Categorization of Technologies: Insights from the Technology Acceptance Literature

Michael E. Ellis
University of Central Arkansas

Miguel I. Aguirre-Urreta
Texas Tech University

Kiljae (Kay) Lee
Embry-Riddle Aeronautical University

Wenying Nan Sun
Washburn University

Yucong Liu
Mansfield University

Juan Mao
University of Texas at San Antonio

George M. Marakas
Florida International University

This study develops a technology category framework to enable the investigation of a possible moderating effect of technology type on adoption behavior by extracting and analyzing the technology descriptions from 950 papers covering over 20 years of technology acceptance research. We utilize both human judgment and statistical techniques by using the results of the manual sorting of technology descriptions by six individuals as input for a multidimensional scaling and cluster analysis to group them into hierarchical cluster structures. One of several potential cluster solutions is selected for further discussion along with its limitations and the future work it suggests.

INTRODUCTION

The individual decision to adopt and use technology is one of the constructs at the core of the Information Systems field. Understanding the various factors that influence such decisions, their relative importance, and whether they vary by the type of technology, by the different organizational or personal contexts in which the decision is made, and by individual differences related to the adopter would be of great value to the development and implementation of change management and training programs.

The current paradigm by which such an adoption decision is investigated is the one begun with the publication of the Technology Acceptance Model (TAM) by Davis and his colleagues (F. Davis, Bagozzi, & Warshaw, 1989). TAM and the variations which evolved from it, such as TAM2 (Venkatesh & Davis, 2000) and the Unified Theory of Acceptance and Usage of Technology (UTAUT) (Venkatesh, Morris, Davis, & Davis, 2003) are based upon the use of the theories of reasoned action and planned behavior (Ajzen, 1991; Ajzen & Fishbein, 1980) for the examination of individual adoption behavior pertaining to information technologies. The basic tenet of TAM is that three sets of beliefs – comprised of the utilitarian value of the technology, its ease of use, and the social adoption context – are the primary determinants of the intention to adopt the technology, which, in turn, influences actual behavior. Various moderators of these relationships have been investigated, such as the effects of the potential adopter's gender, age, prior experience with the technology, and the degree to which adoption is voluntary.

It appears to be the consensus in the field that the most researched stream in information systems (IS) literature is that based upon the TAM. Thousands of studies have employed TAM in whole or in part as the theoretical basis for their research models, with the two articles from 1989 (Fred Davis, 1989; F. Davis et al., 1989) having been cited over forty thousand times through the end of 2015 according to Google Scholar search results. The vastness of this literature makes any attempt to comprehensively review it and quantify its findings a daunting task. While there have been some attempts to meta-analyze this stream of research (e.g., King & He, 2006; Legris, Ingham, & Collerette, 2003; Ma & Liu, 2004; Wu & Lederer, 2009), those studies have focused on a specific aspect of the TAM (such as voluntariness of use) or included only a very limited sample of studies out of the multitude available. These attempts, while interesting in their own right, have been far from comprehensive. A comprehensive meta-analysis of the entire body of technology acceptance research would provide a clearer picture of the overall story to be told by this massive research stream.

One aspect of TAM research that becomes apparent when reviewing over 25 years' worth of work is the wide array of different technologies employed in TAM research. Between the variation in technologies of interest to researchers across different disciplines and the technological progress since the birth of TAM, it would appear that few forms of technology are overlooked. This proliferation of technology across the literature makes it difficult at best to investigate any possible moderating effects in adoption behavior attributable to the technology involved. When combined with the centrality of the technological artifact to the IS discipline, this is problematic. One solution is to investigate the effects of classifications or types of technology as opposed to individual technological instances.

At this time, however, there is no generally accepted way of classifying technologies into distinct groups. There are some classifications that appear within general areas of technologies, such as group support systems (Zigurs & Buckland, 1998), or that refer to specific dimensions of technologies (Fiedler, Grover, & Teng, 1996). None of these niche category systems is inclusive enough to encompass the entirety of technology acceptance studies, let alone the universe of all technology research. In this study we use the manual sorting of technologies used in TAM-related research into naturally emerging categories combined with multidimensional scaling analysis to create such a classification system. Multidimensional scaling (MDS) is a statistical technique that helps aggregate the understandings of individual sorters, in the form of similarity judgments, into a two-dimensional map of coordinates showing the distance between different technologies. These coordinates can then be used in a cluster analysis to determine the number of technology groupings that best describe the data. An exemplar of the use of MDS can be found in Jackson and Trochim (2002).

