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## Using Embedded Mixed Methods in Studying IS Phenomena: Risks and Practical Remedies with an Illustration

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### Abstract:

Drawing on lessons learned from a mixed-methods research project, we illustrate how mixed research approaches are fruitful in studying the complexities and interactions inherent in IS phenomena, which is particularly relevant when one investigates relatively new and “messy” phenomena in that many opportunities for errors and omissions can arise. Mixed-methods research designs can also prove to be valuable in exploratory or new areas of research and provide empirical evidence from multiple sources and types of data that one can truly triangulate. In this paper, we discuss the risks associated with using a specific mixed-methods research strategy (i.e., embedded mixed-methods design) and the practical remedies we used to address them. This discussion provides operational guidance to researchers interested in adopting mixed research designs to study emergent IS phenomena.

**Keywords:** Mixed Methods, IS Research, Embedded Mixed Research Design, Shared Mental Models.

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## 1 Introduction

Mixed-methods (MM) research or mixed research refers to those research designs in which a researcher mixes or combines quantitative and qualitative research techniques, methods, approaches, concepts, or data into a single study to more broadly and deeply understand a phenomenon (Creswell & Clark, 2010; Denzin, 1970). Historically, researchers first proposed mixed methods to converge findings or cross-validate them (Campbell & Fiske, 1959). Mixed research designs became popular in social science studies for their many other advantages including the ability to leverage the strengths of varied methods, provide richer insights into phenomena of interest that one cannot fully understand using only quantitative or qualitative methods, and address research questions that call for real-life contextual understanding, multi-level perspectives, and cultural influences (Johnson & Onwuegbuzie, 2004; Johnson, Onwuegbuzie, & Turner, 2007; Morgan, 1998; Venkatesh, Brown, & Bala, 2013; Venkatesh, Brown, & Sullivan, 2016).

IS researchers have recently started to pay closer attention to mixed methods. For example, Venkatesh et al. (2013, p. 36) suggests that a mixed research approach is particularly useful when researchers want to obtain “a holistic understanding of a phenomenon for which extant research is fragmented, inconclusive, and equivocal”. They further state:

*If IS researchers continue to publish single method papers from mixed methods programs, they are likely to miss the opportunity to discover, develop, or extend a substantive theory in richer ways than possible with single method papers. A mixed methods approach, particularly the associated meta-inferences, offers mechanisms for discovering substantive theory by allowing researchers to not only unearth components related to a phenomenon, but also unveil interrelations among these components and boundary conditions surrounding these interrelations. (p. 31)*

Despite the potential benefits of adopting them, conducting mixed research studies can be challenging (Creswell & Clark, 2010; Johnson & Onwuegbuzie, 2004; Tashakkori & Teddlie, 2003; Venkatesh et al., 2013). Researchers generally consider a mixed-methods approach to be technically challenging compared with single-threaded approaches mainly because one needs to: 1) either be adept at multiple methods or collaborate with others who specialize in complimentary methods and 2) know how to mix multiple methods appropriately (Creswell & Clark, 2010). Additionally, compared with traditional qualitative and quantitative methods, graduate students do not receive much training on using mixed methods (Jick, 1979). Indeed, Bryman (2007) conducted a series of interviews of mixed-methods researchers and found that most of them could not locate or remember any exemplars of mixed-methods research.

Venkatesh et al. (2013, 2016) propose high-level guidelines for conducting mixed-methods research in IS, provide an integrative validation framework for mixed-methods approaches, and suggest how IS researchers can be flexible in adopting mixed-methods approaches to suite their research purposes. However, we believe that, given the many potential opportunities to use a variety of techniques in conducting mixed-methods research, it would be very useful to learn from IS studies that use mixed methods about the specific challenges and potential opportunities of such approaches. Thus, in this paper, we explicitly focus on practical experiences and lessons learned from conducting a specific mixed-methods research study (see Appendix A for a detailed description of our illustrative study). As Venkatesh et al. (2013, 2016) suggest, researchers should consider using mixed methods only when the research question, objective, and context require such an approach. Based on the exploratory nature of our illustrative study and the difficulties of measuring the constructs, we chose a mixed-methods research design for two purposes: completeness and corroboration.

Overall, we illustrate how mixed-methods approaches offer a rich research design strategy for studying emergent complexities and interactions inherent in IS phenomena and, in particular, provide guidance to researchers on ways to address the challenges of mixed-method research designs. To do so, we discuss our trials and tribulations in operationalizing a specific mixed research design to address our research questions and the ensuing challenges that we had to address. Thus, we help researchers learn from our experiences in conducting MM research and suggest ways to ameliorate challenges that often crop up in such studies. Our focus also aligns with Creswell and Clark’s (2010, pp. 273-275) call to mixed-methods researchers to not only report on completed domain-specific mixed research studies but also “contribute or extend” mixed-methods literature by writing a methodological paper. We heed their advice and follow their proposed structure for such a paper in this effort.

Creswell and Clark (2010) propose four major types of mixed-methods research designs: 1) convergent (parallel or concurrent) design, 2) embedded (or nested) design, 3) sequential (explanatory sequential or exploratory sequential) design, 4) and multiphase designs. In this paper, we illustrate the use of an embedded mixed-methods (EMM) research design. Creswell and Clark (2010, pp. 90-93) describe embedded mixed-methods designs as follows:

*The researcher combines the collection and analysis of both quantitative and qualitative data within a traditional quantitative research design or qualitative research design.... The collection and analysis of the secondary data set may occur before, during, and/or after the implementation of the data collection and analysis procedures traditionally associated with the larger design.... In an embedded mixed methods case study, the researcher collects and analyzes both quantitative and qualitative data to examine a case.*

Accordingly, our particular illustrative study belongs to the EMM research design strategy in which a complementary quantitative study is embedded in a primarily qualitative study (Creswell & Clark, 2010; Johnson & Onwuegbuzie, 2004; Johnson et al., 2007). In this approach, the quantitative strand mixes with the qualitative approach when one collects, explores, analyzes, and visualizes data. This mixing of strands in a research study can be emergent or fixed (Creswell & Clark, 2010); our illustration falls in the emergent category. Emergent approaches use mixed methods when issues develop when conducting the research that require the researchers to adjust the research strategy instead of predetermining it at the study's outset. In contrast, in fixed approaches to mixed-methods studies, researchers predetermine when they will use quantitative and qualitative methods at the start of the research process and implement them as planned.

We contribute to the literature in several key ways: we 1) illustrate in detail how one can implement and report EMM studies, 2) briefly discuss the paradigmatic issues with mixed-methods research, 3) analyze in detail the particular challenges faced in the various stages of conducting mixed research and potential tactics and guidance to ameliorate them, and 4) describe techniques or practices that are useful to mix, analyze, and visualize data for sensemaking and to draw meaningful insights.

## 2 A Brief Aside: The Paradigm Debates of Mixed Methods

While mixing paradigms has its risks, one can overcome them by combining methods based on clearly understanding the paradigms being used. We agree with Morgan (1998, p. 363) that "if a particular paradigmatic stance provides the framework for a project, then selecting an appropriate method or combination of methods does become a largely technical task".

Researchers have intensely debated the epistemological issues associated with the mixed-methods approach. Some researchers argue that, by blending two research approaches together, researchers have mixed world views in terms of knowledge's nature and the way they obtain it (Venkatesh et al., 2013).

In contrast, Sechrest and Sidani (1995) argue that there is no epistemological conflict between mixed-methods approaches. They assert that:

*Quantitative and qualitative methods are, after all, empirical, [and] dependent on observation. Although empirical inductivists and phenomenologists (also empiricists) differ in their philosophical assumptions and, consequently, the ways in which they go about collecting and making sense of their data, their ultimate tasks and aims are the same: describe their data, construct explanatory arguments from their data, and speculate about why the outcomes they observed happened as they did. The differences, in our view, have to do with the details, with exactly "what is observed by whom". (p. 78)*

In addition, we agree with their contention that the only key difference between qualitative and quantitative researchers is in their preferences for numerical precision.

In this vein, along with other researchers, we contend that mixed-methods researchers should adopt a philosophy of *pragmatism* for designing and conducting mixed dualisms. Ontologically, the mixed research approach adopts a belief in *fallible realism* (i.e., "all theories are approximations") where researchers "recognize the existence and importance of the natural or physical world as well as the emergent social and psychological world" (Johnson & Onwuegbuzie, 2004, p. 18). Furthermore, this thinking incorporates methodological pluralism or eclecticism, which frequently results in superior research compared to mono-

method research (Johnson & Onwuegbuzie, 2004; Johnson et al., 2007). Epistemologically, findings are generated through interaction between researcher and data by using a logic of inquiry that includes using induction (or discovery of patterns), deduction (testing of theories and hypotheses), and abduction (uncovering and relying on the best of a set of explanations for understanding one's results) (Johnson & Onwuegbuzie, 2004). Axiologically, mixed-methods researchers are value neutral: they make no distinction between applied and basic research.

