Factors Influencing User-level Success In Police Informationsharing: An Examination Of Florida's Finder System

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FACTORS INFLUENCING USER-LEVEL SUCCESS IN POLICE INFORMATION SHARING: AN EXAMINATION OF FLORIDA’S FINDER SYSTEM

by

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ABSTRACT

An important post-9/11 objective has been to connect law enforcement agencies so they can share information that is routinely collected by police. This low-level information, gathered from sources such as traffic tickets, calls for service, incident reports and field contacts, is not widely shared but might account for as much as 97% of the data held in police records systems. U.S. policy and law assume that access to this information advances crime control and counter-terrorism efforts. The scarcity of functioning systems has limited research opportunities to test this assumption or offer guidance to police leaders considering investments in information sharing. However, this study had access to FINDER, a Florida system that shares low-level data among 121 police agencies. The user-level value of FINDER was empirically examined using Goodhue’s (1995) Task-Technology Fit framework. Objective system data from 1,352 users, user-reported “successes,” and a survey of 402 active users helped define parameters of user-level success. Of the users surveyed, 68% reported arrests or case clearances, 71% reported improved performance, and 82% reported improved efficiency attributed to FINDER. Regression models identified system use, task-fit, and user characteristic measures that predicted changes in users’ individual performance. A key finding was that FINDER affirmed the importance of sharing low-level police data, and successful outcomes were related to its ease of use and access to user-specified datasets. Also, users employed a variety of information-seeking techniques that were related to their task assignments. Improved understanding of user-defined success and system use techniques can inform the design and functionality of information sharing systems. Further, this study contributes to addressing the critical requirement for developing information sharing system metrics.
ACKNOWLEDGMENTS

I express my heartfelt appreciation to my committee members, Dr. Mike Reynolds, Dr. Pam Griset, Dr. Larry Martin, and Dr. Bernie McCarthy, for their commitment of time and energy to this dissertation project. Mike Reynolds, as my major professor and the catalyst for FINDER’s creation, is responsible for convincing me to embark on this adventure and (more importantly) was critical in seeing me through the process. Pam Griset offered a valuable perspective as an expert on qualitative approaches to research and employed (repeatedly) her keen eye for proper writing. Larry Martin (both as committee member and course instructor) provided pragmatic critiques and offered a much-needed perspective from the public administration arena. Finally, Bernie McCarthy has been a longtime supporter of the applied research that this study is intended to report, and his support was instrumental to making both FINDER and this dissertation possible.

It is also important to acknowledge the support for and contributions to my work made by Captain Mike McKinley and Master Deputy/Detective Jim McClure, both of the Orange County (Florida) Sheriff’s Office. Captain McKinley and Detective McClure are why the FINDER project has been successful. Their insights to the application of technology for on-the-street law enforcement officers helped guide my study.

Finally, the greatest accolades should go to the hundreds of anonymous line-level officers, deputies, and analysts who, through surveys, phone calls, and emails, provided the data and information that was necessary to complete this study. They are the people who make police information sharing a reality and a success.
This work is dedicated to Elaine, Andy, and Michael. Thank you for your patience with and support of this late-in-life scholar.
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CHAPTER 1: INTRODUCTION

The terrorist attack of September 11, 2001 produced policy and law directed at preventing future attacks. Broad anti-terrorism policies such as the Homeland Security Strategy ("Strategy," Office of Homeland Security [OHS], 2003) and laws such as the Intelligence Reform and Terrorism Prevention Act of 2004 ("Act") have been implemented with a sense of urgency.

One of the imperatives found in both the Strategy and the Act is the development of information sharing systems intended to help identify terrorists before they strike. The Act, particularly, focuses on information sharing between intelligence and law enforcement entities, and affirms the perceived importance of law enforcement information sharing. Law enforcement information sharing (“police information sharing”), as represented in the Act and other post-9/11 literature, refers to the data that are collected by the nation’s police agencies, but are not shared between them. This represents the vast majority of police records.

While it may be commonly believed that police agencies share all their records through a mammoth database, most police records are not shared. This includes “low-level” data that are generated by routine police activities such as traffic stops, crime reports, administrative reports, calls for service, and miscellaneous contacts with people who are not arrested or who are charged with minor offenses (Carter, 2004; Reynolds, Griset & Eaglin, 2005). Indeed, it is the absence of sharing the information that arises from everyday police operations that has been identified as a factor contributing significantly to the 9/11 terrorists’ ability to execute their crimes (National Commission on Terrorist Attacks [9/11 Commission], 2004; National Governors’ Association [NGA], 2002).
The information sharing deficit was a concern long before terrorism shaped a new operational landscape for U.S. police leaders. The ability of criminals to offend undetected in many jurisdictions has perplexed police and researchers for many years. Assumptions about criminal mobility have been based largely on data gathered from those offenders that have been arrested. The questionable accuracy of self-reports by arrested offenders and the unidentified mobility patterns of those not arrested leaves room for considerable speculation about offenders’ actual behaviors relative to time and place (Burton et al, 2002).

Further, the concept of criminal mobility continues to change. While transportation systems and urban structure have been long-recognized as enabling offenders to travel across police jurisdictions (Brantingham & Brantingham, 1984; Capone & Nichols, 1976; Rengert, Piquero & Jones, 1999), the widespread availability of the Internet has created a new category of multi-jurisdictional offenders for whom “time and place” are meaningless (Hinduja, 2004). These changes in the offending environment coincide with a contemporary police focus on data-driven decision making. Data-driven strategies rely on analysis capabilities, and the analysis capacity of any police agency is dependent on the information available for that purpose (Faggiani & McLaughlin, 1999; Markle Foundation, 2003).

Thus, police information sharing is perceived as critical to both counter-terrorism and crime-fighting goals (Carter, 2004; U.S. Department of Justice [DOJ], 2004). Consequently, information sharing between police agencies has become a priority objective in the contemporary American policing environment (Bureau of Justice Assistance [BJA], 2005; Mitretek Systems, 2005; Reynolds et al, 2005) and has increased the visibility of a topic that has long been of interest to police leaders across the U.S. (Estey, 2005a). Since police agencies have not shared broad sets of information in the past, police leaders and researchers have been forced to rely on
theory and limited evidence to guide the police response to the mobile offender – a response that is seen as even more critical in the post-9/11 environment. (Burton et al, 2002; Brantingham & Brantingham, 1984; Capone & Nichols, 1976; Cohen & Felson, 1979; Markle Foundation, 2003; Rengert et al, 1989).

This study examines the users of FINDER, a Florida information system that shares low-level police data. The study seeks to make an important contribution to understanding the user-level benefits of police information sharing, and how those benefits can be maximized. This is accomplished in two steps. First, the nature of those benefits, and the factors that influence them, must be defined and measured. There are no established definitions or measures currently in place. Second, using the measures identified by this study, analyses will be conducted to determine which of the identified factors can be used to predict successful outcomes at the law enforcement user level.