The main contribution of this paper lies in the development of a framework of information technologies that can be used to categorize existing research and derive and test hypotheses in new research investigating possible moderating effects based on differing technology types. While the results of this exercise are limited by the range of technologies investigated in technology acceptance research, the vastness of this literature provides enough input to the process that the results can be of value beyond TAM. The results will also reflect the ways in which the researchers involved in the sorting process organize and structure existing technologies; the use of multiple sorters, however, alleviates concerns about the possibility of the resulting grouping be overly idiosyncratic.

This paper builds upon the preliminary version of this exercise reported in Aguirre-Urretta, et.al. (2010). That first study was based upon a sample of 200 papers from TAM research through 2008 and the use of three sorters, while this study includes all qualified TAM papers through 2010 and six sorters. As will be shown below, this larger dataset and higher number of sorters results in a more complete and robust set of technology categories.

The rest of the paper is organized as follows. First, we describe the methodology used to locate, qualify, and code the studies from which the technology descriptions which form the basis for this study are extracted. Next, we discuss the manual sorting procedures employed and the statistical analyses conducted to arrive at the resulting technology clusters. We then present and discuss our results, limitations, and directions for future research.

STUDY QUALIFICATION

The first necessary step in the process of determining which research to use as source material is to set a baseline. We selected the ten prominent TAM papers shown in Table 1, beginning with Davis et al. (1989) and continuing through the UTAUT model proposed by Venkatesh, Morris, Davis, and Davis (2003) as the foundational papers for the TAM research stream. Papers published from the introduction of TAM in 1989 through 2010 were collected by searching the ISI Web of Science and Google Scholar for citations of these ten papers and briefly inspecting them for the inclusion of empirical results. Journals not indexed by the Web of Science, such as *The Journal of the Association for Information Systems* (JAIS), *The DATA BASE for Advances in Information Systems*, and *Communications of the Association for Information Systems* (CAIS), were manually scanned across the same time span. Manual searches of MISQ and ISR were also conducted to minimize the possibility that a relevant paper was overlooked. The papers from all of these sources were combined to create a preliminary list of 3,815 candidate papers thought to contain empirical, TAM-related results.

TABLE 1
PROMINENT TAM PAPERS USED AS A BASELINE

Authors	Year	Journal
Davis, F., Bagozzi, R. and Warshaw, P.	1989	Management Science
Davis, F.	1989	MIS Quarterly
Taylor, S. and Todd, P.	1995	MIS Quarterly
Taylor, S. and Todd, P.	1995	Information Systems Research
Szajna, B.	1996	MIS Quarterly
Venkatesh, V.	1999	MIS Quarterly
Venkatesh, V.	2000	Information Systems Research
Venkatesh, V. and Morris, M.	2000	MIS Quarterly
Venkatesh, V. and Davis, F.	2000	Management Science
Venkatesh, V., Morris, M., Davis, G. and Davis, F.	2003	MIS Quarterly

The TAM research stream primarily investigates nine variables: perceived usefulness, perceived ease of use, attitude towards technology, subjective norms/social influence, perceived behavioral control, behavioral intention, adoption behavior, performance expectancy, and effort expectancy. The first pool of candidate papers were qualified for inclusion in this study if they appeared to contain empirical results for at least two of these nine TAM variables, resulting in a set of 920 identified papers. Upon closer review, papers with results for only one TAM variable, along with theoretical, review, and other papers without empirical results were excluded. Papers appearing in conference proceedings were also excluded to avoid the possibility of using results from both a preliminary conference version of a study and a finalized journal version. Through this process the original pool of 920 candidate TAM papers was reduced to 777 qualified empirical papers.