According to Johnson and Onwuegbuzie (2004), mixed research design fundamentally involves researchers' collecting data by using different strategies, approaches, and methods in such a way that the resulting mixture or combination will likely result in complementary strengths and non-overlapping weaknesses. These authors further argue that effectively ensuring one follows this principle is a major source of justification for mixed-methods research because the product will be superior to mono-method studies. Additionally, the mixed research approach allows one to explore the meaning of a construct or phenomenon from more than one perspective (Johnson & Onwuegbuzie, 2004).

### 3 Risks and Remedies

To illustrate how one can operationalize an embedded mixed-methods (EMM) research design in practice, we summarize our research project in the domain of "virtual teams" research in Appendix A (Yu, 2013). Figure 1 below illustrates the EMM research design procedure we used for the study. Drawing on this study and prior literature on mixed-methods research, we identify nine risks or challenges in using EMM research designs (Figure 2). In addition to elucidating these challenges, based on our specific experience, we propose remedies and strategies to address these challenges. Risk 1 addresses a general challenge associated with mixed-method research designs. Risks 2 to 4 relate to data preparation in mixed-research designs. Risks 5 to 8 relate to data-analysis and interpretation problems in mixed-method research designs. Risk 9 relates to reporting mixed-method findings. Appendix C summarizes all the identified risks and remedies.

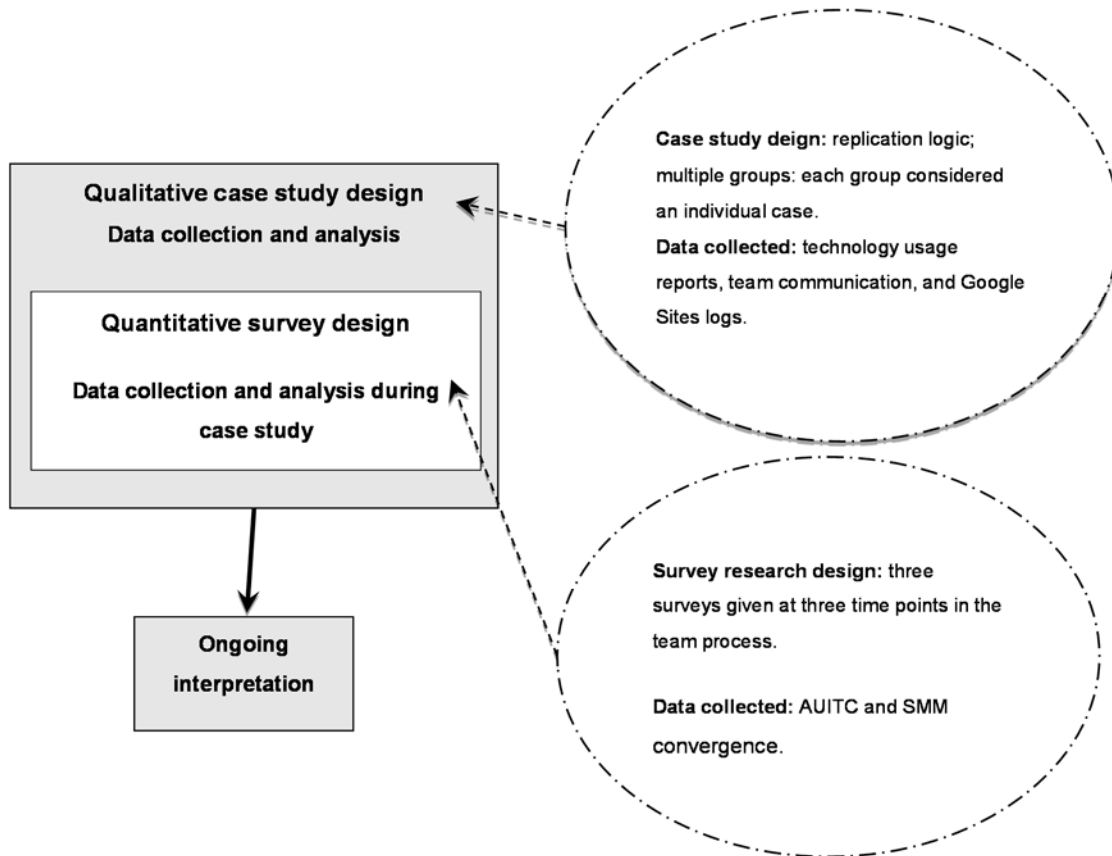


Figure 1. Embedded Mixed-methods Research Design Procedure

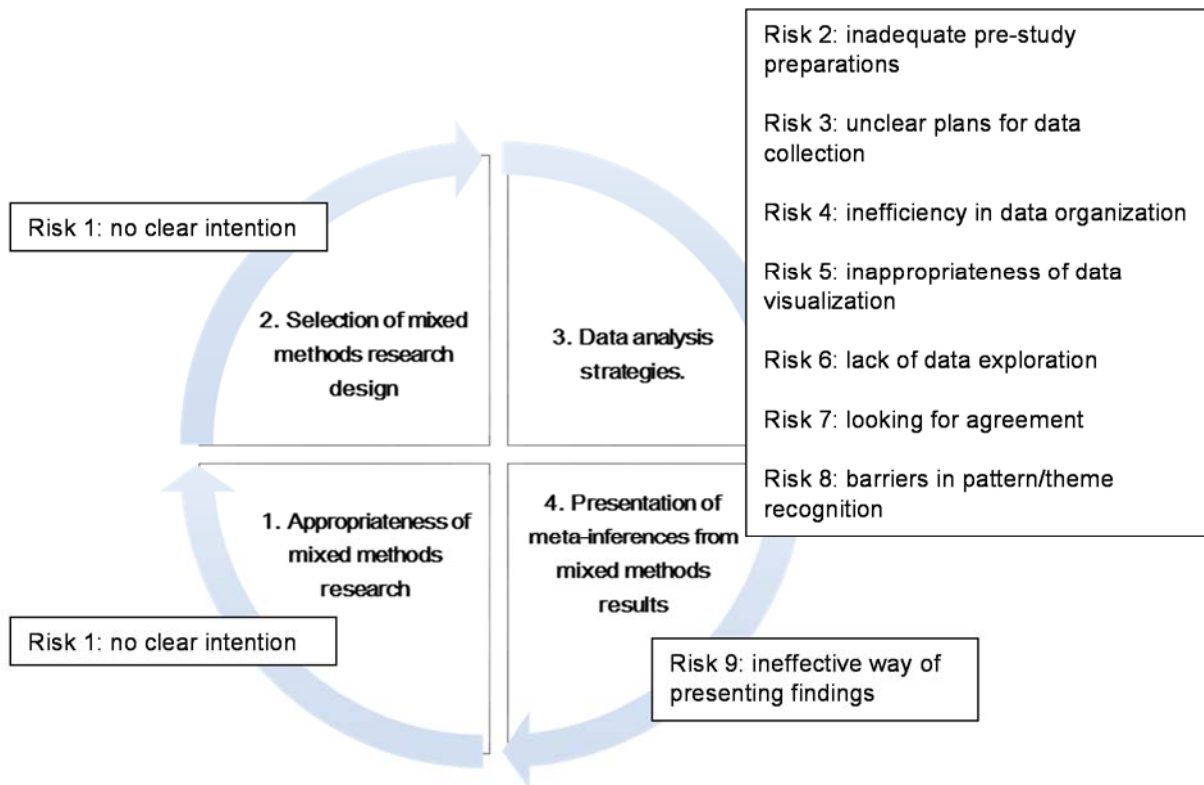


Figure 2. Risks and Research Cycle of a Mixed-methods Study

### 3.1 Risk 1: No Clear Intention

Every mixed-methods study should begin with a good reason or reasons; researchers who use mixed methods tend to struggle with keeping that reason or reasons in mind when conducting their research. Many researchers report findings from different methods in parallel (or independent of each other) with little effort to “genuinely” combine their findings (Jick, 1979). They often do so because they can get immersed and then lost in the complex process of conducting mixed methods and analyzing the data in various forms (Venkatesh et al., 2013). For example, the data we collected in our “virtual teams” research study was both messy and voluminous. The concurrent (not sequential) occurrence of all these types of data added more complexity to the overall research process (refer Table A3 in the Appendix). These types of complexities in mixed-methods research pose significant cognitive challenges to researchers to process information and make meaningful interpretations from the data they collect.

