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HOW MANY TECHNOLOGY TYPES ARE THERE? PRELIMINARY RESULTS FROM THE TECHNOLOGY ACCEPTANCE LITERATURE

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ABSTRACT

To investigate a generalizable moderating effect of the type of technology tested upon its acceptance, a classification of technologies is needed. This study aims to develop a preliminary framework to describe information technologies based upon 200 randomly selected technology descriptions taken from a comprehensive TAM meta-analysis effort currently in progress. We report on the use of a classification method involving both human judgment and statistical techniques. A manual sorting process is followed by multidimensional scaling (MDS) and cluster analysis to aggregate the individual interpretations of the sorters into hierarchical cluster structures. The results of this method reveal several potential technology grouping solutions, one of which was selected for further discussion. Limitations and future research are also discussed.

Keywords

Technology acceptance, card sorting, multidimensional scaling, framework, hierarchical clustering

INTRODUCTION

The individual decision to adopt and use technology is of paramount importance to 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 a decision is investigated is the one that started with the publication of the Technology Acceptance Model (TAM) by Davis (1989). TAM and its variations, such as TAM2 (Venkatesh et al. 2000a) or the Unified Theory of Acceptance and Usage of Technology (Venkatesh et al. 2003), are based on adaptations of the Theories of Reasoned Action and Planned Behavior (Ajzen 1991; Ajzen et al. 1980) to the examination of one particular behavior, individual adoption of information technologies. The basic tenet of the theory is that three sets of beliefs, including the utilitarian value of the technology, its ease of use, and the social adoption context, are the primary determinants of the intention to adopt such a technology. Intention to adopt, 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, to name a few.

It appears to be the consensus in the field that this is the most researched stream in our literature. Literally hundreds of studies have employed TAM or some variation of it as the theoretical basis for their research models, and the original article by Davis (1989) has been cited almost 2,000 times according to *ISI Web of Knowledge*, and over 6,900 times according to *Google Scholar*. 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 (King et al. 2006; Legris et al. 2003; Ma et al. 2004; Wu et al. 2009), those studies have focused on a specific aspect, such as voluntariness of use, or included only a very limited sample of studies out of the hundreds available. Conducting a comprehensive meta-analysis of technology acceptance research that quantifies the magnitude of the relationships in the model, as well as examines whether there are moderating effects due to the technologies, characteristics of the subject population, or the organizational context tested will provide a clearer picture of the overall story told by this research stream. The magnitude of the findings, the adequacy of using college students as surrogates for organizational knowledge workers, the areas where research saturation has been reached, the areas where more research is needed, and novel findings worthy of further consideration will become more apparent in the light of a comprehensive examination of the entire body of work. We are in the process of conducting such a meta-analysis, answering the call for such research issued by Straub and Burton-Jones (2007).

In order to uncover whether there is a moderating effect of technology on the relationships, such that their magnitude and/or significance vary depending on the focal technology, a classification of technologies is needed. While the technology artifact is central to our discipline, there is no generally accepted way of classifying technologies into distinct groups. There are some classifications within specific groups of technologies, such as group support systems (Zigurs et al. 1998), or referring to specific dimensions of technologies (Fiedler et al. 1996), but none is rich and diverse enough to encompass the universe of technology acceptance studies. In this study we combine the manual sorting of technologies into naturally emerging categories 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 clusters (i.e., groups of technologies) that best describe the data. The process utilized in this research is described in more detail later, and an exemplar of this application can be found in Jackson and Trochim (2002).

The main contribution of this paper lies in the development of a preliminary framework of information technologies that can be used to categorize existing research and derive and test hypotheses about moderating effects based on different 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 into the process that the results can be of value beyond this particular stream of research. 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.

The rest of the paper is organized as follows. First, we describe the methodology used to locate, qualify, and code the different studies from which the technology descriptions are extracted. As noted before, our review of the technology acceptance literature is comprehensive. Next, we discuss the card sorting procedures employed and the statistical analyses conducted to arrive at clusters of similar technologies. We then present and discuss our results, limitations, and directions for future research.

