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Guidelines for Conducting Mixed-methods Research: An Extension and Illustration

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Abstract:

In this paper, we extend the guidelines of Venkatesh et al. (2013) for mixed-methods research by identifying and integrating variations in mixed-methods research. By considering 14 properties of mixed-methods research (e.g., purposes, research questions, epistemological assumptions), our guidelines demonstrate how researchers can flexibly identify the existing variations in mixed-methods research and proceed accordingly with a study design that suits their needs. To make the guidelines actionable for various situations and issues that researchers could encounter, we develop a decision tree to map the flow and relationship among the design strategies. We also illustrate one possible type of mixed-methods research in information systems in depth and discuss how to develop and validate meta-inferences as the outcomes of such a study.

Keywords: Mixed-methods Research, Meta-inferences, Research Design, Qualitative, Quantitative.

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1 Introduction

Mixed-methods research[1] (i.e., research that combines elements of qualitative and quantitative research approaches) has gained popularity as a method of choice for studying phenomena in information systems (IS) research (e.g., Bhattacherjee & Premkumar, 2004; Keil & Tiwana, 2006; Koh, Ang, & Straub, 2004). Mixed-methods research provides an opportunity to develop novel theoretical perspectives by combining the strengths of quantitative and qualitative methods. Thus, it provides rich insights by overcoming limitations associated with either method alone and results in "meta-inferences"—an integrative view of findings from qualitative and quantitative strands of mixed-methods research (Creswell, 2009; Teddlie & Tashakkori, 2003; Venkatesh, Brown, & Bala, 2013). However, the application of this method in the IS field has been quite limited (see Venkatesh et al., 2013). The different paradigms underlying the knowledge about research methodology have constrained IS scholars' contributions to understanding business phenomena using mixed-methods research (Greene & Caracelli, 2003; Petter & Gallivan, 2004; Teddlie & Tashakkori, 2003; Venkatesh et al., 2013). Venkatesh et al. (2013) suggest that IS researchers could collaborate to leverage different paradigmatic views and, at the same time, conduct rigorous mixed-methods research because, with it, one can embrace diverse methodological approaches and, thus, reduce the tension between different paradigms (Ågerfalk, 2013).

Despite a need for IS research to bridge the gap between different paradigms and/or methods, IS researchers have provided no real mixed-methods guidelines in the emerging paradigms in the IS field. In response to this need, Venkatesh et al. (2013) developed a set of guidelines for conducting mixed-methods research and illustrated the applicability of these guidelines using two published IS papers. Although their guidelines focus on the different types of mixed-methods research by identifying possible combinations of qualitative and quantitative methods, they discuss only the time ordering of the qualitative and quantitative methods in a single research inquiry and focus less on how to design different types of mixed-methods studies based on various criteria (e.g., priority, stage of integration, epistemological perspective).

Early approaches to mixed-methods designs (e.g., Creswell, 2003; Greene, Caracelli, & Graham, 1989; Tashakkori & Teddlie, 2003b) have been primarily typological (Maxwell & Loomis, 2003). For example, Creswell (2003) identify two basic types of mixed-methods designs: concurrent and sequential. Although a typological approach of mixed-methods research could help researchers select a particular design for their study (Teddlie & Tashakkori, 2003), mixed-methods studies have a far greater diversity than any single typology can actually capture (Caracelli & Greene, 1997; Guest, 2012; Maxwell & Loomis, 2003; Tashakkori & Teddlie, 2003b). In particular, the existence of more than two paradigms (e.g., positivist, critical realist, postpositivist), the diversity of qualitative and quantitative approaches that one can employ, the wide range of purposes of mixed-methods research, and differences with respect to time orientation have made actually using a mixed-methods design far more complicated than simply fitting it in a typology framework (Maxwell & Loomis, 2003). Consistent with Maxwell and Loomis (2003), we believe that one can use a more flexible approach to mixed-methods research designs to address the limitations of the typology approach. Thus, rather than categorizing mixed-methods designs into a typology framework, we view the design of a study as comprising several different dimensions (from many different typologies) that researchers can flexibly integrate to meet their studies' purposes.

Against this backdrop, we augment the mixed-methods guidelines that Venkatesh et al. (2013) propose by leveraging variations in mixed-methods research. Instead of focusing on one typology or framework, we approach mixed-methods designs by identifying different properties or typologies of mixed-methods research. We provide guidelines that are flexible enough to accommodate different types of mixed-methods research. By considering different properties of mixed-methods research (e.g., purposes, research questions, epistemological assumptions), our guidelines demonstrate how researchers can flexibly identify the existing variations in mixed-methods research and proceed accordingly with a study design that suits their needs (see Maxwell, 1996; Maxwell & Loomis, 2003; Nastasi, Hitchcock, & Brown, 2010). In addition,

[1] Although researchers have used the terms mixed methods and multimethod interchangeably in social and behavioral science, the two do differ conceptually (Venkatesh et al., 2013). Teddlie and Tashakkori (2003) identify two major types of multiple methods research: 1) mixed-methods research and 2) multi-method research. In mixed-methods research, one uses quantitative and qualitative data-collection procedures (e.g., survey and focus group interviews) or research methods (e.g., ethnography and field experiment) to answer the research questions (Tashakkori & Teddlie, 2003a). In contrast, in multi-method research, one addresses the research questions by using two or more quantitative data-collection procedures or research methods (e.g., survey and experiment) or two or more qualitative data-collection procedures or research methods (e.g., ethnography and case study) (Teddlie & Tashakkori, 2003). Mixed-methods research requires a combination of qualitative *and* quantitative procedures, whereas multimethod research requires a combination of qualitative *or* quantitative procedures.

we comprehensively illustrate how to apply a mixed-methods approach based on different properties of mixed-methods research. We also discuss how to develop and validate meta-inferences as the outcomes of a mixed-methods research project. Bryman (2006), as cited in Harrison and Reilly (2011), found that scholars have had a difficult time in identifying exemplary mixed-methods research due to the absence of best practice templates from which to draw on when it comes to triangulating the findings. By illustrating how to develop and validate meta-inferences, we highlight a key advantage of mixed-methods research over a single method design.

This paper proceeds as follows. In Section 2, we summarize mixed-methods research and overview the guidelines for mixed-methods research that Venkatesh et al. (2013) propose. In Section 3, we discuss the variations in mixed-methods research, leverage them to extend Venkatesh et al.'s (2013) guidelines, and present a decision tree to map the flow and relationship among the design strategies. In Section 4, we offer an illustrative study of one possible type of mixed-methods research and concomitant meta-inferences. Finally, in Section 5, we conclude the paper with implications and suggestions for future research.

2 Overview of Mixed-methods Research

In general, one can categorize research in the social sciences into three groups: 1) qualitative research (i.e., research dominated by, but not exclusively based on, constructive paradigms and focused on analyzing narrative data) (Tashakkori & Teddlie, 2003b); 2) quantitative research (i.e., research dominated by positivist paradigms and focused on analyzing numerical data) (Orlikowski & Baroudi, 1991); and 3) mixed-methods research (i.e., research dominated by other paradigms, such as pragmatism, critical realism, and transformative-emancipatory and focused on analyzing both narrative and numerical data) (Teddlie & Tashakkori, 2003). Scholars have defined the concept of mixed-methods research in several ways. In an effort to precisely define mixed-methods research, Johnson, Onwuegbuzie, and Turner (2007) review various definitions for the term. Based on their review, they define mixed-methods research as:

> *the type of research in which a researcher or team of researchers combines elements of qualitative and quantitative research approaches (e.g., use of qualitative and quantitative viewpoints, data collection, analysis, inference techniques) for the broad purposes of breadth and depth of understanding and corroboration.* (p. 123)

This definition suggests that mixed-methods research can involve mixing two or more different methods "within a single study" or "within a program of research" and that "mixing [methods] might occur across a closely related set of studies" (Johnson et al., 2007, p. 123).

Researchers have identified three advantages of mixed-methods research: 1) it enables researchers to simultaneously address confirmatory and explanatory research questions and, therefore, evaluate and generate theory at the same time; 2) it enables researchers to provide stronger inferences than a single method or worldview; and 3) it provides an opportunity for researchers to produce a greater assortment of divergent and/or complementary views (see Venkatesh et al., 2013). When used in combination, quantitative and qualitative methods complement each other and allow for a more robust analysis (Ivankova, Creswell, & Stick, 2006; Tashakkori & Teddlie, 2008). However, mixed-methods research does not replace either a quantitative or a qualitative approach but rather draws from the strengths and minimizes the weaknesses of both methods (Creswell, 2003; Jick, 1979; Johnson & Onwuegbuzie, 2004; Venkatesh et al., 2013).

Venkatesh et al. (2013) have proposed the most recent guidelines for conducting mixed-methods research. They divide their guidelines into two major areas: 1) general guidelines (i.e., appropriateness of mixed-methods research and meta-inferences) (Steps 1 to 4) and 2) validation (Steps 5 to 6). We summarize the guidelines next.

2.1 Step 1: Decide on the Appropriateness of a Mixed-methods Approach

At the initial stage of their study, researchers should carefully think about their research questions, purposes, paradigmatic views, and contexts to decide on the appropriateness of a mixed-methods approach. In mixed-methods research, research questions (or research objectives) drive the methods used in the study and set boundaries on the research project. Researchers should employ a mixed-methods design only when they intend to holistically explain a phenomenon for which extant research is fragmented, inconclusive, and/or equivocal.

2.2 Step 2: Develop Strategies for Mixed-methods Research Designs

Once one has determined the research questions, rationale, and objectives, one should next identify the research design strategies. Although mixed-methods researchers have suggested several design strategies, the guidelines focus on two of the most widely used mixed-methods research designs: concurrent and sequential. Researchers should develop a design strategy that best fits their research questions and objectives.

2.3 Step 3: Develop Strategies for Collecting and Analyzing Mixed-methods Data

Researchers can employ multiple modes of data collection and proceed with a mixed-methods data-analysis approach. Researchers may find it beneficial to develop a strategy for mixed-methods data analysis in which "both quantitative and qualitative data are analyzed rigorously so that useful and credible inferences can be made from these individual analyses" (Venkatesh et al., 2013, p. 38).

2.4 Step 4: Draw Meta-inferences from Mixed-methods Results

The term meta-inference describes "the theoretical statements, narratives, or a study inferred from an integration of findings from quantitative and qualitative strands of mixed methods research" (Venkatesh et al., 2013, p. 29). A strong inference is only possible if one has a well-implemented design that is appropriate for the research question. Thus, researchers must determine which research design is most suitable to address their research question(s) and derive their studies' meta-inferences or conclusions based on the design they select.

2.5 Step 5: Assessing the Quality of Meta-inferences

Teddlie and Tashakkori (2003) propose the term inference quality to refer to issues associated with validity in the context of mixed-methods research. According to Teddlie and Tashakkori, a mixed-methods nomenclature for validation can help differentiate mixed-methods validation from quantitative and qualitative validation (Venkatesh et al., 2013). Thus, consistent with Teddlie and Tashakkori, we use the umbrella term inference quality to refer to validity in mixed-methods research. Venkatesh et al. (2013) propose four stages of assessing the quality of meta-inferences: 1) discuss quality criteria in quantitative and qualitative research, 2) use mixed-methods research nomenclature when discussing inference quality, 3) discuss quality of mixed-methods findings and/or meta-inferences (i.e., explanatory quality), and 4) discuss quality from a research design point of view (i.e., design quality). To assess the quality of inferences, one should assess each component of the study using criteria appropriate for its methodology. Only after one has done this step can one apply the quality assessment of the mixed-methods study to evaluate the quality of meta-inferences.

2.6 Step 6: Discuss Potential Threats and Remedies

Finally, researchers should discuss the potential threats to quality that may arise during the data-collection and analysis phases. Because any serious threats will compromise the quality of inferences, researchers should also discuss the potential remedies to overcome or minimize the threats.

3 Variations in Mixed-methods Research: An Extension

Although Venkatesh et al.'s (2013) guidelines discuss several properties of mixed-methods research (i.e., paradigmatic assumptions, purposes of mixed-methods research, time orientation, and quality of meta-inferences), the guidelines do not discuss other properties that one can use to develop strategies for conducting mixed-methods research. Further, although some researchers have previously attempted to integrate different properties of mixed-methods research (e.g., Maxwell & Loomis, 2003; Nastasi et al., 2010), existing mixed methods do not elaborate on different design variations and the relationships among them. Thus, we extend Venkatesh et al.'s (2013) guidelines by integrating different properties of mixed-methods research into the guidelines. Identifying how different properties are related and determining how one design decision may lead to another decision will help researchers develop a high-quality mixed-methods study (Guest, 2012; Tashakkori & Teddlie, 2003b).

To integrate the design variations that encompass the existing typologies, we reviewed the literature in depth and discussed different variations of mixed-methods research based on the existing typologies in mixed-methods research. From the review, we identified 14 important properties of mixed-methods research (see Table 1) (Appendix A presents the literature review in more detail)[2]. Table 1 lists the 14 properties of mixed-methods research and the possible dimensions that researchers can use to design their studies. We organize these properties into three categories: 1) foundations of design decisions (i.e., preliminary decisions used to guide the research design), 2) primary design strategy decisions (i.e., decisions related to the strands/phases of research and process of designing research), and 3) inference decisions (i.e., decisions related to the development of meta-inferences, data interpretation, and inference quality). Table 1 also provides a list of questions to help researchers select mixed-methods designs that might be the best fit for their study. Table 2 maps the 14 properties to Venkatesh et al.'s (2013) guidelines.

Table 1. Variations in the Properties of Mixed-methods Research[3]

Property of mixed-methods research	Design question addressed by the property	Possible dimensions
Foundations of design decisions		
Research questions	How will the researcher write the research questions?	• Rhetorical style—format: questions, aims, and/or hypotheses • Rhetorical style—level of integration • The relationship of questions to other questions: independent or dependent • The relationship of questions to the research process: predetermined or emergent
Purposes of mixed-methods research	Which of the following purposes does the research design serve?	• Complementarity • Completeness • Developmental • Expansion • Corroboration/confirmation • Compensation • Diversity
Epistemological perspectives	Does the study involve one paradigm or multiple paradigm stances?	• Single paradigm stance • Multiple paradigm stance
Paradigmatic assumptions	What paradigmatic perspective will guide the research design?	• Pragmatism • Critical realism • Dialectical • Other major paradigmatic perspectives (e.g., postpositivism)
Primary design strategies		
Design-investigation strategies	Does the study develop or test a theory?	• Exploratory investigation • Confirmatory investigation
Strands/phases of research	Does the study involve one or multiple phases?	• Single phase (or single study) or monostrand design • Multiple phases (or research program) or multistrand design
Mixing strategies	Does the design involve using both qualitative and quantitative research across all components of a study?	• Fully mixed methods • Partially mixed methods

[2] Although typologies that integrate two or more properties of mixed-methods research exist (e.g., Johnson & Onwuegbuzie, 2004; Tashakkori & Teddlie, 1998), we exclude these typologies from our review because we do not study a mixed-methods research design as a choice from a fixed set of possible arrangements. Instead, we discuss the basic typologies of mixed-methods research that are flexible enough to accommodate different types of mixed-methods designs.

[3] Among these properties, Venkatesh et al. (2013) cover the purposes of mixed-methods research (i.e., complementarity, completeness, developmental, expansion, corroboration/confirmation, compensation, and diversity), paradigmatic assumptions (i.e., pragmatism, transformative-emancipatory, and critical realism), time orientation (i.e., concurrent and sequential), and inference quality (design quality and explanation quality). The guidelines also discuss (albeit briefly) the types of reasoning in mixed-methods research. In our current guidelines, we discuss the 14 properties listed in Table 1 in more detail.

Table 1. Variations in the Properties of Mixed-methods Research[3]

Time orientation	Do the quantitative and qualitative data collection occur sequentially or concurrently?	• Sequential designs • Concurrent designs
Priority of methodological approach	Does the qualitative or quantitative component have priority or are they equally important?	• Equivalent status design • Dominant-less dominant design (i.e., qualitative dominant or quantitative dominant)
Sampling design strategies	Which of the following sampling designs does the researcher use in the data-collection stage?	• Basic mixed-methods sampling strategies • Sequential mixed-methods sampling • Concurrent mixed-methods sampling • Multiple mixed-methods sampling strategies
Data-collection strategies	What are the best strategies to collect the quantitative and qualitative data?	• Multiple modes of data collection (both quantitative and qualitative data collection techniques)
Data-analysis strategies	How does the researcher analyze the qualitative and quantitative data?	• Concurrent mixed analysis • Sequential qualitative-quantitative analysis • Sequential quantitative-qualitative analysis
Inference decisions		
Types of reasoning	Will a particular theoretical perspective drive the design?	• Inductive theoretical reasoning • Deductive theoretical reasoning • Inductive and deductive theoretical reasoning • Abductive theoretical reasoning
Inference quality	Which quality issues does the researcher address in the study?	• Design and explanatory quality • Sample integration • Inside-outside • Weakness minimization • Conversion • Paradigmatic mixing • Commensurability • Multiple validities • Political

Table 2. Guidelines to Properties Mapping

Guidelines (Venkatesh et al. 2013)	Properties of mixed-methods research
1) Decide on the appropriateness of a mixed-methods approach.	**Foundations of design decisions:** • Research questions • Purposes of mixed-methods research • Epistemological perspectives • Paradigmatic assumptions
2) Develop strategies for mixed-methods research designs.	**Primary design strategies:** • Design investigation strategies • Strands/phases of research • Mixing strategies • Time orientation • Priority of methodological approach
3) Develop strategies for collecting and analyzing mixed-methods data.	• Sampling design strategies • Data-collection strategies • Data-analysis strategies
4) Draw meta-inferences from mixed-methods results.	**Inference decisions:** • Types of reasoning
5) Assess the quality of meta-inferences.	• Inference quality
6) Discuss potential threats and remedies.	

In Sections 3.1 to 3.6, we discuss how the steps of our procedure for conducting mixed-methods research integrate the 14 properties.

3.1 Step 1: Decide on the Appropriateness of a Mixed-methods Approach

When determining whether mixed-methods research suits one's research, one needs to make decisions associated with 1) research questions, 2) research purposes, 3) selection of theoretical perspectives/worldviews or paradigms, and 4) epistemological perspectives. These four mixed-methods research properties make up the foundations of design decisions researchers need to make to determine which approach they will take to establish the boundary assumptions to guide their research project (Creswell, 2003).

3.1.1 Research Questions

Mixed-methods research questions differ from those of qualitative and quantitative research questions. Quantitative research questions tend to be specific in nature (Onwuegbuzie & Leech, 2006). Most quantitative research questions are descriptive (i.e., they simply call for quantifying responses to one or more variables; for example, what is the perception of ease of use of PCs?), comparative (i.e., they call for comparing two or more groups on some outcome variables) (e.g., what is the difference in purchase behaviors between adopters and non-adopters?), or associative (i.e., they deal with trends between (or among) two (or more) variables; for example, what is the nature of the relationship between the intention to adopt and subsequent purchase behavior?) (Onwuegbuzie & Leech, 2006).

In contrast, qualitative research questions are more "open-ended, evolving, and non-directional" (Onwuegbuzie & Leech, 2006, p. 482). Good qualitative questions are broad but specific enough to focus on the issues most relevant to the individuals under investigation (Plano Clark & Badiee, 2010). Qualitative questions generally tend to seek, discover, and explore a process or to describe experiences (Onwuegbuzie & Leech, 2006). Referencing Onwuegbuzie and Leech (2006), Creswell (1998) argues that qualitative research questions can either represent broad questions (e.g., how have new adopters' attitudes toward technology or personal computers evolved as they used the technology every day?) or specific subquestions that address major concerns and complexities that one seeks to resolve (e.g., what does it mean to non-adopters to change their attitudes toward the technology?). The major difference between quantitative and qualitative research questions is that one generally develops quantitative research questions before the study begins; in contrast, one generally develops qualitative questions at the beginning of the study or they emerge at some point throughout the study (Onwuegbuzie & Leech, 2006).