Another reason why mixed-methods researchers tend to lose their direction and initial intent for using mixed methods is that they can offer a variety of benefits: often, researchers try to do much more than their original intention, which results in greater cognitive overload (Bazely, 2002; Bryman, 2007; Collins, Onwuegbuzie, & Sutton, 2006; Johnson et al., 2007; Sechrest & Sidani, 1995). Creswell and Clark (2010, pp. 60, 61) discuss this opportunistic expansion in the following terms:

*One data source alone is insufficient, results need to be explained, exploratory results need to be further examined, a study needs to be enhanced through adding a second method, a theoretical stance needs to be advanced through the use of both types of methods, and a problem needs to be studied through multiple phases of research that include multiple types of methods.*

Thus, mixed-methods researchers may start mixed-methods studies with a purpose and then realize the additional potential of using mixed methods along the way while conducting them. These new “emergent” intentions of doing mixed methods, though appropriate, may add to the cognitive overload and result in confusion about the best approach to analyze the data and report findings. In this vein, Bryman (2006, p. 99) correctly asserts that: “[W]hile a decision about design issues may be made in advance and for good

reasons, when the data are generated, surprising findings or unrealized potential in the data may suggest unanticipated consequences of combining them”.

For example, in our example study, we *emergently* chose an embedded mixed-methods approach because we had no consistent way of assessing both the adaptive use of IT capabilities construct and the construct of shared mental models in the virtual teams context. For the construct adaptive use of IT capabilities (AUITC), some researchers assess IT use with quantitative surveys (e.g., Sun, 2012), and others use a qualitative approach to measure IT use, such as coding the communication messages, and assess the actual usage behaviors or recording the usage logs in technologies. Regarding the construct of shared mental models (SMM), Mohammed, Ferzandi, and Hamilton (2010) recently reviewed the SMM literature and found that, while quantitative approaches (e.g., pathfinder to operationalize team mental models and surveys) seemed to be the primary approach for assessing SMM, to gain richer understanding of the context where teams develop SMM, researchers still explored qualitative approaches such as open-ended interviewing or communication message analysis to measure the similarity of SMM among team members. Considering our purposes here, we also abandoned our initial design of using a purely quantitative approach (i.e., surveys). We decided to not just use mean scores and correlations to describe the interplay between the constructs of interest. We realized that mixed methods not only more richly explained the research question by combining both the qualitative “stories” and the quantitative “data” but also helped us achieve a balance between time and effort rather than using a multi-method type of research design. In addition, by using a mixed-methods approach, we could observe the important interplay between teams’ adaptive use of IT capabilities and shared mental models during the team process and over time. Despite the fact that this change in our thinking added substantive cognitive load, once we decided to use the EMM research design, we premeditatedly developed a plan and conducted a second pilot to verify our intentions.

In conclusion, with regards to this risk, we recommend that MM researchers should plan to review and audit the research design during their study and remind themselves why they chose a mixed-methods approach. Also, if the MM design emerges during the research process despite different intentions (as in our case), we would advise that researchers assess what value this approach would provide them and evaluate the design through an additional pilot. Having a clear, parsimonious goal in mind can help guide researchers to conduct, analyze, and mix methods “genuinely” while balancing the amount of effort with potential outcomes. We should also admit that the issues discussed here are not unique to MM research design. However, our experience with the EMM approach has shown that using mixed-methods approaches requires one to pay closer attention to the issues discussed here due to the inherent complexities of implementing this research design.

### 3.2 Risk 2: Inadequate Pre-study Preparations

It is not uncommon for researchers to start their studies without pre-study preparations (i.e., pilots) (Dubé & Paré, 2003), which can pose risks in answering research questions using the study’s findings. In addition, researchers can use the issues that arise in pilots to clarify and better operationalize elements of the research process for the full study.

One fundamental principle in the pre-study preparation for mixed research is that researchers need to see if the various data-collection methods actually do complement each other’s weakness. For example, in our study, we collected both team members’ technology usage activities through technology logs and survey questions to assess users’ adaptive use of IT capabilities during the team process. During the second pilot, consistent with our intent, we found that the data collected through these two methods provided both the context of members’ technology usage and the numerical rating of members’ AUITC behaviors. Furthermore, in our study, we found that the qualitative approach provided us with a means to assess the “explicit” SMM (i.e., what specific shared knowledge and understanding the members established), while the survey items helped us see the “tacit” SMM (i.e., whether or not virtual teams had smooth team interactions with infrequent harmful conflicts).

Also, researchers need pre-study preparations to obtain a sense of the data that they will collect. We collected users’ technology usage logs in Blackboard, Gmail, and Google Site. Before the full study, our pilot studies allowed us to clearly understand the format of the data logs for the different technology capabilities, the accessibility of these data, and the volume of data that may occur with each type of technology. The lessons we learned from the pilot studies helped us decide the means to organize and present our data for effective analysis. Further, pre-study preparations give researchers a chance to think of the potential ways they can combine data together. Even though researchers often carefully develop

their research plans before study, not everything happens as anticipated. When researchers see the actual data generated, they may discover interesting results or certain unanticipated consequences of combining them (Bryman, 2006). For example, in our study, we intended to collect users' Google Site activity logs to assess how frequently and intensively they used Google Site, which we needed to do to better understand team members' AUITC behaviors. In the pilot studies, we found Google Site activity logs can also be helpful in assessing team members' SMM when we identified salient patterns of using particular Google Site features. In one of the teams, we found that each member would make updates to task management (a feature in Google Site) after they finished some webpage editing activities. This pattern shows the agreement among members and illustrates the way members interact with each other to share the progress of critical tasks. Therefore, the use of Google Site activity logs was a good means of corroborating the findings we obtained from other SMM assessment techniques such as communication logs and responses to the technology usage reports.

### 3.3 Risk 3: Unclear Plans for Data Collection

In EMM research designs, researchers will potentially collect qualitative and quantitative data together to develop an understanding about their questions of interest (Creswell & Clark, 2010; Sieber, 1973). They use "a variety of sources and resources" so that they can potentially "build on the strengths of each type of data collection while minimizing the weaknesses of any single approach" (Patton, 2002, p. 306). Consequently, MM researchers should carefully plan how they will collect data that would help them "(a) to obtain convergence or corroboration of findings, (b) to eliminate or minimize key plausible alternative explanations for conclusions drawn from the research data, and (c) to elucidate the divergent aspects of a phenomenon" (Johnson & Turner, 2003, p. 299).

However, researchers do not often make their data-collection plans explicit when reporting their embedded research design as Creswell and Clark (2010) suggest they should do. According to Creswell and Clark, for embedded research design, researchers should describe "the rationale for embedding one form of data, the timing of the embedded data, and how to address problems that may arise from the embedding" (p. 190). For example, in our research study, we had to decide on several issues. First, we had to decide on our rationale for embedding a survey. The first pilot showed that surveys and qualitative approaches have complementary roles in our study. Qualitative data analysis provided us with a rich study context, an opportunity for making inferences, and also a chance to tell stories. Surveys helped corroborate our findings and also were powerful in facilitating finding interesting insights when surveys and qualitative data analysis results were different or contradictory. Second, we had to decide when (to conduct the surveys (i.e., their timing). To be able to catch potential changes in AUITC and SMM during the virtual team process, we decided to administer surveys at the end of each milestone of the team project. Third, we had to decide how we would develop the strategy for dealing with the convergence and divergence problems with embedding. In our research, we decided that we would use case study data as the primary resource for analyzing data and the survey data as a complementary source (Creswell & Clark, 2010) because we believed that the correlations derived from survey data analysis were too simple to describe and explain the interactions between AUITC and SMM development in virtual teams. Therefore, choosing a qualitative method as the primary method and survey method as the embedded research approach rather than the reverse was more helpful in our uncovering the unknown complexities between AUITC and SMM in virtual teams.

When developing plans for data collection, one should also be aware and identify the limitations of each kind of data-collection technique. For example, in our study, an important limitation with the technology logs data was that it varied in format, quality, and completeness. The logs we used for our study did not necessarily capture all team members' interaction activities through technology (e.g., chat over Google Talk). In addition, limitations of the survey data we collected included possibly distorted responses due to personal bias, anger, and anxiety, and so on (Patton, 2002). Considering the limitations of the study, when making inferences, we carefully corroborated our findings from various data sources to ensure the validity of the assessments and inferences.

### 3.4 Risk 4: Inefficiency in Data Organization

In our EMM study, given the voluminous data and the variety of formats of the data collected, we experienced challenges in figuring out the right approach to organizing the data to engender meaningful comprehension, which was particularly critical for the qualitative data we collected.



By organizing qualitative data in a systematic way, researchers can gather comprehensive, systematic, and in-depth information and represent the data efficiently so they can understand and describe patterns of interest (Patton, 2002). They should also check the “inventory” of what they have before organizing the data (Patton, 2002). Identifying an effective data-organization approach involves building an initial data display so that researchers can obtain a full picture of the case and can do exploratory analysis across cases if the study includes multiple cases.

In our study, we chose to organize the qualitative case data based on their general nature (i.e., technology usage report, communication data, and Google Site activities). For each of these three types of data, we used grids and organized them in order from the first to last case study.