STUDY QUALIFICATION

The ISI Web of Science and Google Scholar were searched for citations of ten prominent TAM papers shown in Table 1, beginning with Davis (1989) and continuing through the unified acceptance model proposed by Venkatesh, Morris, Davis, and Davis (2003). Papers citing these foundational papers, from the introduction of TAM through 2008, were compiled. 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 because they are not indexed by the Web of Science. 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 2,641 candidate papers.

Table 1. Source Articles for Literature Search		
Authors	Year	Journal
Davis, F.	1989	<i>MIS Quarterly</i>
Davis, F., Bagozzi, R. and Warshaw, P.	1989	<i>Management Science</i>
Taylor, S. and Todd, P.	1995	<i>MIS Quarterly</i>
Taylor, S. and Todd, P.	1995	<i>Information Systems Research</i>
Szajna, B.	1996	<i>MIS Quarterly</i>
Venkatesh, V.	1999	<i>MIS Quarterly</i>
Venkatesh, V.	2000	<i>Information Systems Research</i>
Venkatesh, V. and Morris, M.	2000	<i>MIS Quarterly</i>
Venkatesh, V. and Davis, F.	2000	<i>Management Science</i>
Venkatesh, V., Morris, M., Davis, G. and Davis, F.	2003	<i>MIS Quarterly</i>

The criterion for the inclusion of a study in the meta-analysis was the presence of empirical results for at least two of the variables found in this stream of research: 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 candidate papers were individually reviewed and evaluated against the inclusion criterion. Theoretical and review papers were eliminated as well as those that did not include empirical results involving at least two of the variables. Conference proceedings were also eliminated to avoid the potential double-counting of a set of results, as both a conference proceeding and a subsequent journal paper. As a result of these eliminations, the list of candidate papers was reduced to 663 papers.

The remaining candidate papers were then randomly apportioned among the five coders and reviewed in greater detail as their results were extracted using the coding instrument created for this research. In the light of the closer inspection afforded during the coding process it was determined that some of the candidate papers did not in fact satisfy the inclusion criterion and were therefore eliminated. Other papers were found to report the results of multiple studies in a single journal article, providing separate results for different groups, different points in time, or other differences allowing these sets of data to be treated as unique. These studies were separated into individual coding pages, resulting in an increase in the number of studies included. After these adjustments, the final number of studies coded for the meta-analysis from which our sample is taken is 654.

METHODS AND DATA ANALYSIS

The process employed in the codification, sorting, and analysis of the resulting data parallels that of Jackson and Trochim (2002). Out of the final sample of studies that were qualified for inclusion in the meta-analysis, a random sample of two hundred was selected and further examined to extract a description of the technology employed in each study. The resulting list of 200 technology descriptions constitutes the data used in this research. The descriptions of these technologies were printed on individual index cards which were sorted into distinct piles by three of the authors. The sorting procedure was governed by the following set of guidelines.

First, technologies must be grouped with others deemed similar. While these sorting exercises can be performed by focusing on a specific dimension of the objects under examination at a time, given the aim of creating a classification of technologies that emerged naturally from our understanding of the research field, we decided to give sorters the flexibility to create their own classifications. Second, while there is no limit to the number of groups that sorters can create, there can be no miscellaneous pile – 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 a stack of two hundred index cards to be sorted into any number of groups necessary to account for all technologies included in the sample. From the piles of cards that resulted from the sorting exercise, a *dissimilarity* matrix was created for each sorter, and then all three matrices were aggregated to create a composite matrix to be subjected to the multidimensional analysis. A *dissimilarity* matrix is a binary square matrix where the technologies are included in both rows and columns (in this case resulting in a 200x200 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). Aggregating the three matrices results in a 200x200 composite matrix with values ranging from zero (for a pair of technologies that was grouped together by all three sorters) to three (for a pair of technologies that was never grouped together for any of the three sorters) - higher values denote increasing dissimilarity for different pairs of technologies. Figure 1 shows a partial composite matrix for ease of interpretation. In this matrix, technologies 1 and 2, for example, have never been paired together by any of the three sorters (thus showing the highest possible dissimilarity for three sorters, a 3); technologies 2 and 4, on the other hand, have been paired together by two of the sorters, thus showing a 1 in that cell (e.g., one sorter did not pair them together). The intersection of a technology with itself is coded with a 0 by definition.