These papers were randomly distributed among the researchers for coding. The coding process involved the extraction of relevant data from each of the papers for use in a meta-analysis, which includes the description of the technology used in the study underlying the paper. The closer examination afforded by the coding process resulted in two adjustments to the dataset. First, a few papers were found to be lacking all aspects of the requisite empirical data needed for our purposes and were subsequently eliminated from the list of qualified studies. Second, some papers reported the results from more than one study. Each study in a paper was subsequently treated independently, which expanded the list of qualified studies. After these two adjustments, the final source data used in this analysis includes 950 studies containing empirical data on at least two variables from TAM research.

METHODS AND DATA ANALYSIS

The process employed in the codification, sorting, and analysis of the source data parallels that of Jackson and Trochim (2002). The description of the technology employed in each of the qualified studies was extracted to create a list of 950 technology descriptions, which constitutes the data used in this research. The descriptions of these technologies were individually printed on index cards, which were then sorted into distinct piles by six of the authors. The sorting procedure was governed by the following set of guidelines.

First, technologies must be grouped by the sorter with those deemed similar. While these sorting exercises can be performed by focusing on a specific dimension of the objects under examination, given the aim of creating a classification of technologies that naturally emerged from our understanding of the TAM research stream, we decided to give sorters the flexibility to create their own classifications. Second, while there is no predetermined limit to the number of groups sorters can create, no miscellaneous pile would be allowed – all technologies must be classified into a group according to their degree of similarity to others, even if that entails creating groups with a single exemplar in them. This has the effect of increasing the validity of the resulting classification by excluding the possibility of an 'unclassified' group from emerging in the final cluster analysis. Finally, sorters were asked to provide a label for each group that best described their understanding of the technologies included in it.

Thus, each sorter was provided with 950 index cards to be sorted into the number of groups the individual sorter deemed necessary to account for all technologies included in the qualified papers. The results of the sorting exercise were used to create a *dissimilarity* matrix for each sorter. A *dissimilarity* matrix is a binary square matrix where the technologies are included in both rows and columns (in this case resulting in a 950x950 matrix), such that a zero value represents a pair of technologies that was grouped together, and a value of one represents a pair of technologies that was *not* grouped together by the sorter (diagonals, representing the intersection of each technology with itself, are coded with zeros). The six individual sorter matrices were then aggregated to create a composite dissimilarity matrix to be used as input to the multidimensional analysis.

Aggregating the individual matrices results in a 950x950 combined matrix with values ranging from zero (for a pair of technologies that was grouped together by all sorters) to six (for a pair of technologies that was never grouped together by any of the six sorters). It is important to remember that higher values denote a greater dissimilarity between pairs of technologies. Figure 1 shows a partial composite matrix as an example. In this matrix, technologies 1 and 2, for example, have never been paired together by any of the six sorters (thus showing the highest possible dissimilarity for six sorters, a 6); technologies 2 and 4, on the other hand, have been paired together by four of the sorters, thus showing a 2 in that cell (i.e., two sorters did not pair them together); and technologies 3 and 1 were paired together by all sorters, resulting in a value of zero for that cell. The intersection of a technology with itself is coded with a 0 by definition.

FIGURE 1
EXAMPLE COMPOSITE DISSIMILARITY MATRIX

TECH	1	2	3	4	…
1	0	6	0	1	
2	6	0	3	2	
3	0	3	0	2	
4	1	2	2	0	
…					

The resulting composite matrix becomes the input to a multidimensional scaling analysis, performed by the corresponding module of SAS 9.2. A set of coordinate estimates is created that represents the position of each technology on a two-dimensional map, with technologies that were grouped together the least having the greatest distance between them. More than two dimensions can be obtained from the MDS analysis if so desired, but the coordinates become more difficult to interpret visually. Also, two dimensions are recommended when the results of the MDS are intended as the foundation for a cluster analysis (Jackson and Trochim, 2002; Kruskal and Wish, 1978).