During the second pilot study using the EMM research design, we tried to organize the data by specific cases; we also tried to organize the data by each specific technology feature (e.g., BB discussion board), which was a straightforward way of organizing data. However, in contrast to these approaches, we discovered that organizing data into three general types more effectively helped us do both within-case and cross-case analyses. In particular, organizing data by specific cases may be the intuitive approach for researchers to take so that they can corroborate and confirm findings across various data sources and be thorough in carrying out within-case analyses. However, such an approach can significantly hinder researchers’ ability to do cross-case analyses when faced with this information overload.

Therefore, we recommend that researchers explore multiple ways of organizing their data to determine the best one for understanding and presenting it so they can develop focused insights.

### 3.5 Risk 5: Inappropriateness of Data Visualization

Data generated in EMM studies can be messy given the nature and limitation of human beings’ cognition (Creswell & Clark, 2010). Even though visualization techniques for quantitative data are well established (e.g., graphs and charts), techniques for visualizing qualitative data in variety of formats has less guidance. Data visualization is important because these techniques represent “visual sources of information” and entail a decision to organize information in a certain way that could have the potential of deriving interesting and meaningful insights (Sandelowski, 2003).

Miles and Huberman (1994) offer some practical approaches to visualizing qualitative data through tables and maps. As we realized in our research study, it is important to note that using such tables and maps requires thoughtfully considering one’s study’s purpose and the unique strengths of each kind of qualitative data-representation technique.

For example, we wanted to examine the “interplay” between virtual teams’ AUITC and SMM development during a virtual team’s lifecycle. We believe that virtual teams’ adaptive use of IT capabilities, the development of shared mental models, and the interactions between these two constructs are all processes that “a string of coherently related events” can depict (Miles & Huberman, 1994, p. 111). Therefore, for our study, we had to identify the timing and the content of those salient events and the connections between them. We posited that, if we could successfully sort out occurrences of AUITC and SMM while preserving the sequence and showing the salience or significance of preceding events for following events, we could develop a holistic view of the interactions between AUITC and SMM development in virtual teams. Thus, to attain this goal from the massive volume and diversity of data we collected, we surveyed the categories of visualization techniques by Miles and Huberman and found that the time-ordered displays are an appropriate means for visualizing collected data and served the purpose of our study well. In particular, considering the multiple constructs and subconstructs included in our study, we believed time-ordered matrices would be the most useful way to attain our goal. Time-ordered matrices not only aid researchers in keeping records of the chronological events during the study but also allow them to keep track of events in different domains (i.e., constructs or subconstructs). In Table A5, we illustrate the time-ordered matrix we constructed for each team so that we could capture the salient patterns of interplay between the AUITC and SMM development teams.

Clearly, mixed-methods researchers need to visualize their data well to create “a sense of order out of chaos” (Sandelowski, 2003, p. 337). Specifically, we recommend that mixed-methods researchers pay attention to and be innovative with visualizing qualitative data where standard data-visualization methods are still lacking.

### 3.6 Risk 6: Lack of Data Exploration

Data exploration allows researchers to understand the nature of the data they have collected and examine the quality of the information they have collected. Skipping the data-exploration step could have a potential negative impact in that one might ignore important patterns or trends. Qualitative data exploration involves reading through all of the data to develop a general understanding of the database, while quantitative data exploration usually involves inspecting the data and conducting a descriptive statistical analysis to determine the general trends in the data (Patton, 2002).

Appropriate data organization is only one way to facilitate data exploration. Researchers should employ other visual techniques to help clarify and understand the data they have collected. For example, in our study, we built charts to see trends of changes on variables of interest over time (see Figure A2). We also plotted the survey scores of each pair of variables for all teams on a two-by-two matrix (see Figure A3 and Figure A4). These four-cell matrices showed a simplified relationship between variables. In general, we found that visualizing the survey data helped us enhance the efficacy of our qualitative data analysis, especially when we found differences between the two approaches and took a deeper look at the data to draw insights. Therefore, we recommend that MM researchers employ appropriate data-exploration techniques that align with their research questions.

### 3.7 Risk 7: Focusing on Agreement

The conventional purpose of using mixed-methods research is to look for concurrent or convergent evidence for supporting findings across methods or to corroborate findings by leveraging the strengths of various techniques (Rossman & Wilson, 1985). According to Rossman and Wilson (1985, p. 633), “[Q]uantitative techniques are the most appropriate source for corroborating findings initially noted from qualitative methods. Likewise, qualitative methods are best used to provide richness or detail to quantitative findings, but should precede quantitative ones when clarifying the direction of inquiry”.

Despite the importance of looking for “agreement” in mixed methods, one should not overlook “disagreement” in findings, which can also provide valuable insights into the phenomenon under study. Jick (1979, p. 608) argues that the:

*Process of compiling research material based on multi-methods is useful whether there is convergence or not. Where there is convergence, confidence in the results grows considerably. Findings are no longer attributable to a method artifact. However, where divergent results emerge, alternative, and likely more complex, explanations are generated.*

For example, in our research study, the communication log data, Google Site activities data, and survey data suggested that two of the three distinct patterns identified appeared to describe the interplay between AUITC and SMM development in virtual teams (refer Table A7). We generally distinguished these two patterns by how early and actively teams initiated interactions among themselves when accomplishing their task. That is, the earlier the teams engaged in interactions using information technology capabilities, the better the team’s ability to develop SMM convergence. However, one particular team did not fall into either pattern. This particular team started their team interactions earlier but did not converge on their shared mental models as quickly and as well as the other teams. When we looked deeper into the qualitative data, we found that this team had been struggling with coordination among the conflicting schedules of members and a majority of the team was not positively addressing the difficulties that occurred in team coordination. After further analysis of that particular teams’ context, we concluded that we needed a third type of pattern of the interplay between AUITC and SMM development in virtual teams to describe these findings, which we called the “struggle pattern” (Table A7).

In conclusion, mixed-methods researchers need to be open to the idea of divergent findings and be willing to revisit and/or modify their initial theoretical assumptions, hypotheses, or conclusions and to potentially draw on further theoretical concepts that researchers have not yet applied to the domain in question (Erzberger & Kelle, 2003; Erzberger & Prein, 1997; Fielding & Fielding, 1986).

### 3.8 Risk 8: Barriers in Pattern/Theme Recognition

Mixed-methods researchers often face challenges in discovering appealing and cogent themes and patterns from their data due to the volume, diversity, and varying nature of the data they collect. One potential barrier to discovering themes and patterns is a lack of solid evaluation criterion for identifying substantively significant findings. This notion is equivalent to the idea of statistical significance in

quantitative analysis. Patton (2002, p. 467) proposes four questions that one needs to answer when considering the substantive significance of the evidence one has generated.

1. How solid, coherent, and consistent is the evidence in support of the findings?
2. To what extent and in what ways do the findings increase and deepen understanding of the phenomenon studied?
3. To what extent are the findings consistent with other knowledge?
4. To what extent are the findings useful for some intended purpose (e.g., contributing to theory, informing policy, summative or formative evaluation, or problem solving in action research)?

In mixed research, evidentiary interpretation requires:

*Researchers (to) work back and forth between the data or story (the evidence) and his or her own perspective and understandings to make sense of the evidence. Both the evidence and the perspective brought to bear on the evidence need to be elucidated in this choreography in searching of meaning. Alternative interpretations are tried and tested against the data. (Patton, 2002, pp. 477-478)*

In our study, qualitative data told stories of how teams' mental model development may interplay with the adaptive use of IT capabilities (refer Appendix A). For example, we discovered that two virtual teams reached agreements on the same general topic at the same time point in time but by using different technology capabilities. In another finding, two virtual teams developed teamwork mental models about the use of Google Site for team interaction during different phases of their project. Through the time-ordered matrix we built (refer Table A5), we observed certain links between the usage of particular technology capabilities and the similarity of mental models (i.e., level of agreement among team members about the team's shared mental models development). We also observed the influence of certain categories of SMMs on virtual team members' preferences for technologies used. These observations of the linkages between AUITC and SMM, piece by piece, formed the solid, coherent, and consistent evidence base to achieve our final findings. Using Patton's (2002) four criterion of assessing the significance of findings, we tried alternative ways to interpret the interactions between AUITC and SMM from the evidence. We tried to explain the complexities of the interactions through the three dimensions of AUITC: inclusiveness, fit, and usage experience. We also tried to see if the dimensions of SMM could help describe the interplay of the two constructs. However, these approaches were only useful in reaffirming our argument that such interplay of AUITC and SMM does exist. They did not help us in generalizing our findings to a higher level to categorize the nature of the interplay or in leading towards findings that could account for the variances among teams on this interplay.