TECH	<u>1</u>	<u>2</u>	<u>3</u>	<u>4</u>	...
<u>1</u>	0	3	3	3	3
<u>2</u>	3	0	3	1	
<u>3</u>	3	3	0	3	
<u>4</u>	3	1	3	0	
...					

Figure 1. Sample Composite Dissimilarity Matrix

The composite matrix thus obtained 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, such that technologies depicted further away from each other were grouped together less often than those closer together (more than two dimensions can be obtained from the MDS analysis if so desired, but the coordinates become more difficult to interpret visually; in addition, when the results are intended as the foundation of a cluster analysis, two dimensions are recommended; Jackson and Trochim, 2002; Kruskal and Wish, 1978).

The final step in the process entailed using the coordinate estimates as input to a cluster analysis and then determining 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 one of them. Following the recommendation of Jackson and Trochim (2002) we 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 the latter according to their similarity. The most similar objects are first grouped, and then groups are merged according to similarities until there is a single cluster that includes all individual technologies (*divisive* methods, on the other hand, start with a single cluster containing all objects and proceed by dividing it until there are as many cluster as there are objects) (Johnson et al. 2002). Ward's clustering algorithm proceeds by minimizing the loss of information from joining two groups of objects, where loss of information is taken to be 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 researchers employing this methodology. This is because there is no forthright statistical criterion that can be used to choose one solution over another – indeed, the perfect solution is to have as many clusters as there are technologies; on the other hand, clustering all technologies into a single group will display the worst possible fit. Researchers must choose a solution between these two extremes such that it best represents, in their judgment, the structure of the data. The “best” number of clusters is a subjective decision based upon the goals of the study, and the level of specificity desired in the grouping of the data (Jackson et al. 2002).

RESULTS

The 200x200 composite binary square matrix used as input is not included here due to space limitations but is available from the first author upon request. The results of the multidimensional scaling procedure are shown in the form of a two-dimensional map in Figure 2 below. Each point in the map corresponds to one of the 200 technologies included in the sorting exercise (labels omitted for clarity of presentation). The distances between the different symbols in Figure 2 represent how similar the technologies are judged to be by the three sorters, which result from analyzing the composite matrix using multidimensional scaling. The absolute position of a technology in the map is of no importance. Rather, it is the distance between points that matters. Technologies that are judged more similar to each other appear closer than those judged less similar.