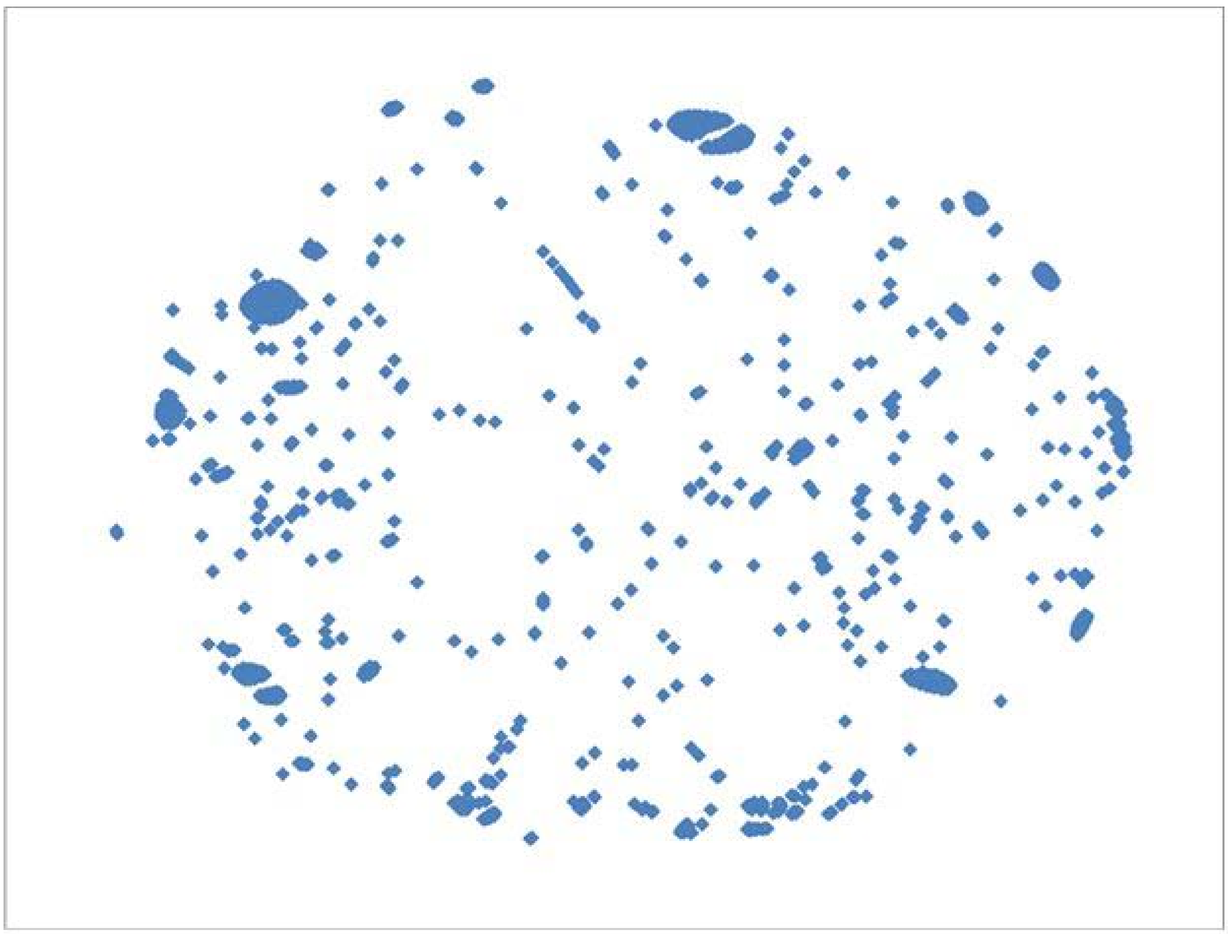
The final step in the process entailed using the coordinate estimates as the input for a cluster analysis, which was in turn used to determine the appropriate number of clusters that best represents the underlying structure of the dataset. There are a number of different clustering techniques available, and multiple variants within each of them. We followed the recommendation of Jackson and Trochim (2002) and used agglomerative hierarchical clustering using Ward's algorithm in this study, also using SAS 9.2. Hierarchical clustering techniques proceed by sequentially merging or dividing groups of items. *Agglomerative* methods, such as the one employed here, start with as many clusters as there are individual objects, and then proceed to group objects according to their similarity. The most similar objects are grouped first, then groups are merged according to similarities until there is a single cluster that includes all individual technologies. *Divisive* methods, on the other hand, work in the opposite direction by starting with a single cluster containing all objects and proceeding to divide it until there are as many clusters as there are objects (Johnson & Wichern, 2002). Ward's clustering algorithm proceeds by minimizing the loss of information when joining two groups of objects, where loss of information is interpreted as an increase in the error sum of squares criterion (the error sum of squares is the sum of squared deviations of every item from the cluster centroid).