The research described in the following pages moves beyond theory and anecdote. This study examines the real-life value of police information sharing at the information system’s user level. Further, this research will suggest what might be done to increase that value. In very practical terms, this study looks at individual law enforcement officers and how information sharing contributes to their on-the-job success. Clearly, the successful performance of America’s police – whether in preventing terrorist acts or capturing neighborhood thieves – is desirable to all but the offender.

Research Problem and Relevance to National Goals

The post-9/11 context is relevant to this study, for it is in the urgency of this context that police information sharing has become a priority for American police executives (Estey, 2005a).
However, this priority has emerged with little proof that the police information sharing emphasized in post-9/11 policies provides value in detecting, predicting, preventing, or solving crimes of any type (e.g., Zaworski, 2004). Only recently has there been a call for research-based evidence to determine the benefits – if any – of police information sharing, and to help establish whether it serves its intended crime-fighting purposes (BJA, 2005).

Developing the processes and systems necessary to share information between police agencies and counter-terrorism intelligence entities is a costly proposition that can significantly affect police budgets (Mitretek Systems, 2005). The Government Accountability Office (GAO, 2006a) estimates that the cost of information technologies to enable sharing just among the Department of Homeland Security agencies was $1 billion per year in fiscal years 2003 and 2004. There is no estimate available for the cost of implementing information sharing systems across the nation’s 18,000 local, state, and tribal law enforcement agencies.

Given the post-9/11 emphasis on sharing information, the lack of objective evidence that information sharing has value, and the absence of credible estimates of information sharing costs, the nature of the police information sharing problem becomes clear: With police information sharing identified as a national priority, how can America’s police leaders make informed decisions about developing and implementing information systems when very little is known about the costs and benefits of such systems?

The problem is aggravated by the absence of relevant experience or models to help inform the cost/benefit analysis. The imperative to share routinely-collected, or low-level, police information is a recent priority, emerging from the post-9/11 perspective. Low-level information includes data from traffic stops, criminal and non-criminal incident reports, pawnshop records, field contact information, calls for service, vehicle tow sheets, and administrative reports that are
routinely generated by police agencies and archived in their records management systems. ¹ Simply, inter-agency sharing of routine or low-level information is a new venture for most police agencies, and there is very little collective experience to guide this venture (BJA, 2005). However, an overview of past law enforcement efforts to share specific sets of data (as opposed to routinely-generated data) provides perspective for understanding contemporary efforts.

**Background of Police Information Sharing: Mixed Results**

The tremendous value of sharing even limited sets of police information has been amply demonstrated over almost forty years through the operation of the FBI’s National Crime Information Center (NCIC). American police would probably find it impossible to perform their contemporary duties without the ability to conduct the nationwide, electronic searches for the crime-related records that the NCIC provides. By 2002, the NCIC was logging over three million police queries per day from U.S. law enforcement agencies (FBI, 2002) and nearly five million per day by 2005 (FBI, 2005b). However, the NCIC is limited to eighteen, structured data sets. These data sets include active files of wanted and missing persons; stolen vehicles; identifiable stolen property; criminal history information; and special databases such as sex offenders, gangs, and terror suspects (FBI, 2005a).

Although the information shared via NCIC is extremely valuable, it is the information that is not shared between police agencies that has become the focus of post-9/11 policy. These are the data that comprise the raw, low-level information collected each day by American police (Carter, 2004; Reynolds et al, 2005). For example, in a study of a single police agency, less than 3% of the agency’s one million recorded calls for service in 2003 generated informational

¹ A more extensive list of low-level information types is provided in Table 2 on page 37.
submissions to the NCIC, and none of the information about the agency’s 23,000 traffic stops that year was submitted (Scott, 2004). The experience of this single agency may be typical since the submission of information to NCIC is tightly governed and structured (FBI, 2006).

Expressed differently, perhaps as much as 97% of the information collected by police in the U.S. is *not* shared between police agencies. It is this tremendous gap between the information-available and information-shared that has become particularly important post-9/11. At a minimum, anecdotal evidence suggests that bridging this gap can have a significant and positive impact on the ability of American law enforcement to combat both terrorism and traditional crime (Estey, 2005b; NGA, 2002; Reynolds et al, 2005).

This information gap, however, is more than a recently-recognized phenomenon. One researcher reported efforts to integrate information in New York State during the 1970s (P. Griset, personal communication, September 13, 2006) and the author attended meetings in mid-1980 during which an information sharing system was promised by that year’s end (but had yet to be delivered twenty-six years later). In 1994 Chemung County (NY) public safety began efforts at linking agencies’ core information sources (Russo, 2002); in 1999 a number of St. Louis-area agencies formed the now-defunct Gateway information sharing project (DOJ, 2002); and in mid-2001 a Florida project that shared pawnshop information between police was shut-down by gun rights activists (Moore, 2001). Unfortunately, there is little research available to describe these pre-9/11, state and local projects and their related, lessons-learned.

There is, however, some research history available with regard to *national* efforts towards integrating police data. For example, the National Incident Based Reporting System (NIBRS) grew out of a Bureau of Justice Statistics (BJS) award to the FBI in 1982 to develop disaggregated, detailed crime data. NIBRS recognized that important details about crimes were
BJS developed a data collection format that was published to law enforcement agencies across the nation. Police agencies were asked to voluntarily submit the specified NIBRS data. By 1996, however, the jurisdictions participating in NIBRS represented less than 6% of the nation’s population, and the BJS authorized a study to determine the cause of low participation rates. The study revealed that state and local agencies chose not to support NIBRS because of its unfunded drain on local resources and the perceived absence of NIBRS benefits at the local level. Almost twenty-five years later, NIBRS still languishes (BJS, 1997, 2005; Dunworth, 2000; Faggiani & McLaughlin, 1999).

The Violent Criminal Apprehension Program (ViCAP) offers a second example of a pre-9/11 national effort to share important information that is not captured by the NCIC or other systems. ViCAP was created by the FBI in 1985 as a database of details about violent criminal acts. The database requires local police agencies to complete a 189-item form that could provide valuable information about violent suspects and/or serial offenders who offend across jurisdictional lines. By 1996, however, less than 7% of the eligible violent crime information was being submitted. Lackluster participation in ViCAP has been attributed to the promise of its benefits being outweighed by its expense to local agencies (Witzig, 2003).

More recently, post-9/11 police information sharing efforts have also suffered setbacks. Issues surrounding politics, organization, technology, and funding have been identified as obstacles. Examples of this include the MATRIX project (Multistate Anti Terrorism Information Exchange) which envisioned interstate information sharing between police intelligence components. MATRIX provided for sharing a mix of publicly-available and law enforcement-
restricted information. However, this project attracted the interest of organizations concerned about privacy issues, and the ensuing media attention and political fallout resulted in the project being discontinued after less than two years in operation (Florida Department of Law Enforcement [FDLE], 2005).

A failed FBI project that was initiated post-9/11 also attracted considerable media and political attention. The FBI’s $170 million effort to build its intra and inter-agency information exchange capacity illustrates how technology planning problems can thwart information sharing. The failure was attributed primarily to poor technology planning processes that included a lack of focus on the end users’ needs (McGroddy & Lin, 2004).