Unlike qualitative or quantitative research questions, mixed-methods research questions are "questions that embed both a quantitative research question and a qualitative research question within the same question" (Onwuegbuzie & Leech, 2006, p. 483). Mixed-methods questions determine one's primary design strategies, including whether one should collect and analyze qualitative data and quantitative data concurrently, sequentially, or iteratively before addressing the questions (Tashakkori & Creswell, 2007). Plano Clark and Badiee (2010) identify four dimensions that describe how researchers can write research questions in the context of their mixed-methods studies: 1) rhetorical style—question format, 2) rhetorical style—level of integration, 3) the relationship of questions to other questions, and 4) the relationships of questions to the research process.

One can state a research question based on the first dimension (i.e., rhetorical style—question format) in three different formats: 1) question (researchers write an interrogative sentence complete with a question mark), 2) aim (researchers write a declarative sentence as an expression of research objectives), and 3) hypothesis (researchers write a statement that predicts an outcome for a research question) (Plano Clark & Badiee, 2010).

Based on the second dimension (i.e., rhetorical style—level of integration), one can write research questions in a mixed-methods study as described by Creswell (2009) in three ways. First, one can independently write quantitative questions and qualitative questions. For example, in a study of online friendship, a quantitative question might be "what is the relationship between online friendship and happiness?" and a qualitative question might be "what factors play a role in meaningful online friendship?" (Plano Clark & Badiee, 2010). Second, researchers can write separate quantitative questions and/or qualitative questions and supplement them with mixed-methods questions. For example, one qualitative question is "what theory explains adolescents' process of using social media?", one quantitative question is "how are the identified factors related?", and one mixed-methods research question is "how do adolescents use social media?" (Plano Clark & Badiee, 2010). Third, researchers can write only mixed-methods questions that reflect the procedures or the research content; for example: “how is an effective online community developed and tested?”.

If researchers attempt to address more than one research question, they should address the third dimension (i.e., the relationship of questions to other questions) (Plano Clark & Badiee, 2010). The relationship among the questions shapes a study’s overall design and informs the relationship between its quantitative and qualitative components (Plano Clark & Badiee, 2010). Plano Clark and Badiee (2010) suggest two relationship alternatives: 1) research questions may be independent of each other and 2) one research question may depend on the results of other questions (Plano Clark & Badiee, 2010).

The last dimension focuses on the relationship of questions to the research process. Research questions in mixed-methods studies may be either predetermined or emergent (Plano Clark & Badiee, 2010). A research question is predetermined when it appears at the beginning of the study based on researchers’ understanding of the literature and practice or disciplinary considerations. In contrast, one forms emergent questions during the design, data-collection, data-analysis, and/or interpretation phases of the research process (Plano Clark & Badiee, 2010).

3.1.2 Purposes of Mixed-methods Research

Based on several resources, including Greene et al. (1989), Creswell (2003) and Tashakkori and Teddlie (2003b), we can summarize the purposes of mixed-methods research into seven categories: 1) complementarity (i.e., to gain complementary views about the same phenomena or relationships), 2) completeness (i.e., to gain a complete picture of phenomena), 3) developmental (i.e., to ensure the questions from one strand emerge from the inference of a previous one or one strand is used to develop hypotheses the researcher will test in the next one), 4) expansion (i.e., to explain or expand on the understanding obtained in a previous strand of a study), 5) corroboration/confirmation or triangulation (i.e., to assess the credibility of inferences obtained from one approach), 6) compensation (i.e., to eliminate potential design weaknesses of one approach by using the other), and 7) diversity (i.e., to obtain divergent views of the same phenomenon) (see Venkatesh et al., 2013).

3.1.3 Epistemological Perspectives

From an epistemological perspective, one can conduct mixed-methods research using a single paradigm or multiple paradigms. A single paradigm perspective proposes that one can accommodate both quantitative and qualitative research under the same paradigm (e.g., positivist, realist) (Tashakkori & Teddlie, 1998). A multiple paradigm perspective claims that alternative paradigms are compatible and can be used in one research project (Teddlie & Tashakkori, 2003). One can view combining multiple paradigms and methodological practices as a strategy that adds rigor, breadth complexity, richness, and depth to a research inquiry (Denzin, 2012). Under this multiple paradigm perspective, researchers have to decide which paradigms best fit their study given they choose to use a particular mixed-methods design (Creswell, Plano Clark, Gutmann, & Hanson, 2003).

3.1.4 Paradigmatic Assumptions

Although specific paradigms are commonly associated with specific methods, one may use both qualitative and quantitative methods appropriately with any research paradigm (Guba & Lincoln, 1994; Tashakkori & Teddlie, 1998). Researchers have proposed several paradigms for mixed-methods research, such as the purist stance (i.e., because the assumptions of different paradigms are incompatible, it is not possible to mix paradigms in the same study), aparadigmatic stance (i.e., driven by research questions and/or purposes), substantive theory stance (i.e., emergent paradigms may be embedded in or intertwined with substantive theories) (Greene, 2007; Venkatesh et al., 2013), complementary strengths stance (i.e., the assumptions of different paradigms are not fundamentally compatible but are different in important ways), dialectic stance (i.e., important paradigm differences should be respectfully and intentionally used together to engage meaningfully with difference), and alternative paradigms stance (i.e., the initiation of a new paradigm that actively embraces and promotes the mixing of methods) (Greene, 2007). From our review, we found that mixed-methods researchers have mostly used the dialectic, alternative paradigms (i.e., pragmatism and critical realism) and complementary strengths stances (i.e., the use of multiple paradigms).

The dialectic paradigm stance generally allows one to use more than one paradigmatic tradition in the same research project or research program because it assumes that using multiple paradigms contributes to better understanding the phenomenon under study (Greene & Hall, 2010; Teddlie & Tashakkori, 2003). This stance recognizes the legitimacy of multiple social inquiry theories and practices because they represent different ways of seeing and understanding the social world (Greene, 2005, 2007; Greene & Hall, 2010). A mixed-methods way of thinking under the dialectic paradigm offers researchers opportunities to meaningfully engage with difference as they encounter it in their studies (Greene & Hall, 2010).

The alternative paradigms stance includes pragmatism and critical realism. One of the central ideas in pragmatism is that "engagement in philosophical activity should be done to address problems, not to build systems" (Biesta, 2010, p. 97). Pragmatism supports using both qualitative and quantitative research methods in the same research study or in multistage research programs (Teddlie & Tashakkori, 2003). Because a pragmatist perspective considers practical consequences to be a crucial component of meaning and truth (Venkatesh et al., 2013), researchers need to articulate a purpose for their mixed-methods study to establish the rationale for why they need to mix quantitative and qualitative methods in the first place (Creswell, 2003).

Critical realists believe that an objective reality exists but that we can understand it only imperfectly and probabilistically (Tashakkori & Teddlie, 1998). They deny that we have any objective knowledge of the world and accept the possibility of alternative valid accounts of any phenomenon (Maxwell & Mittapalli, 2010). Critical realism "embraces various methodological approaches from different philosophical positions by taking a critical stance towards the necessity and validity of current social arrangements without following the extant paradigms' assumptions at face value" (Zachariadis, Scott, & Barret, 2013, p. 856). Thus, critical realism is an ideal paradigm for mixed-methods research because its philosophical stance is compatible with the methodological characteristics of both quantitative and qualitative research (Maxwell & Mittapalli, 2010).

Finally, according to the complementary strengths stance, one can combine and use other major paradigms used in the social and behavioral sciences (e.g., constructivism/interpretivism, positivism, postpositivism) to support mixed-methods research. Constructivism/interpretivism believes that people construct their own understanding and subjective knowledge as they interact with the world around them (Tashakkori & Teddlie, 2003b). Thus, researchers who embrace this paradigm try to understand phenomena by accessing the meanings participants assign to them (Orlikowski & Baroudi, 1991). Phenomenological sociology, hermeneutics, and ethnography exemplify the constructivist approach (Lee, 1991). In contrast, positivism is premised on the existence of a priori fixed hypotheses or relationships among constructs that one typically investigates with structured instrumentation (Lee, 1991; Orlikowski & Baroudi, 1991). Whereas positivists believe that the researcher and the object of inquiry are independent of each other, postpositivists accept that theories and researchers' backgrounds, knowledge, and values can influence the study (Trochim & Donnelly, 2007). One can conduct mixed-methods research by combining these paradigmatic approaches (Creswell et al., 2003; Lee, 1991). For example, researchers might use an ethnographic method to study system analysts and end users (Lee, 1991). Based on the results, researchers might use a positivist approach to formulate a formal, general theory that explains, for instance, end user resistance to systems analysis (Lee, 1991).

In terms of conducting empirical mixed-methods studies, researchers should consider what the alternative paradigmatic positions are and determine which of the alternative positions best suits their studies (Tashakkori & Teddlie, 2010). When developing a mixed-methods study, one should begin by identifying paradigmatic assumptions, including their philosophical assumptions and theoretical framework, as research foundations that intertwine with the research questions and purposes of mixed-methods research.

3.2 Step 2: Develop Strategies for Mixed-methods Research Designs

After one has established the appropriateness of mixed-methods research, one has to make the primary design decisions associated with strands/phases of research, priority of methodological approach, design-investigation strategies, mixing strategies, and time orientation. Although these decisions relate to each other, they can be independent and vary as the study evolves.

3.2.1 Strands/Phases[4] of Research

Based on the strands/phases of research, we can classify mixed-methods designs into two types: mixed-methods monostrand designs and mixed-methods multistrand designs (Tashakkori & Teddlie, 2003b; Teddlie & Tashakkori, 2006). Teddlie and Tashakkori (2009) define strand or phase as encompassing three stages:

[4] Strands can also refer to distinctions with regard to a single study (i.e., monostrand) versus multiple studies in a broader research program (i.e., multistrand) (Nastasi et al., 2007, 2010).

1) conceptualization (i.e., theoretical foundations, purpose, and research methods), 2) experiential (i.e., data collection and analysis), and 3) inferential (i.e., data interpretation and application). A monostrand study involves only a single phase of the conceptualization-experiential-inferential process, yet it consists of both qualitative and quantitative components (Nastasi et al., 2010; Teddlie & Tashakkori, 2006). In contrast, mixed-methods multistrand designs contain at least two research strands (Bryman, 2006; Teddlie & Tashakkori, 2006). In these designs, one can mix the quantitative and qualitative components in or across all stages (i.e., conceptualization-experiential-inferential process) of the study (Teddlie & Tashakkori, 2006). Mixed-methods multistrand designs often involve multiple phases in a broader research program, with each phase encompassing all of the stages from conceptualization through inference (Teddlie & Tashakkori, 2009).

The decision related to strands/phases of research is important because it influences researchers' decisions associated with other design strategies, such as the priority of methodological approach, mixing strategies, and time orientation. Naturally, monostrand designs have their constraints (Teddlie & Tashakkori, 2006). In contrast, one can implement mixed-methods multistrand designs using parallel, sequential, conversion, or multilevel mixed designs (Teddlie & Tashakkori, 2009).

3.2.2 Priority of Methodological Approach

Based on the priority of the methodological approach, one can categorize mixed-methods research into equivalent-status designs and dominant-less dominant status designs. In equivalent-status designs, researchers generally conduct a study using both qualitative and quantitative approaches about equally to understand the phenomena of interest (Tashakkori & Teddlie, 1998). In dominant-less dominant status designs, researchers usually conduct a study in a single dominant paradigm with a small component of the overall research project drawn from an alternative design (Tashakkori & Teddlie, 1998).

One can divide the dominant-less dominant status designs into two categories: qualitative-dominant mixed-methods research and quantitative-dominant mixed-methods research (Johnson et al., 2007). Qualitative-dominant mixed-methods research refers to "the type of mixed research in which one relies on a qualitative, constructivist-poststructuralist-critical view of the research process, while concurrently recognizing that the addition of quantitative data and approaches are likely to benefit most research projects" (Johnson et al., 2007, p. 124). In contrast, quantitative-dominant mixed-methods research is "the type of mixed research in which one relies on a quantitative, postpositivist view of the research process, while concurrently recognizing that the addition of qualitative data and approaches are likely to benefit most research projects" (Johnson et al., 2007, p. 124).

Although determining the priority of methodological approach is important, researchers can modify their priority decision after the study is complete (Teddlie & Tashakkori, 2009). For example, a quantitative-dominant mixed-methods study may become a qualitative dominant study if the qualitative data become more important in understanding the phenomenon under study and vice versa (Teddlie & Tashakkori, 2009). Despite this flexibility, we encourage researchers to refer to their research questions and purposes when deciding whether one component has significantly higher priority than does the other component.

3.2.3 Design Investigation Strategies

The choice of design investigation strategies essentially influences the process of developing inferences through theoretical reasoning techniques (Tashakkori & Teddlie, 1998). Using Patton's (1990) typology of design dimensions, Tashakkori and Teddlie (1998) identify two different types of investigations in mixed-methods research: exploratory and confirmatory. In exploratory investigations, one conducts the study to develop or generate a new theory. These designs include qualitative case studies, experimental designs, and non-experimental studies. In contrast, in confirmatory investigations, one conducts the study to test an existing theory using hypotheses established a priori. These designs include naturalistic inquiry and quantitative explanatory studies, such as surveys (Tashakkori & Teddlie, 1998).

3.2.4 Mixing Strategies

Mixing or integrating methods and data is the core value of mixed-methods research because, by doing so, one can gain insights from multiple methods (Fielding, 2012). Further, one should consider the decisions regarding what types of data one integrates and how one integrates those data when designing a mixed-methods study. Teddlie and Tashakkori (2009) propose two dimensions of mixing strategies: fully mixed methods and partially mixed methods. A fully mixed-methods design involves using both qualitative and quantitative research across all components of a study (e.g., objective, type of data and operations, type of analysis, type of inference) (Leech & Onwuegbuzie, 2009). A fully mixed-methods design (also known as a mixed-model design*)* represents the highest degree of mixing paradigms in which one mixes the qualitative and quantitative paradigms at all or many steps of the study (Tashakkori & Teddlie, 1998). In contrast, a partially mixed-methods design involves conducting a study in which one mixes the quantitative and qualitative portions of the study at specific stages, such as at the sampling, data-collection, data-analysis, or data-inference stages (Teddlie & Tashakkori, 2009). In this design, one could mix their study's quantitative and qualitative portions in a parallel manner, across chronological phases of the study, or across multiple levels of analysis (Teddlie & Tashakkori, 2009).

3.2.5 Time Orientation

Based on its time orientation, one can categorize mixed-methods research into two types: sequential and concurrent. In sequential mixed-methods designs, researchers typically conduct one strand of the study (e.g., qualitative) first and then the other strand of the study (e.g., quantitative) (Creswell, 2003). The sequence depends on the objective of the study and the research questions. Creswell et al. (2003) propose three types of sequential mixed-methods designs: 1) sequential explanatory (i.e., this design is characterized by conducting the study's quantitative phase followed by its qualitative phase), 2) sequential exploratory (i.e., this design is characterized by conducting the study's qualitative phase followed by its quantitative phase), and 3) sequential transformative (i.e., one may prioritize either the quantitative or the qualitative phase and one will generally use a theoretical lens as an overarching perspective in the design that contains both quantitative and qualitative components to guide the study).

A concurrent mixed-methods design is characterized by conducting the study's qualitative and quantitative components during the same stage (Castro, Kellison, Boyd, & Kopak, 2010). This design uses both qualitative and quantitative data and analyses in independent strands to answer the research questions (Teddlie & Tashakkori, 2006). Creswell et al. (2003) identify three types of concurrent mixed-methods designs: 1) concurrent triangulation (i.e., using both qualitative and quantitative data to accurately define relationships among variables of interest), 2) concurrent nested (i.e., a type of design in which one collects both qualitative and quantitative data concurrently but still gives one type of data weight over the other), and 3) concurrent transformative design (i.e., a type of design used to provide support for various perspectives in the context of social change or advocacy). One's research questions and purposes for conducting mixed-methods research influence the decision associated with time orientation. For example, if one conducts a study to understand a phenomenon as it occurs, one should employ a concurrent mixed-methods design (Venkatesh et al., 2013). In contrast, if one conducts a study to identify and test theoretical constructs in a new context, one should employ a qualitative study followed by a quantitative study (Venkatesh et al., 2013).

3.3 Step 3: Develop Strategies for Collecting and Analyzing Mixed-methods Data

After researchers have made the primary design decisions associated with strands/phases of research, design investigation strategies, priority of methodological approach, mixing strategies, and time orientation, they need to develop a set of strategies for collecting and analyzing mixed-methods data. Before collecting data for their study, researchers should decide on the strategy to select the participants and the number of participants (i.e., sampling design strategies) (Collins, 2010).

3.3.1 Sampling Design Strategies

Sampling is an important step in a research process because it helps determine the inference quality that researchers make and influences the degree to which one can generalize the findings to other individuals, groups, or contexts (Collins, Onwuegbuzie, & Jiao, 2007). In mixed-methods investigations, researchers must make sampling decisions for both the qualitative and quantitative components of the study. Teddlie and Yu (2007) propose five different types of mixed-methods sampling strategies: 1) basic, 2) sequential, 3) concurrent, 4) multilevel, and 5) multiple. To the same end, Onwuegbuzie and Collins (2007) develop a framework for formulating sampling decisions in mixed-methods research based on 1) the time orientation of the component (i.e., simultaneous or sequential) and 2) the relationship between the qualitative and quantitative samples (i.e., identical versus parallel versus nested versus multilevel). Onwuegbuzie and Collin's framework is similar to Teddlie and Yu's strategies to the degree that one can categorize them into either sequential or concurrent mixed methods. We discuss four types of mixed-methods sampling designs by integrating these two typologies: basic, sequential, concurrent, and multiple sampling designs.

Basic mixed-methods sampling strategies typically include probability sampling (i.e., researchers randomly select the sampling units that are representative of the population) (Collins, 2010), stratified purposive sampling (i.e., researchers first divide the group of interest into strata and then select a small number of cases to study intensively in each strata using a purposive sampling technique), and purposive random sampling (i.e., researchers take a random sample of a small number of units from a much larger target population) (Teddlie & Yu, 2007). Probabilistic sampling designs are generally associated with quantitative studies, whereas purposive sampling designs are associated with qualitative studies (Collins, 2010), and one can use both probabilistic and purposive sampling in quantitative and qualitative studies (Onwuegbuzie & Collins, 2007).

Sequential sampling strategies typically involve using methodology and results from the first strand to inform the methodology employed in the second strand (Teddlie & Yu, 2007). According to Onwuegbuzie and Collins (2007), one can categorize sequential mixed-methods sampling designs based on their sampling strategies: 1) identical samples—the same sample members participate in both the qualitative and qualitative phases of the investigation, 2) parallel samples—the samples for the quantitative and qualitative components of the study are different but drawn from the same underlying population, 3) nested samples—the sample members selected for one phase of the study represent a subset of those participants chosen for the other component of the study, and 4) multilevel samples design—involves using two or more sets of samples obtained from different levels of the study (Collins et al., 2007).

Concurrent sampling strategies allow researchers to triangulate the results from the separate quantitative and qualitative components of their research (Teddlie & Yu, 2007) and confirm, cross-validate, or corroborate their findings in a single study (Creswell et al., 2003). Like the sequential sampling designs, one can categorize the concurrent mixed-methods sampling strategies into four types of designs (see previous paragraph).

Finally, multiple sampling strategies generally involve using more than one sampling technique, such as integrating a stratified purposive sampling with concurrent mixed-methods sampling (Teddlie & Yu, 2007).

3.3.2 Data-collection Strategies

One can categorize data-collection strategies in mixed-methods research based on their degree of predetermined nature, their use of closed- (e.g., a set of questions about users' attitude toward a particular technology) and open-ended questions (e.g., conducting an interview in which individuals can talk openly about a topic), and their focus for numeric versus non-numeric data analysis (Creswell, 2003). Mixed-methods data-collection strategies can be either quantitative (involves relatively planned "instruments" or predetermined questions for collecting data) or qualitative (mostly unstructured methods of collecting data for measurement or observation) (Tashakkori & Teddlie, 1998). Also, the type of data may be numeric or text, audio recording of participants' voice, or written notes (Creswell, 2003). In a mixed-methods study, one must recognize that those data-collection strategies have their limitations and their strengths (Johnson & Turner, 2003). Therefore, researchers can use the strengths of one method to overcome the weaknesses of another method by using both in a research study (Johnson & Onwuegbuzie, 2004).