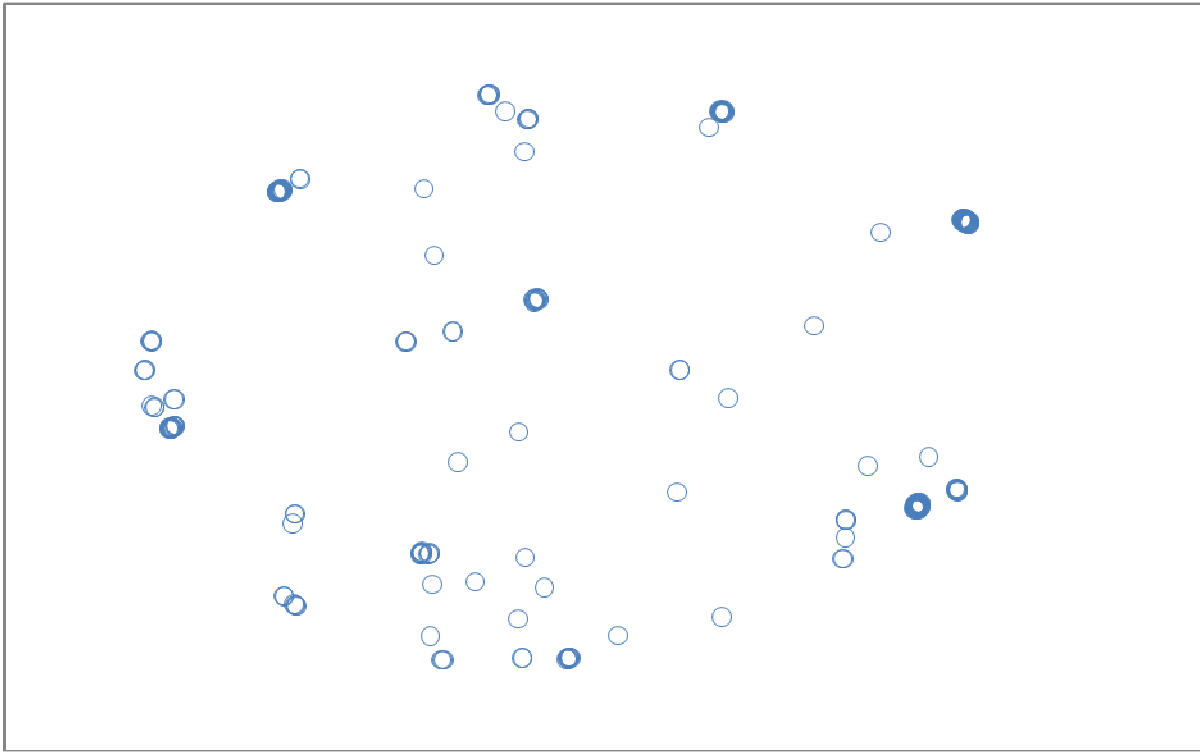


Figure 2. Multidimensional Scaling Map of Technologies

An examination of Figure 2 clearly reveals a number of areas with a higher concentration of technologies close together, and in many cases due to heavy overlap it can only be noted by the varying intensity of their display. These results were then subjected to a hierarchical clustering procedure using Ward's algorithm, as described above. Various cluster solutions in the same range as the original number of groups created by each of the three sorters were examined to find the best representation of the data, with the general criteria of including an increasing number of clusters until additional clusters did not appear visually different to the authors. A solution with 10 clusters was chosen, represented in Figure 3 with separate symbols for technologies belonging to each cluster.