A lack of understanding end users’ needs and objectives also contributed to the dissolution of a project that provided for information sharing between local and federal intelligence officials. In 2005, a disagreement on the types of information to be shared – and by whom – caused problems. A law enforcement oversight board comprised of local officials pulled the Joint Regional Information Exchange System (JRIES) from a planned integration with the Department of Homeland Security’s (DHS) Homeland Security Information Network (HSIN). The inclusion of JRIES in the HSIN had been expected to provide the core of HSIN information sharing capacity, but JRIES officials were concerned that the HSIN would provide sensitive information to non-law enforcement users. The departure of JRIES left the fate of the HSIN in doubt (U.S. House Committee on Homeland Security Democratic Staff, 2006).

Thus, the information sharing gap remains. The GAO reported in mid-2006 that “[m]ore than 4 years after September 11, the nation still lacks government wide policies and processes to help… improve the sharing of terrorism-related information that is critical to protecting our
homeland” (p. 1). While the GAO report centers on federal efforts to share information for terrorism, the GAO criticisms may be relevant to similar efforts at state and local levels.

As most of the examples above suggest, the missing “policies and processes” cited by the GAO (2006) include failure to adequately address police information sharing costs and needs at the local agency level (cities, counties and states), or to consider the pragmatic needs and objectives of the end users. National law and policy is built on the premise that law enforcement information sharing should be a priority across all levels of government, and that the expected benefit of information sharing is an enhanced ability to both prevent terrorism and traditional crime (Act, 2004; Strategy, 2003).

**Purpose and Importance of this Study**

The foregoing pages briefly describe how police information sharing has emerged as a stated national priority following the terrorist attack of 9/11. In addition, an overview has been provided demonstrating that the need for police information sharing is not a newly recognized phenomenon. There have been a number of both successful and unsuccessful attempts to bridge the gap between information that is actually shared (e.g., the NCIC) and the information that is available but is not shared (the routine, or low-level police data). It is these routine, or low-level data that are believed to be important to meeting both counter-terrorism and crime fighting goals. However, there is little precedent or evidence to guide the development of low-level information systems, or to estimate the costs and benefits of such systems. It is the lack of evidence about police information sharing costs and benefits that created the motivation for this study.

In the simplest of terms, this study looked at the way individual police officers and police staff use low-level information. In addition, this study sought to identify things that influenced
whether the use of that information resulted in “success” for the individual users. Thus, “user-level success” was the outcome of primary interest. Success is a relative term; it could mean making an arrest, finding a missing person, recovering stolen property, identifying a terrorist group, or locating a witness. Regardless of the individual user’s definition of success, the total of individual successes represents an advance to meeting public safety goals.

The purpose of this study was to first identify the benefits of police information sharing and, second, how to increase those benefits in terms of user-level success. The first step, alone, posed a significant challenge. Because there are so few systems that share low-level data, there was very little guidance to identifying and measuring user-level success and other components of information sharing. Consequently, a variety of measures were explored and tested. Second, using combinations of measures that were newly identified through FINDER data sources, statistical tests were conducted to identify the combinations of measurable influences in the FINDER environment that best predicted user-level success.

This study is an important step in helping police leaders estimate the cost/benefit balance associated with information systems. It was intended to enhance understanding of the benefits of information sharing at the user level, and offer guidance for increasing those benefits. Armed with this information, police leaders can make evidence-based judgments about information sharing costs and benefits relative to the advancement of crime fighting goals.

**Study Context and Objectives**

A study of police information sharing system users and the factors influencing their successes first required, at a minimum, a system and its users that were available as the subjects of study. Second, once the study subjects (system and users) were identified, the research
question was posed. Third, the research question’s component variables were identified through an examination of the theoretical and research literature. The relationships of these variables were then considered relative to the research question. Fourth, a study methodology was crafted in an effort to answer the research question. These components of the research process are summarized below.

The Subjects of this Study: FINDER Users

The research purpose was identified as examining the user-level benefits of sharing low-level police information. Preceding pages have described low-level police information sharing as a recent priority, and that there is a lack of models – or existing low-level information systems – to help understand information sharing benefits. However, this study had the advantage of access to the Florida Integrated Network for Data Exchange and Retrieval, or FINDER. The FINDER system collects detailed information about user-level successes and user activity in the system (Public Safety Technology Center [PSTC], 2006a).

FINDER is a police information sharing system developed by Florida police agencies and the University of Central Florida.² The system originated as an effort to share pawnshop data, but it was rapidly expanded to share a broad set of data that permitted general searches for information about people, places, property, and vehicles (PSTC, 2006a). It presented a unique research opportunity. By 2006, there were roughly 120 Florida police agencies involved in sharing FINDER’s low-level information. FINDER was believed to be one of very few systems that represented a functional example of the type of police information sharing envisioned by

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² The author has been involved with founding, managing, and expanding the Florida Law Enforcement Data Sharing Consortium and FINDER since their inception.
post-9/11 policy and law (Scott, 2005). This belief was supported by the reported scarcity of operational police information sharing systems in the U.S.; the scarcity was attributed to the “newness” of national information sharing policy (BJA, 2005). Thus, FINDER was the information sharing system chosen as the subject of this study.

However, the research plan was founded on the belief that the performance of police information sharing relative to policy goals is gauged by the aggregate experience of the system’s users. In other words, to assess the benefits of a police information sharing system, the proper unit of analysis is the system’s individual user. This approach was supported by the research literature (Bharati & Chaudhury, 2004; Davis, 1989; Goodhue, 1995, 1998; Lin, 2004; Zaworski, 2004). Consequently, the study focused on the benefits to or successes of FINDER’s individual users. This focus can also be considered as an examination of user-level performance.

**The Research Question**

In the research process, the research question helps specify what information is sought in response to the research problem (Gliner & Morgan, 2000). The research problem in this study was identified as a lack of information about the benefits of police information sharing. The research subject was identified as FINDER’s users, with the focus of interest on the users’ successes with police information sharing. As discussed, a desired goal of police information sharing is to maximize benefits while minimizing costs.

Given an understanding of the problem, the context in which this problem could be examined, and the goal (or purpose) of the research, the following question served as the foundation for conducting this study: *What factors influence user-level success in the FINDER system?*
Variables of Interest: Guidance from Theory and Prior Research

A review of theories and prior research applicable to the research question was conducted to help build a research plan for conducting this study. This review was made difficult by the fact that the police information sharing priority is a relatively new phenomenon and there was very little prior research specifically about this topic (BJA, 2005). Therefore, the research question was broken down into its three component concepts: low-level information sharing, user-level success, and factors influencing success. The research literature was examined for clues about how these component parts might fit together in the FINDER study.

