

Second, TTF theory proposes that TTF mediates the relationship between the interaction of task and technology characteristics with performance outcomes, and TTF is not a characteristic of tasks or technologies themselves. As events occur during a task, the ability of a technology to address these task events determines the resultant TTF. TTF then mediates any interactive effects of task and technology characteristics on performance outcome.

Third, although not directly suggested by TTF theory, most authors assume that TTF has an identical effect on user reactions as it does on performance outcomes [14,97,2,6]. When a user applies a technology that matches the task well, they are expected to perceive this match. In turn, they are also expected to perceive the benefits of TTF to performance, and even appreciate these benefits. From these sequential links, TTF is believed to impact user reactions, which includes perceived utility and enjoyment.

Fourth, TTF theory suggests that utilization moderates the relationship of TTF with performance and user reactions [34–37]. Even the best technologies are useless if the user does not use them, and TTF has no effect on performance or user reactions when technologies are not used.

Fifth, although not directly suggested by TTF theory, again, most authors assume that TTF has a direct effect on utilization [8,9]. It may be unusual for a predictor to have an effect on a moderator, but there is no theoretical or statistical reason that this cannot occur [38,39]. In the case of TTF theory, there is a strong reason to believe that TTF may predict the moderator of utilization ([13,29,49,81). As users notice the benefits of the technology for a task, they are expected to subsequently choose to continue using the technology.

Using these points as a guide, many authors have applied TTF theory in a useful manner. Most often, studies have shown that self-report TTF scales have significant relationships with important antecedents or outcomes [4,26,40]. Less often, studies have shown that certain task and technology characteristics interact to predict outcomes, and the effects are ascribed to TTF [41–43]. Very rarely, self-reported TTF is tested alongside this interaction, and both are used to predict outcomes [44–46]; however, the entire TTF theory framework is generally not tested in these studies.

Further, two notes should be made before continuing. TTF theory proposes that tasks and technologies interact to produce TTF. Then, TTF predicts user reactions and performance, as moderated by utilization. It is almost certain that, independent of TTF, specific technology and task characteristics have direct effects on user reactions, utilization, and performance [1,2,32,33]; however, these direct effects are not explicitly predicted in TTF theory, as the theory is only concerned with the dynamics of TTF. While these relationships are expected and implied, they are not directly discussed when studying TTF theory. Thus, their exclusion is intentional and not a theoretical oversight.

Additionally, while often overlooked in research, the concept of "fit" can have several meanings. Fit can be conceptualized and discussed in six different ways [47], three of which were identified by Cane and McCarthy [48] as being used in TTF research. The first is fit as moderation, in which fit is studied through interactive effects of certain task and technology characteristics, and it is often gauged on a Likert scale (e.g., What extent does the [technology include] / [task require] these features?). The second is fit as matching, in which fit is studied by comparing many technologies across a single task, many tasks across a single technology, or many technologies across many tasks. The third is fit as profile deviation, in which fit is studied through identifying ideal profiles and gauging deviation from these profiles. Of the approaches, the first two are most common in empirical studies, whereas the third is occasionally used in theoretical discussions of TTF theory [48].

Although authors may study fit via moderation and matching, Cane and McCarthy [48] note that almost all studies obtain self-report user evaluations of TTF – whether also gauging fit via moderation, matching, or not at all. Then, self-reported TTF is used to independently gauge the direct effect of TTF with outcomes. The causes of this trend likely differ for fit as moderation and fit as matching. In the case of moderation, researchers must identify specific task and technology characteristics that interact to influence performance; however, the list of possible task and technology characteristics is almost uncountable, and it grows with each technological development. Although studying a single interaction, or even several, provides insights into the nature of those specific task and technology characteristics, it does not account for the entire scope of TTF. Any results may only reflect certain aspects of TTF, causing authors to likewise test perceived TTF to obtain a more complete view. Alternatively, in the case of matching, authors cannot be certain that performance improvements of a particular pairing are due to TTF. Certain technologies may simply be better than others and certain tasks may be more difficult than others. In these cases, self-reported TTF is used to support the argument that improvements to performance are due to TTF rather than other effects. Thus, while each approach has certain benefits and detriments, self-reported TTF is studied in conjunction to alleviate these detriments.

In placing our expanded conceptualization of TTF in the broader TTF theory framework, we test the relationship of our self-report scales with both TTF as moderation (Study 5) and matching (Study 6). By doing so, we integrate our conceptualization with most all research on TTF and TTF theory. With an overview of TTF theory provided, we now refine and extend TTF and TTF theory to obtain a better understanding of the theory and construct.

2. Refining and extending task-technology fit theory

2.1. Refining conceptualizations

Authors often apply consistent descriptions for TTF theory, but a major concern is the lack of consistency in conceptualizing and defining the construct of TTF. As Furneaux [7] notes, “The apparent consistency in these definitions [of TTF theory] tends, however, to belie the considerable ambiguity and complexity that actually surrounds the notion of TTF” (p. 92). The ambiguity and complexity in TTF is further reflected by the terms that are inappropriately used interchangeably with the construct [13,49,81,2,6,14–20]. Instead of describing a fit or match, most of these terms refer to characteristics or outcomes of tasks and/or technologies. TTF is not entirely an aspect of either as specified by TTF theory. Thus, these terms are not representative of TTF, and several constructs should be clearly differentiated from TTF due to this ambiguity.

To reiterate, TTF is the match between a task and a technology. It is not the properties of tasks or technologies, but it arises from their combination. Common constructs conflated with TTF are performance, user reactions, utility, perceived utility, and utilization. However, each of these constructs is an outcome of TTF, not TTF itself. The two primary outcome categories of TTF are performance and user reactions. Performance is the output from a technology applied to perform a task, whereas user reactions are users’ perceptions of a technology applied to perform a task [14,16]. Both determine the influence of technologies and TTF. Further, utility refers to the extent that a technology successfully facilitates a task, and perceived utility refers to users’ perceptions of utility [6,18]. Utility is considered a performance outcome, perceived utility is considered a user reaction, and both of these are expected outcomes of TTF. Finally, utilization is the extent that users actually use a technology [1,2,29]. While it is also an expected outcome of TTF, utilization is considered separately from performance outcomes and user reactions. Together, these five constructs are entirely distinct from TTF.

An accurate understanding of TTF theory can only be developed through acknowledging the conceptual separation of these constructs. Unfortunately, concerning conceptualizations have led to concerning operationalizations of TTF, which is the second area of refinement.

2.2. Refining operationalizations

Authors have repeatedly applied concerning operationalizations of TTF. Currently, no standard measure exists to gauge TTF, resulting in various self-created scales. The psychometric properties and validity of these scales are rarely studied, and, while concerning, we cannot comment on these aspects of the scales. Instead, we comment on individual items in these scales.

While TTF describes the match between a task and a technology, the scales used to gauge TTF often do not reflect this conceptualization. Instead, items that represent other constructs are regularly seen in such scales, resulting in construct contamination. These other constructs include performance (“Data generated from the information system is accurate,” [97], reactions (“I have fun using the Web,” [49]), utility (“The functionalities of the [technology] were very useful,” [22]), perceived utility (“I see that other people benefit from using the Web,” [13]), utilization (“I can count on the Intranet to be ‘up’ and available when I need it,” [23]), and others (“Using YouTube would fit well for the way I like to learn procedural tasks,” [6]; “e-learning technology fits with the way I work,” [21]). The inclusion of these items misrepresents modern conceptualizations of TTF. Any observed relationships using these scales are not fully representative of TTF, possibly causing inaccurate inferences about TTF theory.

Additionally, many authors study TTF by analyzing the direct effects of task and technology characteristics with various outcomes, and these characteristics are often gauged through self-report (e.g., The technology is easy to learn; the task requires up-to-date information). When studied in this manner, scales that are believed to be representative of TTF, and labeled as such, instead capture many different aspects of the task or technology. For instance, the subdimensions of TTF scales created from this conceptualization include task complexity, task interdependence, cost, system reliability, ease of use, level of detail, and many others [2,5,18,24–28]. These subdimensions do not gauge constructs that arise from combinations of tasks and technologies; they describe aspects of the tasks or technologies, and the scales do not adhere to the conceptualization of TTF proposed by TTF theory. Again, due to these concerning operationalizations, any observed results may not be representative of TTF, which may result in inaccurate inferences about TTF theory.

For TTF to be studied in a reliable manner, a satisfactory measure is required. Before creating such a measure, we consider the limited perspective of TTF taken in prior research, and we extend this perspective and TTF theory in the present article.

2.3. Extending TTF theory

Even when conceptualized correctly, a narrow perspective of TTF is often taken, possibly resulting in construct deficiency. Those applying TTF theory almost always analyze TTF and ignore TTM [7,98], which we define as a mismatch between task and technology characteristics. Some authors study TTF by applying an adequate technology and a clearly upgraded technology, and the benefits of the upgraded technology are attributed to TTF. Most of the authors study TTF by applying one-dimensional self-report scales of TTF, and not reporting TTF is considered to be indicative of TTM. It is possible that not reporting TTF is conceptually distinct from TTM. For instance, TTF may be produced by a technology including extra nonrequired, helpful features to complete a task, but the absence of these features may not necessarily indicate that a technology and task produce TTM. More importantly, different types of TTM may have varying effects on outcomes. Indeed, for a technology to *perfectly* match with a task, it must provide no more or less than what is needed. With this assumption, TTM may be due to the technology including too few or too many features to perform the task. As such, we differentiate these two forms of TTM.

The first form of TTM occurs when a technology does not include the desired features to perform a task, which we label “Too Little.” We expect Too Little to worsen user reactions and performance. When a technology includes too few features, users may not be able to perform the necessary functions of a task and become frustrated. The second form of TTM occurs when an applied technology includes too many features to perform a task, which we label “Too Much.”

We suggest that, although both are forms of TTM, Too Little and Too Much have differing antecedents and outcomes, which justifies their conceptual separation and empirical study. Too Little is believed to have a broader negative effect on user outcomes, as the technology may not possess the necessary features to effectively complete the task. In turn, the user may perform worse and have negative reactions to the technology. The potential effects of Too Much are more uncertain than Too Little. Excessive technology features may cause users to become overwhelmed, thereby worsening reactions and performance outcomes. Excessive features may also cause users to believe that they can accomplish more tasks and address unexpected events, thereby improving reactions and task self-efficacy. This increased self-efficacy may improve performance outcomes [50,51]. While Too Little likely reduces user reactions and performance outcomes, the relationships of Too Much are much less clear, and empirical research is needed to determine its effects.

Finally, no scale separates the dimensions of TTF and TTM. Even if authors propose differing effects of the two constructs, they could not test their hypotheses. Without being able to test hypotheses involving both TTF and TTM, only a partial understanding of TTF theory can be achieved. Thus, research and practice on TTF theory is hindered by conceptual and measurement limitations that should be addressed to better understand the theory.

3. Background summary

Prior research has conceptualized TTF inconsistently with TTF theory, created scales that may not accurately gauge TTF, and ignored differences between TTF and TTM. These issues hinder our understanding of TTF theory, as prior results may not reflect the true nature of TTF. To avoid prior concerns and improve future research, we create two psychometrically sound scales that are valid for gauging TTF and TTM. The first is a one-dimensional scale that gauges TTF, as this has been the focus of prior research. The second is a three-dimensional TTF and TTM scale that gauges TTF and two types of TTM, Too Little and Too Much. By creating these scales, researchers can be more certain about the accuracy of their results, and they can expand analyses to include TTM. After creating the scales, we integrate our three-dimensional conceptualization into the larger TTF framework, allowing us to refine TTF theory further.

4. Scale development

Several guides were applied to create both scales [52–56]. The following steps were included in the scale development process: item-sort task (Study 1), which creates the initial scales; exploratory factor analysis (EFA; Study 2), which reduces the scales and explores their factor structure; confirmatory factor analysis (CFA; Study 3), which confirms their factor structure; and convergent validity test (Study 4), which tests the scales’ relationships with theoretically similar constructs.