While we built a summary table (see Table A6) by combining both types of data for each construct of interest across teams, we found that the initial interaction of teams and virtual teams' awareness of IT capabilities are two important dimensions that can help one categorize virtual teams' varied outcomes on shared mental models convergence and on the varied paths by which they adaptively used IT capabilities (AUITC). Further, we identified three salient patterns (see Table A7). We iteratively derived a plausible set of logical patterns that seemed to coherently explain the evidence we had generated from both the qualitative and quantitative data.

As Jick (1979, p. 608) accurately contends:

*[O]verall, the triangulation investigator is left to search for a logical pattern in mixed-method results. His or her claim to validity rests on a judgment, or as Weiss (1968, p. 349) calls it, "a capacity to organize materials within a plausible framework".*

To identify the themes and patterns, we recommend mixed-methods researchers be flexible in choosing pattern extraction strategies; that is, identify the patterns/themes from qualitative study analysis and validate them with quantitative analysis, identify the patterns/themes from quantitative study analysis and validate them with qualitative analysis, or identify the patterns/themes from both types of analysis.

### 3.9 Risk 9: Ineffective Way of Presenting Findings

Researchers often struggle with writing up their findings from mixed-methods studies (Bryman, 2007). One challenge stems from the varied styles of communicating facts and meaning from the qualitative and quantitative paradigms. In other words, the qualitative and quantitative paradigms have different implicit conventions for reporting findings. Researchers who follow the qualitative paradigm prefer words to form a

holistic picture of the evidence, while researchers who use the quantitative paradigm prefer numbers and statistical significance testing. To address this challenge of mixed research design, we started with a clear research question in our mind, which made the task of writing our EMM research design findings more about “how best to accommodate the mixes in mixed methods studies” (Tashakkori & Teddlie, 2003, p. 345). Furthermore:

*[C]rafting convincing mixed methods studies texts requires using words—especially the epistemologically and emotionally loaded terms qualitative and quantitative—in ways that will be accessible and appealing to the mixed audiences for mixed methods studies and respectful of the highly diverse communities participating in the creation of and served by mixed methods studies. (Tashakkori & Teddlie, 2003, p. 345)*

Another challenge to presenting findings originates from the difficulty of explicitly presenting high-quality integrative inferences in mixed methods (i.e., meta-inferences) (Venkatesh et al., 2013, p. 38). Researchers have suggested that meta-inferences are at the core of high-quality mixed-methods validation-assessment criteria. For high-quality meta-inferences, researchers need to explicitly state how they integrate data analyses from qualitative studies and quantitative studies.

Mixed-methods researchers can attain meta-inferences following different approaches (e.g., transformation or non-transformation approaches) depending on their mixed-methods design (Venkatesh et al., 2013). Based on our own experience, we recommend researchers to be flexible in how they integrate qualitative and quantitative studies at the meta-inference stage. Our experience illustrates that finding the appropriate path to build meta-inference out of findings from a mixed-methods study is an iterative process that involves trial and error. For example, in our research (Yu & Khazanchi, 2016), during the pilot study data analysis, we quickly realized that merging the findings for survey and case studies kept us from building an accessible, appealing, and logical description using a holistic understanding because of high information overload. By trial and error, we decided to use the survey findings as the starting point to unveil the stories in the large volume of qualitative data collected and then more deeply analyze the qualitative study findings. If we had not chosen this effective path, we would have been distracted and potentially overwhelmed by the diversity and amount of qualitative data and, therefore, would not have been able to discover the three distinct interplay patterns (refer Table A7).

## 4 Conclusion

Mixed-methods research designs offer both opportunities and challenges for researchers interested in studying the complexities of IS-related phenomena. Given mixed research’s strengths in providing a more holistic, contextually sensitive view about the phenomenon of interest and its potential for allowing researchers to explore relatively “new” and “emergent” topics, it is important to have a sense of the risks and challenges of using mixed-methods research designs. Although the literature is replete with general guidance on mixed-methods research designs and examples thereof, we lack clarity and guidance to address operational challenges while implementing mixed-methods research design strategies. Drawing on prior research in other disciplines and our own specific experience with an EMM study, we identify nine risks of conducting mixed-methods research. In discussing each of the risks, we illustrate the risks using our research study and provide some practical remedies based on our own experiences. We also call on likeminded researchers to share more practical remedies for conducting mixed research.

Of course, many interesting issues about implementing mixed-methods research design remain open to further study. One critical area for further research concerns data visualization and data fusion. Given that we collected a variety of data, it would be pertinent to study optimal approaches to visualizing and fusing qualitative and quantitative data during the sensemaking process. A second area of interest in IS research will continue to involve developing approaches to resolve conflicting data when using multiple research methods. Are there systematic ways of doing it more effectively? How does one make choices when looking at conflicting data? Another interesting research issue is how to build the inferences when corroboration becomes difficult because of the missing data regarding the constructs of interest among multiple methods used in one particular study design.

## Acknowledgments

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## Appendix A: Embedded Mixed-methods Research Design Study

In this study, we address the research question: “what is the interplay of two emergent processes within virtual teams, namely, adaptive use of IT capabilities (AUITC) and shared mental models (SMM) development?” (Yu, 2013). We study how these two emergent processes interplay with each other in the context of virtual teams. We argue that answers to this question can help us better understand the complex dynamics of virtual team behaviors and, therefore, build more effective virtual team management practices (Yu & Khazanchi, 2016). We further assert that, though previous studies have contributed significantly to our knowledge about the nature of individual’s IT/S use, less knowledge has accumulated on IT/S use at the group level, and even fewer studies have considered some distinct group-level associated constructs as compared to individual ones.

Consistent with Venkatesh et al. (2013), we agree that the first step to take when considering a mixed-methods approach is to assess its appropriateness. In addition to the aspects of research question, objective, and context, Venkatesh et al. suggest that researchers, editors, and reviewers consider the strengths and purpose of mixed-methods approaches to assess if one actually needs to use a mixed research design (i.e., whether they add significant value to one’s study). Table A1 characterizes our mixed-methods research study based on the strengths and purposes of mixed methods.

As Table A1 shows, we had two main reasons to use a mixed-methods approach for our example study: completeness and corroboration. First, we wanted to develop a holistic understanding of the complexities inherent in a virtual team’s use of IT artifacts and shared mental models development. Previous studies provide fragmented knowledge about the nature of AUITC in virtual teams, AUITC’s impact on another emergent team process, and potential influence of SMM on AUITC in virtual teams. We thought using mixed methods could help enhance our chance to fully capture the developmental stages involved in the emergent process. Second, the literature lacks a consistent means for assessing the AUITC and SMM constructs. Combining both qualitative and quantitative methods would create an opportunity to enhance the credibility of the constructs’ assessments and strengthen the inferences.

**Table A1. Appropriateness of the Mixed-methods Approach (Adapted from Venkatesh et al., 2013)**

<b>Strengths of mixed-methods research</b>			
Address confirmatory and exploratory research questions simultaneously			N
Provide stronger inferences than a single method through meta-inferences			✓
Assortment of divergent and/or complementary views			N
<b>Purposes of mixed-methods research</b>			
Complementarity	N	Corroboration/confirmation	✓
Completeness	✓	Compensation	N
Developmental	N	Diversity	N
Expansion			

For our purposes here, we summarize the key research constructs and related concepts in Table A2. Readers can obtain additional details about the theoretical and conceptual foundations of this research question and the theoretical origins of these constructs from the authors.

We conducted the mixed-methods research study in an asynchronous, online undergraduate-level course taught at a Midwestern University in the USA. Participants of the study were students enrolled in an online class. We assigned a total of 17 participants into five teams of three to four. Gmail (i.e., email), Blackboard (BB), and Google Sites were the primary collaborative technologies we used in this study. The task was a group project that lasted seven-weeks and the goal was to develop an e-commerce business plan. Participants had to submit three deliverables related to the final business plan; namely, the business concept/model, the IT platform design, and a design of the ecommerce website with a mockup. Figure 1 in the main paper body depicts the overall research design we used for the study: one can see how we mixed a quantitative survey with the primary traditional qualitative multiple case study (Creswell & Clark, 2010). To collect qualitative data, we first used self-reports with open-ended questions regarding members’ usage and feelings about various technology capabilities periodically (i.e., weekly). Second, we collected all the IT-enabled team communication texts (after students read the consent forms and agreed to be research subjects). Third, we collected the qualitative posts from Google Sites logs (i.e., comments). Regarding the quantitative survey design, we mainly adapted measures on constructs from previous



literature. With this design, we could capture not only the numerical scores for each construct but also the rich context in which emergent team behaviors regarding the use of IT capabilities and shared understanding occurred.