FINDER and sharing low-level police information

The term “police information sharing” as used in this study required specific definition. It has been noted that “police” in this context refers to law enforcement and intelligence agencies at all levels of government. These levels include local, state, tribal, and federal agencies (Carter, 2004). “Information” has been conceptually offered in the context of “low-level” information. Low-level information has been described as that which has not been shared in the past. This kind of information is routinely collected through the everyday operations of police agencies. Low-level information is distinct from purpose-driven information such as that previously described as collected by the NCIC, or intended for collection by ViCAP or NIBRS. “Sharing” is defined as the automated, bi-directional exchange of data. Thus, police information sharing means the automated, bi-directional exchange of low-level police information between police agencies. The FINDER system fits this definition (Reynolds et al, 2005).
**User-level success**

The principle concept of interest was “user-level success.” It is this success, or system benefit, that is the important issue for police leaders and policy makers. The research literature indicated that measuring “success” with technology systems is a complex and difficult task because success is relative to both the user and the system (Goodhue, 1995, 1998; Goodhue & Thompson, 1995). This task may be particularly difficult in the context of police technology systems (Nunn, 2001; Nunn & Quinet, 2002; Zaworski, 2004), and there are no commonly accepted measures of user-level success identified by researchers. Instead, the users’ intended or perceived frequency of system use (Davis, 1989; Nunn & Quinet, 2002; Venkatesh & Davis, 2000); or the users’ perceptions of how the system affects their performance (Goodhue, 1995; 1998; Goodhue & Thompson, 1995; Zaworski, 2004) are frequently considered as surrogate, or substitute, measures of success.

These surrogate measures of success are not believed to be entirely adequate for gauging the benefits of police information sharing (BJA, 2005). Thus, this study was designed to move beyond surrogate measures and identify more objective success measures. The FINDER measures of user-level success in this study are characterized as “metrics.” Metrics are standards that help assess performance levels and require specific, measurable, attainable, realistic, and timely data (U.S. Department of Energy, 1995). FINDER appeared to satisfy these conditions for metric development.

Some FINDER users report their success experiences, and these reports were available as part of this study (FINDER, 2006). It is important to note that, before this study began, FINDER’s user-level success records were explored for clues about the dynamics of how FINDER’s users achieve successes. This exploratory look at success records revealed great
variation in the level of reported successes among FINDER users. This variation was important because it suggested differences among the users. The existence of differences between more-successful and less-successful FINDER users is what this study sought to identify. It will be shown that, theoretically, “good” differences between users might be exploited and “bad” differences suppressed in order to improve success rates.

In addition to the collection of success reports, the FINDER system automatically records information about system use. This system use information is captured in “Query Logs” that provide a detailed record about each user’s FINDER activity. Levels of system use are one of the surrogate measures for system success discussed above (e.g., Davis, 1989; Goodhue, 1995). Integrating system use data from the Query Logs with users’ success reports permitted an expansion of prior success concepts. Thus, with regard to the “user-level success” component of the research question, a combination of success indicators was used to build a user-level success metric.

**Factors influencing user-level success and theoretical framework**

Identifying the factors that might influence FINDER users’ successes was a critical step in designing this study. There was little research available to guide the identification, but theories related to information technology and user performance were useful. These theories offered suggestions about what types of factors influence users’ technology behaviors, and helped build a theoretical framework within which this study could be conducted.

After a review of relevant theories, Goodhue’s (1995) Task-Technology Fit theory (TTF) was selected as the framework for this study. In its simple form, depicted in Figure 1, TTF suggests that technology, user characteristics, and the fit of technology to the user’s task needs
predict technology use and user-level performance related to that technology. Thus, TTF provided guidance to three factors that are independent variables: technology, user characteristics, and technology fit. When the TTF factors and framework were applied to this study, the factors emerged as the independent variables that might influence FINDER’s user-level successes: the technology (police systems), user characteristics (characteristics of FINDER’s police users), and technology fit (how well FINDER fits police users’ task needs).

Figure 1: Basic Task-Technology Fit Model (Goodhue, 1995)

Relationship of variables to the research question

Goodhue’s (1995) TTF work was valuable to identifying the indicator variables underlying the TTF factors, but Goodhue’s work involved corporate technologies, not public safety technologies. Thus, the research literature and subject matter experts were also consulted to help adapt the TTF factors specifically to police information sharing.
As a result, a number of observable indicator variables were identified. For instance, prior research and theory suggested that the FINDER user’s job experience, job assignment, and workload would be valid, observable, and measurable indicators of the “task-technology fit” factor proposed by Goodhue’s (1995) model. The general relationships of the basic indicator variables to the TTF-suggested factors are summarized in Table 1 (specific definitions of these variables and their relationships are presented in Chapter 2).

Table 1: Relationship of FINDER Indicator Variables to TTF Factors

<table>
<thead>
<tr>
<th>Goodhue’s (1995) Task- Technology Fit (TTF) Factors</th>
<th>TTF-Related Indicator Variables in the FINDER User Study (measures at user level)</th>
</tr>
</thead>
<tbody>
<tr>
<td>User-level performance</td>
<td>Success reports</td>
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<tr>
<td></td>
<td>FINDER usage rate</td>
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<tr>
<td>Task-technology fit</td>
<td>Job assignment</td>
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<td></td>
<td>Job experience</td>
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<td></td>
<td>Workload</td>
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<td>User characteristics</td>
<td>Computer literacy</td>
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<td>FINDER training</td>
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<td>FINDER experience</td>
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<td></td>
<td>Workplace environment</td>
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<tr>
<td>Technology</td>
<td>User access to other systems</td>
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<tr>
<td></td>
<td>Number of agencies’ information available</td>
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<tr>
<td></td>
<td>Voluntariness of FINDER use</td>
</tr>
</tbody>
</table>

Formulation of hypotheses

Table 1 provides an overview of how the theoretical factors offered by the TTF
framework were operationalized into observable and measurable variables. TTF suggests that the factors task-technology fit, user characteristics, and technology will predict user-level performance. Hypotheses were formed that the FINDER-based indicator variables representing TTF factors (as in Table 1) could predict FINDER’s user-level successes. These hypotheses are detailed in Chapter 2, but a conceptual representation of these hypothetical relationships and their relationship to the TTF model is provided in Figure 2.

Figure 2: Conceptual Relationships: FINDER Variables and TTF Factors

Methodology

At this point, a number of variables have been described as important to this study. The measures of two variables, user-level success and FINDER system use, are available directly through the FINDER system (FINDER, 2006). However, while other important variables have
been identified, a method for collecting their measures has not been discussed. This section describes the methods used to collect that information.

An important characteristic of the FINDER system is that it relies on a distributed technology architecture. This means that there is not a central database or control point shared by FINDER users. Rather, FINDER access and user information is controlled at the local agency level, and (with the exception of success reports and Query Logs) the user information is not available to other agencies (PSTC, 2006c).

Because the distributed architecture prevented access to user information directly through the FINDER system, an alternative method was required to gather the data about users. This user-based data is required in order to test the relationships of the study variables in the TTF framework. To acquire this data, an online user survey was constructed and distributed, via email notice, to all FINDER agencies.

The FINDER user survey incorporated 85 items, or questions, intended to capture measures of the above-described study variables. The survey was directed to the universe of FINDER users; roughly 1,600. Details about this survey, and a description of its results, are provided in Chapters 3 and 4.