5. Study 1 – item-sort task

To develop a scale, many authors have suggested initially creating and subsequently reducing an over-representative item list to ensure adequate content validity of the final scale [56–58], which was done in the present study. To create the one-dimensional TTF over-representative item list, items were gathered from over 20 articles that provided their one-dimensional TTF scale. These items were altered to include consistent wording, resulting in a collection of 43 items. To create the three-dimensional TTF and TTM over-representative item list, 18 items were created to gauge TTF, 18 items were created to gauge Too Little, and 18 items were created to gauge Too Much.

An item-sort task with 10 subject matter experts, undergraduates and graduates in an applied psychology/management research lab, was performed to reduce the item lists and remove items that may not gauge their intended constructs. Item-sort tasks can identify items with poor substantive validity, which is indicative of an eventual scale’s construct validity [56,57]. The details of the item-sort task are provided in Supplemental Mat. A that closely followed the guidelines of Anderson and Gerbing [57] and Howard and Melloy [56]. The item-sort task reduced the 43 one-dimensional TTF items to an initial 11-item TTF scale. It also reduced the 54-item, three-dimensional TTF and TTM item list to an initial 40-item three-dimensional scale that gauged TTF (14 items), Too Little (15 items), and Too Much (11 items). Finally, the item sort task also identified five items that participants consistently identified as gauging perceived utility, resulting in an initial five-item perceived utility scale to use in subsequent studies to test the scales’ discriminant validity.

In addition to creating initial scales, these results suggest that prior TTF scales contain items that are not representative of the construct. The one-dimensional TTF over-representative item list was entirely created from scales used in prior studies. As the raters judged the majority of these items to not measure TTF, and many were judged to gauge utility, it appears that prior studies indeed misapplied TTF theory in their conceptualization and operationalization of TTF. As such, these results further support the importance of creating new TTF scales.

6. Study 2 – exploratory factor analysis

Any scale should have a supported factor structure [53–55]. Study 2 tests the factor structures of the two scales, and some items are expected to be removed.

7. Method

7.1. Participants

Sample A. Sample A included 219 participants (M_{age} = 32.94, SD_{age} = 9.57; 37% female; 76% Caucasian) recruited from Amazon’s MTurk in return for a small amount of monetary compensation. MTurk is a website that connects individuals willing to perform tasks on a computer, such as taking a survey, with those needing the tasks completed. Several prior studies have shown that results obtained from MTurk samples are reliable and valid, even when studying special populations [59–61]. All the participants were employed, and those that failed an attention check were removed. All statistics, including descriptive information, reflect the sample after removing these participants.

Sample B. Sample B included 210 participants (M_{age} = 31.96, SD_{age} = 8.24; 35% female; 44% Caucasian) recruited from MTurk in return for a small amount of monetary compensation. All participants were employed, and those that failed an attention check were removed.

8. Measures

8.1. One-dimensional TTF scale

The initial 11-item one-dimensional TTF scale created in Study 1 was administered to Sample A.

8.2. Three-dimensional TTF and TTM scale

The initial 40-item three-dimensional TTF and TTM scale created in Study 1 was administered to Sample B.

8.3. Perceived utility

The five-item scale created in Study 1 was given to Samples A and B.

9. Procedure

Participants signed-up for the study via MTurk and were given the following prompt:

"At work, employees are often expected to use many different technologies. Think about the technology that you use the most at work. If you are thinking about a technology that can run many different programs, such as a computer, think about a specific program on that technology. Please write the technology that you are thinking about in the space below. Some examples are: mobile commerce platform, internal information system, mechanical press, compact excavator, wheel forwarder, IBM SPSS, Adobe Dreamweaver, and Microsoft Outlook."

After listing the technology, they were also given the following prompt: "Now, think about the task that you use this technology for most often. Write two to four words describing this task in the space below." After listing the task, they were asked to complete the survey with the listed technology and task(s) as the references for the scales. Finally, they were informed of the purpose of the study.

A note should be made about the research design. Often, authors studying TTF choose a particular context to study, such as bank employees adopting a new e-commerce system [62,63]. The research design for the current study, however, is another dominant method for TTF research [5,12,29]. By obtaining a broad sample responding in regards to multiple technologies, the results are more likely to generalize to a larger population. Also, when studying scales' psychometric properties, it is beneficial to ensure variance in responses [64]. When studying a single technology, participants are more likely to provide homogeneous responses. When studying many technologies, participants report on an array of perceptions, allowing greater variance in responses. Thus, the research design provided many benefits.

10. Results and discussion

EFAs were performed to identify the factor structure of the one-dimensional TTF scale and the three-dimensional TTF and TTM scale. As suggested by others [53–55], a principal axis factoring method with direct oblimin rotation was chosen to perform the EFA, and a visual scree plot analysis and parallel analyses were used to determine the factors to retain. The 11-item one-dimensional TTF scale was analyzed with the five utility items identified in Study 1 to test the scale's discriminant validity along with its factor structure. From the EFA, two factors clearly emerged via the visual scree plot analysis (*Eigenvalues* = 9.795, 1.718, .654, …) and parallel analysis (*95% Parallel Analysis Eigenvalues* = 1.687, 1.550, 1.450, …). All TTF items loaded strongly on the first factor (> .60), whereas four of five utility items loaded strongly on the second factor (> .65). No TTF items cross-loaded greater than .25 on the second factor. As short measures are preferred in research, items that loaded on the first factor below .70 were removed, resulting in an eight-item one-dimensional TTF scale. When rerunning the EFA with these eight items, each loaded .75 or above. The scale's Cronbach's alpha was .96. Henceforth, these eight items are labeled the TTF scale (Supplemental Mat. B).

Also, the initial 40-item three-dimensional TTF and TTM scale was analyzed with the five utility items. The scree plot analysis suggested a four-factor solution (*Eigenvalues* = 17.926, 9.683, 3.919, 1.503, 1.077, …), but the parallel analysis suggested a three-factor solution (*95% Parallel Analysis Eigenvalues* = 2.373, 2.224, 2.124, 2.034, 1.961, …). Given the adherence to prior theory, the four-factor solution was chosen. All TTF, Too Little, and Too Much items loaded strongly on their respective factors (> .50), whereas four of five utility items loaded strongly on their respective factor (> .55). No TTF, Too Little, or Too Much items cross-loaded greater than .25. Because short measures are preferred in research, only the six highest loading items in each factor were retained. This resulted in an 18-item three-dimensional TTF and TTM scale. When rerunning the EFA with these 18 items, each loaded .75 or above. The Cronbach's alphas of the TTF dimension was .94, the Too Little dimension was .97, and the Too Much dimension was .95. Henceforth, these 18 items are labeled the Three-Dimensional TTF and TTM (TTF/M) scale (Supplemental Mat. C). Together, the psychometric properties of the TTF and TTF/M scales were supported, and both scales demonstrated satisfactory discriminant validity.

Also, these results demonstrate that prior studies have concerning conceptualizations and operationalizations of TTF. The perceived utility items were taken from prior TTF scales, and these items were shown to represent a conceptually distinct factor in both EFAs. Thus, the scales created in the present article can greatly benefit research and practice involving TTF and TTM.

11. Study 3 – confirmatory factor analysis

Study 3 confirms the factor structure of the two scales through CFA, which is a necessary step in the scale creation process [53,54,65,66].

12. Method

12.1. Participants

Sample A. Sample A included 204 participants (M_{age} = 31.75, SD_{age} = 9.15; 34% female; 80% Caucasian) recruited from MTurk in return for a small amount of monetary compensation. All participants were employed, and those that failed an attention check were removed.

Sample B. Sample B included 246 participants (M_{age} = 32.93, SD_{age} = 9.57; 35% female; 60% Caucasian) recruited from MTurk in return for a small amount of monetary compensation. All participants were employed, and those that failed an attention check were removed.

13. Measures

13.1. TTF and TTF/M scales

The TTF scale was given to Sample A (α = .96). The TTF/M scale was given to Sample B (TTF, α = .94; Too Little, α = .97; Too Much, α = .95).

13.2. Procedure

The entire procedure for Study 3 was identical to Study 2.

14. Results and discussion

To perform the CFA, the suggestions of prior authors were applied [53,54,65,66]. A listwise deletion method was used to handle missing data, and IBM AMOS was used to conduct the analyses. The reported information reflects the samples after removing participants with any missing data. For the TTF scale, all items were forced to load onto a single latent factor. Each item loaded extremely well (> .80). Most fit indices (CFI = .97, NFI = .96, TLI = .96, SRMR = .03) met suggested cutoffs for great fit (> .95, < .05). Some fit indices only approached these cutoffs (GFI = .92, RMSEA = .11, χ^2/df = 3.34). As prior authors have noted [65,67], however, these latter fit indices have a negative bias when model size is small, which may have caused them to only approach their cutoffs. Likewise, GFI has been shown to be particularly sensitive to sample size and may produce worse fit when sample sizes are not "very large" (e.g., > 400; [68];). Some authors have even recommended not reporting GFI in favor of the other fit indices that are less sensitive to sample size [68,69]. Due to these concerns, we holistically interpret these model fit indices, rather than overly focus on the few indices that only approached cutoffs. Thus, the majority of model fit indices indicated appropriate model fit, and the one-dimensional model seems to fit the TTF scale well.

Next, for the TTF/M scale, each item was forced to load onto its respective latent factor (TTF, Too Little, and Too Much). Then, the three factors were covaried. Each item loaded well onto its latent factor (> .55). Most fit indices (CFI = .91, NFI = .89, TLI = .90, RMSEA = .10) met or approached suggested cutoffs for acceptable fit (> .90, < .10), but some indices fell short of these suggested cutoffs (SRMR = .12, GFI = .81, χ^2/df = 3.57). When analyzing methods to improve model fit, the modification indices suggested that model fit could be improved by covarying the error terms of the first two Too Much items. When covarying these error terms, most fit indices exceeded the cutoff for acceptable fit (CFI = .94, NFI = .91, TLI = .93, RMSEA = .09, χ^2/df = 2.90), but some still did not (SRMR = .12, GFI = .85). While GFI is again downward-biased with sample-size is not large, SRMR does not have such concerns and should be directly interpreted alongside the other fit indices. Therefore, while the model fit for the TTF/M scale was not as ideal as the TTF scale, these results suggest that the proposed factor structure of the scale is an overall acceptable explanation for its underlying dimensions.

15. Study 4 – convergent validity

All scales should strongly relate to other scales of the same or similar constructs, known as convergent validity. The TTF scale and the TTF dimension of the TTF/M scale should be strongly and positively related, whereas these two measures should be negatively related to the Too Little and Too Much dimensions of the TTF/M scale. Also, the former two measures should be positively related to perceived utility, whereas the latter two measures should be negatively related to perceived utility. These relationships are tested in Study 4.

16. Method

16.1. Participants

Study 4 included 49 participants (M_{age} = 31.08, SD_{age} = 8.27; 33% female; 71% Caucasian) recruited from MTurk in return for a small amount of monetary compensation. All participants were employed, and those that failed an attention check were removed

17. Measures

17.1. TTF and TTF/M scales

The TTF and TTF/M scales were administered in Study 4.

17.2. Perceived utility

The four utility items that loaded onto a dimension separate from TTF in Study 2 were administered in Study 4. This scale is included in Supplemental Mat. D.

Table 1
Correlations of Measures Administered in Study 4.

	1	2	3	4	5
1.) TTF – TTF Scale	.95				
2.) TTF – TTF/M	.95**	.92			
3.) Too Little – TTF/M	−.59**	−.59**	.95		
4.) Too Much – TTF/M	−.06	−.05	−.01	.88	
5.) Perceived Utility	.61**	.66**	−.55**	.18	.83

Cronbach's alphas included on diagonal. * $p < .05$, ** $p < .01$ (two-tailed).

17.3. Procedure

The entire procedure for Study 4 was identical to Studies 2 and 3.

18. Results and discussion

Table 1 presents the correlations of all measures in Study 4. First, the relationship between the TTF scale with the TTF dimension of the TTF/M scale was analyzed. Their correlation was .95 ($p < .01$), showing satisfactory convergent validity.