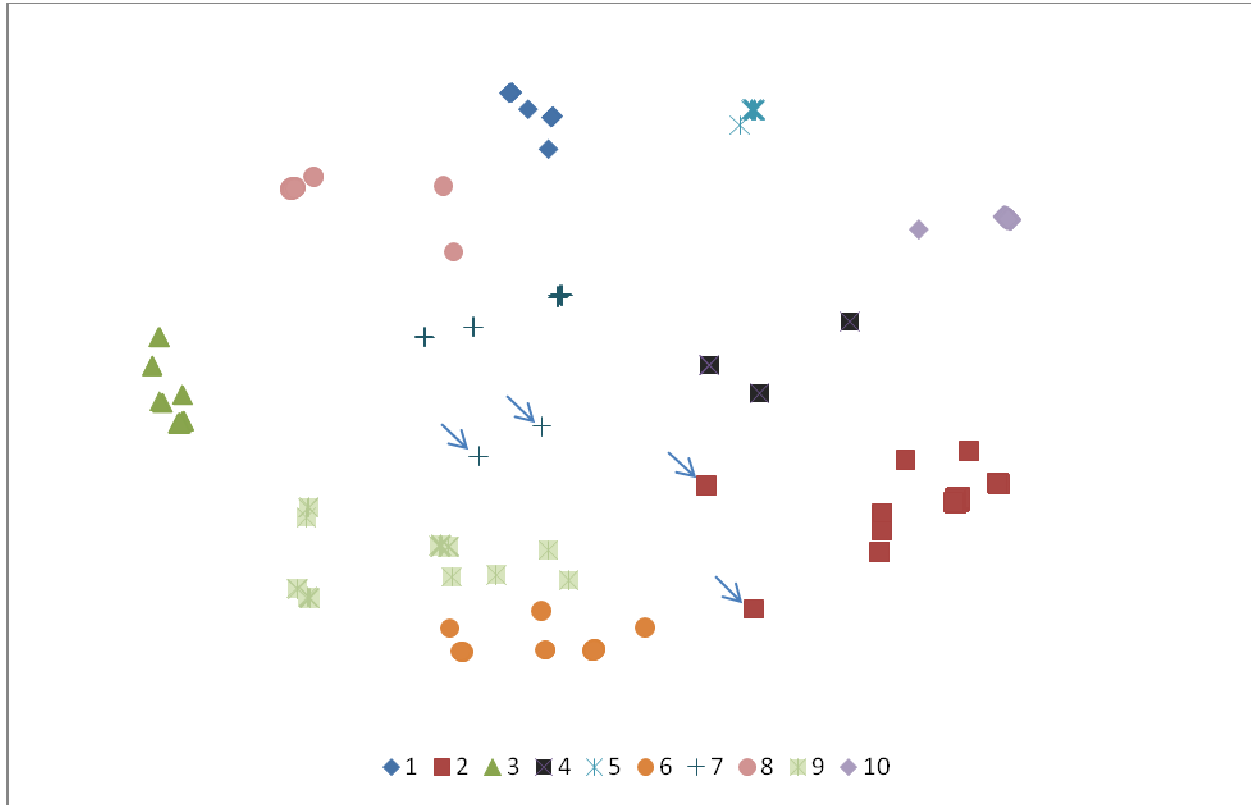


Figure 3. Clustered Multidimensional Scaling Map of Technologies

Figure 3 shows how the majority of the technologies in any cluster are close together in the spatial map, with only a few outliers that, while necessarily belonging to one cluster, seem to stand apart from the rest (indicated in Figure 3 with arrows). Given that these 4 technologies represent a small proportion (2%) of the sample, we retained this solution. Table 2 next provides a listing of these few technologies that did not directly fit into the otherwise close clusters.

Table 2. Outlier Technologies in the 10-Cluster Solution
Computerized reservation systems at travel agencies (from Lee, Lee and Kwon, 2005)
Graphic creation packages (from Davis, Bagozzi and Warshaw, 1992)
Virtual community (avatars, from Song and Kim, 2006)
Web-based front-end for informational and transactional systems (from Venkatesh, Maruping, and Brown, 2006)

The final step in this research involved the examination of the technologies included in each of the clusters in order to provide a meaningful label that best describes the contents of each group. The complete listing of the 200 technologies included in this exercise is not included here due to space limitations. Table 3 describes the list of clusters included in the final solution, together with the number of technologies contained in each, a label for each cluster, and a brief description of the cluster with selected examples.

Table 3. Cluster Labels and Descriptions		
Cluster Label	Number of Technologies	Description and Examples
Computers, operating systems, and basic software	11	Computers in general (e.g., studies dealing with the general adoption of computer technology without specific references to a particular technology), Windows operating system, basic office software (spreadsheets, word processing)
E-business and online applications	48	Includes technologies related to the provision of online services and commerce, but not basic web-based infrastructure. Examples include internet banking, online legal services, electronic shopping and purchasing, digital goods, electronic tax filing, etc.
Communication and collaboration	24	Instant messaging, email, voice mail, group support systems, groupware, commercial collaborative software, instant online communication tools
Commercial mobile services	4	Includes commercial applications based on a mobile platform, but not adoption of mobile platforms themselves. Examples: mobile ticketing services, mobile banking, mobile payment services
Healthcare technologies	13	Electronic medical record systems, health information websites, telemedicine technology, referrals DSS, medical information systems, etc.
Functional applications	15	Technologies related to specific functions or industries. Examples include accounting information systems, agricultural technologies, building management systems, hotel front office systems, etc.
Mobile infrastructure	17	Includes the adoption of mobile platforms in general as well as basic services generally associated with those. Examples: smart phones, cell phones, cell service, handheld devices, mobile data services, text messaging, etc.
Internet infrastructure	20	Technologies related to general Internet infrastructure, such as the Web, websites, search engines, online information, etc.
Development tools and enterprise systems	22	This cluster includes both tools geared towards the software development process (CASE, debuggers, secure application development, software development methodologies) and large-scale enterprise systems (ERPs, OLAP, centralized application servers)
Education and course delivery	26	Web-based learning technologies, online teaching and course delivery, course management systems (Blackboard, WebCT), mobile learning, etc.