**Summary and Organization of this Dissertation**

This introductory chapter has described how sharing low-level police information has become a national priority in the post-9/11 era. This type of information sharing is believed to be of critical value in preventing terrorism and addressing traditional public safety needs. However, low-level information sharing has not existed in the past, so there is little experience or research to guide efforts to address this recently-emerged priority. Thus, police leaders and
policy makers have not been able to make informed decisions about the costs of police information sharing, nor whether it provides its intended benefits in terms of enhanced public safety.

This study is believed to add important knowledge that can help police leaders and policy makers better understand the benefits of police information sharing, and how those benefits can be increased. The study examined a functioning information sharing system, FINDER, which provides the low-level police data believed necessary to fulfill national goals. Policing successes, reported by FINDER’s users, were a critical part of the study. This success data provided a significant contribution to building a performance metric for police information sharing.

The study used the Task-Technology Fit framework (Goodhue, 1995) to identify factors that influenced user-level success among FINDER’s users. The data used to identify these factors were collected from both automated FINDER system records and a survey distributed to 1,600 FINDER users.

The remaining chapters of this dissertation provide details in support of the introductory overview, the findings of this study, and conclusions and recommendations based on the study results. Chapter 2 encompasses a review of research literature related to the study topics and more extensively describes the FINDER system. In addition, Chapter 2 justifies the identification and operationalization of the study variables and specifies their hypothetical relationships.

Chapter 3 addresses the methodology used to collect data for this study and details the development and distribution of the survey instrument. Chapter 4 describes the data (from both the survey and FINDER system records) and the analyses conducted to test the specified,
hypothetical relationships. Chapter 5 reviews the findings of the analyses and what they suggest in terms of FINDER’s user-level success. These findings are then incorporated in conclusions and recommendations regarding the maximization of benefits in the police information sharing environment.
This literature review accomplishes several purposes. First, the low-level information concept offered in the introduction is expanded and discussed in greater detail. Second, the state of police information sharing and related research is described, particularly in its relationship to low-level police data. Third, the Task-Technology Fit (Goodhue, 1995) theoretical framework is elaborated and justified as the guiding framework for this study. Fourth, additional details about FINDER are provided to clarify FINDER’s attributes as they relate to building the research model and methodology. Fifth, the research, theory, and FINDER attributes are brought together to define and operationalize the study variables of interest. Finally, the theoretical framework and study variables guide the development of hypotheses about influences on user-level success.

The Importance of Low-Level Police Information

Chapter 1 described how police information sharing became a policy priority following the 9/11 terrorist attacks. An initial definition of police information sharing was offered as the automated, bi-directional exchange of low-level data between police agencies. This definition has only recently been visible in the literature and is important in establishing FINDER and its users as the research context of this study proposal. Further, distinguishing FINDER from other types of information systems is important.
Police information sharing was conceptualized as encompassing three factors:

1. “Police” includes law enforcement agencies and their officers at all levels of government (Carter, 2004);
2. “Information” is focused on “low-level” police information. This information is routinely collected by police agencies, and includes data gathered from both criminal and non-criminal events; and,
3. “Sharing” is the automated (computer-based), bi-directional exchange of information between police agencies.

The term “low-level” information requires elaboration. Reynolds et al (2005) describe low-level information as including:

… the vast bulk of information collected by law enforcement and generally stored in automated records management systems. These may include information on suspects, witnesses, pawn shop transactions, vehicle stops, field interviews, suspicious vehicles, towed vehicles, criminal incident reports, non-criminal incident reports, calls for service, property, evidence, and other types of police notes or records (p 129).

Low-level information differs from that gathered in specialized police databases described in Chapter 1, such as the NCIC, ViCAP, and NIBRS; or in statewide networks that parallel the NCIC dataset (US Department of Justice [DOJ], 2003). This low-level data may account for more than 97% of the data routinely collected by police agencies (Scott, 2004).

The absence of low-level information sharing has helped drive the police information
sharing initiative and indicates why it is important to gain an understanding of information system dynamics. For instance, reputed 9/11 mastermind Mohamed Atta escaped arrest in July 2001 because police in neighboring jurisdictions did not share low-level arrest warrant information. In that case, a deputy sheriff in Broward County, Florida, stopped Atta’s vehicle. The deputy issued Atta a ticket for driving without a license and ordered him to appear in court, but the deputy did not have access to information indicating that Atta was on a terrorist “watch list.” Atta failed to appear in court that May and a misdemeanor warrant was issued for his arrest. In July, Atta was stopped for another traffic infraction by police in Delray Beach. Due to the absence of low-level information sharing between Delray Beach and Broward County (which are less than ten miles apart), the Delray officer did not know about the outstanding warrant, nor that Atta was on the terrorist watch list. Atta was allowed to continue on his way and complete his terrorist plan (NGA, 2002).

Carter (2004), in Law Enforcement Intelligence: A Guide for State, Local, and Tribal Law Enforcement Agencies, articulates that low-level data provides the raw information that is critical to both developing counter-terrorism intelligence and fight crime on the local level. The National Criminal Intelligence Sharing Plan (DOJ, 2004) emphasizes this link, and quotes President Bush asserting that: “All across our country we’ll be able to tie our terrorist information to local information banks so that the front line of defeating terror becomes activated and real, and those are the local law enforcement officials” (p iii). Further, the plan explicitly identifies police information sharing as “…a key tool that law enforcement agencies can employ to support their crime fighting and public safety efforts… this is information that will help [the officers on the streets] do their job” (p iii).

Another post-9/11 development is the design and propagation of the Global Justice XML
Data Model (GJXDM). This model represents a data “map” that provides guidance in moving information between agencies via automated networks. GJXDM is an effort of the Department of Justice and, essentially, establishes information sharing data standards for the justice community. In the law enforcement context of this community, GJXDM identifies low-level, police data sets as part of the data sharing map intended to meet national information sharing goals (DOJ, 2006).

It is clear that the importance of low-level police information is recognized as part of the emerging, national information sharing strategy. However, it is important to understand the distinction between “police information sharing” and other forms of justice information sharing that are also valuable, but which were not the subject of this study. For example, “Justice” or “Integrated Justice” information sharing is commonly referenced as “IJIS” (or “ICJIS”) and represents integrated justice or integrated criminal justice information sharing. IJIS projects may be easily confused with police information sharing. ¹ However, the IJIS model incorporates data exchange between courts, police, corrections and their various sub-units (e.g., probation and parole; clerks of courts; prosecutors) versus exchange exclusively among police agencies.

A primary goal of the IJIS information sharing model is to facilitate justice *administration* versus crime-solving or intelligence development. Thus, while police may contribute information to IJIS projects, these projects are not “police information sharing” and are not addressed in this study. The reader is referred to the Integrated Justice Information Systems Institute for an overview of the IJIS model and related projects (http://www.ijis.org/rs/home).

¹ In 2004 and 2005 the author met with a variety of Congressional members and Florida legislators and their staffs to discuss FINDER funding. These meetings revealed widespread confusion about the difference between police information sharing and ICJIS projects.
The State of Police Information Sharing and Related Research

This section of the literature review first addresses the state of police information sharing research and, second, explores non-police information systems research that may be relevant to assessing performance within police systems. A review of the relevant literatures reflects that scarce research exists to help guide this study.