3.3.3 Data-analysis Strategies

Based on the order of data analysis, one can use three strategies to analyze data in mixed-methods research: 1) concurrent mixed analysis (one analyzes both qualitative and quantitative data simultaneously), 2) sequential qualitative-quantitative data analysis (one analyzes qualitative data then quantitative data), and 3) sequential quantitative-qualitative data analysis (one analyzes quantitative data then qualitative data) (Tashakkori & Teddlie, 1998).

One can use several analysis tools or methods for analyzing mixed-methods data (e.g., data reduction, data transformation, data correlation) (see Johnson & Onwuegbuzie, 2004). One of the most common data-analysis practices is data conversion or transformation (i.e., one converts qualitative data into numerical codes that one can represent statistically (quantized), or one converts quantitative data into narrative data that one can analyze qualitatively (qualitized)) (Teddlie & Tashakkori, 2009).

One can quantize qualitative data to integrate them with quantitative data to "answer research questions or test hypotheses addressing relationships between independent variables and dependent variables" (Fielding, 2012, p. 126). The quantizing practice also provides useful information by obtaining the numerical values of observations in addition to researchers' narrative descriptions (Onwuegbuzie & Johnson, 2006; Sandelowski, 2000).

In contrast, one can adopt qualitizing techniques if one seeks to extract more information from quantitative data or to confirm interpretations of those data (Sandelowski, 2000). We have fewer examples of qualitizing data than those of quantizing data (Teddlie & Tashakkori, 2009). As Creswell and Plano Clark (2007, p. 188) in Teddlie and Tashakorri (2009) note: “More work needs to be done to expand the techniques for quantifying qualitative data and to develop the analysis options for such transformed data. Writers have written even less about transforming quantitative data into qualitative data. This area is ripe for researcher innovation and future research.”.

One possible qualitizing technique is to take a distribution of numeric data on a single variable and then generate separate narrative categories based on the ranges of values in that distribution (i.e., cluster analysis) (Teddlie & Tashakkori, 2009). Joseph, Boh, Ang and Slaughter (2012) in their study on IS career histories is one example of IS research that has used a qualitizing technique. The researchers used quantitative cluster analysis to identify distinct career paths in their quantitative data. Their analysis yielded three clusters of IS career paths: information technology, professional labor market, and secondary labor market career. This type of qualitizing is called narrative profile formation because it involves constructing qualitative profiles from quantitative data (Teddlie & Tashakkori, 2009).

In general, researchers may plan a decision to transform data before conducting their study, but they generally do it after collecting data (Teddlie & Tashakkori, 2006). For example, in monostrand mixed-methods designs, researchers usually plan data transformation prior to the study because they generally collect only one type of data (either qualitative or quantitative data) and convert that type of data into the other and analyze them accordingly (Teddlie & Tashakkori, 2006). Researchers can also do data transformation in multistrand designs depending on their methodological approach and/or the findings from each phase of their study. For example, if researchers prioritize collecting and analyzing qualitative data, they should perform a quantizing technique to help explain the qualitative results (Creswell, Fetters, & Ivankova, 2004). However, if one believes that the results of each strand of research are sufficient (based on the theoretical concepts), transforming the data might not significantly contribute to the findings. In most cases, data transformation occurs serendipitously (Teddlie & Tashakkori, 2009). For example, researchers may determine that their interview data reveal emerging patterns that they can convert into numerical forms and analyze quantitatively. This practice allows researchers to more thoroughly analyze the data and, thereby, strengthen the inference quality (Teddlie & Tashakkori, 2006).

Whereas transforming data in mixed-methods research has several benefits, it also has several limitations and challenges. First, although qualitizing techniques can help researchers gain more insights from their quantitative data, one should use qualitizing techniques cautiously because such techniques might represent an over-generalization of the observed numeric data (Teddlie & Tashakkori, 2009). It is also possible that profiles emerging from qualitizing techniques yield an unrealistic representation (Sandelowski, 2000).

Second, data transformation might cause one to lose depth and flexibility of data interpretation (Driscoll, Apiah-Yeboah, Salib, & Rupert, 2007). Qualitative data are generally multidimensional (i.e., they can provide insights into a host of interrelated conceptual themes during analysis). These themes are also flexible (i.e., researchers can revisit them during analysis in an iterative analytical process to help them recognize emergent patterns) (Bazeley, 2004). However, quantized data are usually fixed and unidimensional—they comprise a single set of responses that represent a conceptual category determined prior to data collection (Driscoll et al., 2007). To overcome this limitation, researchers have to be able to switch back and forth from a qualitative lens to a quantitative lens by revisiting qualitative data components associated with significant statistical findings (Driscoll et al., 2007). Further, researchers should always assess the conversion legitimation when their data analysis and designs involve data transformation (Onwuegbuzie & Johnson, 2006).

The third challenge of data transformation comes from a quantitative research perspective. Quantitative researchers argue that quantized data are vulnerable to the problem of multicollinearity, wherein response categories are themselves linked to one another as a result of the coding strategy (Driscoll et al., 2007). Further, the need to collect and analyze qualitative data can force researchers to reduce their sample size, which can limit the kinds of statistical procedures that they can use to analyze data (Driscoll et al., 2007). To overcome the collinearity issue, researchers can use available statistical remedies (e.g., separating dichotomized codes derived from a single open-ended question in subsequent statistical analysis) (Driscoll et al., 2007). Moreover, if researchers cannot collect a sufficient sample size for accurate estimation, they should avoid doing data transformation.

3.4 Step 4: Draw Meta-inferences from Mixed-methods Results

Developing high-quality meta-inferences depends on the quality of the data analysis in a study's qualitative and quantitative components (Venkatesh et al., 2013). Given that meta-inferences are generally theoretical statements about a phenomenon, including its interrelated components and boundary conditions, the process of developing inferences is conceptually similar to the process of developing theory from observation (Venkatesh et al., 2013). Thus, one can develop inferences inductively, deductively, or abductively depending on the existence of theoretical foundations or conceptual frameworks underlying the study (Morse, 2010).

3.4.1 Theoretical Reasoning

When researchers use a mixed-methods approach to examine their research questions, they generally switch between different modes of generalizability (Tashakkori & Teddlie, 1998). One can categorize these differences in generalizability concerns into four modes: inductive reasoning, deductive reasoning (Tashakkori & Teddlie, 1998), the combination of inductive and deductive reasoning (Tashakkori & Teddlie, 1998), and abductive reasoning (Van de Ven, 2007). In inductive reasoning, researchers generally gather data from specific instances to build up a theory. Thus, inductive reasoning involves generalizing a theory confirmed in one specific setting to another context as the theory evolves (Tashakkori & Teddlie, 1998). In general, one uses inductive theoretical reasoning in qualitative studies (Merriam, 1998). However, although qualitative studies mostly adopt inductive reasoning, some adopt deductive reasoning processes (Creswell, 2003). In deductive reasoning, researchers generally predict outcomes that are supposed to occur in a theoretical population. Thus, deductive reasoning involves making generalizations from a specific sample that one uses for that theoretical population (Tashakkori & Teddlie, 1998).

Although a particular study may adopt either deductive or inductive theoretical reasoning, one will likely use both types of theoretical reasoning simultaneously in developing meta-inferences (Miller, 2003; Tashakkori & Teddlie, 1998). According to pragmatism, mixed-methods researchers can select both the inductive and deductive logic and use them simultaneously in the course of conducting research that focuses on addressing research questions (Tashakkori & Teddlie, 1998).

Finally, in abductive reasoning, (Van de Ven, 2007), researchers make a logical connection "between data and theory" and often use it to theorize "about a surprising event" (Feilzer, 2010, p. 10). In this reasoning, researchers move back and forth between theories and data: they "first convert observations into theories and then assess those theories through action" (Morgan, 2007, p. 71). This type of reasoning requires using different approaches to theory and data and offers great opportunity to triangulate inferences developed from qualitative and quantitative research (Feilzer, 2010; Morgan, 2007).

Developing meta-inferences depends on research questions, specific methods employed, and empirical domains under investigation (Erzberger & Kelle, 2003). Erzberger and Kelle (2003) suggest that researchers should always look for sufficient empirical evidence for their theoretical statements and avoid any additional assumptions that they cannot examine with the help of empirical data. Given that the most important step in mixed-methods research is triangulating the results (i.e., findings, inferences) from the qualitative and quantitative studies into a coherent conceptual framework that provides an effective answer to one's research questions, one needs to properly develop good inferences in each strand of the study.

In qualitative research, a good inference should "capture the meaning of the phenomenon under consideration for study participants" (Teddlie & Tashakkori, 2009, p. 295). A good qualitative inference is a credible inference; that is, "there is a correspondence between the way respondents actually perceive social constructs and the way researchers portray their overviews" (Mertens, 2005, p. 254). Venkatesh et al. (2013) summarize a variety of techniques for evaluating and enhancing the quality of inferences in qualitative research (i.e., design validity, analytical validity, and inferential validity). We discuss more details about these types of quantitative validities in Section 4.

In quantitative research, a good inference has the following characteristics: 1) it establishes relations between variables and provides reasonable certainty that such relationships do not happen by chance; 2) its intensity matches the demonstrated magnitude of the relationship between variables, which the results of analyzing the data support; and 3) it is free of systematic bias in interpreting the results (Teddlie & Tashakkori, 2009). One can use some validity criteria, such as statistical conclusion validity, internal validity, construct validity and external validity, to evaluate the quality of quantitative inferences (Venkatesh et al., 2013). We discuss more details about these types of quantitative validity in Section 4.

Findings from mixed-methods research have three possible patterns: divergence, convergence, and complementarity (Erzberger & Kelle, 2003). If the qualitative and quantitative methods applied in the study lead to divergent results (i.e., the qualitative and quantitative results contradict each other), two possible explanations exist: either the divergence is the result of methodological mistakes or the initial theoretical assumptions are incorrect (Erzberger & Kelle, 2003). One should modify and revise theoretical assumptions as a consequence of divergent findings carefully. Researchers have to formulate ad-hoc hypotheses based on already-collected empirical data that may lead them to retain their initial theories and formulate "far-reaching speculations that lack a sound empirical basis" (Erzberger & Kelle, 2003, p. 483). These newly developed hypotheses must increase the empirical content of the initial theoretical assumptions without diminishing their consistency, or these hypotheses must improve the consistency of the initial theory without losing empirical content. One also needs to empirically test the newly developed hypotheses using new data, and the newly developed hypotheses should be adaptable to other well-established theories about the phenomena under investigation (Erzberger & Kelle, 2003). If the divergence results from methodological mistakes, researchers must engage in a re-examination process to assess whether the divergent findings are associated with the quality issues in one or more of the methods used or if they suggest a greater complexity inherent in the phenomenon under study (da Costa & Remedios, 2014).

If the quantitative and qualitative methods lead to convergent results (i.e., the qualitative and quantitative methods lead to the same results), then the integration may provide good arguments for the quality of the inferences and strengthen the initial theoretical assumptions (Erzberger & Kelle, 2003). Finally, if a mixed-methods approach leads to complementary results (i.e., the qualitative and quantitative results relate to different objects or phenomena but may complement each other), then the integration provides a more complete picture of the empirical domain under study (Erzberger & Kelle, 2003).

3.5 Step 5: Assess the Quality of Meta-inferences

To maximize the quality of meta-inferences drawn from the qualitative and quantitative components, one must examine inference quality, including design quality, explanatory quality, and other legitimation criteria.

3.5.1 Inference Quality

One assesses the quality of meta-inferences by simultaneously examining the design quality (i.e., the degree to which a researcher has selected the most appropriate procedures for answering the research questions) and the explanatory quality (i.e., the degree to which one has made credible interpretations based on the obtained results) (see Tashakkori & Teddlie, 2010; Teddlie & Tashakkori, 2003; Venkatesh et al., 2013). Appendix B defines the different types of inference quality. In addition to design and explanatory quality, Onwuegbuzie and Johnson (2006) propose a typology including nine mixed-methods legitimation types: 1) sample integration, 2) inside-outside, 3) weakness minimization, 4) sequential, 5) conversion, 6) paradigmatic mixing, 7) commensurability, 8) multiple validities, and 9) political legitimation. Whereas Tashakkori and Teddlie's (2010) quality framework assumes legitimation as an outcome that revolves around inference quality, Onwuegbuzie and Johnson's typology views legitimation as a continuous process that one should evaluate at each stage of the mixed-research process. By bringing together Tashakkori and Teddlie's (2010) concept of inference quality and Onwuegbuzie and Johnson's nine aspects of legitimation, one can extensively assess the quality of a mixed-methods study by not only using the appropriate qualitative and quantitative quality standards but also applying the quality criteria that address the entire mixed-methods study.

Sample integration legitimation applies to situations in which researchers aim to make statistical generalizations from a sample population to a larger population (Onwuegbuzie & Johnson, 2006). Inside-outside legitimation refers to "the extent to which the researcher accurately presents and appropriately utilizes the insider's view and the observer's views for purposes, such as description and explanation" (Onwuegbuzie & Johnson, 2006, p. 57). Weakness minimization legitimation refers to "the extent to which the weakness from one approach is compensated by the strengths from the other approach" (Onwuegbuzie & Johnson, 2006, p. 57). Sequential legitimation refers to "the extent to which one has minimized the potential problem wherein the meta-inferences could be affected by revising the sequence of the quantitative and qualitative phases" (Onwuegbuzie & Johnson, 2006, p. 57). To assess sequential legitimation, researchers can change the sequential design to a multiple wave design (i.e., one collects and analyzes the qualitative and quantitative data multiple times) (Onwuegbuzie & Johnson, 2006; Sandelowski, 2003). Conversion refers to the extent to which quantizing and qualitizing lead to interpretable data and high inference quality. Paradigmatic mixing legitimation refers to the extent to which researchers successfully combine and blend their paradigmatic assumptions underlying the qualitative and quantitative approaches "into a usable package" (Onwuegbuzie & Johnson, 2006, p. 57).

To meet commensurability legitimation, mixed-methods researchers need to be able to make Gestalt switches (i.e., to switch back and forth from a qualitative lens to a quantitative lens). This iterative process can create a viewpoint separate from and goes beyond what either a qualitative or quantitative viewpoint alone provides. Multiple validities legitimation refers to the extent to which one uses all relevant research strategies and the study meets multiple relevant validity criteria. Political legitimation, the last legitimation type, refers to "the extent to which consumers of mixed methods research value the meta-inferences stemming from both the qualitative and quantitative components of a study" (Onwuegbuzie & Johnson, 2006, p. 57). One of the strategies to achieve this legitimation is to use multiple perspectives and to generate practical theories or results that consumers will value because the results answer important questions and provide practical solutions (Onwuegbuzie & Johnson, 2006).

Based on our discussion regarding the development and validation of inferences in mixed-methods research in steps 4 and 5, we summarize the general guidelines for developing high-quality meta-inferences in mixed-methods research in Table 3.

3.6 Step 6: Discuss Potential Threats and Remedies

One can use the legitimation framework that Onwuegbuzie and Johnson (2006) propose and that we discuss previously to identify the quality threats that may potentially compromise the credibility of meta-inferences[5]. Given that threats to inference quality may vary depending on the types of design decisions one uses, we discuss more details about these threats in Section 4.

3.7 Model of Decision Choice for Conducting Mixed-methods Research

To provide guidance for mixed-methods researchers in selecting the most suitable designs for their studies, we develop a decision tree to map the flow and relationship among the design strategies. Figures 1-4 present the decision tree depicting various design decisions that mixed-methods researchers have to make. The rectangles represent basic steps or process and design options in a research project, the diamonds indicate design decisions that researchers need to make, the arrows represent relationships between design decisions and/or processes, and the numbers inside the boxes represent the steps in conducting mixed-methods research as Table 2 describes.

Our decision tree also shows that, although mixed-methods research always starts with one or more research questions, one can approach the other decisions in any order (i.e., one need not address them linearly or unidirectionally), and sometimes one can revise questions and/or purposes when needed (Johnson & Onwuegbuzie, 2004). Further, a decision at an earlier stage may or may not influence a decision at a later stage of research. For example, the decision associated with strands or phases of research influences the decision related to data collection and analysis; however, mixing strategies do not necessarily influence the decision associated with time orientation.

[5] Onwuegbuzie (2003) identifies 22 threats to internal validity in quantitative research (e.g., history, maturity, testing) and 12 threats to external validity (e.g., population validity, ecological validity, multiple treatment interference) at the data-collection stage. Onwuegbuzie identifies 21 threats (e.g., statistical regression, multicollinearity, violated assumptions) and five threats (e.g., matching bias, researcher bias) to internal validity and external validity at the data-analysis stage. Finally, Onwuegbuzie identifies seven and three threats to internal validity and external validities (respectively) at the data-interpretation stage (see Onwuegbuzie & Johnson, 2006). Further, Onwuegbuzie and Leech (2007) identify 14 threats to external credibility (e.g., catalytic validity, communicative validity, action validity) and 15 threats to internal credibility (e.g., observational bias, researcher bias, confirmation bias) in qualitative research.