It should be noted that while the hierarchical cluster structure is wholly determined by the statistical procedure, the choice of how many clusters to retain is based on the judgment of the authors. This is because there is no forthright statistical criterion that can be used to choose one cluster solution over another. The perfect statistical solution providing the best fit is to have as many clusters as there are technologies, a solution that is clearly at odds with the purpose of the exercise. The other extreme, clustering all technologies into a single group, will display the worst possible fit. Researchers must therefore choose a solution located between these two extremes such that it best represents, in their judgment, the structure of the data. While it is based firmly in statistical methods, the "best" number of clusters is ultimately a subjective decision based upon the goals of the study, and the level of specificity desired in the grouping of the data (Jackson & Trochim, 2002). The researchers examined all of the candidate cluster groupings produced by the analysis, including all of the points at which new clusters were introduced, to determine the number of technology clusters in the solution.

RESULTS

The 950x950 composite binary square matrix used as input is not included here due to space limitations but is available from the authors upon request. The results of the multidimensional scaling procedure are shown in the form of a two-dimensional map in Figure 2. Each point in the map corresponds to one of the 950 technologies included in the sorting exercise and is mapped as a result of the multidimensional scaling procedure. The position of a technology on the map has no bearing on the outcome of the process; it is the distance between technologies that matters. Intertechnology distances are based upon the degree of similarity the sorters felt existed between the technologies, with more similar technologies appearing closer to each other on the map.