**Table A2. Definitions of Key Constructs**

Construct	Definitions
Adaptive use of IT capabilities (AUITC)	<ul style="list-style-type: none"> <li>• <b>AUITC</b> refers to the process by which virtual team members collectively use or modify one or more IT capabilities to perform a task (Burton-Jones &amp; Straub, 2006).</li> <li>• <b>IT capabilities</b> used in virtual teams can be broadly classified into three categories: <i>communication, team process, and interaction</i>.               <ul style="list-style-type: none"> <li>• Communication capabilities refer to any capabilities that support a virtual team's communication and collaboration.</li> <li>• Interaction capabilities refer to any capabilities that support the process of individuals' working with others and engaging with the virtual collaborative environment.</li> <li>• Team process capabilities refer to any capabilities that support team processes, such as process structure, information processing, appropriation support, and socialization/community building (Davis et al. 2009; Zigurs et al. 1998).</li> </ul> </li> <li>• <b>Usage experience, inclusiveness, and fit</b> are the three most salient factors in understanding AUITC at the team level (Yu &amp; Khazanchi, 2016).               <ul style="list-style-type: none"> <li>• Usage experience refers to total amount of time and frequency of using IT capabilities.</li> <li>• Inclusiveness refers to the extent to and purpose for which users explore diverse IT capabilities.</li> </ul> </li> </ul> <p>Fit refers to the process when virtual team members actively find a match between the use of IT capabilities and the need of their tasks and/or the need of their team (Khazanchi, 2005; Zigurs &amp; Buckland, 1998).</p>
Shared mental models (SMM)	<ul style="list-style-type: none"> <li>• <b>SMM</b> refers to "knowledge structures held by members of a team that enable them to form accurate explanations and expectations for the task, and in turn, to coordinate their actions and adapt their behavior to demands of [their unique domain]" (Cannon-Bowers, Salas, &amp; Converse, 1993, p. 228). In virtual teams, the development of teams' shared understanding about taskwork, teamwork, and IT capabilities are essential to positive virtual team outcomes.               <ul style="list-style-type: none"> <li>• A team's taskwork mental models (SM-TS) are knowledge structure and beliefs held by the team about the task goals and steps to accomplish the tasks.</li> <li>• The teamwork mental models (SM-TM) refer to the knowledge structure and beliefs held by the team about the team interaction and team members' roles, skills, and knowledge.</li> </ul> </li> </ul> <p>A team's equipment mental models (SM-EQ) are knowledge structure and beliefs held by the team about the technologies' functions, strengths and likely failures (Mathieu et al. 2000).</p>
Interplay	<p><b>Interplay</b> refers to the dynamic, emergent, and interdependent relationship between AUITC and SMM development (Yu &amp; Khazanchi, 2016).</p>

This illustrative study followed an emergent mixed-methods (EMM) research design as contrasted with a fixed mixed-methods design. According to Creswell and Clark (2010, p. 54), emergent mixed-methods research designs are useful when issues develop when conducting research that result in researchers' adding a second approach because they find one method to be inadequate. In our first pilot, we planned a purely quantitative survey based research design, but, after doing our first pilot, we realized that mixing a primarily qualitative approach with quantitative methods throughout the research study constituted a better approach to examine the interplay between AUITC and SMM. For example, when we wanted to assess virtual teams' AUITC, the numerical ratings in the survey could not adequately explain the contexts of members' technology usage, such as the timing, content, and perception of the usefulness of the IT capabilities in use. We realized during the pilot study that the interplay we were investigating was more complex and dynamic than we anticipated and that it was not adequate to look at mere correlations between constructs alone to explain this phenomenon. This observation also illustrates the importance of conducting detailed pilot studies before conducting a full-fledged mixed-methods research design (or, for that matter, any other research approach) to develop a strong understanding of the data, timing, and mechanism for mixing a data-collection approach at each stage of a mixed-methods research study design.

Therefore, one can describe the specific MM research design we used for our research study as an embedded mixed-methods design with the survey design's complementing the primary case study research design (Creswell & Clark, 2010; Johnson & Onwuegbuzie, 2004; Johnson et al., 2007).

## Pre-study Preparations

As a precursor to the full study, we conducted two detailed pilots to test the validity of both the qualitative and quantitative strands in the EMM design and the mechanism and timing for embedding the quantitative survey during the case study. We decided to embed the survey during the data-collection phase and develop techniques to combine the data based on Miles and Huberman's (1994) suggestion. The pilot studies helped us further refine the case study protocol (Yin, 1984) and provided us an opportunity to validate the technology capabilities, task, research procedure, qualitative data-collection approach, and the data-coding scheme. With respect to the embedded survey design, conducting the pilot studies helped us adapt and validate survey items from previous research to this particular study. In fact, once we completed the pilot and made the decision to use an EMM research design approach, we essentially used the second pilot to ensure that the EMM design would work in the full study.

## Data Collection

We used lessons learned from the two pilot studies to guide how we collected data for the study. In particular, as we explain in the previous section, we decided to overlap the case study and survey data collection over time. The entire study lasted seven weeks from when the teams formed to when they disbanded. We collected the case study data throughout the entire study, and we administered three surveys at multiple points during the study (i.e., the third, fifth, and seventh weeks).

Table A3 shows the details of each data-collection method and the nature and timing of the data collected.

**Table A3. Study Design, Data-collection Methods, and the Data's Nature and Timing**

Study design	Data type	Data-collection technique	What	When	Where we collected the data
Case study design	Qualitative	Open-ended questions	Specific technology capabilities they have used and their reflections on their usage experience.	At the end of each week.	Students completed the open-ended questions online.
	Qualitative and quantitative	Technology usage data	<ul style="list-style-type: none"> <li>• Email messages</li> <li>• Google Site activity logs</li> <li>• Blackboard discussion board</li> <li>• Blackboard journal</li> <li>• Blackboard blog</li> <li>• Blackboard wiki</li> </ul>	When subjects used the IT capabilities.	Real-time data collected in Gmail, Blackboard, Google Site.
Survey method	Quantitative	Quantitative surveys	Items for measuring AUITC and SMM.	At the end of the week 3, 5, 7 (i.e., the milestone times for the groups).	Students completed the surveys.

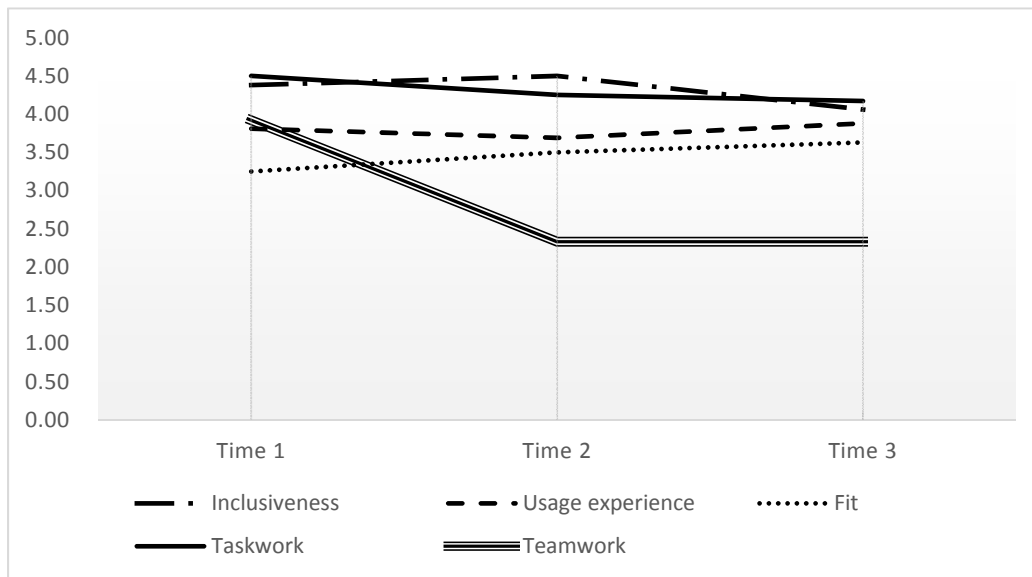
## Data Visualization

Data visualization involves organizing collected data and presenting it in an appropriate way so that one can identify patterns. Table A3 shows the three major kinds of data we collected. For each data source, we first carefully examined the format and quantity of the data and put them into organized files. Then we used different data-visualization techniques based on the nature of the data and our purposes. In general, for qualitative data, we compiled the data into structured files for each group to prepare it for the next step of data exploration. For the quantitative data, we used charts and tables to visualize the results. Table A4 shows more specifics about the data-visualization, data-exploration, and data-analysis techniques we used in the study.