Table 3. Guidelines for Developing Inferences and Meta-inferences

Component	Guidelines
General guidelines	1. In making inferences, keep the research purposes and research questions in the foreground when analyzing and interpreting data. 2. If one investigates more than one research question, state each question separately and examine or summarize all of the results that are relevant to that question. 3. Review the statistical results, text information, field notes, and summary notes from the literature reviews. 4. Make tentative interpretations about each part of the results to address each research question. 5. After going through several iterations of interpretations, examine the answers to the questions or the interpretation to see if they can be combined. Compare, contrast, combine, or try to explain differences.
Qualitative inferences	1. In qualitative research, inferences should capture the meaning of phenomena under consideration for the participants. 2. Inferences should be made based on of qualitative data-analysis results. 3. Research questions and design decisions will influence the theoretical reasoning technique (i.e., deductive versus inductive) that researchers use to develop qualitative inferences. 4. Use the appropriate qualitative standards to assess the quality of qualitative inferences.
Quantitative inferences	1. Inferences should establish relationships between variables while providing reasonable certainty that such relationships do not happen by chance. 2. Inferences should be made based on quantitative data analysis. 3. Inferences should be free of systematic bias in interpreting the results. 4. Use the appropriate quantitative standards to assess the quality of quantitative inferences.
Meta-inferences	1. In mixed-methods research, the quality of inferences depends on the strength of inferences that emerge from the study's qualitative and quantitative strands. 2. To develop meta-inferences in mixed-methods research, one can use inductive, deductive, both inductive and deductive, or abductive theoretical reasoning. 3. Meta-inferences must directly address the initial and intended purposes for using mixed methods. 4. Researchers' study designs also influence their inferences. For example, in sequential mixed designs, researchers have to determine the purpose at the beginning of the study, or it might emerge from the inferences of the first strand. 5. One should assess the quality of meta-inferences made based on qualitative and quantitative inferences using design quality and explanatory quality (see Appendix B). One should also address other relevant legitimation types, such as sample integration legitimation, inside-outside legitimation, and conversion legitimation. 6. Possible patterns of mixed-methods research findings include: divergence, convergence, and complementarity. If the results diverge, one needs to identify the cause and re-examine the results. If the results converge, then the integration may provide a good argument for inference quality. If the results complement one other, one needs to use two or more methods to investigate the phenomenon under study.
Note: we primarily adapted these guidelines from Teddlie and Tashakkori (2009) and Erzberger and Kelle (2003)	

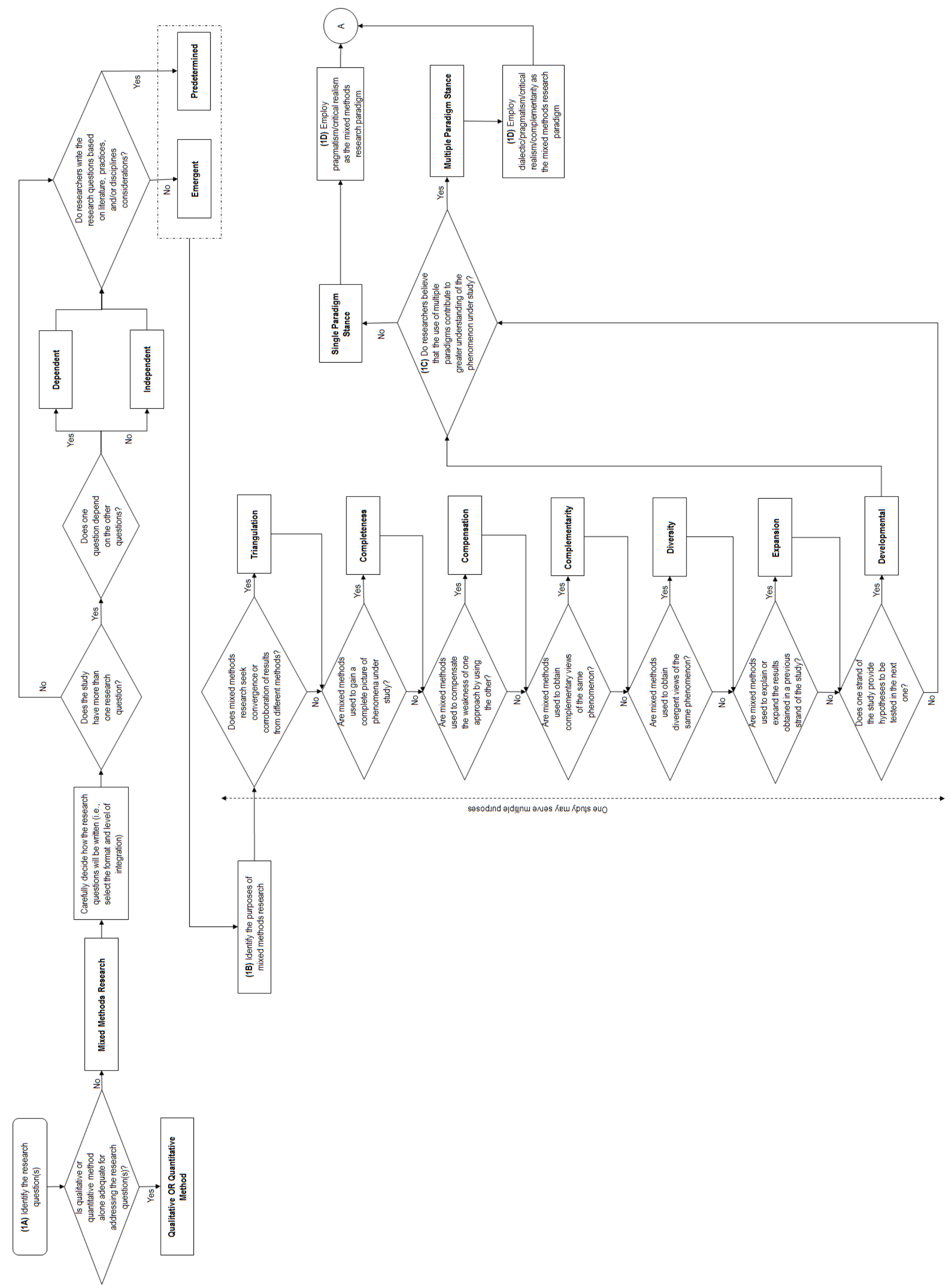

Figure 1: Model of Decision Choice for Conducting Mixed-methods Research (Step 1)

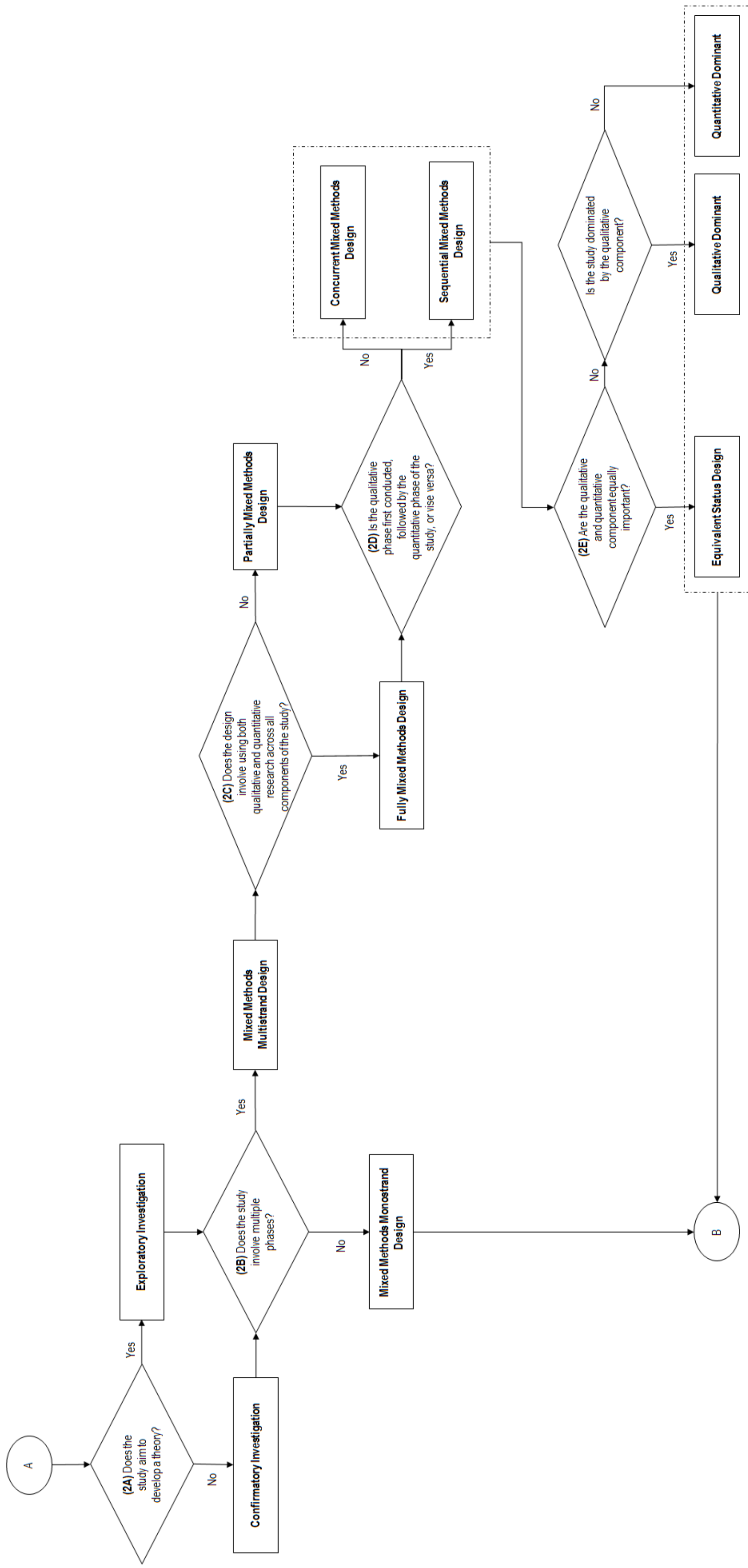

Figure 2: Model of Decision Choice for Conducting Mixed-methods Research (Step 2)

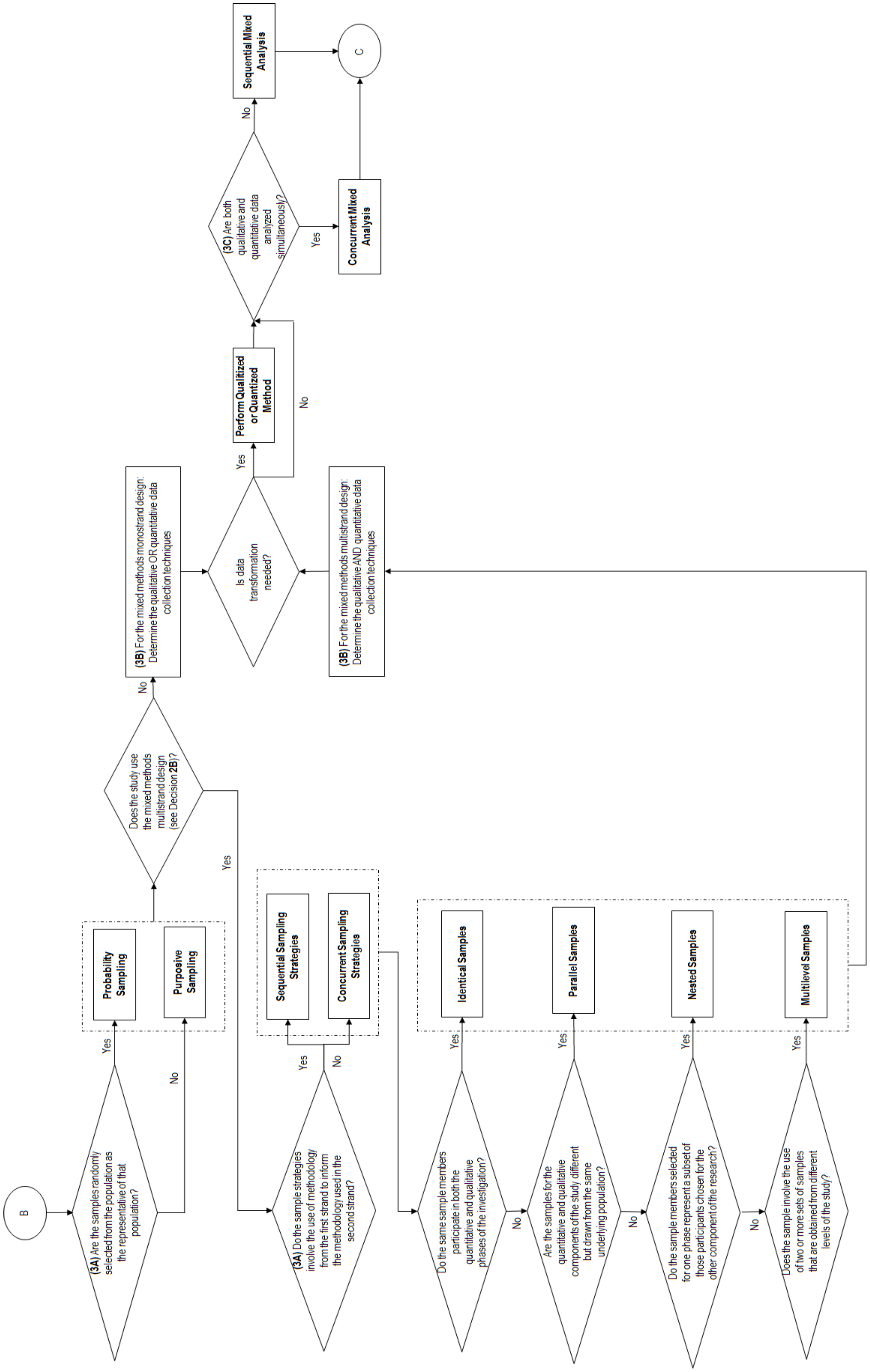

Figure 3: Model of Decision Choice for Conducting Mixed-methods Research (Step 3)

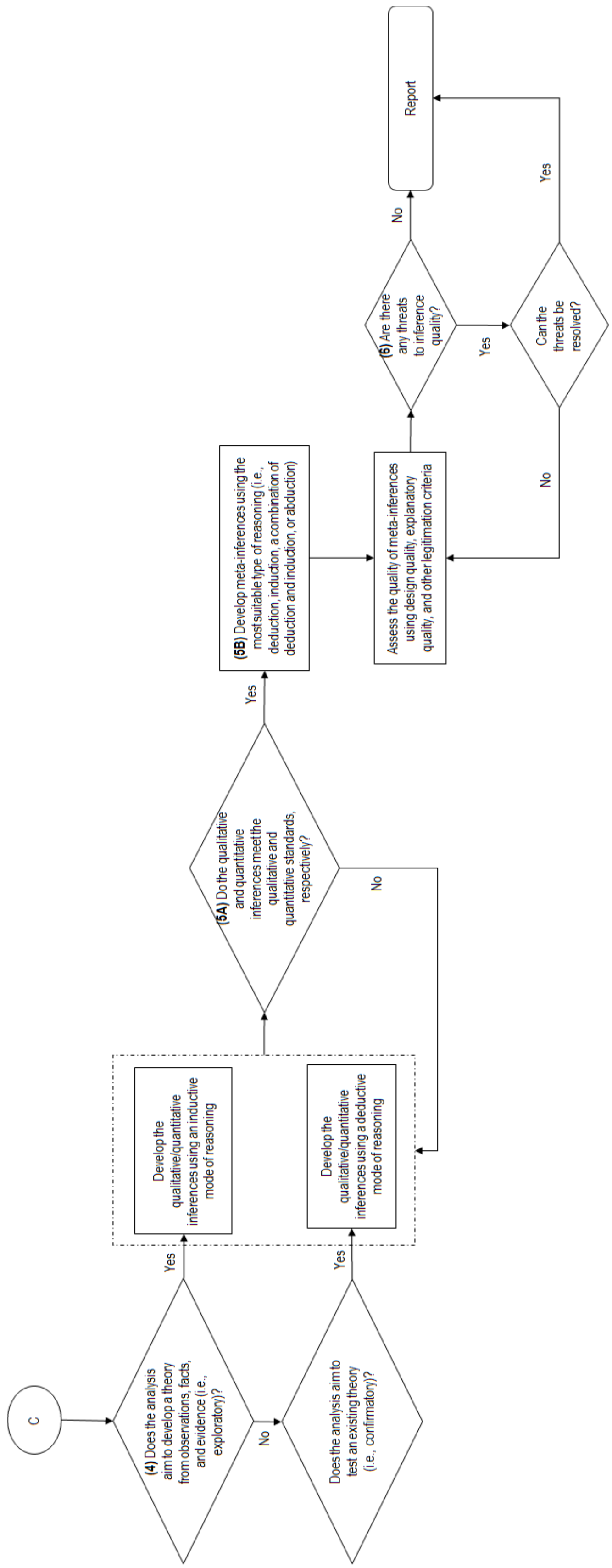

Figure 4: Model of Decision Choice for Conducting Mixed-methods Research (Steps 4, 5, & 6)

4 An Illustrative Study

With the 14 classification dimensions of mixed-methods research we discuss in Section 3, studies can involve a mixed-methods approach in many possible ways. In this section, we illustrate one possible type of mixed-methods study in depth. We apply the guidelines we discuss previously to examining factors that influence technology adoption in households. For this illustration, we re-analyzed the qualitative data from Venkatesh and Brown (2001) and the quantitative data from Brown and Venkatesh (2005) using a mixed-methods research approach. Table 4 summarizes this illustrative study. We also include references to the model of decision choice (Figures 1 to 4) in Table 4.

In Sections 4.1 to 4.8, we discuss the mixed-methods study in detail. We discuss each step of the study, which includes our selecting the design and our applying the mixed-methods guidelines we present in Section 3.

4.1 Step 1: Decide on the Appropriateness of a Mixed-methods Approach

In reporting the appropriateness of a mixed-methods approach, researchers need to describe why a mixed-methods study is necessary. Researchers should start with and clearly state their research questions and then the purposes of mixed-methods research (Leech, 2012). Further, they need to state their study's epistemological assumptions.

The illustrative study addresses three research questions: one qualitative research question, one quantitative research question, and one mixed-methods research question. Although Venkatesh and Brown (2001) frame their study with objectives, we can translate them into the following question: "What are the factors that determine household PC adoption among adopters and non-adopters?" This research question was addressed in study 1. The qualitative component in this research question is broad (identifying the adoption factors) but specific enough to focus on the issue of technology adoption in households. Prior literature, at the time of the original research activities (late 1990s), did not provide adequate foundation for understanding IT adoption in households. For this reason, using qualitative data to answer this exploratory question was appropriate. Using data collected by Venkatesh and Brown, we employed a quantizing method to transform the qualitative data.

We addressed the quantitative research question from Brown and Venkatesh's (2005) paper[6] in the second study (study 2); that is: "Does the model of adoption of technology in households (MATH) explain household adoption and non-adoption of PCs?". Brown and Venkatesh (2005) addressed this question using a survey methodology to operationalize the constructs identified in the qualitative phase of the study and empirically test MATH. We investigated the following mixed-methods question: "In what way do the results from the quantitative data collection (study 2) support or refute the results from the qualitative data collection (study 1)?". We state our mixed-methods research question using a procedural focus—it explicitly directs the procedures for mixing the strands of a mixed-methods study and is tied to the specific design being used (Plano Clark & Badiee, 2010). This mixed-methods question focuses on the need to triangulate the findings from the study's qualitative and quantitative phases.

Because we can address the quantitative research question only after answering the qualitative research question, the questions depended on each other. Further, we can conduct triangulation only after addressing both the qualitative and quantitative research questions. The relationship of our research questions to the research process was predetermined—that is, we stated the questions at the beginning of the study based on our understanding of the literature.

[6] Brown and Venkatesh (2005) also address the second research question: "Does the inclusion of the household lifecycle components improve MATH?". However, this question was not relevant for the illustrative study because study 2 tested the model (i.e., MATH) developed in study 1, which did not include the household lifecycle components. Thus, we do not discuss it here.

Table 4. Summary of the Illustrative Study

	Property	Decision consideration	Other design decision(s) likely to affect current decision	Design decision and reference to the decision tree
Step 1: decide on the appropriateness of mixed-methods research	Research questions	Qualitative or quantitative method alone was not adequate for addressing the research question. Thus, we used a mixed-methods research approach.	None	Identify the research questions *(Decision tree: Figure 1, #1A)* • We wrote the qualitative and quantitative research questions separately first and a mixed-methods research question second. • The qualitative research question was: "What are the factors that determine household PC adoption among adopters and non-adopters?". • The quantitative research question was: "Does MATH explain household adoption and non-adoption of PCs?". • The mixed-methods research question was "In what way do the results from quantitative data collection (study 2) support or refute the results from qualitative data collection (study 1)?". • We wrote the research questions in the question format. • The quantitative research question depended on the results of the qualitative research question. The mixed-methods question depended on the results of both qualitative and quantitative research questions. • The relationship between the questions and the research process is predetermined.
	Purposes of mixed-methods research	• Mixed-methods research helps researchers seek convergence or corroboration of results from different methods. • We used mixed-methods research to obtain complementary views of the same phenomenon.	Research questions	Corroboration/confirmation with an emergent element of complementarity. (*Decision tree: Figure 1, #1B*)
	Epistemological perspective	Both qualitative and quantitative components of the study used the same paradigmatic assumptions.	Research questions, purposes of mixed methods	Single paradigm stance. *(Decision tree: Figure 1, #1C)*

Table 4. Summary of the Illustrative Study

	Paradigmatic assumptions	The researchers believed in the importance of research questions and embraced various methodological approaches from different worldviews.	Research questions, purposes of mixed methods	Pragmatism (we used positivism in both qualitative and quantitative components of the study). *(Decision tree: Figure 1, #1D)*
Step 2: develop strategies for mixed-methods research designs	Design investigation strategy	The mixed-methods study aimed to develop and test a theory.	Research questions, paradigmatic assumptions	• Study 1: exploratory investigation. • Study 2: confirmatory investigation. *(Decision tree: Figure 2, #2A)*
	Strands/phases of research	The study involved multiple phases.	Purposes of mixed-methods research	Multistrand design. *(Decision tree: Figure 2, #2B)*
	Mixing strategy	The qualitative and quantitative components of the study were mixed at the data-analysis and inferential stages.	Purposes of mixed-methods research, strands/phases of research	Partially mixed methods. *(Decision tree: Figure 2, #2C)*
	Time orientation	We started with the qualitative phase, followed by the quantitative phase.	Research questions, strands/phases of research	Sequential (explanatory) design. *(Decision tree: Figure 2, #2D)*
	Priority of methodological approach	The qualitative and quantitative components were equally important.	Research questions, strands/phases of research	Equivalent status design. *(Decision tree: Figure 2, #2E)*
Step 3: develop strategies for collecting and analyzing mixed-methods data	Sampling design strategies	The samples for the quantitative and qualitative components of the study differed, but they came from the same underlying population.	Design investigation strategy, time orientation	Probability sampling with sequential design using parallel samples. *(Decision tree: Figure 3, #3A)*
	Data collection strategies	• Qualitative data collection in study 1. • Quantitative data collection in study 2.	Sampling design strategies, time orientation, strands/phases of research	• Study 1: closed- and open-ended questioning (i.e., Venkatesh and Brown (2001) drew the methodology employed in study 1 from the concepts of qualitative interviewing). • Study 2: closed-ended questioning (i.e., traditional survey design). *(Decision tree: Figure 3, #3B)*
	Data analysis strategy	• We analyzed the qualitative data quantitatively. • We analyzed the qualitative data first and the quantitative data second.	Time orientation, data collection strategy, strands/phases of research	Sequential qualitative-quantitative analysis. *(Decision tree: Figure 3, #3C)*

Table 4. Summary of the Illustrative Study

Step 4: draw meta-inferences from mixed-methods results	Types of reasoning	In our analysis, we focused on developing and testing/confirming hypotheses.	Design-investigation strategy	Inductive and deductive theoretical reasoning. *(Decision tree: Figure 4, #4)*
Step 5: assess the quality of meta-inferences	Inference quality	• The qualitative inferences met the appropriate qualitative standards. • The quantitative inferences met the appropriate quantitative standards. • We assessed the quality of meta-inferences.	Mostly primary design strategies, sampling-design strategies, data-collection strategies, data-analysis strategies, type of reasoning	Design and explanatory quality; sample integration; inside-outside; weakness minimization; conversion; multiple validities. *(Decision tree: Figure 4, #5A & 5B)*
Step 6: discuss potential threats and remedies	Inference quality	We discussed all potential threats to inference quality and provided remedies.	Data-collection strategies, data-analysis strategies	Threats to sample integration; inside-outside; data conversion; and multiple validities. *(Decision tree: Figure 4, #6)*

Based on our research questions, the primary purpose of our illustrative study is triangulation or corroboration/confirmation, with an emergent element of complementarity. We used qualitative and quantitative techniques to validate the results through triangulation, and we used both qualitative and quantitative data to produce a more complete understanding of PC adoption and use through complementarity. The complementarity purpose seeks to enhance, illustrate, or clarify results from one method type using results from other methods (Caracelli & Greene, 1993). Because we used the results from study 2 to test and confirm the results from study 1, we can consider complementarity as a secondary purpose of our illustrative study.