Prior pages briefly described the post-9/11 move to quickly create police information sharing systems. Due, in part, to the rapid development of these systems, the research literature has not kept pace with the policy and practice priorities. The research deficit is described by CRISP (Comprehensive Regional Information Sharing Project), a project funded through the Department of Justice:

Currently, many state and local law enforcement agencies obligate large portions of their yearly operational budgets in support and development of multi-jurisdictional information sharing systems (ISSs). However to date, no single document or system analysis has been developed that maps or describes how multi-jurisdictional ISSs work. During 2005 and extending into 2006, the CRISP project is beginning to address this need by evaluating and documenting the information exchanges of selected operational ISSs around the country, to determine their benefit to street-level law enforcement. The project is addressing both technical and functional characteristics of each ISS, how the ISS supports policing functions, and what specific information is being delivered to law enforcement officers on the street (Mitretek, 2005).

CRISP affirms the importance of understanding performance in police information sharing and
the absence of research providing evidence of effective policy or systems. In November 2005, the CRISP evaluation team met with FINDER staff, which included the author. The CRISP team lamented the absence of “hard” performance data attributed to police information sharing. They discussed the difficulty of defining, acquiring, and measuring such data (CRISP team, personal communication, November 11, 2005).

The CRISP position is supported by the Bureau of Justice Assistance (BJA), Center for Program Evaluation. The BJA has called for “outcome evaluations” that assess the performance of police information sharing. The BJA notes that prior research has focused on user evaluations, user perceptions, or system case studies versus measurable outcomes. In addition, the BJA attributes the lack of outcome or success-based research to the “newness” of the police information sharing topic (BJA, 2005).

The BJA Center for Program Evaluation (BJA, 2005) also provides a reference list of roughly seventy publications identified as relevant to police information sharing research. While these are not individually discussed here, these publications have been reviewed, and none are oriented to objectively measuring or predicting actual outcomes attributed to the exchange of low-level police information. Rather, this body of literature focuses on the organizational dynamics of justice information sharing systems (e.g., BJA, 2002), the technologies or potential technologies underpinning information sharing (e.g., Hauck et al, 2001), or the prospective preferences of police for information sharing system design (e.g., Chen et al, 2002).

In addition, a search was conducted of the scholarly, professional, and popular literature in an effort to identify police information projects and any related outcome evaluations or research. The search, conducted in 2005, included over 4,000 articles, publications or websites that appeared relevant to police information sharing. However, this search produced information
about only one project, ARJIS, that appears to have been the topic of an outcome-focused research effort (Scott, 2005).

The ARJIS Study

The single piece of research identified that touches on performance in police information sharing was conducted by Zaworski (2004) as a comparison between a non-sharing police agency in Florida and agencies participating in a form of information sharing via the San Diego ARJIS (Area Regional Justice Information Sharing) project. While ARJIS is a “justice” (versus “police”) project, Zaworski focused on police data.

Zaworski (2004) relied primarily on user perceptions, expectations, and user-recall about the value of information sharing (and technology in general) to individual performance. He did not include objective measures of individual performance. He did make an effort to link information sharing to agency level, objective performance measures; in this case, aggregate crime solving and arrest rates found in the Uniform Crime Reports. Zaworski found no significant difference between the sharing/non-sharing agencies in the aggregate performance measures and concluded that a police agency’s management priorities, versus information sharing, may have a greater effect on aggregate crime control measures.

While Zaworski’s (2004) findings seem to show that police information sharing lacks demonstrated (as opposed to perceived) crime-solving value, it is important to note that he was contrasting individual user’s perceptions against their agencies’ aggregate crime statistics. Zaworski recognized the link from the individual to the aggregate as tenuous and elaborated on the difficulty of collecting good, user performance data in the applied setting.
Zaworski’s (2004) research remains important, however. First, he collected a large sample (600 users) of baseline data on user perceptions related to the individual value of police information sharing, albeit in an IJIS-influenced environment. If new research, such as that conducted here, collects additional user perception data and links it to strong performance measures, a better understanding of relationships between user perceptions and actual performance may be possible. Second, Zaworski examined potential linkages between user characteristics and individual performance perceptions. These characteristics (such as education, training, and experience) have value in this study, and are considered in the research framework.

**Police and Information Systems Usage: Link to User Success**

A third contribution made by Zaworski’s (2004) research involves information sharing system use. Zaworski’s data indicates a strong link between users’ reports of system use and their perceptions of information sharing value. While the theoretical linkage of technology use and technology value will be discussed later, Zaworski’s findings parallel that of technology systems research in both police and non-police environments.

Lin (2004), for instance, studied police use of emerging technology and their perceptions of its value. Lin found (not surprisingly) that police detectives reported their intent to use a technology system that fulfilled their task needs: investigating and solving crime. Further, Lin reported that these detectives would use the system even if it were difficult to use or required significant training. Although Lin did not attempt to identify individual performance measures related to the technology, Lin’s findings parallel those of Zaworski (2004): police report that they will use technology systems that help them perform their jobs.
Other research affirms the link between user-perceived benefit and the police user’s intended use of technology systems. Ioimo (2000) and Ioimo and Aronson (2003) found significant relationships between user expectations of success and the use of mobile computing systems. Colvin and Goh (2005) explored factors of police officers’ acceptance and intended use of new technology related to its officer safety value, and Nunn and Quinet (2002) tried to examine the relationship between actual system use and the system’s contribution to meeting community policing goals.

In each of these research efforts that address the prospective use of information systems, specific outcomes or objective performance measures of technology use were not captured, but the researchers concluded that police would not use a technology system that failed to address their pragmatic policing needs. Conversely, these researchers generally concur that police report the intent to use technology that does meet their policing needs. This link between police users’ needs and system use is important to the current research model.

Related Research from Outside the Policing Environment

The difficulty in measuring information systems’ value at the user level is not unique to policing. Parallel studies in other disciplines can help guide research in the police information sharing context. For example, Goodhue and Thompson (1995) tried to assess individual performance in technology systems that spanned a variety of users in two different business environments. They found that common performance measures could not be defined, and they relied on user perceptions of how system performance might translate to individual performance.

Bharati and Chaudhury (2004) research on web-based decision support systems examines which systems consumers prefer (“decision support systems” are, essentially, on-line shopping
websites). They supported prior research that user acceptance and intended system use depends on expected results rather than ease of use. Bharati and Chaudhury indicate that where the user has a choice to use any of a number of systems, the user will select that system that best meets the user’s pragmatic needs, versus systems that are easier to use or more graphically appealing.

Davis’ (1989) seminal work on user acceptance of technology and his Technology Acceptance Model (TAM) has been widely used in an effort to explain why users do or do not employ the technology available to them. The TAM’s primary components are measures of system usability and ease of use that are based on user perceptions and intentions versus objective measures. Other researchers assert that TAM requires a marriage with different models if it is to be effective in predicting actual use or performance (Legris, Ingham, & Collerette, 2003), and Venkatesh’s and Davis’ (2000) more recent proposal of the TAM II model expands TAM to incorporate a larger set of user and environmental characteristics on technology outcomes.