Figure 4 graphically depicts the final representation of all technology clusters with their associated labels. The degree of homogeneity or heterogeneity included in our cluster solution is evident from Figure 4. Whereas some groups of technologies, such as the Healthcare cluster or the Communication and Collaboration cluster, have been grouped together by all three sorters in almost every case, other clusters display a larger degree of heterogeneity in the way the technologies included in them have been classified. These results are, to some extent, a function of the limitations of this research discussed in the next section. These preliminary results do provide, however, a validation of the applicability of the proposed methodology to this research issue, and at the same time display a high degree of face validity.

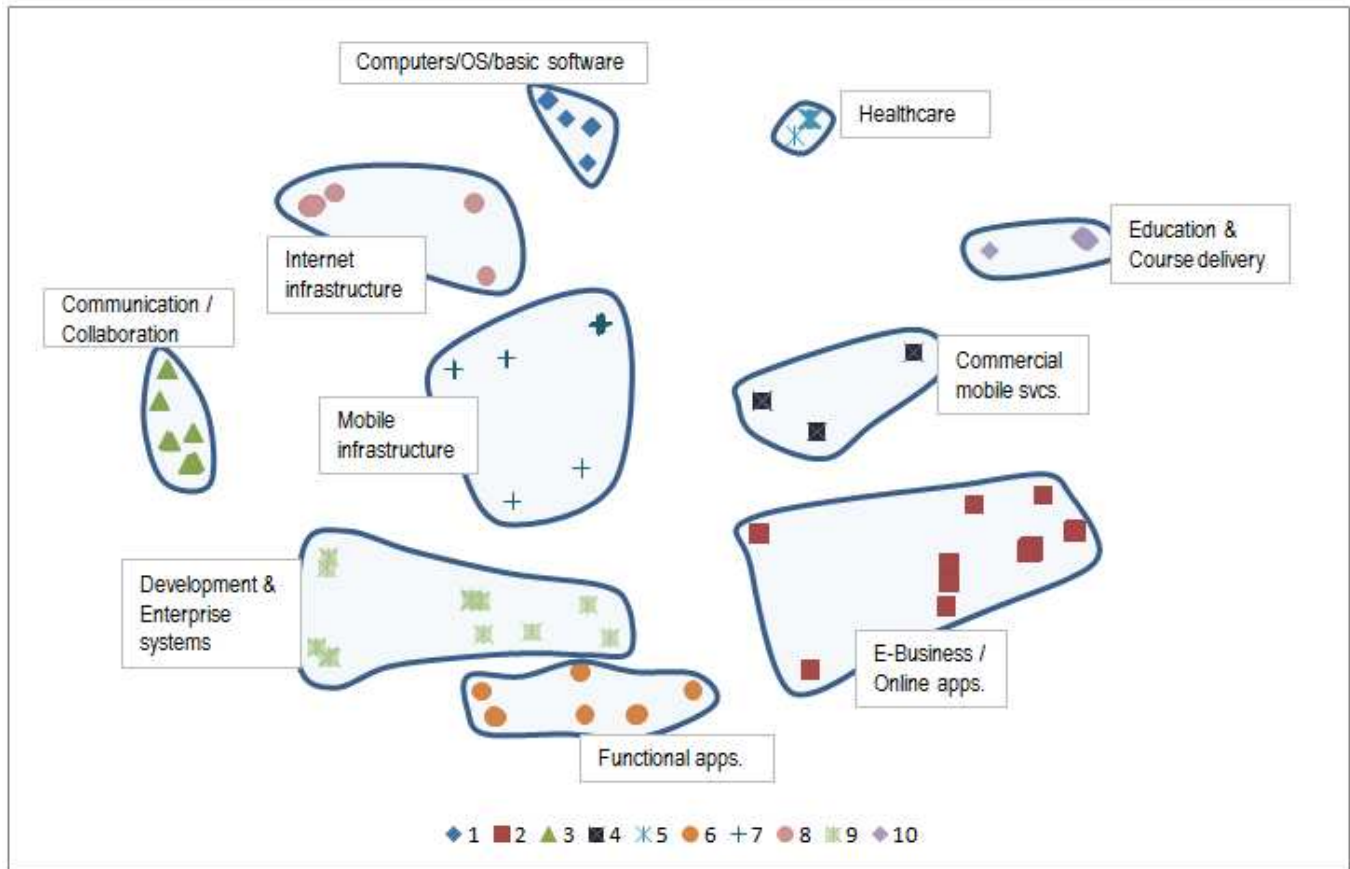


Figure 4. Final Cluster Solution with Labels

DISCUSSION, LIMITATIONS, AND FUTURE RESEARCH

This research identified an approach toward the classification of technologies investigated in the technology acceptance literature into a manageable number of categories that can be used to further analyze this extensive stream of research. The classification method introduced in this study combines human judgment and statistical analysis. The three researchers involved in the sorting process were free to develop their own classifications without any constraints on the number of groups they could create. Multidimensional scaling and cluster analysis were then utilized to aggregate the individual understandings of the three sorters to form hierarchical cluster structures statistically. Based on the potential groupings suggested by the statistical techniques, human judgment was involved again to select the solution that seemed the most appropriate.

Based on our judgment and understanding of this literature, we selected a particular cluster solution we believe best represents the underlying structure of the sample of technologies included in this study. While it may be argued these results are particular to the three sorters involved and the specific random sample of technologies included, they nonetheless display a high degree of face validity. Further work along the lines discussed above will help both expand and solidify this grouping of technologies into a more stable framework that can then be employed