In the illustrative study, we adopted a single paradigm perspective. The overall mixed-methods study adopted the pragmatism paradigm (i.e., it combined positivist qualitative data collection and analysis with the positivist quantitative data collection and analysis). Although the nature of data in study 1 is qualitative, pragmatists believe that one can conduct a qualitative study using the positivist paradigm. Given the nature of the qualitative data analysis and subsequent statistical analysis in study 1, we consider study 1 to be a positivist qualitative study. Similar to study 1, study 2 adopted the positivist paradigm. Using two different methods supported our triangulation purpose, that is, to corroborate results across studies.

The illustrative study focused on MATH and empirically derived and validated this model for adopters and non-adopters to identify the factors that influence technology adoption in households. Venkatesh and Brown (2001) proposed MATH using the theory of planned behavior (TPB) (Ajzen, 1985, 1991) as the framework. According to the TPB, behavioral intention, which was the theory's key dependent variable, is determined by attitude toward behavior, subjective norm, and perceived behavioral control. Using this framework, Venkatesh and Brown sought to understand and explain household PC adoption.

4.2 Step 2: Develop Strategies for Mixed-methods Research Designs

In this stage, we determined the strands/phases of research, design investigation strategy, priority of methodological approach, mixing strategy, and time orientation of the study. When reporting the strategies, researchers need to delineate why they used a mixed-methods research design (Leech, 2012). Consistent with the research questions and paradigmatic assumptions discussed previously, we characterized study 1 as a predominantly exploratory study: although Venkatesh and Brown (2001) drew the initial constructs' definitions from previous literature, they derived the final MATH constructs from the qualitative data. Study 2 was a confirmatory quantitative study: we analyzed quantitative data and operations with statistical analysis and inference. To achieve the purposes of mixed-methods research, a mixed-methods multistrand design was the appropriate design because study 2 needed to validate the results of study 1.

Based on the strategy of mixing, this study adopted a partially mixed-methods design in which mixing occurs at the data analysis and inferential stages. Given that both the qualitative and quantitative components of the study contributed equally to address the research questions, our illustrative study followed an equivalent status design. Further, based on our research questions, the study's overall mixed-methods research design followed a sequential design approach in which findings from the qualitative study informed the quantitative study (see Creswell et al., 2003; Creswell & Plano Clark, 2007). Therefore, we needed to conduct the qualitative study before the quantitative study.

4.3 Step 3: Develop Strategies for Collecting and Analyzing Mixed-methods Data

When writing a mixed-methods research report, much like all research reports, one should include enough information so that readers can fully understand how the researchers conducted the research (Gliner, Morgan, & Leech, 2009; Leech, 2012). Given that our mixed-methods study used a sequential mixed-methods design to develop and test MATH, our mixed-methods sampling-design strategy was a probability sampling with sequential design using parallel samples. The qualitative study was longitudinal: that is, it comprised data that Venkatesh and Brown (2001) collected from an initial interview of factors influencing purchase or use decisions and follow-up interviews six months after the initial interview to measure the dependent variables (i.e., purchase or use behaviors). Similarly, study 2 was longitudinal: that is, it comprised data Brown and Venkatesh (2005) collected from an initial survey to identify factors influencing purchase or use decisions and a follow-up survey six months after the initial survey to measure purchase behavior for those who did not own a PC at the time of the initial survey and use behavior for owners at the time of the initial survey. Thus, each study comprised two sub-samples: adopters and non-adopters. We used actual use behavior and purchase behavior as the dependent variables of adopters and non-adopters, respectively (see Brown & Venkatesh, 2005). Appendix C overviews the studies, sample sizes, and measurement timing. Brown and Venkatesh (2005) developed, pre-tested, and tested the scales for the MATH constructs.

In writing a mixed-research report, researchers also need to describe and justify the analysis and explain how they combined and integrated their data sets. Consistent with our time-orientation, sampling-design, and data-collection strategies, we used *a* sequential qualitative-quantitative analysis design strategy with an emergent element of data-transformation technique (i.e., quantized) as our data-analysis strategy. In Sections 4.4 and 4.5, we discuss the qualitative and quantitative data analysis in study 1 and study 2, respectively.

4.4 Study 1 Data Analysis

In our illustrative study, we re-analyzed Venkatesh and Brown's (2001) data set[7] to examine not only its descriptive statistics but also its quantized data. An important component of the method in Venkatesh and Brown's (2001) study was that, once respondents who were primary decision makers in households identified a particular factor, the interviewers asked them to indicate the degree to which that factor was important in their decision to adopt or not to adopt a PC for household use. This technique provided not only the factors that the coders derived from coding the qualitative data but also the associated magnitude of importance (Babbie, 1990; Stone, 1978).

4.4.1 Coding and Data Transformation

Venkatesh and Brown (2001) employed two individuals to code the qualitative data. They provided the coders with construct definitions from existing models as Miles and Huberman (1994) suggest. Each coder preliminarily analyzed 30 randomly selected participants' responses. Each participant could have provided multiple responses (reasons) for each decision. After this first round of coding, Venkatesh and Brown brought the coders together to discuss their coding. They resolved inter-coder discrepancies via discussion. The coders then coded the remaining data and held out any responses that did not fit easily into any of the constructs. Consistent with Weber (1990), they coded a given response against each of the constructs to determine the fit of the response with the conceptual definitions of the constructs. Although traditional content coding relies on an existing, tested coding scheme, no such coding scheme existed for household adoption of PCs when Venkatesh and Brown (2001) conducted the study. Thus, they derived a coding scheme from the TPB framework (Venkatesh & Brown, 2001). For example, if the respondents indicated that entertainment was a factor that drove their decision to buy a PC for household use, the coder coded this response as "applications for fun" and as a hedonic outcome under an attitudinal belief structure.

[7] Please see Venkatesh and Brown (2001) for full methodological details, including the interview script used to gather data.

Appendix D provides other coding examples. The coding process revealed 13 key factors of technology adoptions in households (i.e., MATH). These factors include attitudinal beliefs (i.e., applications for personal use, utility for children, utility for work-related use, applications for fun, and status gains), normative beliefs (i.e., friends and family influences, secondary sources' influences, and workplace referents' influences), and control beliefs (i.e., fear of technological advances, declining cost, cost, perceived ease of use, and requisite knowledge). Appendix E presents the construct definitions of MATH.

Venkatesh and Brown (2001) identified the key factors of technology adoption in households through a coding process and, in this illustrative study, we converted the qualitative data into quantitative data (i.e., quantized them). Appendix F reports the descriptive statistics and correlations of the quantized data analysis. Given that we elicited open-ended responses and measured the magnitude of importance on a five-point scale, each coded response and the associated importance resulted in a single indicator for a specific construct. Therefore, in this case, the indicator variables and latent variables had a one-to-one correspondence. Although using single indicators does pose a potential problem, such use of coded qualitative data and the corresponding magnitudes (quantitative data) was consistent with approaches that Babbie (1990) and Miles and Huberman (1994) suggest. We assessed the quantitative validity of quantized data using several different techniques (see Appendix G).

4.4.2 Qualitative Validation of Study 1

Before we analyzed the quantized data, we needed to establish validity in the qualitative data-collection procedures. We report three types of validity as Venkatesh et al. (2013) discuss: 1) design validity, 2) analytical validity, and 3) inferential validity.

Design validity comprises descriptive validity, credibility, and transferability. We established descriptive validity (i.e., the accuracy of what researchers report) by providing information about the research setting (see earlier discussion about data-collection strategies) (Maxwell, 1992). To ensure study 1's credibility and transparency (i.e., the extent to which qualitative research's results are credible and believable), Venkatesh and Brown (2001) collected data from a large random sample of households via telephone interviews. To ensure transferability (i.e., the degree to which one can generalize qualitative research results to other contexts), Venkatesh and Brown used a longitudinal study with two waves of measurement: an initial interview (during a three-week window in March/April 1997) and a follow-up interview six months later. Venkatesh and Brown compared the characteristics of the sample to the population in general and found that the random sample of households included in this study highly represented the population of American households (see Venkatesh & Brown, 2001).

Analytical validity comprises theoretical validity and plausibility, dependability, and consistency. During the data collection, Venkatesh and Brown (2001) established theoretical validity and plausibility (i.e., the extent to which a study's theoretical explanations and the findings fit the data and are, therefore, credible and defensible) by using a well-designed protocol to collect the data (Orlikowski, 1993). They first pre-tested the interview protocol to solicit comments and suggestions about the instrument from respondents (Venkatesh & Brown, 2001). With the pre-test, they also identified wording issues that they needed to address. During the interview, the interviewers asked every question and in the prescribed order per the interview protocol, which helped maintain data reliability and credibility (Judd, Smith, & Kidder, 1991). To promote theoretical validity, they also used an existing theory (i.e., TPB) along with several established research bases in technology adoption, customer behavior, and psychology as guiding frameworks for the proposed theoretical model (see Venkatesh & Brown, 2001). Dependability in qualitative research emphasizes the need for the researcher to account for every change that occurs in the setting (Venkatesh et al., 2013). Venkatesh and Brown assessed dependability through inter-rater (or coder) reliability (IRR), which measures consistency in qualitative data-analysis procedures. The IRR was .89, which indicates a high degree of consistency. Venkatesh and Brown used triangulation to identify themes that several data sources shared and derived the coding schemes from an existing theoretical framework (Jick, 1979). To maintain consistency, Venkatesh and Brown trained 12 interviewers who had an average of 3.2 years' experience in interviewing (including at least six months' experience in telephone interviewing) on this particular interview protocol/script. Interviewers followed the same interview protocol/script for all the interviewees.

Inferential validity comprises interpretive validity and confirmability. Little (if any) IS research has reported inferential validity. We believe that one needs to report this type of validity because qualitative researchers focus on not only validly describing the objects, events, and behaviors in the setting they study but also what these objects, events, and behaviors mean to the people engaged with them (Maxwell, 1992). In the original study, Venkatesh and Brown (2001) achieved interpretive validity (i.e., the degree to which researchers accurately understand participants' views, thoughts, feelings, intentions, and experiences) by obtaining participant's feedback during the interview. They also coded and reported the data as close as possible to participants' accounts and interview transcripts and notes. They documented all procedures for checking and cross-checking the data throughout the study to ensure the qualitative study's confirmability (i.e., the degree to which one can confirm or corroborate results with others) (Lincoln & Guba, 1985).

4.4.3 Results of Study 1

Among users that already possessed a PC at the time of the initial survey (n = 201), we tested the model with use as the dependent variable. Appendix H presents the results of study 1. MATH with five key predictors—all three utilitarian outcomes, applications for fun, and status gains—explained 58 percent of the variance in use behavior. Appendix H also presents the results associated with the model for households that did not possess a PC at the time of the initial survey with follow-up purchase behavior that we measured six months after the initial survey as the dependent variable (n = 435). MATH explained 57 percent of the variance in purchase behavior.

4.5 Study 2 Data Analysis

The results of study 1 suggest that various factors in MATH influence adoption and use of technologies in households. In study 2, we operationalized the MATH constructs for survey research. We reported construct reliability and validity.

4.5.1 Quantitative Validation of Study 2

We re-analyzed Brown and Venkatesh's (2005) data using PLS. The measurement model results supported reliability and convergent and discriminant validity: all ICRs were greater than .70 and all AVEs were greater than inter-construct correlations. Acceptable loadings (>.65) and low cross-loadings (<.30) in model tests for adopters and non-adopters further supported discriminant validity. Appendix I presents the ICRs, AVEs, descriptive statistics, and correlations. Although internal validity is a weakness of survey-based research, the longitudinal data collection here helped us provide better support for causality. The demographics comparison between the respondents and non-respondents at both periods (i.e., the initial survey and the follow-up survey conducted six months after the initial survey) showed no significant differences, which indicates that threats to internal validity (e.g., selection, history, maturation) did not influence the results (Brown & Venkatesh, 2005). We measured statistical conclusion validity by using an appropriate data-analysis procedure and tool and by ensuring no statistical assumptions were violated. These validity criteria (i.e., internal validity, construct validity, discriminant validity, and statistical conclusion validity) also confirmed that the quantitative inference criteria were met (Venkatesh et al., 2013).

4.5.2 Results of Study 2

Among users that already possessed a PC at the time of the initial survey (n = 370), we tested the models with use as the dependent variable. Appendix H shows the belief structures of MATH explained 57 percent of variance in use behavior. Appendix H also presents the PLS analysis results associated with the model testing of the data from households that did not possess a PC at the time of the initial survey with follow-up purchase behavior conducted six months after the initial survey as the dependent variable. MATH explained 50 percent of the variance in purchase behavior.

4.6 Step 4: Draw Meta-inferences from Mixed-methods Results

In making the qualitative inferences, we followed the guidelines in Table 3. At the beginning of study 1, we inductively built a theoretical framework based on previous models (e.g., TPB). We used the resulting theoretical framework as the basis of study 2. We used inductive and (primarily) deductive theoretical reasoning to develop the meta-inferences. In our mixed-methods study, we assessed the credibility of inferences obtained from analyzing qualitative and quantitative data (i.e., triangulation with the emergence of complementarity). To do so, we used a triangulation technique to develop the meta-inferences. Triangulation techniques: 1) allow researchers to be more confident in their results, 2) can stimulate the creation of inventive methods and new ways of understanding a problem from multiple perspectives, 3) may help uncover various dimensions of a phenomenon, and (4) can lead to a synthesis or integration of theories (Jick, 1979).

We developed the qualitative inferences first and the quantitative inferences second (see Table 5). In our illustrative study, the results showed a great deal of convergence but also revealed some inconsistent findings. Overall, we found that the same set of factors represented significant predictors of home PC adoption and use in both the qualitative and quantitative studies. Although the questionnaire used in the quantitative study was derived from the results of the interviews, we found two significant differences in findings between the studies. In the qualitative study, requisite knowledge was significant for current non-adopters but not significant in the quantitative study. In the qualitative study, status gains was significant for adopters but not significant in the quantitative study.

One of the limitations of our study was that we did not re-examine the divergent findings using a new dataset (Erzberger & Kelle, 2003). However, we offered a theoretical explanation to resolve the divergent findings. Because these divergent findings unlikely resulted from the authors' mistake in collecting or analyzing the data (see Sections 4.4 and 4.5), we felt that re-examining theoretical assumptions was sufficient to address this issue. We explain these divergent findings next.

First, analyzing the qualitative data for the current non-adopters group showed that the majority of respondents indicated requisite knowledge influenced their decision to adopt a PC. At the same time, they considered fear of technology change to be the main barrier. Based on the arguments they formulated, current non-adopters found requisite knowledge a dominant issue because they found learning a new technology to be difficult. Thus, requisite knowledge likely had no direct effect (or the effect was small) on purchase behavior. However, other variables could mediate this relationship. For example, in their study, Kim and Kankanhalli (2009) found that requisite knowledge (i.e., self-efficacy) had no direct effect on user resistance. Rather, switching cost mediated the effect of self-efficacy on user resistance. With respect to our results, we need further investigation to test whether requisite knowledge has an indirect effect on purchase behavior through mediating variables. For instance, individuals' belief that they have the knowledge necessary to use a PC may influence their perception of the utility they would achieve when using the PC, which, in turn, would influence their purchase behavior. This potential mediating relationship could, therefore, explain the non-significant direct effect of requisite knowledge that we found in study 2.

Second, we found status gains to be significant among current adopters in the qualitative study but not significant in the quantitative study. Contrary to the finding from the quantitative study, prior research has reported that status gains was an important determinant of adoption behaviors (e.g., Fisher & Price, 1992; Kim & Han, 2009). Moreover, the innovation literature has indicated that social outcomes, such as status gains, are important in the early stage of technology adoption (Venkatesh & Brown, 2001). Social rewards do not likely influence later adopters because the status value of adopting diminishes as more people adopt (Brown & Venkatesh, 2003).

Overall, our meta-inferences are consistent with MATH's theoretical concepts. Integrating the qualitative and quantitative research strands has successfully added value beyond the individual studies. Given that study 1 and 2 data are from different sets of participants and different data-collection procedures, the findings' similarity indicates we used strong theoretical models as our research foundation. The results' richness and robustness gives us confidence about the factors that predict household PC adoption and use. The mixed-methods design helped us identify and understand the factors that influence household PC adoption and use. The qualitative study helped us identify a set of factors and their importance, and the quantitative study helped us empirically examine the theoretical model (developed from the qualitative study) to identify what factors drive household PC adoption and use and how these factors help explain the behavior differences between adopters and non-adopters. Taken together, these studies explain the factors that drive household PC adoption and use. Table 5 summarizes our meta-inferences.