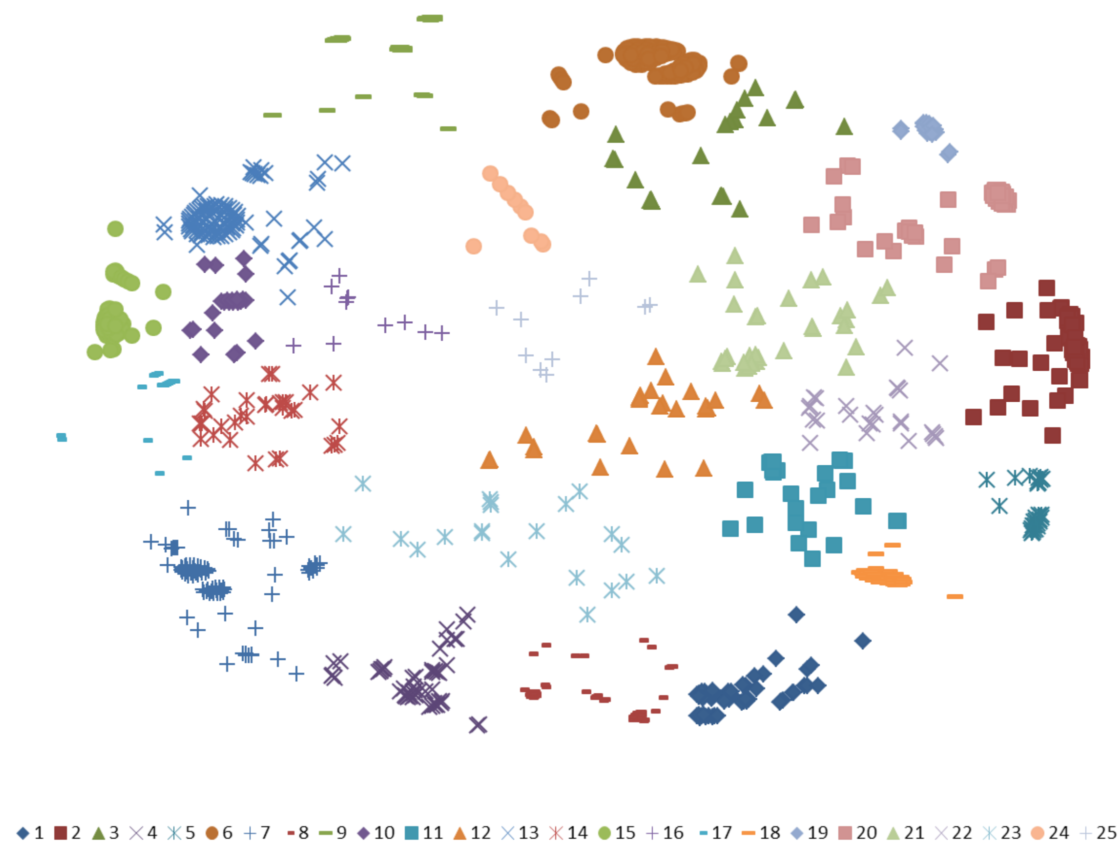
FIGURE 2
MULTIDIMENSIONAL SCALING MAP OF TECHNOLOGIES



An examination of Figure 2 clearly reveals a number of areas where technologies are tightly grouped, to the point of overlapping so extensively the individual symbols are not visible. The results shown in the Figure 2 map were then subjected to a hierarchical clustering procedure using Ward's algorithm as described above. This procedure was conducted multiple times in an effort to determine the "best fit" for the number of final clusters. As previously mentioned, the final determination of the number of appropriate technology clusters representing the "best fit" to the data is a judgment call on the part of the researchers, based upon the statistical information provided by the analysis and the experience of the researchers. After multiple tests the number of clusters decided upon with this dataset was 25.

Figure 3 shows the final 25 cluster groupings that emerged from the analysis. Technology clusters are differentiated by using unique combinations of symbols and colors for each cluster. To simplify any discussion of the resulting technology clusters, the technologies appearing in each of the clusters were reviewed and a label was assigned to each one. Table 2 (found in the Appendix) describes the final list of 25 clusters, together with the number of technologies contained in each cluster, the label assigned to each cluster, and a brief description of the technologies found within each cluster.

FIGURE 3
CLUSTERED MULTIDIMENSIONAL SCALING MAP OF TECHNOLOGIES



DISCUSSION, LIMITATIONS, AND FUTURE RESEARCH

This research combines human judgment and statistical rigor to develop a framework of technology categories based upon the extensive body of work emanating from the Technology Acceptance Model (TAM).The judgment of the researchers was first used to develop individual technology groupings based upon their own perceptions and without prior restraint. Multidimensional scaling and cluster analysis were then utilized to aggregate the selections of the individual sorters to form statistically constructed hierarchical clusters. Judgment was again applied to select the solution that seemed the most appropriate from the candidate solutions produced by the aggregated cluster analysis.

This paper represents an expansion and extension of Aguirre-Urreta, et.al. (2010), which reported a cluster solution of 10 categories based upon a sample of 200 papers and the use of three sorters. The current study addresses the limitations of the earlier study's sample size and number of sorters by greatly increasing both quantities, to 950 papers and 6 sorters. The effects of these changes can be seen in the increased complexity of the developed solution as previously undiscovered groupings emerged from the larger dataset. While this complexity does not automatically mean the current solution is more valid than the previous one, the increases in these factors suggest the current cluster structure is more representative of the universe of technologies than the previous one. The different versions of technology acceptance investigated by the research efforts underlying this study have been successful in widely varying contexts since the introduction of the original TAM (F. Davis et al., 1989). We believe the considerable expansion of the number of studies used in the current research more accurately reflects that variety and, by extension, technologies in general.

The intended goal of this exercise is twofold. First, our meta-analysis research has raised the issue of categorizing the technologies found in TAM studies to allow for a meaningful discussion of the possible differences (or similarities) between them. Treating each of these 950 technology instances as independent is impractical and limits the generalizability of research results. For example, discussing behaviors surrounding the adoption of Microsoft Excel, Adobe Acrobat, and all other business software individually creates a large number of very specific results. If we can group them as a technology type, (perhaps called "Business Software") the results can be more easily generalized to not only discuss the behaviors but to use them proactively in new adoption situations involving similar software.

The second goal is to provide a foundation for a larger underlying general taxonomy of technologies. Such a taxonomy could be of value to researchers when attempting to identify scenarios in which effects are moderated or otherwise different than expected. This type of taxonomy could also highlight parts of the IS literature that have been either under or over researched. By providing a way to easily categorize numbers of studies, categories with extremely high or low levels of research will be more apparent.