by researchers to further understand the causes of differential effects of certain relationships based on the particular type of technology under examination. Whereas a contributing factor to the success of the various technology acceptance models described in this research lies in the high level of generality in which they are proposed, some researchers have attempted in the past to augment these basic models with specific variables that reflect the particular application contexts in which the research was conducted. It is our hope that a framework of technologies such as the one described here can be of value to assist researchers in identifying the scenarios in which certain relationships exhibit stronger or weaker effects, as well as pointing out gaps in our literature that can be further investigated.

Like any other research endeavors, this study has limitations. First, our analysis was based on a limited sample of technologies from 200 studies in the technology acceptance literature. Even though this could be considered a representative sample of the total population, including technologies from the remaining qualified technology acceptance studies would

certainly make the analysis results more complete. The inclusion of our entire pool of qualified studies should also provide additional opportunities for other hitherto unknown groups of technologies to emerge, as is suggested by the outliers shown in Table 2. Second, only three people were involved in the sorting process. More sorters would improve the ability to discriminate among groups by providing greater discrepancies between technologies that are commonly sorted together and those that are not. While we are not aware of any specific guidelines as to the number of sorters that should participate in this type of research, most published applications of these techniques have employed more sorters than has been the case here.

Ongoing and future research of the authors will address the above limitations. We will include all the technologies from the remaining studies we identified and will involve more people in the sorting process in the final version of this research. 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 and statistical clustering and visualization techniques to identify the one most suitable for this area of study.

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