Table 5. Development of Qualitative Inferences, Quantitative Inferences, and Meta-inferences

Context	Qualitative inference	Quantitative inference	Meta-inference	Explanation
Attitudinal belief structures	The effect of applications for personal use was significant for both current adopters and non-adopters.	Consistent with the qualitative findings.	Utilitarian outcomes (i.e., personal use and work-related) were positively associated with use behavior (for current adopters) and purchase (for non-adopters).	-

Table 5. Development of Qualitative Inferences, Quantitative Inferences, and Meta-inferences

	Utility for children and utility for work-related use were positively associated with the use behavior of current owners. However, only utility for work-related use was significant for non-adopters.	Consistent with the qualitative findings.		
	Applications for fun was positively associated with the use behavior of current owners and purchase behavior of non-owners.	Consistent with the qualitative findings.	Hedonic outcome (i.e., applications for fun) was positively associated with use behavior (for current adopters) and purchase (for non-adopters).	-
	Status gains was significant for current owners but not for current non-owners.	Status gains was not significant for both groups.	There was *no* relationship between status gains and use behavior (for current owners) and purchase (for current non-owners).	The innovation literature has indicated that social outcomes, such as status gains, are important in the early stage of technology adoption (Venkatesh & Brown, 2001). Social rewards do not likely influence later adopters because the status value of adopting diminishes as more people adopt (Brown & Venkatesh, 2003).
Normative belief structures	Friends and family and secondary sources positively influenced purchase behavior of current non-owners. However, neither predictor was significant for current owners.	Consistent with the qualitative findings.	• There was *no* relationship between social influences and use behavior. • There was *no* relationship between secondary sources and use behavior of current owners. • Social influences and secondary sources were positively associated with purchase behavior.	-

Table 5. Development of Qualitative Inferences, Quantitative Inferences, and Meta-inferences

Control belief structures	Fear of technology change, declining cost, perceived ease of use, and requisite knowledge for PC use were not significant for current owners. However, they were significant only for current non-owners.	Consistent with the qualitative findings, except the qualitative study found that requisite knowledge was significant for current non-owners, whereas the quantitative study found that requisite knowledge was not significant for current non-owners.	• One's control beliefs (i.e., fear of technology change, declining cost, and perceived ease of use) were *not* associated with use behavior. • One's control beliefs (i.e., fear of technology change, declining cost) were negatively associated with purchase. • One's control belief (i.e., perceived ease of use) was positively associated with purchase.	Based on the arguments they formulated, current non-adopters found requisite knowledge a dominant issue because they found learning a new technology to be difficult. Thus, requisite knowledge likely had no direct effect (or the effect was small) on purchase behavior. However, other variables could mediate this relationship. We need further investigation to test whether requisite knowledge has an indirect effect on purchase behavior through mediating variables. For instance, individuals' belief that they have the knowledge necessary to use a PC may influence their perception of the utility they would achieve in using the PC, which, in turn, would influence their purchase behavior. This potential mediating relationship could, therefore, explain the non-significant direct effect of requisite knowledge we found in study 2.

4.7 Step 5: Assess the Quality of Meta-inferences

After we discussed the validity of quantitative and qualitative components (see Sections 4.4 and 4.5), we assessed the quality of the meta-inferences. As we state in Section 4.6, the results from both studies were consistent, which evidences the mixed-methods data's high quality (i.e., reliability). We ensured the design quality by selecting the most appropriate research designs based on our research questions and the purposes of our mixed-methods study. We checked the explanation quality following the procedures that Venkatesh et al. (2013) recommend. Table 6 presents each type of validity criterion. Further, we assess the quality of meta-inferences using Onwuegbuzie and Johnson's (2006) typology (see Table 7).

Table 6. Quality of Meta-inferences

Criteria	Indicators
Design suitability	• The study started with the qualitative phase (study 1) to address the first research question (i.e., what are the factors that determine household PC adoption among adopters and non-adopters?) followed by the quantitative phase (study 2) to address the second research question (i.e., does MATH explain household adoption and non-adoption of PCs?). We addressed the first question from Venkatesh and Brown (2001) using a qualitative method because, at the time when they conducted the study, prior literature did not provide adequate foundation for understanding IT adoption in households. We addressed the second research question from Brown and Venkatesh (2005) using a survey methodology to operationalize the constructs identified in the qualitative phase of the study (study 1) and empirically test the model of adoption of technology in households. • We answered the mixed-methods research question (i.e., in what way do the results from the quantitative data collection (study 2) support or refute the results from the qualitative data collection (study 1)?) by triangulating the findings from the qualitative and quantitative studies. • Based on the research questions and specified purposes of the project, we carefully selected the mixed-methods designs (see Table 4).
Design adequacy	• We integrated various design components (e.g., sampling, data collection and analysis procedures) and applied the selected criteria to address the research questions. • We used two major sources of data: 1) open- and closed-ended qualitative interviews (Venkatesh & Brown, 2001) and 2) standardized questionnaire surveys to measure the various constructs described in MATH (Brown & Venkatesh, 2005). • Both the qualitative and quantitative study were longitudinal. In collecting the qualitative data, the interviewers followed the same protocol to maintain consistency. A comparison between the sample characteristics and the population characteristics in general showed that the sample represented the population. In collecting the quantitative data, the measurement items were carefully developed, pre-tested, and tested based on the results of study 1.
Analytical adequacy	• We adopted a sequential mixed-methods data-analysis approach to analyze the data. • We converted qualitative data into quantitative data. We statistically analyzed quantized data to test the hypothesized relationships. • We analyzed quantitative data using PLS-SEM. We chose PLS because it is robust and has few identifiability issues (Hair, Ringle, & Sarstedt, 2011). • Percentage of explained variance in the structural model of both the qualitative and quantitative studies was consistent, which suggests the study designs were appropriate to create the expected effect.
Integrative efficacy	• Meta-inferences resulted from triangulating the qualitative and quantitative findings. For example, the qualitative inference is "The effect of applications for personal use was significant for both current adopters and non-adopters" and the quantitative inference is "Utility for children and utility for work-related use were positively associated with the use behavior of current owners. However, only utility for work-related use was significant for non-adopters.". We integrate these inferences to develop a meta-inference (i.e., utilitarian outcomes (i.e., personal use and work-related) were positively associated with use behavior (for current adopters) and purchase (for non-adopters)) (see Table 5 for details). • We theoretically explain the inconsistent findings across studies. For example, the qualitative study revealed that status gains was significant for owners but not for current non-owners, whereas the quantitative study showed status gains was not significant for both groups. We explain this consistency by reviewing the innovation literature (see Table 5 for details).
Inference transferability	• Inferences were consistent with the initial hypotheses of MATH. • The model is generalizable to the household population in the US but not necessarily to other countries, unless individuals adopted the PC in a similar way in these countries. • The outcomes and inferences might be applicable to study the adoption of other related technologies.
Integrative correspondence	Meta-inferences clearly represented the study's initial purposes. The study's primary purpose was triangulation or corroboration/confirmation, with an emergent element of complementarity. The mixed-methods designs implemented in the illustrative study were sufficient to achieve the study's goals. Using the qualitative study, we identified the factors that determine household PC adoption among adopters and non-adopters. We then examined the predictive power of these factors in the quantitative study.

Table 7. Legitimation of Meta-Inferences (Onwuegbuzie & Johnson, 2006)

Legitimation	Indicators
Sample integration legitimation	The study adopted a sequential mixed-methods sampling strategy with parallel samples to collect the qualitative and quantitative data.
Inside-outside legitimation	• The researchers (i.e., Venkatesh & Brown (2001)) employed two individuals/coders to code the qualitative data. • Everyone on the research team reviewed the data analysis and integration.
Weakness minimization legitimation	We identified the potential threats and remedies of each method were (see step 6).
Conversion legitimation	• We conducted conversion based on theoretical perspectives. • We established the validity of the quantified data.
Multiple validity legitimation	• When addressing the legitimation of the qualitative component, we addressed and established the relevant qualitative validities. • When addressing the legitimation of the quantitative component, we addressed and established the relevant quantitative validities. • We also addressed the relevant mixed-methods legitimation types.
Political legitimation	• We developed meta-inferences based on the qualitative and quantitative inferences. • The results supported the theory. • We addressed research questions using mixed-methods research.

In our illustrative study, although we addressed most of the legitimation issues, we did not address sequential legitimation, paradigmatic mixing, and commensurability legitimation. One method to assess sequential legitimation is to change the sequence of the research study. Because we re-analyzed already-collected data for this illustration, we could not assess sequential legitimation in this work. However, because most of our qualitative and quantitative inferences were consistent, we believe that the threat to sequential legitimation is not a major issue in our study. We did not address paradigmatic mixing in our illustration because we employed a pragmatism paradigm (i.e., both studies used a positivist approach). However, we successfully integrated the qualitative and quantitative inferences to develop meta-inferences. We also discussed the inference quality of the qualitative and quantitative data analysis. Finally, one can address commensurability legitimation if one can negotiate cognitively the importance of Gestalt switches—switching back and forth from a qualitative lens to a quantitative lens (Onwuegbuzie & Johnson, 2006). Onwuegbuzie and Johnson (2006) suggest that one can do so through cognitive and empathy training, and, if researchers have a limited ability to do this gestalt switch, then the researchers can ignore commensurability legitimation.

Conducting mixed-methods research involves inherent challenges that make it more difficult than conducting a monomethod study. We review some of the challenges we encountered in the illustrative study (see Appendix B). First, researchers must understand and explain the rationale for using a mixed-methods research approach in their study (Teddlie & Tashakkori, 2009). Although we used two, independent papers for our illustrative study, they were from the same research program in which the authors employed a mixed-methods approach for collecting and analyzing the data. The initial challenge we encountered in this illustrative study was finding the rationale for combining the qualitative and quantitative data in the face of seemingly incompatible paradigms. Selecting an appropriate paradigm is a necessary step to justify one's using a mixed-methods approach. To deal with this issue, we employed a pragmatism paradigm approach by combining the positivist qualitative data collection and analysis with the positivist quantitative data collection and analysis. Understanding the philosophical assumptions underlying each paradigm can also be a challenge for researchers because it requires knowledge and methodological expertise in multiple areas.

The second challenge is associated with selecting the most suitable design to address the research questions. The process of selecting the best mixed-methods research design involves several steps as the decision tree presents (see Figure 1). To select the most appropriate design, researchers need to understand the characteristics and goals of each design choice. For example, in our illustrative study, we discussed the rationale for selecting a multistrand design that led to our selecting a sequential (explanatory) design and an equivalent status design. The design options discussed in this paper could be overwhelming, especially for those who are new to the field. Conducting mixed-methods research also requires more time and resources (e.g., funding, staffing). Without enough time and resources in one's research team, a mixed-methods research project can be challenging.

The issue of nomenclature and basic definitions used in mixed-methods research is another challenge in conducting a mixed-methods study (Teddlie & Tashakkori, 2003). For example, although quantitative research studies routinely use the term "validity", many qualitative researchers object to using this term (Onwuegbuzie & Johnson, 2006). In contrast, some qualitative researchers (e.g., Maxwell, 1992) do not refute using the term "validity" in qualitative research. Similarly, in the context of mixed-methods research, some scholars have used different terms to refer to the same concepts. For example, Teddlie and Tashakkori (2003) propose the term inference quality to refer to validity in the context of mixed-methods research (Venkatesh et al., 2013), whereas Onwuegbuzie and Johnson (2006) recommend that validity in mixed-methods research be termed legitimation. We believe that mixed-methods researchers should adopt a common nomenclature for validation to differentiate mixed-methods validation from qualitative and quantitative validation (Teddlie & Tashakkori, 2003; Venkatesh et al., 2013). We should diminish the differences in terminology to maintain consistency across mixed-methods studies.

In our illustrative study, some of the results from the qualitative study were inconsistent with the qualitative study. As a result, we had to examine our findings more closely and review the existing literature more carefully to create a more advanced theoretical explanation (Teddlie & Tashakkori, 2009). Identifying the major source of inconsistency can be challenging in mixed-methods research because it requires researchers to reexamine the data, reassess the inference quality, go back to the literature, and even collect a new dataset (Erzerber & Kelle, 2003). Despite the challenge of identifying the source of inconsistency, divergent inferences in a mixed-methods study might lead to a better understanding of the phenomenon under study (Teddlie & Tashakkori, 2009).

4.8 Step 6: Discuss Potential Threats and Remedies

Although several possible threats to the inference quality of mixed-methods research exist, one can minimize these threats through several remedial actions. Table 8 lists the threats and remedial actions in our illustrative study.

Table 8. Potential Threats to Inference Quality and Remedial Actions (Adapted from Creswell & Plano Clark, 2007)

Areas	Legitimation type	Threats	Remedial actions
Data collection	Threat(s) to sample integration	Selecting different individuals for the qualitative and quantitative data collection.	1. The researchers involved in collecting data for study 1 and 2 drew the sampling frame for the quantitative and qualitative data collection from the same population.
		Unequal sample sizes for the qualitative and quantitative dataset.	2. Both studies had a fairly large sample size.
	Threat(s) to inside-outside legitimation	Introducing potential bias in the data-collection techniques.	3. A professional marketing firm collected data, and the interviewers involved in collecting data used a specific interview protocol/script for all interviewees.
Data analysis	Threat(s) to data conversion	Inadequate data transformation approaches.	1. We quantized the qualitative data by creating codes and then counting codes and evaluating their weights.
	Threat(s) to multiple validities	Not addressing validity issues.	2. We assessed and discussed validity for both studies.

In our illustrative study, we discuss only one of many alternative designs that mixed-methods researchers can use. Researchers can be flexible in selecting their designs based on the objectives of their study. For example, one can use a multiple paradigmatic stance (e.g., researchers might use interpretivism in their qualitative study and positivism in their quantitative study) to address the research questions proposed in our illustrative study. Researchers can also adopt either qualitative dominant or quantitative dominant designs depending on the purpose of their study. For example, if one primarily focuses on identifying factors that determine PC adoption in households, then one should select the qualitative dominant design with the interpretivism paradigm and sequential-exploratory design.

Researchers can flexibly integrate the 14 properties discussed to help them select the most suitable mixed-methods designs for their studies. We suggest that, when planning a mixed-methods study, researchers should consider these properties and select those most relevant to the objectives of their study. Among these 14 properties, research questions, purposes of mixed-methods research, and paradigmatic assumptions are absolutely fundamental during the study's conceptualization stage. For example, in our illustrative study, we used the research questions and purposes of mixed-methods research as our basic foundation for selecting the mixed-methods design based on the assumptions underlying pragmatism. At the methodological stage, the components of time orientation, data collection strategies, and data analysis strategies are critical and should not be overlooked in mixed-methods research because they determine the quality of inferences. Other properties, such as priority of methodological approach, can be less salient depending on the research questions. For example, if it is unclear whether the qualitative or quantitative data will ultimately be the most important in the results and inferences, then priority of approach is not a critical element of design dimensions (Teddlie & Tashakkori, 2010). One should also assess the inference quality carefully because inferences are the most important aspects or outcomes of mixed-methods research (Teddlie & Tashakkori, 2010).

5 Discussion

This paper extends Venkatesh et al.'s (2013) guidelines by identifying and integrating 14 variations of mixed-methods research properties. These guidelines offer a new perspective to accommodate the diversity of mixed-methods designs. Further, we illustrate one possible type of mixed-methods research in depth. We also discuss the development and validation of meta-inferences (i.e., validation of mixed-methods research) in our illustrative study. This paper contributes to the development of mixed-methods research by viewing mixed methods as an integrative model of design based on various properties of mixed-methods research (Maxwell & Loomis, 2003). Finally, this paper advances our understanding of mixed-methods research by presenting the variety of possible mixed-methods applications and demonstrating that a mixed-methods approach may generate stronger inferences because such an approach integrates qualitative and quantitative inferences.

5.1 Contributions

This research makes several key contributions to the literature on mixed methods. First, we extend the guidelines of Venkatesh et al. (2013) for mixed-methods research by integrating 14 properties of mixed methods into the guidelines. Our guidelines complement the other existing mixed-methods research guidelines (e.g., Maxwell & Loomis, 2003; Nastasi et al., 2010; Tashakkori & Teddlie, 1998, 2003b). Critically, our guidelines integrate various dimensions of mixed-methods research to accommodate different types of mixed-methods designs. Although we position the guidelines in an IS context, due to the dearth of guidance on how to better execute mixed-methods research, they are also broadly applicable beyond IS.

Second, we show how one can use mixed-methods research to extract significant findings that the limitations inherent in a single method alone can compromise. Through this study, we provide researchers with the information necessary to select the best mixed-methods designs for their research project based on 14 general properties of the studies that scholars have well established in mixed-methods research. We also offer a decision tree to map the flow and relationship among the design strategies.

Third, we illustrate one possible type of mixed-methods research in depth by characterizing the study from multiple dimensions of mixed-methods research. Our illustration shows that researchers can select the designs of mixed-methods research that best fit with their research questions and purposes. This illustration provides an opportunity to open up the research process from which the research community may learn about the best practices and the challenges in conducting mixed-methods research.

Fourth, we contribute to the development of mixed-methods research, particularly in the IS field. We argue that the use of mixed methods, if done well, may drive the development of IS research. Although using mixed-methods research in social science is in its adolescence (Teddlie & Tashakkori, 2003), its use in IS is relatively new. We suggest that IS researchers familiarize themselves with the theoretical paradigms and different properties of mixed-methods research. Although research methods and theoretical paradigms that underlie these methods should follow the research questions, IS researchers should be able to integrate those different paradigms and not rely solely on a single paradigm (Tashakkori & Teddlie, 1998; Venkatesh et al., 2013). We also advise IS researchers to be flexible in making their research design decisions depending on the purposes of their mixed-methods research study.

Finally, we illustrate only one possible type of mixed-methods study. Thus, we need future research to illustrate how to conduct different types of mixed-methods studies based on different properties of mixed-methods research discussed in this paper. For instance, one could conduct mixed-methods research to answer a research question with expansion and developmental purposes to increase the validity of constructs and inquiry results by selecting the most appropriate methods and maximizing the method strengths (Greene et al., 1989). Based on their research question(s) and well-defined purposes, researchers then can select the most appropriate paradigmatic assumptions and determine their mixed-methods design strategies.

6 Conclusions

In this paper, we extend Venkatesh et al.'s (2013) guidelines for mixed-methods research by elaborating various properties of such studies. The integrative framework that we presented accommodates different types of mixed-methods research. We deliberately tried to be comprehensive in selecting and reviewing the mixed-methods properties to offer researchers the opportunity to properly use a mixed-methods approach in their study. We illustrate one possible type of mixed-methods research in depth—one of the first illustrations that applies various properties of mixed-methods research by incorporating qualitative and quantitative data collection and analysis in a sequential manner and that explains the decisions made at various stages of the research endeavor. In this illustration, we also present how we developed and validated meta-inferences in a broader research program.

Note that the specific guidelines we propose and illustrate reflect a certain set of preferences and are dominated by our paradigmatic assumptions in-use. We do not seek to constrain all mixed-methods researchers to follow the same research designs as our example illustrates. Instead, we provide general guidelines that enable authors to critically think about their designs prior to the study and offer justification of their approaches after the study. Thus, authors and reviewers need to be flexible in adapting the guidelines based on the objectives of their study and the ontological and epistemological assumptions underlying the different components of their mixed-methods studies. We hope this work motivates researchers to adopt mixed methods in their research projects to gain richer insights into phenomena they investigate.

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Appendix A: Review of Selected Theoretical Literature in Mixed-methods Research

Table A1. Review of Selected Theoretical Literature in Mixed-methods Research

Property of mixed-methods approach	Reference(s)	Dimensions	Description
Research questions	Creswell (2009)	Type I	Researchers write separate quantitative questions or hypotheses and qualitative questions or hypotheses.
		Type II	Researchers write separate quantitative questions or hypotheses and qualitative questions or hypotheses and follow them with a mixed-methods question.
		Type III	Researchers write only mixed-methods questions that reflect the procedures or the content (or write the mixed-methods question in both a procedural and a content approach) and do not include separate quantitative and qualitative questions.
	Plano Clark & Badiee (2010)	Rhetorical style: format	Mixed-methods researchers could state their research questions in the form of questions, aims, and/or hypotheses.
		Rhetorical style: level of integration	• Separate questions only: "the researcher writes separate questions for the qualitative and quantitative strands of the study" (Plano Clark & Badiee, 2010, p. 290). • General, overarching mixed-methods question: "the researcher writes a broad question that is addressed with both quantitative and qualitative approaches" (Plano Clark & Badiee, 2010, p. 290). • Hybrid mixed-methods issue question: "the researcher writes one question with two distinct parts and uses a quantitative approach to address one part and a qualitative approach to address the other part" (Plano Clark & Badiee, 2010, p. 290). • Mixed-methods procedural question: "the researcher writes a narrow question that directs the integration of the qualitative and quantitative strands of the study" (Plano Clark & Badiee, 2010, p. 291). • Combination: "the researcher combines at least one mixed methods question with separate quantitative and qualitative questions" (Plano Clark & Badiee, 2010, p. 291).
		The relationship of questions to other questions	• Independent: "the researcher writes two or more research questions that are related, and one question does not depend on the results of the other questions" (Plano Clark & Badiee, 2010, p. 291). • Dependent: "the researcher writes a question that depends on the results of another research question" (Plano Clark & Badiee, 2010, p. 291).
		The relationship of questions to the research process	• Predetermined: "the researcher writes a question based on literature, practice, personal tendencies, and/or disciplinary considerations at the outset of the study" (Plano Clark & Badiee, 2010, p. 292). • Emergent: "the researcher formulates a new or modified question during the design, data collection, data analysis, and interpretation" (Plano Clark & Badiee, 2010, p. 292).