Second, the relationships between the TTF scale and the TTF dimension of the TTF/M scale with the Too Little and Too Much dimensions of the TTF/M scale were analyzed. The correlations of the TTF scale with Too Little and Too Much were -.58 ($p < .01$) and -.06 ($p > .05$). The correlations of the TTF dimension with Too Little and Too Much were -.59 ($p < .01$) and -.05 ($p > .05$). Also, the interrelationships of the TTF/M scale were analyzed with responses from Studies 2 and 3. The correlation of the TTF dimension with Too Little was -.44 (*Study 2,* $p < .01$) and -.46 (*Study 3,* $p < .01$), and the correlation of the TTF dimension with Too Much was .07 (*Study 2,* $p > .05$) and .14 (*Study 3,* $p < .05$). On average, TTF had a correlation of -.52 with Too Little and .03 with Too Much. Overall, the relationship of TTF and Too Little was expected, but the relationship of TTF with Too Much was unexpected.

Third, the relationship between Too Little and Too Much was analyzed, resulting in a correlation of -.01 ($p > .05$). Using responses from Studies 2 and 3, their correlation was .30 (*Study 2,* $p < .01$) and .16 (*Study 3,* $p < .05$). Again, these results are also somewhat unexpected.

Fourth, the relationship of perceived utility with each measure was analyzed. Its correlation was .61 with the TTF scale ($p < .01$), .66 with the TTF dimension of the TTF/M scale ($p < .01$), -.55 with Too Little ($p < .01$), and .18 with Too Much ($p > .05$). Also, the relationships of utility were tested with responses from Study 2. Using this data, its correlation was .56 with the TTF scale ($p < .01$), .55 with the TTF dimension ($p < .01$), -.18 with Too Little ($p < .01$), and .31 with Too Much ($p < .01$). These relationships with utility support the convergent validity and theoretical importance of the TTF measures and each dimension. Once again, however, the relationships of Too Much were contrary to expectations.

These results provide several inferences. They show the satisfactory convergent validity of the TTF scale and the TTF/M scale. The TTF scale and the TTF dimension of the TTF/M scale were strongly and positively related, and both were strongly and positively related to utility. The Too Little dimension of the TTF/M scale was negatively related to the TTF scale, the TTF dimension, and utility. While these findings adhered to expectations, the relationships of the Too Much dimension of the TTF/M scale did not. This dimension was largely unrelated to TTF, positively related to Too Little, and positively related to utility. Nevertheless, these results demonstrate the theoretical importance of differentiating types of TTM.

A perfectly fitting task and technology results in maximum TTF and minimum TTM. Most often, adding an extraneous feature would not cause a task and technology pairing to entirely lose its TTF. In this case, users may report some TTF and some TTM, moderate TTF and some TTM, high TTF and some TTM, or even maximum TTF and some TTM.

This may explain the null relationship between TTF and Too Much, as the two constructs are not orthogonal. Also, when a technology has TTM, it is possible that it lacks features for certain purposes but also has too many features for other purposes. This may explain the small, but significant, relationship between Too Little and Too Much, as the two constructs may indeed occur simultaneously. Finally, users may perceive a technology as capable of handling an array of circumstances when it includes too many features, possibly explaining the observed relationship of Too Much with perceived utility. In other words, while it may have too many features for the tasks under investigation, users may nevertheless perceive the technology at being apt at performing the specific task and several others. Thus, while the relationships of Too Much did not adhere to expectations, these results draw importance to distinguishing instances of TTM.

Together, Studies 1 through 4 created two satisfactory scales for gauging TTF and TTM. In this scale creation process, we conceptualized TTF in a manner consistent with TTF theory, operationalized TTF in a manner consistent with TTF theory, and supported our expanded three-dimensional view of TTF. Thereby, we refined and extended TTF theory based on three noted aspects, and aided future research on TTF and TTF theory. The following includes two empirical studies to better understand TTF and address a final aspect in need of refinement.

19. Study 5 – empirical study 1

19.1. Refining the foci of TTF theory research

As mentioned, prior studies have over emphasized direct effects and under emphasized moderating and mediating effects when applying TTF theory. Indeed, when applying TTF theory, many authors measure an array of task and technology characteristics and test their direct relationship with TTF and/or outcomes, such as the relationship of technology quality with performance [26], task requirements with TTF, technology functionality with TTF [18], task characteristics with TTF, technology characteristics with TTF [11], and a host of other relationships [13,81,15,16,19,20,25,70]. These direct effects are likely not due to TTF. Several other theories suggest the properties of certain task and technology characteristics that relate to performance, such as MST or the TAM [1,33], but these direct relationships are omitted in TTF theory. Instead, TTF theory only pertains to the interactive effects of tasks and technologies. To ensure that certain tasks and technology characteristics influence outcomes due to TTF, the ideal method is to show that an interactive effect predicts TTF *and* TTF mediates the relationship between this interactive effect and outcomes.

We test the interactive effect of several task and technology characteristics in predicting TTF, and we test whether TTF mediates the relationship between this interactive effect with two outcomes, user reactions, and utilization. This approach is consistent with prior TTF research that conceptualizes fit as moderation [48], and it results in an overall mediated moderation model. In testing these relationships, we predict that higher levels of paired task and technology characteristics (interaction effects) result in even higher TTF and lower TTM than the direct effects alone. Likewise, we suggest that TTF positively predicts user reactions and performance outcomes, Too Little negatively predicts these outcomes, and Too Much has a null relationship with these outcomes. In testing TTF and TTM in this manner, we refine TTF theory to understand the effect of task and technology characteristics on TTF, and we integrate the two new dimensions of TTM into the broader TTF theory framework.

20. Method

20.1. Participants

Study 5 included 330 participants (M_{age} = 31.76, SD_{age} = 8.62; 31% female; 79% Caucasian) recruited from MTurk in return for a small amount of monetary compensation. All participants were employed. Study 5 used a four-wave time-separated design. Time 1 included 330 participants, Time 2 included 159 participants, Time 3 included 136 participants, and Time 4 included 119 participants. All participants were employed, and those that failed an attention check were removed.

21. Measures

21.1. Task and technology characteristics

No existing measure gauges task characteristics that are matched with technology characteristics. For this reason, we used a modified version of Morgeson and Humphrey [71] Work Design Questionnaire (WDQ; Supplemental Mat. E). The WDQ was originally intended to gauge multiple job characteristics. Jobs can be considered a collection of tasks, and the characteristics of jobs may be able to describe the characteristics of their representative tasks [72,73]. As detailed below, we asked participants to list a technology that they use at work as well as the task(s) that this technology is meant to perform. When completing the modified WDQ, participants reported the extent that “The task(s) involve(s)…” and “The technology helps with…” Example items are, “Doing multiple tasks or activities at a time” and “Deciding on how to go about my work.” Only the five primary dimensions of the WDQ were included in analyses: autonomy (nine items; task α = .90, technology; α = .89), variety (four items; task α = .95, technology; α = .94), significance (four items; task α = .90, technology; α = .91), identity (four items; task α = .90, technology; α = .92), and feedback (three items; task α = .91, technology; α = .94).

21.2. TTF and TTF/M scales

The TTF and TTF/M scales were administered in Study 5.

21.3. User reactions

Two scales created by Moore and Benbasat [74] were used to gauge user reactions. The first was their eight-item *Relative Advantage* scale (α = .97), and the second was their six-item *Ease of Use* scale (α = .89). An example item from the former scale is “Using the technology improves the quality of work I do,” whereas an example item from the latter scale is “Overall, I believe that the technology is easy to use.”

21.4. Utilization

A self-created, five-item scale was used to gauge utilization (α = .80). The items were “I often use the technology to perform the task(s) at work,” “I cannot imagine completing the task(s) without using the technology,” “More often than not, I use the technology to complete the task(s),” “I almost always use the technology to complete the task(s),” and “I rarely perform the task(s) without using the technology.”

21.5. Procedure

Study 5 used a time-separated design. At Time 1, participants signed-up for the study online and completed a demographic survey. A day later, at Time 2, participants were asked to write the most recent technology that has been implemented at their work. If no technology had been implemented since they started, they were asked to write the technology that they used the most. They were also asked to write the task(s) that the technology is meant to perform, and they were told that their described task(s) and technology would be the reference for all subsequent surveys. Then, they completed the survey on task and technology characteristics. A day later, at Time 3, they completed the TTF and the TTF/M scales. Another day later, at Time 4, they completed the user reactions and utilization scales. Through this design, the

Table 2
Correlations of Measures Administered in Study 5.

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
1.) TTF – TTF Scale	.96																
2.) TTF – TTF/M	.91**	.93															
3.) Too Little – TTF/M	−.64**	−.66**	.96														
4.) Too Much – TTF/M	−.04	−.04	.06	.90													
5.) Task Autonomy	.08	.00	.05	.08	.90												
6.) Tech Autonomy	.07	.05	−.03	.15	.82**	.89											
7.) Task Variety	.17	.12	−.08	.14	.33**	.30**	.95										
8.) Tech Variety	.25**	.21*	−.12	.21*	.34**	.41**	.78**	.94									
9.) Task Significance	.02	−.02	.09	.00	.30**	.29**	.26**	.30**	.90								
10.) Tech Significance	−.03	−.06	.09	−.01	.28**	.33**	.20*	.30**	.87**	.91							
11.) Task Identity	.15	.10	−.07	−.10	.33**	.32**	.28**	.26**	.26**	.23**	.90						
12.) Tech Identity	.15	.11	−.13	−.03	.31**	.35**	.27**	.33**	.28**	.27**	.85**	.92					
13.) Task Feedback	−.16	−.14	.09	.04	.31**	.35**	.22**	.19*	.21**	.19*	.17*	.22**	.91				
14.) Tech Feedback	−.10	−.09	.04	.15	.27**	.35**	.18**	.21**	.26**	.22**	.10	.18*	.79**	.94			
15.) Relative Advantage	.65**	.68**	−.54**	−.01	.23*	.32**	.23*	.34**	.16	.14	.13	.18	.09	.12	.97		
16.) Ease of Use	.59**	.62**	−.55**	−.17	.03	.08	.20*	.25**	−.05	−.08	.09	.10	.10	.11	.65**	.89	
17.) Utilization	.62**	.59**	−.40**	−.06	.13	.22*	.21*	.30**	.17	.19*	.20*	.30**	−.05	−.03	.63**	.44**	.80

Cronbach's alphas included on diagonal. * $p < .05$, ** $p < .01$ (two-tailed).

mediation proposed by TTF theory could be gauged with a day between each step.

22. Results and discussion

Table 2 presents correlations and Cronbach's alphas. All analyses, aside from basic correlations, controlled for age and gender. TTF had a positive, strong, and significant relationships with both user reactions; Too Little had a negative, strong, and significant relationships with both user reactions; and Too Much had a negative, small, and nonsignificant relationships with both user reactions. TTF had a positive, strong, and significant relationship with utilization (*TTF Scale*, $r = .62$, $p < .01$; *TTF/M Scale*, $r = .59$, $p < .01$), Too Little had a negative, strong, and significant relationship with utilization ($r = -.40$, $p < .01$), and Too Much had a negative, small, and nonsignificant relationship with utilization ($r = -.06$, $p > .05$). These results show that TTF has a similar influence on utilization as it does user reactions.

To test for interactive effects of task and technology characteristics on TTF, all predictors were mean-centered, the pairs of centered predictors were multiplied to create interaction terms, and the TTF dimensions were regressed onto the centered predictors and their interaction terms (Table 3). The interactions of three task and technology characteristic pairs were significant in predicting TTF as measured by both the TTF scale (autonomy, $B = .210$, $t = 2.178$, $p < .05$; variety, $B = .330$, $t = 3.332$, $p < .01$; identity, $B = .330$, $t = 3.053$, $p < .01$) and the TTF/M scale (autonomy, $B = .228$, $t = 2.387$, $p < .05$; variety, $B = .318$, $t = 3.170$, $p < .01$; identity, $B = .291$, $t = 2.673$, $p < .01$). The interactions of two task and technology characteristic pairs were significant in predicting Too Little (variety, $B = -.222$, $t = -2.125$, $p < .05$; significance, $B = -.232$, $t = -2.595$, $p < .05$). The interaction of one task and technology characteristic pair was significant in predicting Too Much (significance, $B = -.190$, $t = -2.121$, $p < .05$). Only two direct effects were significant, which was the effect of technology variety on TTF (*TTF Scale*, $B = .378$, $t = 2.817$, $p < .01$; *TTF/M Scale*, $B = .369$, $t = 2.714$, $p < .01$) and the direct effect of technology feedback on Too Much ($B = .356$, $t = 2.316$, $p < .05$). These results indicate that several task and technology characteristics indeed have an interactive effect to produce TTF, but the relationships of these effects are nuanced. For instance, some characteristics had interactive effects that only predicted TTF, others only predicted TTM, and even others predicted both. As noted in the general discussion, while these results show that interactive effects – not direct effects – primarily predict TTF, future research is needed to better understand these effects.