**Table A4. Data-visualization, Data-exploration, and Data-analysis Strategies for each Data-collection Technique**

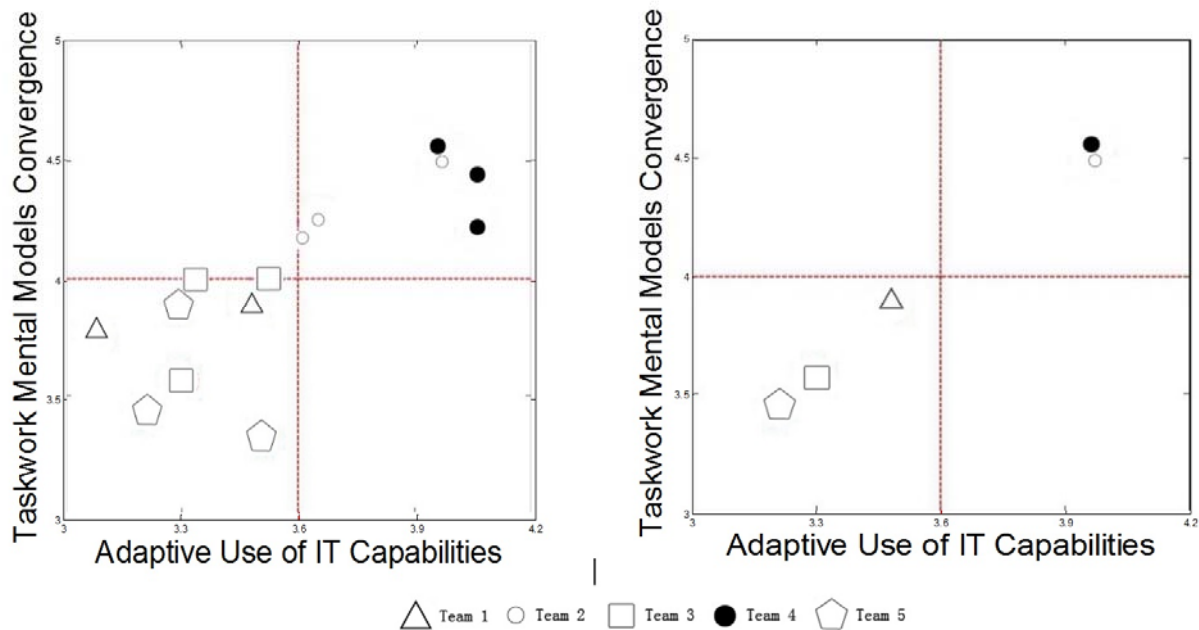
Data-collection technique	Data visualization	Data exploration	Data analysis
Open-ended questions	Compile the surveys for each group.	Read through several times	<ul style="list-style-type: none"> <li>Data coding (what IT capabilities the group uses; what are their SMM regarding IT capabilities)</li> <li>Develop the time-ordered matrix using based on data coding.</li> <li>Develop the summary table based on the time-ordered matrix results.</li> </ul>
Technology usage data	We used a variety of data-visualization techniques. For example, we compiled emails for each group/case, summarized Google Site activity logs in both tables and line charts, and compiled all of the texts in Blackboard into one document for each group/case.	Read through several times and scan the charts and tables	<ul style="list-style-type: none"> <li>Data coding (AUITC and SMM on taskwork and teamwork)</li> <li>Develop the time-ordered matrix based on the coding.</li> <li>Develop the summary table based on the time-ordered matrix results.</li> </ul>
Quantitative surveys	Line charts (showing the trend of each group's AUITC and SMM) and matrix-like charts (showing the relationship between AUITC and SMM) based on the descriptive statistics of the surveys	Review statistics and charts	<ul style="list-style-type: none"> <li>Identify patterns of the interplay between AUITC and SMM</li> <li>Develop a sensemaking summary table based on integration of data from the statistics and the visualization of the results.</li> </ul>

According to Table A4, to visualize the survey data, we merged surveys collected at all three temporal events together into a single spreadsheet by adding a new variable, time (range 1 to 3), to indicate the timing when we administered and collected a particular survey. Further, we imputed missing values by replacing them with the average score of before and after items. Then, we computed the descriptive statistics, such as the means and standard deviations. Next, we visualized the mean scores for each construct per team through the line chart shown in Figure A1.

**Figure A1. An Example of Line Chart of Means on Variables of Interest for One Team**

We also visualized the survey data by compiling the data by each construct using matrix-view plots as Figure A2 shows. In the matrix-view plots, we plotted the mean AUITC score and each type of SMM convergence into appropriate cells in the picture. Figure A2 (on the right) displays the virtual teams' mean AUITC score and taskwork mental model convergence scores at a single time point. In contrast, Figure A2 (on the left) displays all five virtual teams' mean AUITC scores and taskwork mental model convergence score at all three time points, which helped us ultimately understand, identify, and describe the patterns

that are common between the teams with regards to the interplay between IT capabilities and mental model convergence.



**Figure A2. An Example of Matrix View of Survey Data at All Three Times (Left) and Single Time Point (Right)**

## Data Exploration

During the data-exploration phase, we read through the compiled documents and also scanned the visualized charts to identify important patterns with a focus on the relationship between AUITC and SMM. As a result, we came to generally understand the entirety of the data we collected. This general understanding gave us a clue to how we would proceed with analyzing and interpreting the data.

## Data Analysis and Interpretation

In the data-analysis phase, we kept our two reasons for conducting mixed-methods research in mind (i.e., attaining completeness and corroboration). To achieve this goal, we chose two particular techniques: the time-ordered matrix and the summary table. In particular, we synthesized the data we collected using both the case study and survey research methods by adapting the time-ordered matrix technique to build a valid chronology of the events' salient sequential characteristics (Miles & Huberman, 1994).

As Table A5 shows, we arranged the columns by week from the first week to the last week of the case study project. From the first pilot study, we learned that a “week” fit our study because a week could capture the separate events and their sequence; otherwise, the events would have blended together. We used the key constructs, AUITC and SMM, as rows of the matrix. The AUITC components captured the virtual teams' adaptive usage behaviors with respect to three types of IT capabilities. The SMM components include three types of SMM suggested in previous literature. Furthermore, we also added one row for documenting the field notes. We developed specific rules for entering data into the time-ordered matrix according to the pilot data-analysis experience. For each week, if a change in a component occurred, we entered a short description of the change. A blank cell meant no change occurred for a specific component at a specific time period.

By using this approach for displaying data, one can identify the strengths of interaction between AUITC and SMM development. The time-ordered table (A5) helps identify if a team's adaptive use of IT capabilities affects the convergence of the team's mental model. For example, the table illustrates that Team 1 used BB discussion board as the main method for team communication in the first week. In subsequent weeks, the team continued to use BB discussion board for organizing their discussion. We can conclude that Team 1 was satisfied with their choice because of their reported comments that “BB....is great to organize the discussion and present them orderly”. The time-ordered table also shows

how teams' mental model convergence influenced their subsequent adaptive use of IT capabilities. For example, in the third week of the team project, Team 1 only used the BB discussion board for team communication rather than using both email and BB discussion board as they did in the previous two weeks. From the time-ordered table, we can infer that the team made this change because members converged on their shared understanding of the usefulness and fit of the BB discussion board for team communication.

**Table A5. The Time-ordered Matrix for Team 1**

		Week 1	Week 2	Week 3
AUITC	Communication	Email, BB discussion board	Email as optional, main method is BB discussion board	BB discussion board
	Team process	Email	N/A	Google Site deliverable, Task management
	Interaction	Google Site set up	Google Site calendar	
SMM	IT/Equipment	Email works for initial contact	BB discussion board is great to organize the discussion and present them orderly	N/A
	Taskwork	Not yet converged	Brainstorming and reached agreement on task goal and strategies	
	Teamwork	N/A	Agreed on communication channel would be BB discussion board	Agreed on roles and assignments
		Week 1: 23/9*	Week 2: 30/9	Week 3: 7/10
AUITC	Communication	Email, BB discussion board	Email as optional, main method is BB discussion board	BB discussion board
	Team process	email	N/A	Google Site deliverable, task management
	Interaction	Google Site set up	Google Site calendar	
SMM	IT/Equipment	Email works for initial contact	BB discussion board is great to organize the discussion and present them orderly	N/A
	Taskwork	Not yet converged	Brainstorming and reached agreement on task goal and strategies	
	Teamwork	N/A	Agreed on communication channel would be BB discussion board	Agreed on roles and assignments

\* Day/month.

Next, we developed an index-based summary table based on the time-ordered matrix and statistical analysis. Table A5 shows how we synthesized the primary qualitative and the embedded quantitative data to make meaningful sense of the results. To summarize the findings from the case study evidence, we employed a high-moderate-low index rating for constructs relating to group/case. We used both objective and subjective methods to assign the index for each constructs that related to each group. Specifically, based on a construct's operational definition, we first identified each particular incident of each construct from the time-ordered matrix and then counted incidents for each construct. Based on the occurrences of the incidents, we assigned indices. When we found incidents difficult to identify, such as in cases with missing video/audio chat logs, we subjectively assigned indices according to the strength of the evidence inferred from a cross-case analysis of the qualitative and quantitative data. We also corroborated findings of this stage by looking at the technology usage logs. After comparing and contrasting across cases, we could finally assign the rating to each construct for all teams. In addition, the summary tables provided survey statistics (particularly the means of the construct across a particular team for each of the constructs) as Table A6 shows.