The research described above relies almost exclusively on users reporting their perceptions and intentions about technology use as opposed to actual behaviors or outcomes. The literature cited is replete with discussion that objective performance data is difficult or impossible to measure or gather, and gauging individual, technology-driven performance based on self-reported perceptions or intentions may create questionable results (e.g., Goodhue, 1995; Zaworski, 2004). As of mid-2006, there does not appear to be any research literature that provides meaningful guidance in objectively measuring individual user’s performance in a police information sharing system.
Discussion and Summary

A brief discussion is in order to frame and summarize the literature review. First, this review, in conjunction with Chapter 1, is believed to have clearly established that an understanding of the dynamics and value of police information sharing is an important research topic. Second, it is believed that the literature review has provided a clear definition of “police information sharing” and what it does – and does not – encompass. Third, it has been asserted and supported that there is a void in the literature with regard to measuring performance in police information sharing. Fourth, a review of non-police technology literature reflects similar difficulties with objective performance measures, and expected performance or intended system use are suggested as proxy measures for the user-level success metric (e.g., Goodhue, 1995; Davis, 1989).

Theoretical Framework

The use of established theory is recommended in building a framework to help architect the structure of the research plan; identify appropriate study variables; and develop theoretically-sound hypotheses (Gliner & Morgan, 2000; Senese, 1997). This section of the dissertation discusses Task Technology Fit (Goodhue, 1995, 1998; Goodhue & Thompson, 1995) as the theoretical underpinning of this study. In addition, this section describes FINDER; identifies datasets that are available via FINDER and its users; proposes an initial set of hypotheses and study variables that are based on the theoretical framework and prior research; and supports the selection of FINDER and its users as the research subjects.
Task Technology Fit Theory

A variety of guiding theories and models were considered in the development of this study. Many of the models that try to explain the relationship between users and technology appear founded in TRA, the Theory of Reasoned Action (Fishbein & Ajzen, 1975). TRA proposes that a person’s attitudes are shaped by their beliefs and subjective norms. Attitudes influence intentions, which form the basis of actual behavior. In the technology context, TRA proposes a relationship between the user’s context-based perceptions about how the technology of interest serves the user’s needs, and the user’s behavioral intentions with regard to using the technology (e.g., Goodhue, 1995; Lin, 2004).

Davis’ (1989) Technology Acceptance Model (TAM) and Venkatesh and Davis’ (2000) TAM II models, which were initially considered as the framework for this study, are consistent with TRA. TAM, particularly, has received considerable attention and expansion in the literature (e.g., Legris et al, 2003). The TAM’s relationships between technology usability perceptions and use intention has been repeatedly validated, but it and other intention-based “usability” models do not describe a relationship between usability intentions and actual performance.

However, Goodhue’s (1995) Task Technology Fit (TTF) model addresses the theoretical gap between usability theories and individual performance. It is this pragmatic link to performance that makes TTF suited to a study of user-level success in police information sharing. TTF proposes that an impact on individual performance can be predicted by an understanding of the user’s task needs, individual characteristics, and the technology of interest.

The TTF model (Goodhue, 1995) suggests that when an information technology satisfies the job tasks of the system’s users, the users are more likely to use the system and employ the technology to have a positive impact on individual performance. Goodhue acknowledged that
this is a complicated, feedback relationship with complex interactions, and that the absence of objective performance measures in the research environment make it difficult to test the TTF theory. Therefore, to date, validation of TTF has been based largely on user perceptions about task fit, how users intend to use technology, and what performance gains users expect to achieve.

The TTF (Goodhue, 1995) model depicted in Figure 3 serves as the theoretical framework for this study of FINDER users. Figure 3 is different than the basic TTF model offered in Chapter 1 as it is expanded to consider a user who has the discretion to use or not use a particular system, or to choose among systems. Figure 3 shows the theorized relationship between task-fit factors and system use.

Figure 3: Task Technology Fit Model: Linked to Use and Performance (Goodhue, 1995)
The model in Figure 3 proposes both a direct effect of task fit on performance and an indirect effect mediated by system use. This is an important relationship. Both performance and system usage have to be modeled as dependent variables if the TTF framework is followed. In addition, the “individual [user] characteristics” and “other factors” influences in the model require contextual interpretation. Unfortunately, these influences receive little attention in Goodhue’s (1995, 1998; Goodhue & Thompson, 1995) applied efforts to validate the TTF model.

In an effort to validate the model, Goodhue (1995) and Goodhue and Thompson (1995) developed a thirty-two item TTF measurement instrument, and Goodhue (1998) later produced a similar, forty-seven item instrument. The original (1995) instrument, hereinafter referred to as the TTF instrument, assesses the user’s perception of technology-fit across twelve dimensions. Thus, as the Task-Technology Fit theory can help guide research, the TTF-type measurement instrument can be useful in empirical testing of hypotheses related to task-fit. However, as Goodhue (1998) notes, his TTF instrument is not suitable for examining “individual application systems” (p. 106), and other research employing the TTF model has produced modifications of the TTF instrument to address contextual demands (e.g., Ioimo, 2000; Zaworski, 2004).

**FINDER**

**FINDER**, the Florida Integrated Network for Data Exchange and Retrieval, is an information sharing technology created by a consortium of Florida law enforcement agencies and the University of Central Florida’s Public Safety Technology Center (PSTC). **FINDER**, was initiated in 2002 and shares only low-level police information, only between police agencies, and encompasses a large and diverse service group of agencies and users (PSTC, 2006c).
As of mid-2006, FINDER involved approximately 60 Florida police agencies that were exchanging low-level data. In addition, at least 60 other agencies had individual users authorized to make queries to FINDER, but were not yet engaged in contributing data to the information exchange. Although only about 30% of Florida’s 400 or so police agencies were involved in FINDER, these agencies’ jurisdictions were estimated to service about 63% of Florida’s population (U.S. Census Bureau, 2005).\(^2\) Geographically, agencies participating in FINDER were distributed across the state, but were concentrated in Central Florida (PSTC, 2006b).

In a very broad sense, FINDER operates in a Google-like fashion. FINDER is a web-based, distributed architecture. This means that each participating agency controls which parts of its data are visible to other FINDER members, and there is not a data warehouse that stores all of the participants’ data. The shared data are not “entered” into the system through keystrokes on a computer. Rather, the data being shared have already been collected by the member agency and stored in its own, stand-alone records management system, or RMS (PSTC, 2006c). This is the low-level, ‘raw information’ that has not generally been shared in the past (Carter, 2004). Table 2, on the next page, depicts a partial list of the low-level data shared through FINDER. The items listed in Table 2 do not include any of the 400 or so criminal offense fields that are also available through the system (FINDER, 2006).