We also tested for the mediating effect of TTF and TTM between the interaction of task and technology characteristics on both user reactions and utilization. To do so, we followed the procedure outlined by Preacher and Hayes, Hayes [38,39,75] and MacKinnon et al. [76,77], which allows for the testing of an entire mediated moderation model. In this method, the predictor is shown to significantly predict the mediator (Step 1), the mediator is shown to significantly predict the outcome (Step 2), and then the indirect effect of the predictor through the mediator is shown to significantly predict the outcome (Step 3). If these steps are successful, then the mediated effect is significant. The first step was performed in the preceding paragraph. For the second step, Table 4 includes the results of user reactions and utilization regressed on TTF, TTM, task characteristics, technology characteristics, and the interaction of the latter two. TTF was significant in all analyses. Too Little was not significant in predicting relative advantage or utilization, but it was significant in all analyses predicting ease of use. Too Much was not significant when predicting relative advantage or utilization, but it was significant in four of five analyses predicting ease of use. Thus, TTF may serve as a mediator for all relationships, but Too Little and Too Much may only serve as a mediator for ease of use.

For the third step, Table 5 includes results regarding the indirect effects of the interaction terms through TTF, Too Little, and Too Much. These results were calculated using Hayes's (2013) PROCESS bootstrapped estimates and confidence intervals. In the following, we only discuss the indirect effects in which the interaction was significant in predicting TTF, Too Little, or Too Much *and* the significantly predicted mediator had a significant effect on the outcome. Again, this approach is consistent for broader tests of mediated moderation models.

Of these possible ten indirect effects, seven were statistically significant, whereas three were not statistically significant. For both user reactions, the indirect effects of the autonomy interaction and the variety interaction through TTF were significant, but the indirect effect of the identity interaction through TTF was not significant. For ease of use (user reaction), the indirect effect of the variety interaction through Too Little was not significant. For utilization, the indirect effect of the autonomy and variety interactions through TTF were significant, but the indirect effect of the identity interaction was not significant.

These results again suggest that the dynamics of TTF and TTM are nuanced when studying the three-dimensional conceptualization, but they also show that TTF and TTM serves as a mediator between the interaction of certain task and technology characteristics and outcomes. Further, as only one interaction was significant when accounting for TTF, the majority of these significant mediating effects were full mediations. Relatedly, the direct effects of only one task characteristic was significant in any analyses, whereas the direct effects of technology characteristics were only significant in two. In line with addressing the

Table 3
Regression Results of TTF, Too Little, and Too Much on Task Characteristics, Technology Characteristics, and Their Interaction.

	TTF – TTF Scale		TTF – TTF/M		Too Little – TTF/M		Too Much – TTF/M	
	B	t	B	t	B	t	B	t
Constant		21.448**		19.404**		4.906**		6.291**
1.) Task Autonomy	.136	.867	−.044	−.286	.095	.606	−.220	−1.422
2.) Tech Autonomy	.017	.117	.151	1.041	−.140	−.949	.285	1.967
3.) Interaction	.210	2.178*	.228	2.387*	−.158	−1.628	−.112	−1.171
ΔR^2 R^2	.04	.05	.04	.06	.02	.04	.01	.06
Constant		22.178**		19.887**		5.002**		6.996**
1.) Task Variety	.062	.451	.010	.074	−.036	−.247	−.031	−.217
2.) Tech Variety	.378	2.817**	.369	2.714**	−.208	−1.470	.187	1.347
3.) Interaction	.330	3.332**	.318	3.170**	−.222	−2.125*	−.118	−1.149
ΔR^2 R^2	.07	.15	.07	.12	.03	.05	.01	.08
Constant		22.088**		20.136**		5.068**		7.162**
1.) Task Significance	.230	1.273	.077	.424	−.091	−.512	−.047	−.260
2.) Tech Significance	−.208	−1.183	−.073	−.415	.143	.820	−.013	−.072
3.) Interaction	.157	1.736	.173	1.912	−.232	−2.595*	−.190	−2.121*
ΔR^2 R^2	.02	.04	.03	.04	.05	.06	.03	.06
Constant		21.686**		19.809**		5.051**		6.757**
1.) Task Identity	.214	1.298	.143	.854	.040	.235	−.242	−1.426
2.) Tech Identity	.170	1.043	.167	1.015	−.287	−1.720	.068	.405
3.) Interaction	.330	3.053**	.291	2.673**	−.212	−1.923	−.172	−1.560
ΔR^2 R^2	.07	.11	.05	.07	.03	.05	.02	.05
Constant		22.641**		20.621**		4.629**		6.481**
1.) Task Feedback	−.233	−1.562	−.187	−1.228	.159	1.044	−.263	−1.755
2.) Tech Feedback	.071	.464	.060	.386	−.079	−.507	.356	2.316*
3.) Interaction	.163	1.872	.097	1.095	−.145	−1.637	−.079	−.907
ΔR^2 R^2	.03	.07	.01	.04	.02	.04	.01	.07

Notes: ΔR^2 values represent the R^2 change from including the interaction term. R^2 values represent the final R^2 of the model. All analyses control for age and gender. * $p < .05$, ** $p < .01$.

Table 4
Regression Results of Task Characteristics, Technology Characteristics, Their Interaction, and TTF on User Reactions and Utilization.

	Relative Advantage – User Reactions			Ease of Use – User Reactions			Utilization		
	B	t	R^2	B	t	R^2	B	t	R^2
Constant		1.351			2.204*			2.460*	
1.) Task Autonomy	.071	.663		.215	1.825		−.011	−.084	
2.) Tech Autonomy	.205	2.003*		−.018	−.157		.217	1.770	
3.) Interaction	−.027	−.384		.183	2.369*		.063	.746	
4.) TTF – TTF/M	.597	6.993**		.476	5.059**		.563	5.505**	
5.) Too Little – TTF/M	−.138	−1.638		−.200	−2.163*		−.018	−.183	
6.) Too Much – TTF/M	−.055	−.862	.59	−.129	−1.829	.50	−.078	−1.018	.41
Constant		1.560			2.476*			2.616*	
1.) Task Variety	.017	.154		.127	1.110		.025	.199	
2.) Tech Variety	.169	1.531		.106	.905		.182	1.410	
3.) Interaction	−.062	−.749		−.003	−.034		.068	.699	
4.) TTF – TTF/M	.575	6.317**		.466	4.814**		.538	5.041**	
5.) Too Little – TTF/M	−.129	−1.479		−.190	−2.055*		−.013	−.125	
6.) Too Much – TTF/M	−.068	−1.003	.56	−.190	−2.648**	.51	−.083	−1.053	.40
Constant		1.078			1.855			2.295*	
1.) Task Significance	.104	.793		.103	.724		.107	.716	
2.) Tech Significance	.055	.435		−.112	−.808		.084	.577	
3.) Interaction	−.041	−.580		−.010	−.134		−.021	−.261	
4.) TTF – TTF/M	.607	6.878**		.515	5.373**		.591	5.863**	
5.) Too Little – TTF/M	−.149	−1.668		−.182	−1.885		−.029	−.290	
6.) Too Much – TTF/M	−.012	−.175	.55	−.142	−1.941	.47	−.051	−.668	.41
Constant		.958			1.907			2.170*	
1.) Task Identity	−.023	−.189		−.052	−.405		−.060	−.434	
2.) Tech Identity	.105	.879		.071	.565		.276	2.073*	
3.) Interaction	−.007	−.080		−.116	−1.351		.087	.963	
4.) TTF – TTF/M	.604	6.628**		.521	5.444**		.576	5.675**	
5.) Too Little – TTF/M	−.123	−1.351		−.184	−1.919		.011	.110	
6.) Too Much – TTF/M	−.011	−.156	.53	−.154	−2.132*	.48	−.052	−.678	.41
Constant		.747			1.642			2.041*	
1.) Task Feedback	.257	2.285*		.231	1.918		.051	.337	
2.) Tech Feedback	−.059	−.510		−.027	−.218		.052	.381	
3.) Interaction	−.047	−.707		.010	.142		.052	.663	
4.) TTF – TTF/M	.640	7.366**		.543	5.850**		.607	5.866**	
5.) Too Little – TTF/M	−.144	−1.652		−.193	−2.076*		−.006	−.056	
6.) Too Much – TTF/M	−.010	−.153	.57	−.139	−1.958	.50	−.054	−.682	.38

Note: All analyses control for age and gender. * $p < .05$, ** $p < .01$.

Table 5
Indirect Effects of Task and Technology Interaction Term through TTF, Too Little, and Too Much.

	1	Relative Advantage – User Reactions		2	Ease of Use – User Reactions		3	Utilization		4
		Effect (S.E.)	95% C.I.		Effect (S.E.)	95% C.I.		Effect (S.E.)	95% C.I.	
Autonomy Interaction										
1.) TTF	✓	.065 (.034)	.008 - .143*	✓	.052 (.027)	.004 - .114*	✓	.049 (.031)	.002 - .124*	✓
2.) Too Little		.008 (.010)	−.004 - .038		.012 (.014)	−.006 - .048	✓	.001 (.007)	−.009 - .022	
3.) Too Much		.004 (.007)	−.003 - .028		.010 (.011)	−.003 - .043		.005 (.007)	−.003 - .029	
Variety Interaction										
1.) TTF	✓	.072 (.027)	.031 - .144*	✓	.058 (.026)	.022 - .123*	✓	.053 (.022)	.017 - .108*	✓
2.) Too Little	✓	.010 (.001)	−.003 - .037		.015 (.011)	.001 - .049*	✓	.001 (.007)	−.015 - .016	
3.) Too Much		.004 (.006)	−.003 - .024		.012 (.009)	−.000 - .037	✓	.004 (.005)	−.001 - .020	
Significance Interaction										
1.) TTF		.037 (.030)	−.008 - .118	✓	.032 (.026)	−.014 - .087	✓	.029 (.024)	−.009 - .081	✓
2.) Too Little	✓	.012 (.010)	−.001 - .040		.015 (.012)	−.000 - .055		.002 (.008)	−.010 - .024	
3.) Too Much	✓	.001 (.007)	−.011 - .017		.014 (.009)	.001 - .037*		.004 (.006)	−.005 - .019	
Identity Interaction										
1.) TTF	✓	.062 (.041)	−.025 - .144	✓	.054 (.031)	−.011 - .121	✓	.047 (.032)	−.013 - .119	✓
2.) Too Little		.011 (.011)	−.005 - .042		.016 (.013)	−.002 - .052		−.001 (.008)	−.020 - .012	
3.) Too Much		.001 (.007)	−.011 - .019		.013 (.011)	−.006 - .040	✓	.003 (.006)	−.004 - .027	
Feedback Interaction										
1.) TTF		.012 (.026)	−.049 - .058	✓	.010 (.022)	−.033 - .055	✓	.009 (.020)	−.026 - .051	✓
2.) Too Little		.005 (.007)	−.004 - .025		.007 (.009)	−.004 - .032	✓	.000 (.005)	−.007 - .012	
3.) Too Much		.000 (.004)	−.006 - .011		.006 (.006)	−.002 - .023		.002 (.004)	−.003 - .013	

Note: Gender and age was included as a covariate in all analyses. * 95% CI does not include zero. Checkmark in column labeled 1 indicates that the interaction was significant in predicting TTF, Too Little, or Too Much (Table 3). Checkmark in column labeled 2 indicates that TTG, Too Little, or Too Much was significant in predicting Relative Advantage (Table 4) Checkmark in column labeled 3 indicates that TTG, Too Little, or Too Much was significant in predicting Ease of Use (Table 4) Checkmark in column labeled 4 indicates that TTG, Too Little, or Too Much was significant in predicting Utilization (Table 4).

final aspect of refinement for TTF theory (overemphasis of direct effects), these results suggest that the direct effects of task and technology characteristics may be unimportant when accounting for TTF, supporting the focus of the theory on interactive effects, and their indirect effects through TTF may be the largest influence on outcomes, again supporting the focus of the theory on the mediating effect of TTF. Finally, the results of Study 5 replicated those of Study 4 regarding the interrelationships of TTF and TTM and their relationships of outcomes.