Like any other research endeavors, this study has limitations. First, our analysis was based on a sample of technologies taken only from the technology acceptance literature. As we previously argued, we believe the vastness of TAM literature makes it representative of the entire universe of technologies being used. It is possible, however, there is an important technology studied in the IS literature that falls outside the TAM canon that has not been included here. Second, only six people were involved in the sorting process. More sorters would improve the ability of the cluster analysis to discriminate among technology groups by providing more data points as input to the algorithm. While we have not yet found any firm guidelines concerning an ideal number of sorters and we do employ more sorters than the previous study, we believe using more sorters with our 950 point dataset would be beneficial. Finally, an inspection of the technology descriptions found in each of the resulting clusters reveals a small amount of "noise" in the dataset. There are instances of technology descriptions with the exact same wording coming to rest in different clusters. While there are only a few, cleaning up these issues would make the results more reliable.

Ongoing and future research of the authors will address the above limitations. Since this is part of a larger research effort, we will recruit more sorters where appropriate to improve the cluster analysis dataset. We have also begun the investigation into the aforementioned noise in the sorting dataset. Another area we would like to investigate is the use of alternative sorting methods and analytical techniques. In this study we followed the approach outlined by Jackson and Trochim (2002) for use in concept-analysis research. However, other approaches and techniques are available. We intend to compare and contrast different sorting mechanisms, statistical clustering, and visualization techniques to identify the tools most suitable for this area of study.

If it is deemed by the IS research community to be a worthwhile goal, developing a general technology taxonomy will take considerable future effort. This effort will require input from multiple stakeholders during its development. We hope this early effort can provide a starting point.

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APPENDIX

TABLE 2
LABELS AND EXAMPLE TECHNOLOGIES FOR EACH CLUSTER

Cluster #	# of Items	Label	Examples
1	52	Communication	Instant messaging, computer-mediated communication, email, voice mail
2	55	Healthcare	Computerized physician order entry, electronic medical records, telemedicine, clinical DSS
3	22	Academic Support	Technology acceptance by teachers, digital libraries, digital repositories, student information systems
4	50	Mobile	Mobile Internet, mobile services, PDAs, handheld internet devices, mobile wireless technology
5	30	DSS, Expert & ERP	DSS, expert systems, ERP, negotiation systems, intelligent systems
6	98	Education & Training	WebCT, Blackboard, Moodle, computer-based tutorials, web-based training, e-learning, online learning tools
7	84	General Internet & Web	Internet, websites, intranet, Internet use, web use, web technologies, search engines
8	41	Social Networking & Virtual Communities	Social websites, Facebook usage, virtual communities, social network services, Web 2.0 technologies, blogs
9	29	Security & Government	e-Government services, protective technology, spyware, smart cards, e-government initiatives
10	24	Online Auctions & Trading	Online auctions, online bidding, online trading, electronic stock brokers
11	27	End-user Computing & Adoption of New Technologies in the Workplace	End-user computing, organizational systems, new technology in companies, newly implemented systems
12	27	Business Operations	Hotel information systems, sales information systems, broker workstations, business process applications
13	98	e-Commerce and Online Shopping	e-Commerce technologies, e-commerce websites, online shopping, B2C websites, online book purchasing
14	32	Self-service Systems	Travel websites, ticketing services, airline websites, technology-based self-service systems, online hotel reservation systems
15	52	Banking & Financial Services	Internet banking, online banking, e-banking services, mobile banking, ATM use
16	11	Voice-enabled Web Applications	Voice-enabled web systems, voice-enabled web applications
17	16	Mobile Banking and Payment	Mobile banking, mobile payment, mobile payment services, mobile wallet
18	39	General Computer Usage	PC, computers, computer usage, microcomputers, using computers, general computer use

19	21	Productivity Software	MS Office, Word, WordPerfect, productivity suites, text editor, charting software
20	42	Development Tools & Methodologies	Rapid application development, new development methodologies, maintenance software tools, process modeling grammars
21	33	Data Management	Document management systems, information retrieval technologies
22	26	Enterprise Software	Supply chain management systems, customer relationship management systems
23	21	Internet Services	IP-based technologies,
24	10	Entertainment	Internet television and gaming.
25	10	Business Support Services	Procurement and tendering systems, negotiation support, sales support.