**Table A6. Illustrative Case Study and Survey Evidence Analysis for Inclusiveness**

Construct	Team 1	Team 2
INC <sup>a</sup>	The team identified specific IT features that worked out for communication, team process, and interaction. The level of involvement from each team members was the key factor that affected the IT choices that the team made.	Team 2 did most of their team interaction through the BB discussion board. The team organized their team communication well through the forums, threads, and replies. We found little explicit team process usage of IT.
	<b>Index = low</b> (survey = 3.72 )	<b>Index = high</b> (survey = 4.3)

Based on this high-level analysis and comparison across groups/cases, we ultimately derived three distinct patterns that describe the interplay between AUITC and SMM development in virtual teams: the SMM-driven pattern, the AUITC-driven pattern, and the struggle pattern. For the SMM-driven pattern, teams tend to develop their shared mental models on task, technology, and team early in the team process. Compared to the SMM-driven pattern, teams fell into the AUITC-driven pattern tend to develop their knowledge about how diverse IT capabilities can fit their teams best in the entire team process as needed. In the struggle pattern, teams tend to be uncomfortable with both shared mental models development and adaptively using IT capabilities due to variety of team contingent factors. Table A7 provides some of the key characteristics of these patterns.

**Table A7. Salient Characteristics of Three Patterns of the Interplay between AUITC and SMM in Virtual Teams**

Salient characteristics	SMM-driven pattern	AUITC-driven pattern	Struggle pattern
<b>Initial interaction</b>	<ul style="list-style-type: none"> <li>Members engaged in initial interactions early in the project, relatively low time pressure.</li> </ul>	<ul style="list-style-type: none"> <li>Members engaged in initial interactions late in the project, relatively high time pressure.</li> </ul>	<ul style="list-style-type: none"> <li>Members engaged in initial interactions early in the project, relatively low time pressure.</li> </ul>
<b>Awareness of IT capabilities</b>	<ul style="list-style-type: none"> <li>Members were aware of the diverse technology capabilities and the diverse requirements to accomplish tasks.</li> </ul>	<ul style="list-style-type: none"> <li>Members adapted diverse technology capabilities given various task needs and team interaction needs over time.</li> </ul>	<ul style="list-style-type: none"> <li>Members were aware of the diverse technology capabilities and the diverse requirements to accomplish tasks.</li> </ul>
<b>SMM convergence</b>	<ul style="list-style-type: none"> <li>Early convergence of SMM on technology capabilities' usage for supporting team interaction and task completion.</li> </ul>	<ul style="list-style-type: none"> <li>Members tried to follow the direct sequence of completing project or tasks, from problem identification to execution, while paying little to no attention to the relationship building among team members and the potential of using technology capabilities to enhance team interaction.</li> </ul>	<ul style="list-style-type: none"> <li>Teams were unsuccessful in one or more these areas: 1) coping with team members' conflicting work schedule, 2) adapting technology capabilities to the task/team needs when needed, and 3) identifying the particular fit between a particular bundle of activities and a particular period of time (McGrath, 1991).</li> </ul>
<b>Level of AUITC</b>	<ul style="list-style-type: none"> <li>Relatively high AUITC evidenced by quality IT usage, inclusive IT capabilities, and fit between tech and task.</li> </ul>	<ul style="list-style-type: none"> <li>Members experienced increasing degree of AUITC evidenced by increasingly usage of IT capabilities in communication, team process, interaction, and the increasingly usage of diverse IT capabilities or in increasingly diverse ways.</li> </ul>	<ul style="list-style-type: none"> <li>Relatively low to moderate degree of AUITC evidenced by low degree of fit between technology capabilities and the team/task's requirement.</li> </ul>
<b>Level of SMM convergence</b>	<ul style="list-style-type: none"> <li>Relatively high SMM convergence.</li> </ul>	<ul style="list-style-type: none"> <li>Members achieved a higher degree of convergence on SMM when there was a fit between the technology capability and the requirements for building particular type of mental models.</li> </ul>	<ul style="list-style-type: none"> <li>Relatively low to moderate degree of SMM.</li> </ul>

## Appendix B: Survey

### Section A: demographic information

Group number: \_\_\_\_\_

Gender: Male Female

Status: Freshman Junior Sophomore Senior Graduate or post-baccalaureate.

Age: \_\_under 20\_\_ 20-24\_\_ 25-29\_\_ 30-34\_\_ 35-39\_\_ 40-44\_\_ over 44

### Section B: technology capabilities adaptation

*Circle the number that most closely described your opinion about your experience of interacting with the technologies on the line preceding the statement:*

Strongly Disagree --1--2--3--4--5--Strongly Agree

*Dimension: inclusiveness*

- \_\_\_1. I played around with features in Google Sites.  
 \_\_\_2. I played around with features in Blackboard.  
 \_\_\_3. I figured out how to use certain Google Sites features.  
 \_\_\_4. I figured out how to use certain Blackboard features.

*Dimension: usage experience*

- \_\_\_5. Compared to other students, I believe I spent above than average time on Google Sites.  
 \_\_\_6. Compared to other students, I believe I spent above than average time on Blackboard.  
 \_\_\_7. Compared to other students, I believe I spent above than average time on Google Sites.  
 \_\_\_8. Compared to other students, I believe I visited Google Sites more frequently.  
 \_\_\_9. Compared to other students, I believe I visited Blackboard more frequently.  
 \_\_\_10. Compared to other students, I believe I used Email more frequently.

*Dimension: fit*

- \_\_\_12. I created work-a-rounds to overcome system restrictions.  
 \_\_\_13. I combined features in Google Sites with features in blackboard to finish a task.  
 \_\_\_14. I used some features in Google Sites in ways that are not intended by the developer.  
 \_\_\_15. I used some features in blackboard in ways that are not intended by the developer.

### Section C: shared mental models

*Circle the number you feel that most closely represents how you feel with each the following statements on the line preceding the statement:*

--1--2--3--4--5--

None a lot

*Mental model: equipment model*

- \_\_\_16. How am I familiar with the capabilities provided by Email.  
 \_\_\_17. How am I familiar with the capabilities provided by Blackboard.  
 \_\_\_18. How am I familiar with the capabilities provided by Google Sites.

*Mental model: task model*

- \_\_\_19. How frequently are there conflicts about understanding project goals in your team?  
 \_\_\_20. How often do people in your team disagree about opinions regarding the work to be done?

\_\_\_21. How much conflict is there about the work you do?

\_\_\_22. How frequently do members disagree about the way to complete a team task?

*Mental model: team interaction model*

\_\_\_23. To what extent did team members alert each other to impending decisions and actions.

\_\_\_24. To what extent did team members seek out and pass along information to rest of team.

\_\_\_25. To what extent was the team's behavior coordinated

*Mental model: team model*

\_\_\_26. How often do members disagree about who should do what?

\_\_\_27. How much conflict about delegation of tasks exists in your team?

\_\_\_28. Did the team members adjust individual task responsibilities to prevent overload?



## Appendix C: Summary of Risks and Remedies

**Table C1. A List of Risks and Remedies**

<b>Risks</b>	<b>Remedies</b>
1. No clear intention	Given the complexities of implementing MM studies, MM researchers should plan to review and audit the study design during the study and remind themselves why they chose a mixed-methods research design. They need to be careful about the impact of cognitive overload by carefully balancing the goals of MM research design with the effort needed to conduct it.
2. Inadequate pre-study preparations	Check if the various data-collection methods complement each other's weakness. Obtain a sense of the data that one will collect and think of the potential ways one can combine data together.
3. Unclear plans for data collection	Develop plans for data collection (i.e., the form, the timing, and the rationale of including the specific type of data). One should also be aware and identify the limitations of each kind of data-collection technique.
4. Inefficiency in data organization	Explore multiple ways of organizing the data to determine the best one for understanding and presenting it and, therefore, engendering the ability to draw focused insights.
5. Inappropriateness of data visualization	Paying attention to and being innovative in visualizing the qualitative data where standard data-visualization methods are lacking so as to complement the well-established approaches of analyzing quantitative data.
6. Lack of data exploration	Derive multiple data-exploration purposes based on research questions and then employ data-exploration techniques accordingly to maximize the benefits of data exploration.
7. Focusing on agreement	Be open to the idea of divergent findings and be willing to revisit and/or modify initial theoretical assumptions, hypotheses, or conclusions and to potentially draw on further theoretical concepts that researchers have not yet applied to the domain in question.
8. Barriers in pattern/theme recognition	Be flexible in choosing pattern distraction strategies; that is, identify the patterns/themes from qualitative study analysis and valid them in quantitative study analysis, identify the patterns/themes from quantitative study analysis and valid them in qualitative study analysis, or identify the patterns/themes from both types of study analysis.
9. Ineffective way of presenting findings	Be flexible and innovative in accommodating the mixes in mixed methods when presenting findings.

## About the Authors

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