23. Studystudy 6 – empirical study 2

Study 5 showed the need to study interactive effects when applying TTF theory, and it positioned our conceptualization of TTF and TTM into the broader theoretical framework. Although this study had several methodological benefits, such as its time-separated design, it also suffered the same weakness as all the other prior studies in the present article: a reliance on the survey design. In Study 6, the validity of the three-dimensional TTF conceptualization and its placement in the broader TTF framework is tested, again, through analyzing the following relationships: the effects of tasks and technologies on TTF and TTM, the effect of TTF and TTM on user reactions, the effect of TTF and TTM on performance, and the mediating effect of TTF and TTM between the impact of task and technology characteristics on user reactions and performance. In doing so, we apply an alternative methodology that is also important to TTF research, which is used when fit is conceptualized as matching [48].

Researchers are sometimes unable to test the interactive effect of tasks and technologies when applying TTF theory, such as the case of applying several technologies for a single task [24,78,79]. In these instances, the technology that facilitates best is often claimed to have the best fit, but such inferences may be misleading. It is possible that the best-performing technology is simply better than the other technologies, and this technology would outperform the others across any task. For instance, a high-resolution computer monitor may be more effective than a blurry monitor to perform any task, but this does not necessarily mean that the technology fits better with the tasks. In this case, the results would not be due to TTF or TTM. In all applications of TTF theory, but particularly when multiple technologies are applied for a single task, it is important to show that TTF and/or TTM indeed mediate the relationship between technologies and outcomes. Further, theoretical justification should be provided for the fit of technologies with the task when using this method. Authors should clearly identify the features of technologies that reduce performance if they were increased or decreased. In Study 6, we apply several technologies for a single task to further support our conceptualization of TTF, and we show the importance of these two suggestions.

It should also be highlighted that this methodological design aligns with the matching approach to fit [47,48], such that technologies are matched with specific tasks to identify fit. Therefore, Study 5 tests the relationships of the TTF and TTF/M scales with fit as measured by the moderation approach, and Study 6 tests these relationships with fit as measured by the matching approach.

24. Participants

Study 6 included 77 participants (M_{age} = 19.30, SD_{age} = 2.30; 68% female; 79% Caucasian) recruited from a student participant pool in return for course credit.

25. Measures

25.1. TTF and TTF/M scales

The TTF and TTF/M scales were administered in Study 6.

25.2. User reactions

Two separate scales were used to gauge user reactions. Because the context of Study 6 was a training program, as described below, the Howardson and Behrend [80] trainee reaction scale was used as an indicator of user reactions. This scale consists of four dimensions that can be averaged to obtain an overall score. Items were slightly reworded to better fit the study, changing instances of the word “training” to “task.” An example item is “The task was fascinating”. Also, a 12-item scale was created for the present study to gauge perceived learning. An example item is “I was successful at learning from the presentation."

25.3. Performance

Typically, the primary objective of training programs is education and development. For this reason, the primary indicator of performance in Study 6 was learning, gauged by a 30 item post-test. Each item on the post-test had four possible answers, with only one correct answer. Scores were calculated as the total number of correct answers.

25.4. Procedure

All procedures for Study 6 occurred in a lab setting. Upon arrival, participants completed a prequestionnaire of demographic characteristics. Then, they watched (or listened) to an educational presentation via a computer, meant to represent an education or training experience. The conditions varied the computer program that was used. In the Audio Condition, participants only listed to the audio from the presentation. In the Video Condition, participants watched a video recording of the presentation. In the Theatre Condition, the participants used a program that replicated a digital movie theatre. Participants controlled an avatar, and were instructed to take a seat in the movie theatre. They were also told how to start the presentation, which played on the projector screen, and they could walk around the theatre room after the presentation started (if they chose to do so). After watching (or listening) the presentation, participants completed a postquestionnaire of user reactions followed by a posttest to gauge learning.

A further note should be made about the conditions. To study TTF by the applications of various technologies on a single task, a careful consideration must be given towards the relative fit of these technologies. The task, learning from a presentation, would benefit from the addition of visual information, as learners would be able to clarify concepts via concrete visual images. For this reason, the condition without visual information is considered Poor Fit (Too Little), whereas the condition that includes video of the presentation is considered TTF. Further, adding additional unnecessary visual information is detrimental, as users may become distracted, causing the digital movie theatre condition to also be considered Poor Fit (Too Much). Thus, Study 6 investigates TTF through manipulating various levels of visual information and gauging its impact on learning. The effectiveness of the visual information is believed to be due to fit, because a "sweet spot" must be reached for the visual information to have a positive effect on learning. This approach is in agreement with the matching approach to identifying fit.

26. Results and discussion

Table 6 presents correlations and Cronbach's alphas of all measures. All analyses, aside from basic correlations, controlled for age and gender. The two measures of TTF were significantly and positively related to both user reactions, and Too Little was significantly and negatively related to both user reactions. Too Much, however, was not related to either user reaction. Once again, these results agree with the prior results. Also, the two measures of TTF were significantly and positively related to Post-Test Scores (*TTF Scale* $r = .26, p < .05$; *TTF/M Scale* $r = .25, p < .05$) but Too Little ($r = -.18, p > .05$) and Too Much ($r = .07, p > .05$) were not. This result may suggest that TTF is a more proximal influence on actual performance, whereas Too Much and Too Little may be more distal.

Table 6
Correlations of Measures Administered in Study 6.

	1	2	3	4	5	6	7
1.) TTF – TTF Scale	.97						
2.) TTF - TTF/M	.93**	.97					
3.) Too Little - TTF/M	−.71**	−.71**	.98				
4.) Too Much - TTF/M	−.14	−.13	−.28*	.97			
5.) User Reactions	.45**	.42**	−.25*	−.06	.89		
6.) Perceived Learning	.37**	.34**	−.27*	.05	.77**	.97	
7.) Posttest Score	.26*	.25*	−.18	.07	.58**	.63**	.73

Cronbach's alphas included on diagonal. * p < .05, ** p < .01 (two tailed).

Multiple ANCOVAs tested the differences between the conditions while controlling for age and gender (Table 7). TTF was significantly greater in the Video Condition (*TTF Estimated Marginal Mean [EMM]* = 6.36; *TTF/M EMM* = 6.33) than the Audio (*TTF EMM* = 3.92; *TTF/M EMM* = 3.99) and Theatre Conditions (*TTF EMM* = 5.01, *TTF/M EMM* = 5.00); Too Little was significantly greater in the Audio Condition (*EMM* = 4.70) than Video (*EMM* = 1.78) and Theatre Conditions (*EMM* = 1.89); and Too Much was significantly greater in the Theatre Condition (*EMM* = 4.49) than the Audio (*EMM* = 2.30) and Video Conditions (*EMM* = 2.18). These results show that the TTF and TTF/M scales are able to gauge TTF and TTM as intended in a lab setting.

To test whether TTF mediated the relationships between the conditions and outcomes, Hayes's (2013) PROCESS macro was used. In all analyses, the conditions were dummy-coded, and the Video Condition was always the reference group (coded as 0; Table 8). We again use the procedure outlined by Preacher and Hayes [75] and MacKinnon [76].

The mediation of TTF, Too Little, and Too Much was tested between the three conditions and user reactions. When accounting for fit, the dummy codes of the Video and Audio Conditions (t = -.931, *95% CI* = -1.027 – .374) and Video and Theatre Conditions (t = -.507, *95% CI* = -.789 – .469) were not significant. The omnibus indirect effect through TTF was significant, but the omnibus indirect effects through Too Little and Too Much were not significant. Next, the mediation of TTF, Too Little, and Too Much was tested between the relationship of the three conditions and perceived learning. When accounting for fit, the dummy codes representing the difference of the Video and Audio Conditions (t = -2.397, *95% CI* = -2.127 – -.194) and Video and Theatre Conditions (t = -2.357, *95% CI* = -1.893 – -.157) were still significant. The omnibus indirect effect through TTF was significant, but the omnibus indirect effect through Too Little and Too Much was not significant. These results suggest that TTF mediates the effect of tasks and technologies on user reactions, but it is unclear whether this mediation is full or partial. Too Little and Too Much do not seem to have a mediating effect.

The mediation of TTF, Too Little, and Too Much was tested between the three conditions and posttest scores. When accounting for TTF, the dummy codes representing the difference of the Video and Audio Conditions (t = -3.266, *95% CI* = -.282 – -.068) and the Video and Theatre Conditions (t = -2.034, *95% CI* = −.194 to −.002) were significant. The omnibus indirect effect through TTF was significant; the omnibus indirect effect through Too Little was significant; and the omnibus indirect effect through Too Much was also extremely close to significance. These results suggest that the three dimensions partially mediate the effect of tasks and technologies on performance, and each of the three dimensions may play a role. Together, these results replicate the results of both Studies 4 and 5.

27. Overall discussion

The goal of the present article was to refine or extend four aspects of TTF theory. The first, concerning problematic conceptualizations, was addressed in our review by theoretically placing TTF in the broader nomological net of related constructs, and emphasizing its placement in six subsequent studies. The second, concerning problematic operationalizations of TTF, was addressed through a four-study process that created the satisfactory TTF and the TTF/M scales. The third, a sole focus on TTF, was addressed through differentiating TTM from TTF and distinguishing Too Little and Too Much. The scale creation process likewise provided clear empirical support for this three-dimensional conceptualization. The fourth, a large focus on direct effects of task and

Table 7
ANCOVA Results of Three Conditions in Study 6.

Outcome	Audio Condition	Video Condition	Theatre Condition	F-Value
1.) TTF – TTF Scale	$3.92^{V,T}$	$6.36^{A,T}$	$5.01^{A,V}$	11.158**
2.) TTF – TTF/M	3.99^{V}	$6.33^{A,T}$	5.00^{V}	9.969**
3.) Too Little - TTF/M	$4.70^{V,T}$	1.78^{A}	1.89^{A}	19.453**
4.) Too Much - TTF/M	2.30^{T}	2.18^{T}	$4.49^{A,V}$	9.366**
5.) User Reactions	4.27^{V}	4.97^{A}	4.48	2.987*
6.) Perceived Learning	3.34^{V}	$4.76^{A,T}$	3.80^{V}	5.175**
7.) Posttest Score	$.48^{V}$	$64^{A,T}$	$.54^{V}$	6.747**

Note: Results are presented as estimated marginal means controlling for age and gender.
Superscripts represent significant mean group differences with a Bonferroni adjustment ($p < .05$).
A = Significant difference with Audio Condition.
V = Significant difference with Video Condition.
T = Significant difference with Theatre Condition.
* $p < .05$, ** $p < .01$.

technologies on TTF, was addressed through two empirical studies that studied the interactive and matching effects of task and technologies as well as the mediating effect of TTF. These studies showed that task and technology characteristics have joint effects that predict TTF, TTF effectively predicts user reactions, utilization, and performance, as well as TTF mediates the influence of task and technology characteristics on these outcomes. In analyzing these relations, the two empirical studies integrated the three-dimensional conceptualization of TTF into the TTF framework, providing further support for its validity. Fig. 3 presents the cumulative findings of all studies. As discussed below, these results have several theoretical and methodological implications for research and practice.

28. Conceptual implications

The present article has several implications for the conceptualization of TTF itself, and these implications are centered on refocusing the construct. As mentioned, many authors have conflated their conceptualization of TTF with other constructs, such as utility and utilization [14,16]. From our efforts, the conceptualization of TTF should now be more consistent across all future research, and it should clearly describe a property that arises from tasks and technologies – not a property of one or the other. Likewise, the creation of the TTF and the TTF/M scales should further solidify the conceptualization of TTF as well as its operationalization. No longer should authors apply measures that contain items akin to "The technology is fun" or "The technology is useful," that clearly gauge user reactions or utility. Now, all future research on TTF should accurately gauge the construct.