Table A1. Review of Selected Theoretical Literature in Mixed-methods Research

Paradigmatic perspectives	Venkatesh et al. (2013), Tashakkori & Teddlie (1998, 2003), Morgan (2007), Johnson & Onwuegbuzie (2004)	Pragmatism	This paradigm considers practical consequences and real effects to be vital components of meaning and truth. It rejects a forced choice between existing paradigms with regard to logic, ontology, and epistemology.
	Mertens (2003, 2005)	Transformative-emancipatory	This paradigm considers the ultimate goal for conducting research to be in creating a more just and democratic society.
	Harrits (2011), Maxwell & Mittapalli (2010)	Critical realism	This paradigm does not recognize the existence of some absolute truth or reality to which one can compare an object or account.
	Greene (2007), Greene & Hall (2010)	Dialectical	This paradigm recognizes the legitimacy of multiple paradigmatic traditions because they represent “multiple way of seeing and hearing, multiple ways of making sense of the social world, and multiple standpoints on what is important and to be valued and cherished” (Greene & Hall, 2010, p. 124).
	Teddlie & Tashakkori (2003)	Other major paradigmatic perspectives (e.g., positivist, constructivism, post-positivist)	Researchers can use multiple paradigmatic stances to support mixed-methods research.
Epistemological perspective	Greene et al. (1989), Tashakkori & Teddlie (1998)	Single paradigm stance	Both qualitative and quantitative studies are in the same paradigm.
		Multiple paradigm stance	Qualitative and quantitative studies are in different paradigms.
Purposes of mixed-methods research	Greene et al. (1989), Johnson & Onwuegbuzie (2004)	Triangulation	Researchers use mixed-methods research to seek convergence and corroboration of results from different methods and designs studying the same phenomenon.
		Complementarity	Researchers use mixed-methods research to seek elaboration, enhancement, illustration, and clarification of the results from one method with results from the other method.
		Initiation	Researchers use mixed-methods research to discover paradoxes and contradictions that lead to a re-framing of the research question.
		Development	Researchers use the findings from one method to help inform another method.
		Expansion	Researchers use mixed-methods research to expand the breadth and range of research by using different methods for different inquiry component.
	Creswell (2003), Tashakkori & Teddlie (2003), Venkatesh et al. (2013)	Complementarity	Researchers use mixed-methods research to elaborate, enhance, illustrate, and clarify the results from one method with results from another method.
		Completeness	Researchers use mixed-methods research to make sure they obtain a complete picture of a phenomenon.
		Developmental	Researchers use the findings from one method are used to help inform another method.
		Expansion	Researchers use mixed-methods research to explain or expand on the understanding obtained in a previous strand of a study.

Table A1. Review of Selected Theoretical Literature in Mixed-methods Research

		Corroboration/ confirmation	Researchers use mixed-methods designs to assess the credibility of inferences obtained from one approach.
		Compensation	Mixed-methods designs enable different methods to overcome the weaknesses of each other.
		Diversity	Researchers use mixed-methods research to obtain divergent views of the same phenomenon.
	Newman, Ridenour, Newman, Mario, & DeMarco (2003)	Predict	Mixed-methods research that builds general laws.
		Add to the knowledge base	Mixed-methods research that confirms findings, replicates others' work, reinterprets previously collected data, clarifies structural and ideological connections between important social processes, and strengthens the knowledge base.
		Have a personal, social, institutional, and/or organizational impact	Mixed-methods research that deconstructs/reconstructs power structures, reconciles discrepancies, refutes claims, sets priorities, resists authority, influences change, and sets policy.
		Measure change	Mixed-methods research that measures consequences of practice, tests treatment effects, and measures outcomes.
		Understand complex phenomena	Mixed-methods research that understands phenomena, culture, change, and people.
		Test new ideas	Mixed-methods research that tests innovations, hypotheses, new ideas, and new solutions.
		Generate new ideas	Mixed-methods research that explores phenomena, generates hypotheses, generates theory, uncovers relationships, uncovers culture, and reveals culture.
		Inform constituencies	Mixed-methods research that informs the public, heightens awareness, describes the present, and complies with authority.
		Examine the past	Mixed-methods research that interprets/reinterprets the past, acknowledges past misunderstandings, reexamines tacit understanding, and examines the social and historical origins of current social problems.
Priority/ dominance	Johnson et al. (2007)	Equal status	Mixed-method research in which "researchers are likely to believe that qualitative and quantitative data and approaches will add insights as one considers most, if not all, research questions" (Johnson et al., 2007, p. 123).
		Qualitative dominant	"The type of mixed research in which one relies on a qualitative, constructivist-poststructuralist-critical view of the research process, while concurrently recognizing that the addition of quantitative data and approaches are likely to benefit most research projects" (Johnson et al., 2007, p. 124).
		Quantitative dominant	"Quantitative dominant mixed methods research is the type of mixed research in which one relies on a quantitative, post-positivist view of the research process, while concurrently recognizing that the addition of qualitative data and approaches are likely to benefit most research projects" (Johnson et al., 2007, p. 124).
	Tashakkori & Teddlie (1998)	Equivalent status design	"Researchers conduct the study using both the quantitative and the qualitative approaches about equally to understand the phenomenon under study" (Johnson et al., 2007, p. 18).
		Dominant-less dominant study	"Researchers conduct the study within a single dominant paradigm with a small component of the overall study drawn from an alternative design" (Johnson et al., 2007, p. 18).

Table A1. Review of Selected Theoretical Literature in Mixed-methods Research

		Design with multilevel use of approaches[8]	"Researchers use different types of methods at different levels of data aggregation" (Johnson et al., 2007, p. 18).
Mixing strategies	Teddlie & Tashakkori (2009)	Partially mixed methods	A type of research design in which one mixes the quantitative and qualitative portions of the study at specific stages (e.g., sampling, data collection, data analysis, or data inference).
		Fully mixed methods	A type of research design in which researchers mix the quantitative and qualitative portions of the study at all stages (the objective, data analysis and inference stages of the research process).
	Teddlie & Tashakkori (2009)	Parallel mixed designs	In these designs, one mixes different methods (qualitative and quantitative methods) in a parallel manner either simultaneously or with some time lapse.
		Sequential mixed designs	In these designs, one mixes different methods (qualitative and quantitative methods) across chronological phases of the study.
		Conversion mixed designs	In these parallel designs, one mixes different methods when one transforms and analyzes one type of data both qualitatively and quantitatively.
		Multilevel mixed designs	In these parallel or sequential designs, one mixes different methods across multiple levels of analysis.
		Fully integrated mixed designs	In these designs, one mixes different methods in an interactive manner at all stages of the study.
Time orientation	Creswell (1995), Tashakkori & Teddlie (1998)	Sequential	Mixed-methods research in which "researchers conduct a qualitative phase of a study and then a separate quantitative phase, or vice versa" (Tashakkori & Teddlie, 1998, p. 46).
		Concurrent	"The researchers conducts the qualitative and quantitative phase at the same time" (Tashakkori & Teddlie, 1998, p. 18).
	Creswell (2003)	Sequential	Mixed-methods research "in which the researcher seeks to elaborate on or expand the findings of one method with another method" (Creswell, 2003, p. 16).
		Concurrent	Mixed-methods research "in which the researcher converges quantitative and qualitative data in order to provide a comprehensive analysis a comprehensive analysis of the research problem" (Creswell, 2003, p. 16).
		Transformative	Mixed-methods research "in which the researcher uses a theoretical lens as an overarching perspective within a design that contains both quantitative and qualitative data" (Creswell, 2003, p. 16).

[8] Tashakkori and Teddlie (2003) propose "designs with multilevel use of approaches" as another potential approach.

Table A1. Review of Selected Theoretical Literature in Mixed-methods Research

	Creswell et al. (2003), Creswell (2013)	Sequential	There are three types of sequential mixed-methods designs: (a) Sequential explanatory (i.e., characterized by one's collecting and analyzing quantitative data and, subsequently, collecting and analyzing qualitative data; a theoretical perspective may or may not be present); (b) Sequential exploratory (i.e., characterized by one's initially collecting and analyzing qualitative data and, subsequently, collecting and analyzing quantitative data; a theoretical perspective may or may not be present); (c) Sequential transformative (i.e., one can user either method first; one must prioritize either the quantitative or the qualitative phase; a theoretical perspective is present to guide the study).
		Concurrent	There are three types of concurrent mixed-methods designs: (a) Concurrent triangulation (i.e., one uses two different methods are to confirm, cross-validate, or corroborate findings in a single study; generally no predominant method to guide the project; a theoretical perspective may or may not be present); (b) Concurrent nested (i.e., one collects data in one phase during which one collects quantitative and qualitative data simultaneously; it has a predominant method to guide the project; a theoretical perspective may or may not be present); (c) Concurrent transformative (i.e., one uses a specific theoretical perspective that may take on the design features of either a triangulation or nested design).
Strands/ phases of research	Tashakkori & Teddlie (2003), Teddlie & Tashakkori (2009)	Single phase (or single study)	Researchers conduct qualitative and quantitative studies as part of a single study.
		Multiple phases (or research program)	Qualitative and quantitative studies are parts of research programs.
	Teddlie & Tashakkori (2006)	Quasi-mixed monostrand design (monostrand conversion design)	This type of design involves only one single phase of the conceptualization-experiential-inferential process yet includes both qualitative and quantitative components.
		Mixed-methods multistrand designs	(a) Concurrent mixed designs are "designs in which there are at least two relatively independent strands: one with qualitative questions and data collection and analysis techniques and the other with quantitative questions and data collection and analysis techniques" (Teddlie & Tashakkori, 2006, p. 20). (b) Sequential mixed designs are "designs in which there are at least two strands that occur chronologically" (Teddlie & Tashakkori, 2006, p. 21). (c) Conversion mixed designs are "multistrand concurrent designs in which mixing of qualitative and quantitative approaches occurs in all components/stages, with data transformed (qualitized or quantized) and analyzed both qualitatively and quantitatively" (Teddlie & Tashakkori, 2006, p. 23). (d) Fully integrated designs are "multistrand concurrent designs in which mixing of qualitative and quantitative approaches occurs in an interactive (i.e., dynamic, reciprocal, interdependent, iterative) manner at all stages of the study" (Teddlie & Tashakkori, 2006, p. 23).

Table A1. Review of Selected Theoretical Literature in Mixed-methods Research

<table>
<tr><td></td><td></td><td>Quasi-mixed multistrand designs</td><td>One mixes these designs (including the concurrent quasi-mixed design) at the experiential stage only.</td></tr>
<tr><td rowspan="11">Inference quality</td><td rowspan="9">Onwuegbuzie & Johnson (2006) (see also Dellinger & Leech, 2007)</td><td>Sample integration</td><td>“The extent to which the relationship between the quantitative and qualitative sampling designs yields quality meta-inferences” (Onwuegbuzie & Johnson, 2006, p. 57).</td></tr>
<tr><td>Inside-outside</td><td>“The extent to which the researcher accurately presents and appropriately utilizes the insider’s view and the observer’s view for purposes such as description and explanation” (Onwuegbuzie & Johnson, 2006, p. 57).</td></tr>
<tr><td>Weakness minimization</td><td>“The extent to which the weakness from one approach is compensated by the strengths from the other approach” (Onwuegbuzie & Johnson, 2006, p. 57).</td></tr>
<tr><td>Conversion</td><td>“The extent to which the quantizing or qualitizing yields quality meta-inferences” (Onwuegbuzie & Johnson, 2006, p. 57).</td></tr>
<tr><td>Paradigmatic mixing</td><td>“The extent to which the researcher’s epistemological, ontological, axiological, methodological, and rhetorical beliefs that underlie the quantitative and qualitative approaches are successfully (a) combined or (b) blended into a usable package” (Onwuegbuzie & Johnson, 2006, p. 57).</td></tr>
<tr><td>Commensurability</td><td>“The extent to which the meta-inferences made reflect a mixed worldview based on the cognitive process of Gestalt switching and integration” (Onwuegbuzie & Johnson, 2006, p. 57).</td></tr>
<tr><td>Multiple validities</td><td>“The extent to which addressing legitimation of the quantitative and qualitative components of the study result from the use of quantitative, qualitative, and mixed validity types, yielding high quality meta-inferences” (Onwuegbuzie & Johnson, 2006, p. 57).</td></tr>
<tr><td>Political</td><td>“The extent to which the consumers of mixed methods research value the meta-inferences stemming from both the quantitative and qualitative components of a study” (Onwuegbuzie & Johnson, 2006, p. 57).</td></tr>
<tr><td>Design quality</td><td>“The degree to which the investigator has selected and implemented the most appropriate procedures for answering the research questions” (Teddlie & Taskakkori, 2009, p. 302).</td></tr>
<tr><td rowspan="2">Teddlie & Tashakkori (2009), Venkatesh et al. (2013)</td><td>Explanatory quality</td><td>“The degree to which credible interpretations have been made on the basis of obtained results” (Teddlie & Taskakkori, 2009, p. 338).</td></tr>
<tr><td colspan="2"></td></tr>
<tr><td rowspan="2">Design strategies</td><td rowspan="2">Tashakkori & Teddlie (1998)</td><td>Exploratory investigation</td><td>Researchers typically state the purpose of the study in terms of research questions.</td></tr>
<tr><td>Confirmatory investigation</td><td>Researchers contain at least one research hypothesis in which they make a prediction of results a priori.</td></tr>
<tr><td rowspan="2">Data-collection strategies</td><td>Tashakkori & Teddlie (1998)</td><td>Multiple modes of data collection (both quantitative and qualitative data-collection techniques)</td><td>Researchers combine procedures (i.e., asking individuals for information and/or experiences; seeing what people do, recording what they do, or making inferences; asking individuals about their relationship with others; and using data collected and or documented by others).</td></tr>
<tr><td>Creswell (2003)</td><td>Both predetermined and emerging methods</td><td>Data collection may involve a quantitative checklist or instrument and the visiting of a research site or the observing of the behavior of individuals without predetermined questions.</td></tr>
</table>

Table A1. Review of Selected Theoretical Literature in Mixed-methods Research

		Both open- and closed-ended questions	Data collection might involve a standardized questionnaire and open-ended questions.
		Multiple forms of data drawing on all possibilities	Data collection involves a general combination of qualitative and quantitative data collection.
		Statistical and text analysis	The type of data may be numeric information gathered on scales of instruments or more textual information, audio recording of participant's voice, or written notes.
Data-analysis strategies	Tashakkori & Teddlie (1998)	Concurrent mixed analysis	Researchers simultaneously analyze qualitative and quantitative data (e.g., parallel mixed analysis, concurrent analysis of the same data) (quantitizing/qualitizing).
		Sequential QUAL-QUAN analysis	Researchers analyze qualitative data (subjective/imaginative interpretation) and, subsequently, analyze quantitative data (data/operations and statistical analysis).
		Sequential QUAN-QUAL analysis	Researchers analyze quantitative data analysis (data/operations and statistical analysis) and, subsequently, analyze qualitative data (subjective/imaginative interpretation).
	Creswell & Plano Clark (2007)	Triangulation	Researchers merge qualitative and quantitative data to understand a research problem.
		Embedded	In the embedded design, researchers embed one form of data in another—maybe either a monostrand or multistrand design with concurrent or sequential approach.
		Explanatory	Researchers use qualitative data to help explain or elaborate initial quantitative results.
		Exploratory	In this mixed-methods design, researchers collect quantitative data after collecting qualitative data to test and explain relationships found based on analyzing qualitative data.
Sampling designs	Collins et al. (2007), Onwuegbuzie & Collins (2007)	Concurrent design using identical samples	This design involves a concurrent design using "exactly the same sample members participate in both the qualitative and quantitative phases of the study" (Onwuegbuzie & Collins, 2007, p. 292).
		Concurrent design using parallel samples	This design involves a concurrent design in which "the samples for the qualitative and quantitative components of the research are different but are drawn from the same population of interest" (Onwuegbuzie & Collins, 2007, p. 292).
		Concurrent design using nested samples	This design involves a concurrent design in which "the sample members selected for one phase of the study represent a subset of those participants chosen for the other facet of the investigation" (Onwuegbuzie & Collins, 2007, p. 292).
		Concurrent design using multilevel samples	This design involves a concurrent design using "two or more sets of samples that are extracted from different levels of the study" (Onwuegbuzie & Collins, 2007, p. 292).
		Sequential design using identical samples	This design involves a sequential design using "exactly the same sample members participate in both the qualitative and quantitative phases of the study" (Onwuegbuzie & Collins, 2007, p. 292).

Table A1. Review of Selected Theoretical Literature in Mixed-methods Research

		Sequential design using parallel samples	This design involves a sequential design in which "the samples for the qualitative and quantitative components of the research are different but are drawn from the same population of interest" (Onwuegbuzie & Collins, 2007, p. 292).
		Sequential design using nested samples	This design involves a sequential design in which "the sample members selected for one phase of the study represent a subset of those participants chosen for the other facet of the investigation" (Onwuegbuzie & Collins, 2007, p. 292).
		Sequential design using multilevel samples	This design involves a sequential design using "two or more sets of samples that are extracted from different levels of the study" (Onwuegbuzie & Collins, 2007, p. 292).
	Teddlie & Yu (2007)	Basic mixed-methods sampling strategies	The basic mixed-methods sampling strategies include purposive sampling and probability sampling. Purposive sampling refers to "selecting units (e.g., individuals, groups of individuals, institutions) based on specific purposes associated with answering a research study's questions". Probability sampling involves "selecting a relatively large number of units from a population, or from specific subgroups (strata) of a population, in a random manner where the probability of inclusion for every member of the population is determinable" (Teddlie & Yu, 2007, p. 77).
		Sequential mixed-methods sampling	Sequential mixed-methods sampling involves selecting "units of analysis for an MM study through the sequential use of probability and purposive sampling strategies (QUAN-QUAL), or vice versa (QUAL-QUAN)" (Teddlie & Yu, 2007, p. 89).
		Concurrent mixed-methods sampling	Concurrent mixed-methods sampling involves selecting "units of analysis for a mixed methods study through the simultaneous use of both probability and purposive sampling" (Teddlie & Yu, 2007, p. 89).
		Multilevel mixed-methods sampling	Multilevel mixed-methods sampling refers to "a general sampling strategy in which probability and purposive sampling techniques are used at different levels of the study" (Teddlie & Yu, 2007, p. 89).
		Sampling using multiple mixed-methods sampling strategies	These sampling techniques generally involve using multiple sampling strategies (e.g., using both sequential mixed-methods and concurrent mixed-methods sampling).
Type of reasoning	Morse (2003)	Inductive theoretical reasoning	Inductive theoretical reasoning is the process in which one uses a small observation to infer a larger theory. In inductive reasoning, researchers try to develop a new theory, work in the discovery mode, and try to find answers to relatively new problems.
		Deductive theoretical reasoning	Deductive theoretical reasoning works from a more general theory to a more specific observation or hypothesis. This reasoning tests a theory or hypothesis.