In addition to refocusing the construct, we also provide a broader scope of TTF. A sole focus of TTF can be seen in almost all prior research applying TTF theory [7,98]. We clearly show the importance of studying and differentiating the types of TTM, Too Little and Too Much, as these had very different relationships with antecedents and outcomes compared to TTF alone. In addition to providing a better understanding of TTF, our attention to TTM may also spark new types of TTF research. As mentioned, most experimental studies on TTF investigate a technology and an upgraded technology, which approaches the construct from a TTF perspective. A new method may be to study the abilities of a technology and a reduced technology, which would approach the construct from a TTM perspective. As the dynamics of TTM are different from TTF, comparisons between a technology and a reduced technology may provide different inferences than comparisons between a technology and an upgraded technology. These novel investigations may provide a deeper understanding of TTM, but they may also provide a deeper understanding of TTF altogether.

In broadening the scope of TTF, it is necessary to discuss some of the unexpected findings of the present studies – most notably the null relationships of TTM. The relationship of Too Little and Too Much was nonsignificant across most of the studies, suggesting that users may perceive technologies as having both too many features but also not the necessary features to achieve the specified task. Also, Too Much had a nonsignificant relationship with all outcomes across the studies. This suggests that users may still perceive the technology as being acceptable and use it to perform their necessary tasks even when the technology includes too many features. This finding further emphasizes the need to distinguish different types of TTM. Because Too Little and Too Much had very different relationships with other variables, it is essential that authors distinguish both in their conceptual models and associated theories.

Beyond the construct of TTF, the present article also has several implications for TTF theory. While TTF theory is popular and has led to several important discoveries, many authors have attributed too many observed relationships to the theory [81,18,20]. For example, many studies have suggested that certain technologies or tasks directly influence performance independently of any interactive effects, and TTF theory is often applied to explain these direct effects. These studies also do not position the technology in the context of a certain task (or tasks in the context of certain technologies), as done in Study 6. Certain aspects of technologies or task are almost certain to have a direct effect on outcomes; however, these relationships are not due to TTF, and they cannot be explained by TTF theory. Direct effects do not reflect a property that arises from tasks and technologies. Instead, other theories should be applied to understand these direct effects, and methodologies similar to Studies 5 and 6 should be applied to understand TTF.

When applying methodologies similar to these studies, it is also important to ensure that TTF serves as a mediator between any interactive effects between tasks and technologies. A benefit of TTF theory is that it is among the few theories that describes the causes of improved

Table 8
Omnibus Indirect Effects, Standard Errors, and Confidence Intervals of Condition Dummy Codes through TTF, Too Little, and Too Much.

Outcome	TTF	Too Little	Too Much
1.) User Reactions	.091 (.046) .033 - .213*	.053 (.063) -.060 - .197	.006 (.025) -.038 - .065
2.) Perceived Learning	.076 (.053) .002 - .211*	.068 (.077) -.079 - .233	.048 (.038) -.003 - .157
3.) Posttest Score	.009 (.006) .001 - .022*	.014 (.009) .000 - .036*	.004 (.004) -.002 - .016

Note: Gender and age was included as a covariate in all analyses. * 95% CI does not include zero.

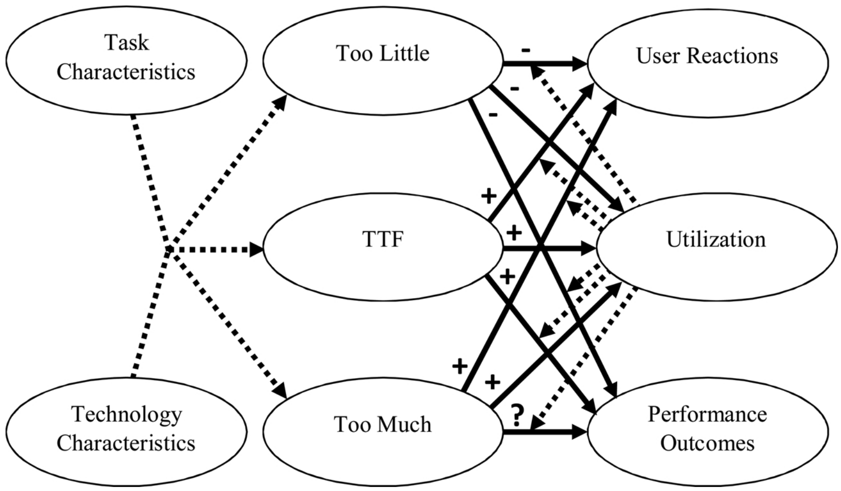

Fig. 2. New Visual Representation of TTF Theory.

outcomes from technologies in certain contexts. This also means that interactive effects between tasks and technologies may also affect outcomes through mechanisms that are yet to be identified. By attributing all effects to TTF, the effects of the construct may be exaggerated.

In addition to clarifying TTF theory, the present article also provides implications for broadening the theory. Through including TTM into the TTF framework, the theory becomes more complex with many new relationships added (Fig. 2). As such, further consideration should be given to a greater number of effects when applying TTF theory, and these relationships may be further explored by integrating TTF theory with other theoretical perspectives – as further discussed in the future directions section below.

The present article also provides important implications for measurement. Not only did prior TTF measures have questionable psychometric properties and validity, but there were few that were repeatedly used. Now that two psychometrically sound and valid measures exist, the TTF and the TTF/M scales, future research can progress more accurately and consistently.

It should be highlighted that, while theses scales gauge TTF and TTM, they do not replace certain other approaches to identify fit. Cane and McCarthy [48] discuss six different approaches to identifying fit aside from direct self-report scale. While the new scales showed theoretically supported relationships with fit as identified by two such approaches (moderation and matching), and it is believed that the scales would likewise show similar relationships to the other four approaches, these other approaches may gauge certain aspects of fit that cannot easily be identified via self-report. Simultaneously, however, self-report scales may gauge certain aspects of fit that are difficult to identify via these other approaches. For example, the TTF and TTF/M scales may gauge a holistic operationalization of fit, whereas the moderation approach tends to gauge fit in a dimensional operationalization that is specific to the tasks and technologies being studied, such that aspects of these tasks and technologies are identified a priori [48]. Therefore, future research should still test the relationships of fit as identified by these other approaches alongside the newly created scales.

29. Practical implications

In addition to conceptual implications, the present article provides several practical implications. The strengthened consistency and accuracy of our conceptualization of TTF, and consequently utilization and utility, can be used to enhance the design and adoption of technologies in business environments. Prior studies applying TTF theory have proposed similar implications, suggesting that a better understanding of TTF could help practitioners develop technologies with stronger fit [26], encourage the utilization of electronic technologies [99,40,81], aid the management of common computing resources and technologies [100,4]), and improve employee and organizational performance [102,103,11]. Regarding performance improvements, an improved

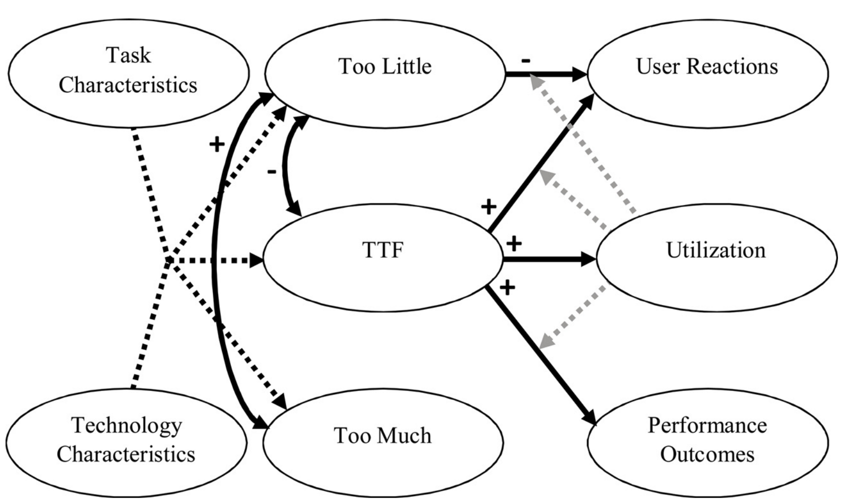

Fig. 3. Observed Results of All Current Studies.

understanding of TTF could also guide practitioners to pair emergent technologies with appropriate tasks [25,45,101,4,82], such as the use of virtual reality for training and development purposes [83,84]. These findings may also apply beyond individual employees in work settings, such as understanding team performance in virtual settings as well ([24,42,28]). For instance, practitioners could identify whether communication software can be Too Much; a video-chat software allow effective communications, but a virtual reality software may produce TTM.

A consistent comprehension of TTF theory could also aid organizations in discovering opportunities to improve their business procedures. For instance, many modern organizations provide their services entirely through digital platforms, such as social networking sites [11], mobile banking [63] , online auctions [102], and general e-commerce [103]. Designing these technologies to better fit with customers' online tasks may improve customer reactions, continuance intentions, and ultimately business success. For instance, pictures may provide appropriate richness to determine whether to buy certain products online, whereas video of the product may produce a Too Much effect (e.g., clothing; beauty products, goods with well-known features and/or uses); in other cases, pictures may produce a Too Little effect, whereas video may provide an appropriate amount of richness (e.g., video games; new kitchen utensils; goods with unfamiliar features and/or uses). Companies should consider these implications when implementing technologies for both employees and customers, as TTF may have a strong impact on adoption, performance, and business success.

30. Future directions

Several future directions should likewise be noted. Of most importance, several previous findings should be retested using the TTF and the TTF/M scales. As mentioned, many prior studies used TTF measures that may partially gauge utility or other constructs ([13,49]; Lam et al., 2007). Any inferences derived from these measures are misleading. Particularly, these measures inflated the observed relationship between TTF and other constructs that contaminated these measures. Although we believe that TTF leads to many important outcomes, the strength of these relationships may be smaller than expected when retested with the psychometrically sound and valid measures created in the present article.

We investigated the primary tenants of TTF theory, but several of its aspects remain largely untested. For example, few – if any – studies have firmly shown that utilization actually moderates the relationship between TTF and performance. Similarly, little research has investigated any further mediators in the overall TTF model, such as possible mediators between TTF and performance outcomes. It is possible that constructs outside the typical boundaries of TTF theory may explain these relationships, such as flow [85].

Similarly, it should likewise be highlighted that the current findings are believed to be consistent across the different methods to identify fit [47,48]. In Study 5, fit was identified via the moderation approach by testing the interaction of task and technology characteristics' relationship with the TTF/M scale. In Study 6, fit was identified via the matching approach by testing the relationship of individually-selected technologies for a specific task with the TTF/M scale. Results were consistent across both studies, and these two methods were selected due to their widespread precedence in prior research on TTF theory. Nevertheless, at least four other methods to identify fit exist, and future research should likewise investigate these other methods. For example, the most ideal technology profile could be identified for certain tasks, and fit could be identified as deviations from this ideal profile. Then, the relationships of these deviations could be analyzed alongside the TTF/M scale. This approach coincides with the profile deviation method for identifying fit, and could provide novel insights into the relationship of tasks, technologies, and TTF/M.

In addition to studying the central tenants of TTF theory, future research should look toward expanding the theory. Recent authors have broadened the scope of the TTF framework to include user characteristics, such as prior experience [4–6,11]. These user characteristics have yet to be integrated with TTF theory itself, as few authors have explicitly provided theoretical justification for the influence of personal characteristics in conjunction with TTF, but user characteristics may predict important outcomes, such as performance, when studied alongside TTF. While we did not study user characteristics, their importance for future research and practice is nevertheless recognized.

Some authors have suggested that TTF may be best studied from a multilevel perspective [24,86]. Technologies are often applied in organizations from a top-down approach, and entire work-units are often expected to implement a technology together [87,88]. It may be appropriate to conceptualize technology as a unit-level construct, tasks as an individual-level constructs, and employee performance as an individual-level construct. Of course, every workplace differs, and some workplaces may have few employees using the same technologies. Therefore, the appropriateness of using a multi-level perspective may depend on the context.

Also, a recent trend in TTF research is to integrate several theoretical perspectives into a single model [6,27,89], and several theories seem apt for integrating with TTF theory, such as MST [1], the TAM [33], and Media Richness Theory [31]. As our studies showed, TTF only partially mediated the relationships of tasks and technologies with outcomes. These other theories suggest direct effects of tasks and technologies on outcomes, possibly explaining certain effects that TTF cannot explain. Through integrating these theories with TTF theory, all relationships of tasks and technologies can be understood – whether direct effects or interactions. Thus, integrating other theories with TTF theory may be a fruitful if not necessary endeavor for future research.

A particularly fruitful integration, which is easier due to the current series of studies, may be the future study of TTF theory alongside Expectancy Disconfirmation Theory (EDT; [30,90,91]). EDT suggests that technology performance can result as expected (confirmation), performance can be better than expected (positive disconfirmation), and performance can be worse than expected (negative disconfirmation). While the current conceptualization of TTM does not directly align with these three perspectives, it does bring TTF theory closer to EDT. Particularly, TTF may represent both confirmation and positive disconfirmation, whereas TTM may represent negative disconfirmation. If true, then prior findings on EDT may be generalized to research and theory regarding TTF – and vice versa. Of course, future research is needed before this notion can be supported.

Certain limitations of the present article should be noted that can be addressed in future research. Both scales were created to be general measures of TTF. Many authors, however, have created TTF conceptualizations that include many specific dimensions [25,26]. We did not create a scale to gauge specific dimensions for multiple reasons. Primarily, these dimensions suffer from the same concern as many prior TTF scales – they describe utility rather than TTF. Also, our scales were created to be applicable for most any task and technology. TTF scales with many specific dimensions are often limited in their possible applications, and they are created for a specific set of jobs. The general nature of the TTF scale and the TTF/M scale is not detrimental.

We chose the standard regression approach to testing for moderation due to suggestions of prior authors and related simulations supporting its accuracy (Busse et al., 2017; Dawson, 2014). While structural equation modeling (SEM) provides certain benefits beyond regression (e.g., modeling latent factors), much is still debated regarding tests of moderation using SEM – the most notable being whether SEM provides more accurate estimates than regression (Busse et al., 2017; Dawson, 2014; Kline, 2010). Because we provided appropriate psychometric evidence regarding the new measures, we were more interested in the direct and moderated effects alone in Studies 5 and 6. Therefore, we opted for the traditional regression approach.

Finally, Study 5 applied a four-wave, time-separated research design. This design alleviates concerns with common-method bias, allowing for more accurate observations of the tested relationships [92,93]. This design also provides stronger support for casual relationships than cross-sectional designs, as a temporal separation can be observed between measurement occasions and the directionality of effects can be better supported [94]. It should be noted, however, that other research designs are more apt at supporting causality. Future research should replicate the current results via these research designs, such as panel studies and/or time-separated studies with a longer temporal separation between measurement occasions. While we believe that the temporal separation between measurement occasions in Study 5 was sufficient to observe the directional effects of TTF and TTM, as their effects are believed to occur almost immediately [24,95,96], it is indeed possible that longer measurement occasions are needed. Similarly, we also urge further researchers to apply experimental designs, akin to Study 6, to also provide support for casual effects regarding TTF and TTM.

31. Conclusion

In the present article, we noted four aspects of TTF theory in need of refinement or extension. These aspects included concerns with the conceptualization and operationalization of TTF as well as the application of TTF theory itself. Through a six-study process, we addressed these aspects through creating two new TTF measures and positing a three-dimensional conceptualization of TTF into the broader TTF theory framework. Together, these efforts will allow future research to progress more quickly, efficiently, and accurately.

Appendix A. Supplementary data

Supplementary material related to this article can be found, in the online version, at doi:https://doi.org/10.1016/j.im.2018.12.002.

References

[1] A.R. Dennis, R.M. Fuller, J.S. Valacich, Media, tasks, and communication processes: a theory of media synchronicity, MIS Q. 32 (3) (2008) 575–600.
[2] W.S. Lin, Perceived fit and satisfaction on web learning performance: IS continuance intention and task-technology fit perspectives, Int. J. Hum. Comput. Stud. 70 (7) (2012) 498–507.
[3] SHRM Foundation, What's next: future global trends affecting your organization, Evolution of Work and the Worker, (2014) http://whitepaper-admin.eiu.com/futurehrtrends/wp-content/uploads/sites/2/2015/03/6-14-EIU-Report-Web.pdf.
[4] S. Chung, K.Y. Lee, J. Choi, Exploring digital creativity in the workspace: the role of enterprise mobile applications on perceived job performance and creativity, Comput. Hum. Behav. 42 (2015) 93–109.
[5] G. Im, Effects of cognitive and social factors on system utilization and performance outcomes, Inf. Manage. 51 (1) (2014) 129–137.
[6] D.Y. Lee, M.R. Lehto, User acceptance of YouTube for procedural learning: an extension of the technology acceptance model, Comput. Educ. 61 (2013) 193–208.
[7] B. Furneaux, Task-technology fit theory: a survey and synopsis of the literature, Information Systems Theory, Springer, New York, 2012, pp. 87–106.
[8] I. Zigurs, B.K. Buckland, A theory of task/technology fit and group support systems effectiveness, MIS Q. (1998) 313–334.
[9] I. Zigurs, D. Khazanchi, From profiles to patterns: a new view of task-technology fit, Inf. Syst. Manage. 25 (1) (2008) 8–13.
[10] R.Z. Kuo, M.F. Lai, G.G. Lee, The impact of empowering leadership for KMS adoption, Manage. Decision 49 (7) (2011) 1120–1140.
[11] H.P. Lu, Y.W. Yang, Toward an understanding of the behavioral intention to use a social networking site: an extension of task-technology fit to social-technology fit, Comput. Hum. Behav. 34 (2014) 323–332.
[12] J.H. Wu, Y.C. Chen, L.M. Lin, Empirical evaluation of the revised end user computing acceptance model, Comput. Hum. Behav. 23 (1) (2007) 162–174.
[13] J. D'Ambra, C.S. Wilson, Use of the world wide web for international travel: integrating the construct of uncertainty in information seeking and the task-technology fit (TTF) model, J. Am. Soc. Inf. Sci. Technol. 55 (8) (2004) 731–742.
[14] R.Z. Kuo, G.G. Lee, Knowledge management system adoption: exploring the effects of empowering leadership, task-technology fit and compatibility, Behav. Inf. Technol. 30 (1) (2011) 113–129.
[15] C.C. Lee, H.K. Cheng, H.H. Cheng, An empirical study of mobile commerce in insurance industry: Task–technology fit and individual differences, Decision Supp. Syst. 43 (1) (2007) 95–110.
[16] J.C. Pai, F.M. Tu, The acceptance and use of customer relationship management (CRM) systems: an empirical study of distribution service industry in Taiwan, Expert Syst. Appl. 38 (1) (2011) 579–584.
[17] M. Pagani, Determinants of adoption of high speed data services in the business market: evidence for a combined technology acceptance model with task technology fit model, Inf. Manage. 43 (7) (2006) 847–860.
[18] Y.Y. Shih, C.Y. Chen, The study of behavioral intention for mobile commerce: via integrated model of TAM and TTF, Qual. Q. 47 (2) (2013) 1009–1020.
[19] D.M. Strong, M.T. Dishaw, D.B. Bandy, Extending task technology fit with computer self-efficacy, ACM SIGMIS Database 37 (2-3) (2006) 96–107.
[20] A. Usoro, S. Shoyelu, M. Kuofie, Task-technology fit and technology acceptance models applicability to e-tourism, J. Econ. Dev. Manage. IT Finance Marketing 2 (1) (2010) 1.
[21] T.J. Larsen, A.M. Sørebø, Ø. Sørebø, The role of task-technology fit as users' motivation to continue information system use, Comput. Hum. Behav. 25 (3) (2009) 778–784.
[22] T.C. Lin, C.C. Huang, Understanding knowledge management system usage antecedents: an integration of social cognitive theory and task technology fit, Inf. Manage. 45 (6) (2008) 410–417.
[23] M. Norzaidi, S. Choy Chong, M. Salwani, Perceived resistance, user resistance and managers' performance in the Malaysian port industry, Aslib Proceedings 6 (3) (2008) 242–264.
[24] R. Fuller, A. Dennis, Does fit matter? Impact of task-technology fit and appropriation on team performance in repeated tasks, Inf. Syst. Res. 20 (1) (2009) 2–17.
[25] R.E. Ioimo, J.E. Aronson, Police field mobile computing: applying the theory of task-technology fit, Police Q. 7 (4) (2004) 403–428.
[26] D. Kim, T. Ammeter, Predicting personal information system adoption using an integrated diffusion model, Inf. Manage. 51 (4) (2014) 451–464.
[27] W. Lin, C. Wang, Antecedences to continued intentions of adopting e-learning system in blended learning instruction: contingency framework based on models of information system success and task-technology fit, Comput. Educ. 58 (1) (2012) 88–99.
[28] R. Rico, D. Bachrach, M. Sánchez-Manzanares, B. Collins, The interactive effects of person-focused citizenship behaviour, task interdependence, and virtuality on team performance, Eur. J. Work Org. Psychol. 20 (5) (2011) 700–726.
[29] D.L. Goodhue, R.L. Thompson, Task-technology fit and individual performance, MIS Q. (1995) 213–236.
[30] R.L. Oliver, A cognitive model of the antecedents and consequences of satisfaction decisions, J. Marketing Res. 17 (4) (1980) 460–469.
[31] A. Dennis, S. Kinney, Testing media richness theory in the new media: the effects of cues, feedback, and task equivocality, Inf. Syst. Res. 9 (3) (1998) 256–274.
[32] K. Mathieson, Predicting user intentions: comparing the technology acceptance model with the theory of planned behavior, Inf. Syst. Res. 2 (3) (1991) 173–191.
[33] V. Venkatesh, F.D. Davis, A theoretical extension of the technology acceptance model: Four longitudinal field studies, Manage. Sci. 46 (2) (2000) 186–204.
[34] M.L. Heine, V. Grover, M.K. Malhotra, The relationship between technology and performance: a meta-analysis of technology models, Omega 31 (3) (2003) 189–204.
[35] M. Karavdic, G. Gregory, Integrating e-commerce into existing export marketing theories: a contingency model, Marketing Theory 5 (1) (2005) 75–104.
[36] P. Pelzer, G. Arciniegas, S. Geertman, S. Lenferink, Planning support systems and task-technology fit: a comparative case study, Appl. Spatial Anal. Policy 8 (2) (2015) 155–175.
[37] T.S. Teo, B. Men, Knowledge portals in Chinese consulting firms: a task–technology fit perspective, Eur. J. Inf. Syst. 17 (6) (2008) 557–574.
[38] A.F. Hayes, Beyond Baron and Kenny: statistical mediation analysis in the new millennium, Commun. Monographs 76 (4) (2009) 408–420.
[39] A.F. Hayes, Introduction to Mediation, Moderation, and Conditional Process Analysis: A Regression-Based Approach, Guilford Press, 2013.
[40] N. Gerhart, D.A. Peak, V.R. Prybutok, Searching for New answers: the application of task-technology fit to E-Textbook usage, Decision Sci. J. Innov. Educ. 13 (1) (2015) 91–111.
[41] F. Calefato, D. Damian, F. Lanubile, August. An empirical investigation on text-based communication in distributed requirements workshops, International Conference on Global Software Engineering (ICGSE 2007), (2007), pp. 3–11 IEEE.
[42] D.S. Kerr, U.S. Murthy, Divergent and convergent idea generation in teams: a comparison of computer-mediated and face-to-face communication, Group Decision Negotiation 13 (4) (2004) 381–399.
[43] Z. Zhou, G. Li, T. Lam, The role of task-fit in employees' adoption of IT in Chinese hotels, J. Hum. Resour. Hospit. Tourism 8 (1) (2008) 96–105.
[44] A. Hayashi, C.C. Chen, H. Terase, Aligning IT skills training with online asynchronous learning multimedia technologies, Inf. Syst. Educ. J. (ISEDJ) 3 (26) (2005) 3–10.
[45] R.E. Ioimo, J.E. Aronson, The benefits of police field mobile computing realized by non-patrol sections of a police department, Int. J. Police Sci. Manage. 5 (3) (2003) 195–206.
[46] M. Maity, M. Dass, Consumer decision-making across modern and traditional channels: E-commerce, m-commerce, in-store, Decision Supp. Syst. 61 (2014) 34–46.
[47] N. Venkatraman, The concept of fit in strategy research: toward verbal and statistical correspondence, Acad. Manage. Rev. 14 (3) (1989) 423–444.
[48] S. Cane, R. McCarthy, Analyzing the factors that affect information systems use: task-technology fit meta-analysis, J. Comput. Inf. Syst. 50 (1) (2009) 108–123.
[49] J. D'Ambra, C.S. Wilson, Explaining perceived performance of the world Wide web: uncertainty and the task-technology fit model, Internet Res. 14 (4) (2004) 294–310.
[50] A. Bandura, On the functional properties of perceived self-efficacy revisited, J. Manage. 38 (1) (2012) 9–44.