Appendix B: Mixed-methods Inference Quality

Table B1. Mixed-methods Inference Quality (Adapted from Venkatesh et al., 2013)

Quality aspects	Quality criteria	Description	Challenges/dilemmas
Design quality	Design suitability/ appropriateness	The degree to which methods selected and research design employed are appropriate for answering the research question.	Selecting the most appropriate paradigm(s) for mixed-methods research and integrating different paradigmatic approaches.
	Design adequacy	*Quantitative*: the degree to which one implements the design components for the quantitative study (e.g., sampling, measures, data collection procedures) with acceptable quality and rigor.	Selecting the most suitable designs to address the research questions. Time and resources required to collect different types of data.
		Qualitative: the degree to which one implements the qualitative design components with acceptable quality and rigor.	
	Analytic adequacy	*Quantitative*: the degree to which the quantitative data analysis procedures/strategies are appropriate and adequate to provide plausible answers to the research questions.	The issue of nomenclature and basic definitions used in mixed-methods research.
		Qualitative: the degree to which qualitative data-analysis procedures/strategies are appropriate and adequate to provide plausible answers to the research questions.	
Explanation quality	Quantitative inferences	The degree to which interpretations from the quantitative analysis closely follow the relevant findings, are consistent with theory and the state of knowledge in the field, and are generalizable.	
	Qualitative inferences	The degree to which interpretations from the qualitative analysis closely follow the relevant findings, are consistent with theory and the state of knowledge in the field, and are transferable.	
	Integrative inference/meta-inference	*Integrative efficacy*: the degree to which one effectively integrates inferences made in each strand of a mixed-methods research inquiry into a theoretically consistent meta-inference.	Identifying the major source of inconsistency when the two sets of inferences do not agree with each other.
		Inference transferability: the degree to which meta-inferences from mixed-methods research are generalizable or transferable to other contexts or settings.	
		Integrative correspondence: the degree to which meta-inferences from mixed-methods research satisfy the initial purpose for using a mixed-methods approach.	

Appendix C: Overview of Research Studies

Table C1. Overview of Research Studies

		Time 1 constructs measured	**Time 2 constructs measured (6 months after time 1)**
Study 1	Adopters/users (N = 201)	Independent variables: application for personal use, utility for children, utility for work-related use, applications for fun, status gains, friends and family, secondary sources, workplace referents, Fear of technological change, decline cost, cost, perceived ease of use, requisite knowledge for PC use.	Dependent variable: usage behavior
	Non-adopters (N = 435)	Independent variables: application for personal use, utility for children, utility for work-related use, applications for fun, status gains, friends and family, secondary sources, workplace referents, fear of technological change, decline cost, cost, perceived ease of use, requisite knowledge for PC use.	Dependent variable: purchase behavior
Study 2	Adopters/users (N = 370)	Independent variables: application for personal use, utility for children, utility for work-related use, applications for fun, status gains, friends and family, secondary sources, workplace referents, fear of technological change, decline cost, cost, perceived ease of use, requisite knowledge for PC use.	Dependent variable: usage behavior
	Non-adopters (N = 610)	Independent variables: application for personal use, utility for children, utility for work-related use, applications for fun, status gains, friends and family, secondary sources, workplace referents, fear of technological change, decline cost, cost, perceived ease of use, requisite knowledge for PC use.	Dependent variable: purchase behavior

Appendix D: Coding for the Study 1

Table D1. Coding for the Study 1 (Adapted from Venkatesh & Brown, 2001)

Belief structure	Example quotes
Applications for personal use	“...my wife uses that cooking program a lot.” “I saw some neat programs like Quicken and Turbo tax so I got a computer.”
Utility for children	“We have a ninth-grader who uses it for his school work…” “The kids have to know computers these days. We make sure they are learning how to use it.”
Utility for work-related use	“I just work from home a lot more now. There’s no way I could have kept my job if I didn’t get a computer.” “I can drive in to work after rush hour because I get work done at home.”
Applications for fun	“We play all sorts of games on it. It’s fun.” “I just have fun...surfing the net, talking with people on golf newsgroups, and what not…”
Status gains	“My friends are counting on me to tell them what machine to get. I gotta keep up with this stuff because that’s why they think I’m cool.” “I don’t know I just always got these toys because people who are smart get them.”
Friends and family influence	“My sons advised me to buy it.” “...two of my church friends who said they are doing amazing stuff with it.”
Secondary sources influence	“There was a 60 Minutes or Dateline special that said something about a stalker or kidnapper ever since that we don’t want our kids to have anything to do with it.” “It’s too scary…there are so many stories in the papers about all these porn on the Internet. I wouldn’t want my son to get near all that…This is just another problem like drugs were when I was growing up.”
Workplace referents influence	“My boss said he has a computer at home, so I thought, gee, maybe I should get one so I can be like him.” “The guy in the next cube told me about how nice it is to work at home and if I got a computer I could probably do that.”
Fear of technological change	“It’s just changing way too fast. If I buy a computer today, it’s like too old tomorrow.” “I am just plain scared that if I buy something, it’s going to be like obsolete in like a year. Then who knows, I have to buy another one.”
Declining cost	“I wanna wait till they’re like VCR prices, so may be in like five years.” “Prices are dropping so fast, and I didn’t buy for so long so I am just going to wait till it’s 50 bucks or maybe 100.”
Cost	“We don’t have the money.” “Computers are for rich people.”
Perceived ease of use	“I did that Windows stuff for a while at work, they’re like too hard to use. I heard that Apples...that’s the same as Macintosh, right? Anyway, they are easy to use but not that Windows stuff, but people are saying like there’s no use learning the Apple stuff.” “It’s way too hard for me. I’m a tailor, even using a cash register is like too hard for me.”
Requisite knowledge for PC use	“I don’t even know how to type. It’ll take me forever to learn it.” “I don’t know a darn thing about computers other than everyone wants to learn something about them.”

Appendix E: Belief Structures of MATH

Table E1. Belief Structures of MATH

Belief structure	Definition
Applications for personal use	“The extent to which using a PC enhances the effectiveness of household activities” (Venkatesh & Brown, 2001, p. 82).
Utility for children	“The extent to which using a PC enhances the effectiveness of household activities” (Venkatesh & Brown, 2001, p. 82).
Utility for work-related use	The extent to which using a PC enhances the effectiveness of performing work-related activities (Venkatesh & Brown, 2001).
Applications for fun	“The pleasure derived from PC use” (Venkatesh & Brown, 2001, p. 82). These are specific to PC use, rather than general traits (see Webster & Martocchio, 1992).
Status gains	The increase in prestige that coincides with a purchase of the PC for home use (Venkatesh & Brown, 2001).
Friends and family influence	“The extent to which members of a social network influence one another’s behavior” (Venkatesh & Brown, 2001, p. 82). In this case, the members are friends and family.
Secondary sources influence	The extent to which information from TV, newspaper and other secondary sources influences behavior (Venkatesh & Brown, 2001).
Workplace referents influence	The extent to which co-workers influence behavior (see Taylor & Todd, 1995)
Fear of technological change	The extent to which rapidly changing technology is associated with fear of obsolescence or apprehension regarding a PC purchase (Venkatesh & Brown, 2001).
Declining cost	The extent to which cost of a PC is decreasing in such a way that it inhibits adoption (Venkatesh & Brown, 2001).
Cost	The extent to which the current cost of a PC is too high (Venkatesh & Brown, 2001).
Perceived ease of use	The degree to which using the PC is free from effort (Davis, 1989; see also Venkatesh & Brown, 2001).
Requisite knowledge for PC use	The individual’s belief that he/she has the knowledge necessary to use a PC. This is very closely tied to the concept of computer self-efficacy (Compeau & Higgins, 1995; see also Venkatesh & Brown, 2001).

Appendix F: Study 1 Descriptive Statistics and Correlations

Table F1. Study 1 Descriptive Statistics and Correlations[a]

	MATH	M	SD	M	SD	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1	Applns. for personal use	4.55	1.04	3.44	1.13		.30***	.44***	.21**	.17*	.21**	.22**	.16*	.02	.06	.02	.20**	.24***	.26***
2	Utility for children	4.57	1.20	3.88	1.03	.29***		.24**	.33***	.20**	.32***	.30***	.16*	-.21**	.10	.03	.02	.01	.27***
3	Utility for work-rel. use	4.77	1.21	4.02	0.90	.37***	.15*		.26***	.23**	.21**	.04	.20**	-.16*	.14*	-.17*	.21**	.20**	.22**
4	Applns. for fun	4.20	1.05	4.17	1.06	.21**	.31***	.22**		.02	.24**	.02	.08	.03	.10	.10	.27***	.17*	.25***
5	Status gains	4.01	0.85	4.03	0.99	.02	.02	.04	.14*		.03	.04	.02	-.21**	.03	.02	.04	.02	.16*
6	Infl. of friends and family	4.03	0.77	3.80	1.06	.19*	.28***	.19*	.22**	.11		.31***	.67***	.02	.01	.16*	.03	.05	.18*
7	Infl. of secondary sources	4.10	0.77	4.14	0.77	.22**	.26***	.22**	.02	.08	.23**		.31***	.10	.06	.02	.02	.10	.21**
8	Peer influence	3.22	0.64	3.66	0.68	.03	.18*	.17*	.22**	.27***	.68***	.35***		-.20**	.01	.10	.04	.19*	.21**
9	Fear of tech. change	3.03	0.60	5.03	0.90	.05	.03	.16*	-.04	-.20**	-.16*	.02	.01		.42***	.27***	-.20**	-.25*	-.35***
10	Declining cost	3.88	0.93	4.98	0.84	.04	.02	.02	-.02	.02	.04	.08	.02	.35***		.40***	.12	.18*	.18*
11	Cost	2.90	0.70	5.06	0.76	.01	.00	.15*	-.17*	.08	-.03	.08	.16*	.21**	.37***		.00	.02	.24**
12	Percd. ease of use	4.61	0.78	2.99	0.78	.22**	.08	.18*	.20**	.18*	.01	.02	.02	-.22**	.04	.12		.34***	.22***
13	Requisite knowledge	4.80	0.77	4.13	0.74	.17*	.03	.15*	.15*	.02	.15*	.01	.15*	-.21**	.02	.11	.31***		.27***
14	Usage/ Purchase	N/A	N/A	N/A	N/A	.28***	.30***	.22**	.20**	.19**	.15*	.21**	.16*	.12	.10	.17*	.22**	.20**	

Below-diagonal elements are correlations for current users with a dependent variable of usage behavior.
Above-diagonal elements are correlations for current non-users with a dependent variable of adoption behavior.
* $p < .05$; ** $p < .01$; *** $p < .001$.
[a] Note that we used a five-point scale for the perceptual measures in this study.

Appendix G: Quantitative Validity of Quantized Data

After we collected the quantitative data, we assessed the validity of the quantized data from study 1 (analyzed in the first phase of the study) using different techniques. First, we performed a normality test to ensure that the model specification was appropriate for our data. The test of normality revealed that the residuals were normally distributed and the skewness and kurtosis coefficients were fairly similar across two datasets. Second, we performed mean differences tests to examine whether the sample means differed across two data collections (see Table G1). Given that we collected the two datasets at different periods using two different methods and scales, we expected nominal significant differences across two datasets. As expected, the results showed some statistically significant differences (e.g., the mean of status gains among adopters was higher in study 2 than in study 1). Because we analyzed the data independently of one another, these mean differences were unlikely a major problem in our study.

Table G1. Mean Difference Test Results

		Adopters (Study 1 vs. Study 2)		Non-adopters (Study 1 vs. Study 2)	
	MATH	t-value	95% CI	t-value	95% CI
1	Applns. for personal use	-1.21	(-0.28) – (0.07)	-1.93	(-0.26) – (0.00)
2	Utility for children	-0.09	(-0.21) – (0.18)	-1.55	(-0.22) – (0.02)
3	Utility for work-rel. use	-1.26	(-0.33) – (0.07)	-1.43	(-0.18) – (0.03)
4	Applns. for fun	-1.44	(-0.31) – (0.04)	2.44*	(0.03) – (0.06)
5	Status gains	-2.90**	(-0.35) – (-0.07)	-3.37***	(-0.31) – (-0.08)
6	Infl. of friends and family	-0.72	(-0.18) – (0.08)	3.59***	(0.10) – (0.35)
7	Infl. of secondary sources	1.37	(-0.03) – (0.22)	3.15**	(0.05) – (0.24)
8	Peer influence	1.67	(-0.01) – (0.19)	5.19***	(0.13) – (0.28)
9	Fear of tech. change	3.27***	(0.06) – (0.27)	-1.62	(-0.19) – (0.02)
10	Declining cost	-2.63**	(-0.36) – (-0.05)	2.13*	(0.01) – (0.21)
11	Cost	-0.84	(-0.16) – (0.06)	3.31***	(0.06) – (0.24)
12	Percd. ease of use	-2.06*	(-0.27) – (-0.01)	2.40*	(0.02) – (0.21)
13	Requisite knowledge	-1.92	(-0.26) – (0.01)	3.39***	(0.06) – (0.24)

* p < .05; ** p < .01; *** p < .001; CI: Confidence Interval

Further, we performed a standardized mean difference (SMD) or Cohen's *d* test to estimate the method effect employed in each phase of the study (see Table G2). The SMD assumes that the differences in standard deviations among studies reflect differences in measurement scales and not real differences in variability among study populations (Higgins & Green, 2011). An SMD of zero indicates that the two samples have equivalent effects and the SMD increases as the difference between two samples increases. Cohen (1988) offers the following guidelines for interpreting the magnitude of the SMD in the social sciences: small, SMD = 0.2; medium, SMD = 0.5; and large, SMD = 0.8. The results revealed that most of the SMD scores in the non-adopters condition were significant, which indicates the two samples have nonequivalent effects. The significance of SMD coefficients confirmed the need to adopt a mixed-methods research approach in this study to minimize the weaknesses of either quantitative or qualitative methods and uncover the contradictory findings (if any) through comparing the qualitative data- and quantitative data-analysis results.

Table G2. Standardized Mean Difference (d) Test Results

		Adopters			Non-adopters		
	MATH	*d*	95% CI	Sig.	*d*	95% CI	Sig.
1	Applns. for personal use	-0.12	(-0.27) – (0.06)	Ns	-0.12	(-0.24) – (0.00)	Ns
2	Utility for children	-0.00	(-1.18) – (0.16)	Ns	-0.09	(-0.22) – (0.02)	S
3	Utility for work-rel. use	-0.11	(-0.28) – (0.06)	Ns	-0.08	(-0.31) – (0.03)	Ns
4	Applns. for fun	-0.13	(-0.30) – (0.04)	Ns	0.15	(0.03) – (0.28)	S
5	Status gains	-0.26	(-0.43) – (-0.09)	S	-0.21	(-0.34) – (-0.09)	S
6	Infl. of friends and family	-0.06	(-2.23) – (0.11)	Ns	0.22	(0.10) – (0.35)	S
7	Infl. of secondary sources	0.12	(-0.04) – (0.29)	Ns	0.19	(0.07) – (0.32)	S
8	Peer influence	0.15	(-0.01) – (0.32)	Ns	0.33	(0.21) – (0.45)	S
9	Fear of tech. change	0.35	(0.18) – (0.53)	S	-0.17	(-0.29) – (-0.05)	Ns
10	Declining cost	-0.23	(-0.40) – (-0.06)	S	0.13	(0.01) – (0.25)	S
11	Cost	-0.07	(-0.24) – (0.09)	Ns	0.21	(0.08) – (0.33)	S
12	Percd. ease of use	-0.18	(-0.35) – (0.00)	Ns	0.14	(0.02) – (0.27)	S
13	Requisite knowledge	-0.16	(-0.34) – (0.01)	Ns	0.22	(0.09) – (0.34)	S

S: Supported; Ns: Not supported

Appendix H: Study 1 and 2 Results

Table H1. Study 1 and 2 Results

	Study 1		**Study 2**	
	Current owners DV: use (**R^2 = .58**)	Current non-owners DV: purchase (**R^2 = .57**)	Current owners DV: use (**R^2 = .57**)	Current non-owners DV: purchase (**R^2 = .50**)
I.V.	ß	ß	ß	ß
Attitudinal beliefs				
Applications for personal use	.30***	.28***	.33***	.28***
Utility for children	.15*	Ns	.17*	Ns
Utility for work-related use	.19**	.20**	.15*	.21**
Applications for fun	.30***	.14*	.28***	.17*
Status gains	.16*	Ns	Ns	Ns
Normative beliefs				
Friends and family	Ns	.21*	Ns	.17*
Secondary sources	Ns	.15*	Ns	.17*
Workplace referents	Ns	Ns	Ns	Ns
Control beliefs				
Fear of technological change	Ns	-.25***	Ns	-.22***
Declining cost	Ns	.14*	Ns	.15*
Cost	Ns	-.19**	Ns	-.16*
Perceived ease of use	Ns	.14*	Ns	.16*
Requisite knowledge for PC use	Ns	.15*	Ns	Ns
* p < .05; ** p < .01; *** p < .001; Ns: not supported				

Appendix I: Study 2 ICRs, AVEs, Descriptive Statistics, and Correlations

Table I1. Study 2 ICRs, AVEs, and Descriptive Statistics

	MATH	M	SD	ICR	AVE	M	SD	ICR	AVE
1	Applns. for personal use	4.66	1.03	.92	.77	3.57	0.98	.81	.89
2	Utility for children	4.58	1.07	.90	.80	3.98	1.02	.80	.85
3	Utility for work-rel. use	4.90	1.10	.88	.83	4.10	0.88	.79	.90
4	Applns. for fun	4.33	0.99	.87	.82	4.01	1.02	.85	.80
5	Status gains	4.22	0.78	.85	.81	4.23	0.88	.81	.80
6	Infl. of friends and family	4.08	0.82	.90	.76	3.57	0.96	.80	.80
7	Infl. of secondary sources	4.01	0.71	.88	.77	3.99	0.74	.75	.87
8	Peer influence	3.13	0.56	.92	.80	3.45	0.59	.75	.77
9	Fear of tech. change	2.86	0.58	.90	.81	5.18	0.86	.80	.80
10	Declining cost	4.09	0.87	.89	.84	4.87	0.80	.82	.75
11	Cost	2.95	0.62	.80	.80	4.91	0.66	.80	.83
12	Percd. ease of use	4.75	0.76	.92	.79	2.87	0.82	.90	.90
13	Requisite knowledge	4.93	0.78	.80	.80	3.98	0.65	.82	.82
14	Usage/purchase	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A

Table I2. Study 2 Correlations[a]

	MATH	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1	Applns. for personal use		.31***	.41***	.22**	.13	.22**	.20**	.16*	.07	.06	.06	.18*	.20***	.27***
2	Utility for children	.28***		.22**	.36***	.19*	.30***	.31***	.15	-.20*	.10	.06	.09	.09	.25***
3	Utility for work-rel. use	.39***	.19*		.22**	.22*	.20*	.10	.19*	-.17*	.03	-.16*	.20***	.21**	.23**
4	Applns. for fun	.20**	.29***	.21**		.08	.22*	.03	.13	.10	.06	.05	.22***	.18*	.20**
5	Status gains	.07	.08	.06	.10		.11	.09	.08	-.20**	.09	.09	.09	.08	.19*
6	Infl. of friends and family	.16*	.28***	.18*	.20*	.13		.29**	.66***	.06	.02	.06	.09	.07	.19*
7	Infl. of secondary sources	.19**	.26***	.19**	.08	.10	.25**		.29***	.13	.06	.09	.06	.13	.20**
8	Peer influence	.08	.16*	.18*	.19*	.26***	.69***	.36***		-.23**	.09	.12	.10	.17*	
9	Fear of tech. change	.08	.08	.13	-.09	-.22**	-.13	.08	.08		.40***	.23***	-.18**	-.23*	.19*
10	Declining cost	.13	.09	.08	-.03	.08	.09	.10	.09	.37***		.39***	.13	.17*	-.36***
11	Cost	.02	.10	.16*	-.12	.03	-.02	.05	.16*	.20*	.34***		.01	.08	.19*
12	Percd. ease of use	.19**	.02	.16*	.19*	.10	.02	.09	.08	-.19	.07	.14		.31***	.22**
13	Requisite knowledge	.18*	.06	.10	.12	.07	.16*	.07	.16*	-.20*	.08	.12	.29***		.24***
14	Usage/ purchase	.26***	.28***	.19**	.19*	.18*	.16*	.19*	.17*	.13	.11	0.18**	.23**	.19*	.23**

Below-diagonal elements are correlations for current users with a dependent variable of usage behavior.
Above-diagonal elements are correlations for current non-users with a dependent variable of adoption behavior (adapted from Brown & Venkatesh, 2005).
* $p < .05$; ** $p < .01$; *** $p < .001$.
[a] Note that we used a seven-point scale for the perceptual measures in this study.

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