[51] M.C. Howard, Creation of a computer self-efficacy measure: analysis of internal consistency, psychometric properties, and validity, Cyberpsychol. Behav. Soc. Network. 17 (10) (2014) 677–681.
[52] A.B. Costello, J.W. Osborne, Best practices in exploratory factor analysis: Four recommendations for getting the most from your analysis, Pract. Assessment Res. Eval. 10 (7) (2005) 1–9.
[53] T.R. Hinkin, A review of scale development practices in the study of organizations, J. Manage. 21 (5) (1995) 967–988.
[54] T.R. Hinkin, A brief tutorial on the development of measures for use in survey questionnaires, Organ. Res. Methods 1 (1) (1998) 104–121.
[55] M.C. Howard, A review of exploratory factor analysis (EFA) decisions and overview of current practices: what we are doing and how can we improve? Int. J. Hum.-Comput. Interact. 32 (1) (2016) 51–62.
[56] M.C. Howard, R.C. Melloy, Evaluating item-sort task methods: the presentation of a new statistical significance formula and methodological best practices, J. Bus. Psychol. 31 (1) (2016) 173–186.
[57] J. Anderson, D. Gerbing, Predicting the performance of measures in a confirmatory factor analysis with a pretest assessment of their substantive validities, J. Appl. Psychol. 76 (5) (1991) 732.
[58] M.C. Howard, Scale pretesting, Pract. Assessment Res. Eval. 23 (5) (2017) 1–14.
[59] M. Buhrmester, T. Kwang, S.D. Gosling, Amazon's mechanical Turk a new source of inexpensive, yet high-quality, data? Perspect. Psychol. Sci. 6 (1) (2011) 3–5.
[60] G. Paolacci, J. Chandler, Inside the turk understanding mechanical turk as a participant pool, Curr. Directions Psychol. Sci. 23 (3) (2014) 184–188.
[61] D.N. Shapiro, J. Chandler, P.A. Mueller, Using mechanical Turk to study clinical populations, Clin. Psychol. Sci. (2013) 2167702612469015.
[62] D.C. Yen, C.S. Wu, F.F. Cheng, Y.W. Huang, Determinants of users' intention to adopt wireless technology: an empirical study by integrating TTF with TAM, Comput. Hum. Behav. 26 (5) (2010) 906–915.
[63] T. Zhou, Y. Lu, B. Wang, Integrating TTF and UTAUT to explain mobile banking user adoption, Comput. Hum. Behav. 26 (4) (2010) 760–767.
[64] L.R. Fabrigar, D.T. Wegener, Exploratory Factor Analysis, Oxford University Press, 2011.
[65] T.A. Brown, Confirmatory Factor Analysis for Applied Research, Guilford Publications, 2015.
[66] B. Thompson, Exploratory and Confirmatory Factor Analysis: Understanding Concepts and Applications, American Psychological Association, 2004.
[67] D. Hooper, J. Coughlan, M. Mullen, Structural equation modeling: guidelines for determining model fit, Electron. J. Bus. Res. Methods 6 (1) (2008) 53–60.
[68] S. Sharma, S. Mukherjee, A. Kumar, W.R. Dillon, A simulation study to investigate the use of cutoff values for assessing model fit in covariance structure models, J. Bus. Res. 58 (7) (2005) 935–943.
[69] D. Kenny, Measuring Model Fit, Retrieved from (2015) http://davidakenny.net/cm/fit.htm.
[70] M. Grossman, J.E. Aronson, R.V. McCarthy, Does UML make the grade? Insights from the software development community, Inf. Software Technol. 47 (6) (2005) 383–397.
[71] F.P. Morgeson, S.E. Humphrey, The work design questionnaire (WDQ): developing and validating a comprehensive measure for assessing job design and the nature of work, J. Appl. Psychol. 91 (6) (2006) 1321.
[72] J. Koopmann, K. Lanaj, J. Bono, K. Campana, Daily shifts in regulatory focus: the influence of work events and implications for employee well-being, J. Organ. Behavior (2016).
[73] F. Morgeson, T. Mitchell, D. Liu, Event system theory: an event-oriented approach to the organizational sciences, Acad. Manage. Rev. 40 (4) (2015) 515–537.
[74] G. Moore, I. Benbasat, Development of an instrument to measure the perceptions of adopting an information technology innovation, Inf. Syst. Res. 2 (3) (1991) 192–222.
[75] K. Preacher, A. Hayes, SPSS and SAS procedures for estimating indirect effects in mediation, Behav. Res. Methods Instrum. Comput. 36 (4) (2004) 717–731.
[76] D.P. MacKinnon, Mediation analysis, in: R.L. Cautin, S.O. Lilienfeld (Eds.), The Encyclopedia of clinical psychology, Wiley, New York, NY, 2008, pp. 1–9, , https://doi.org/10.1002/9781118625392.wbecp314.
[77] D.P. MacKinnon, C.M. Lockwood, J.M. Hoffman, S.G. West, V. Sheets, A comparison of methods to test mediation and other intervening variable effects, Psychol. Methods 7 (1) (2002) 83.
[78] A.P. Massey, Y.T.C. Hung, M. Montoya-Weiss, V. Ramesh, September. When culture and style aren't about clothes: perceptions of task-technology fit in global virtual teams, Proceedings of the 2001 International ACM SIGGROUP Conference on Supporting Group Work, (2001), pp. 207–213. ACM.
[79] P. Todd, I. Benbasat, Evaluating the impact of DSS, cognitive effort, and incentives on strategy selection, Inf. Syst. Res. 10 (4) (1999) 356–374.
[80] G.N. Howardson, T.S. Behrend, Coming full circle with reactions: understanding the structure and correlates of trainee reactions through the affect circumflex, Acad. Manage. Learn. Educ. 15 (3) (2016) 471–492.
[81] J. D'Ambra, C.S. Wilson, S. Akter, Application of the task-technology fit model to structure and evaluate the adoption of E-books by academics, J. Am. Soc. Inf. Sci. Technol. 64 (1) (2013) 48–64.
[82] T.T. Kim, Y.K. Suh, G. Lee, B.G. Choi, Modelling roles of task-technology fit and self-efficacy in hotel employees' usage behaviours of hotel information systems, Int. J. Tourism Res. 12 (6) (2010) 709–725.
[83] M.C. Howard, Virtual reality interventions for personal development: a meta-analysis of hardware and software, Hum.-Comput. Interact. (2018) in press.
[84] F. Nickel, J. Brzoska, M. Gondan, H. Rangnick, J. Chu, H. Kenngott, B. Müller-Stich, Virtual reality training versus blended learning of laparoscopic cholecystectomy: a randomized controlled trial with laparoscopic novices, Medicine 94 (20) (2015).
[85] T. Zhou, Y. Lu, Examining mobile instant messaging user loyalty from the perspectives of network externalities and flow experience, Comput. Hum. Behav. 27 (2) (2011) 883–889.
[86] L.M. Maruping, R. Agarwal, Managing team interpersonal processes through technology: a task-technology fit perspective, J. Appl. Psychol. 89 (6) (2004) 975.
[87] J.H. Marler, S.L. Fisher, An evidence-based review of e-HRM and strategic human resource management, Hum. Resour. Manage. Rev. 23 (1) (2013) 18–36.
[88] D.L. Stone, D.L. Deadrick, K.M. Lukaszewski, R. Johnson, The influence of technology on the future of human resource management, Hum. Resour. Manage. Rev. 25 (2) (2015) 216–231.
[89] M.T. Dishaw, D.M. Strong, Extending the technology acceptance model with task–technology fit constructs, Inf. Manage. 36 (1) (1999) 9–21.
[90] C.M. Chiu, E.T. Wang, F.J. Shih, Y.W. Fan, Understanding knowledge sharing in virtual communities: an integration of expectancy disconfirmation and justice theories, Online Inf. Rev. 35 (1) (2011) 134–153.
[91] A. Zehrer, J. Crotts, V. Magnini, The perceived usefulness of blog postings: an extension of the expectancy-disconfirmation paradigm, Tourism Manage. 32 (1) (2011) 106–113.
[92] J.M. Conway, C.E. Lance, What reviewers should expect from authors regarding common method bias in organizational research, J. Bus. Psychol. 25 (3) (2010) 325–334.
[93] P.M. Podsakoff, S.B. MacKenzie, J.Y. Lee, N.P. Podsakoff, Common method biases in behavioral research: a critical review of the literature and recommended remedies, J. Appl. Psychol. 88 (5) (2003) 879.
[94] J. Antonakis, S. Bendahan, P. Jacquart, R. Lalive, On making causal claims: a review and recommendations, Leadership Q. 21 (6) (2010) 1086–1120.
[95] K. Mathieson, M. Keil, Beyond the interface: ease of use and task/technology fit, Inf. Manage. 34 (4) (1998) 221–230.
[96] A.I. Shirani, M.H. Tafti, J.F. Affisco, Task and technology fit: a comparison of two technologies for synchronous and asynchronous group communication, Inf. Manage. 36 (3) (1999) 139–150.
[97] T. Lam, V. Cho, H. Qu, A study of hotel employee behavioral intentions towards adoption of information technology, Int. J. Hosp. Manage. 26 (1) (2007) 49–65.
[98] I. Junglas, C. Abraham, R.T. Watson, Task-technology fit for mobile locatable information systems, Decision Support Syst. 45 (4) (2008) 1046–1057.
[99] R.M. Greenough, B. Tjahjono, An interactive electronic technical manual for an advanced aerospace assembly machine, Int. J. Adv. Manuf. Tech. 33 (9-10) (2007) 1045–1055.
[100] J. D'Ambra, C.S. Wilson, Use of the World Wide Web for international travel: Integrating the construct of uncertainty in information seeking and the task-technology fit (TTF) model, J. Am. Soc. Inf. Sci. Tech. 55 (8) (2004) 731–742.
[101] B.T. Karsh, R. Holden, K. Escoto, S. Alper, M. Scanlon, J. Arnold, R. Brown, Do beliefs about hospital technologies predict nurses' perceptions of quality of care? A study of task-technology fit in two pediatric hospitals. Intl, J. Human–Com. Int. 25 (5) (2009) 374–389.
[102] H.H. Chang, Task-technology fit and user acceptance of online auction, Int. J. Human-Com. Stud. 68 (1-2) (2010) 69–89.
[103] B.Q. Liu, D.L. Goodhue, Two worlds of trust for potential e-commerce users: Humans as cognitive misers, Inf. Sys Res. 23 (4) (2012) 1246–1262.

Matt C Howard is currently an assistant professor in the Mitchell College of Business at the University of South Alabama. His research typically focuses on (a) statistics and research methodologies, (b) applications of novel technologies to the workplace, (c) employee training and development, and/or (d) personality.

Julia Rose graduated from the Labor and Employment Relations program at the Pennsylvania State University. She is currently a HR Information Systems Cloud Analyst at UPMC (University of Pittsburgh Medical Center).