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\(^2\) Based on July 2004 estimates of populations in counties where FINDER member agencies are located.
There are two important technology functions associated with FINDER, aside from its broad scope, which establish it as a valuable research environment. First, beginning in December 2004, each individual query to the FINDER system was recorded in a “Query Log” database. The query log captured the date and time of the query; identified the agencies to which the query was directed; which user made the query; and the specific parameters of the query (the parameters are what the user was asking about, such as “John Smith” or “red Ford truck”). In other words, the Query Log provided detailed system use information (FINDER, 2006).
However, one drawback due to the distributed nature of FINDER’s technology is that information about individual users is maintained at each agency and is not centrally available. Thus, there is no system-wide ability to establish the number of users with system access, or to know anything about these users. Consequently, only an estimate of the number of FINDER users was available through an analysis of the Query Logs. As of February 2006, an estimated 1,603 users had logged onto the FINDER system (Query Log detail is provided in Chapter 3).

Second, a feature was added to FINDER in 2004 that is referred to as “Success Tagging.” When a user makes a query that returns useful data, a point-and-click “button” appears that is labeled “Click here to tag this report for successes.” This button, the “Success Tag” button, takes the user to a pop-up window. The pop-up window asks the user to describe the “success” that the user is choosing to report. The requested success information includes a brief, text description of the success and automatically references the success tag to the source data that the user has queried. Thus, subject to the user’s inclination, FINDER collects specific, user-level success information. A computer screenshot of FINDER’s success tagging function (with the pop-up window displayed) is pictured in Figure 4 on the next page (FINDER, 2006).
FINDER was well suited for the purpose of this research. Evidence of this suitability includes:

- FINDER meets the definition of a police information sharing system: it involves the automated, bi-directional exchange of low-level information between police agencies.
- FINDER’s four-year, operational history makes it suitable for in-depth analysis.
- FINDER encompasses a relatively large number of agencies that police a large and diverse population.
- The population of FINDER users was estimated at least 1,600. This number of users provided adequate data for valid sampling and analysis.
• FINDER captures system use information. The theoretical framework suggests that objective, system use data is important to understanding user-level performance. More than 1.8 million query log records were collected in the course of this research.

• FINDER captures some specific information about user-level successes. Although the case-by-case details of success tagging data will be more thoroughly explored in Chapter 4, information about more than 700 successes was collected and guided development of the research plan. An initial review of success reports reflects that cases-solved, arrests, or recoveries of stolen property were FINDER users’ primary success topics.

**Theoretically-Informed Study Variables and Hypotheses**

This section considers the relationships proposed by the Task Technology Fit model, and whether related hypotheses could be tested with the data available from FINDER and its users. First, definitions of the study variables are offered and justified. Second, control variables will be discussed. Third, hypotheses suggested by theory or prior research will be presented.

The TTF model incorporates several factors, or theoretical constructs as were defined in Chapter 1. These factors include individual performance, system use, task technology fit, individual characteristics, technology, task characteristics, and other factors. Figure 2 presented a graphic depiction of these relationships. Table 3 on the next page aligns Goodhue’s (1995) TTF factors with parallel relationships that were hypothesized to be relevant in the FINDER context. The variables of hypothetical interest in this study are shown in the right-hand column of Table 3. They are user-level success, FINDER task-fit, computer expertise, user’s usage rate, user’s job assignment, and FINDER training. These variables are discussed below.
Table 3: Task Technology Fit Hypothetical Relationships and Application to FINDER Study

<table>
<thead>
<tr>
<th>RELATIONSHIPS IN GOODHUE’S (1995) TTF MODEL</th>
<th>RELATIONSHIPS IN FINDER CONTEXT*</th>
</tr>
</thead>
<tbody>
<tr>
<td>Task Characteristics → Task Technology Fit</td>
<td>User’s Job Assignment → User’s FINDER task-fit</td>
</tr>
<tr>
<td>Individual Characteristics → Task Tech Fit</td>
<td>User’s computer expertise → User’s FINDER task-fit</td>
</tr>
<tr>
<td>Technology → Task Technology Fit</td>
<td>None identified – explored as control</td>
</tr>
<tr>
<td>Task Technology Fit → System Use</td>
<td>User’s FINDER task-fit → User’s Usage Rate (H6)</td>
</tr>
<tr>
<td></td>
<td>User Job Assignment → User’s Usage Rate (H9)</td>
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<tr>
<td></td>
<td>Technology Acceptance measure → Usage Rate (H8)</td>
</tr>
<tr>
<td>Other Factors → System Use</td>
<td>FINDER Training → User’s Usage Rate (H7)</td>
</tr>
<tr>
<td>Task Technology Fit → Performance</td>
<td>User’s FINDER task-fit → User Level Success (H1)</td>
</tr>
<tr>
<td></td>
<td>User’s Job Assignment → User Level Success (H5)</td>
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<td></td>
<td>User’s computer expertise → User Level Success (H3)</td>
</tr>
<tr>
<td>System Use → Performance</td>
<td>User’s Usage Rate → User Level Success (H2)</td>
</tr>
<tr>
<td></td>
<td>FINDER Training → User Level Success (H4)</td>
</tr>
</tbody>
</table>

* Value in parentheses (Hi) indicates a hypothesis, number i, will be proposed.

**User-level success**

Goodhue’s (1995) “individual performance” term was operationalized as “user-level success” in this study. The change in terminology was supported by this study’s basic premise of examining the user level for indicators of police information sharing success. FINDER’ users (as success tagging is described above) report desirable outcomes as those that they consider to
be “successes.” The “success” characterization employed by FINDER’s users make the term suitable for use in creating a performance metric. User-level definitions of this type may be considered as more useful than terms imposed by administrators, external researchers, or policy makers (Long & Franklin, 2004). Thus, as used in this study, “success” refers to outcomes that the users consider successful, and is not intended to assert system-wide success.

The user-level success variable was carefully considered. This was the outcome variable of critical interest, and the literature review demonstrated that objective success measures are very difficult to define or acquire. Initially, at least, user-level success was operationalized as each instance of a FINDER user reporting a success through FINDER’s success-tagging feature. However, difficulties were anticipated in the use of this measure exclusively for testing success-related hypotheses.

First, as described above, all of the success tagging reports in FINDER are due to voluntary self-reporting. Self-reports such as these are subject to a variety of biases. This is especially a risk because the self-reported FINDER success is a report of the user’s success and, potentially, could enhance the user’s self-image or image in the eyes of others. Bias such as this may be considered “social desirability” or “prestige” bias and must be considered in the analysis of success tag reports (Alreck & Settle, 1995, p. 100).

Second, the author participated in FINDER-user focus groups on October 19, 2004 and November 11, 2005 to inquire about system functionality and user experiences. Both focus groups suggested that FINDER successes might be dramatically under-reported.

The first group (eleven, line-level detectives or squad-level supervisors), convened before the success tag feature was available. This group reported consistent levels of “successful”

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3 The first group consisted entirely of members from one Sheriff’s Office. The second group included members from several police agencies.
FINDER use. Members of the group said FINDER routinely helped them work more efficiently, clear cases, and acquire information that was not otherwise available. Subsequent, informal reports from members of that user group suggested continuing successes over the following year.

By November 2005, the success tag feature had been in place for almost one year, but reported successes were not reflecting the “constant” success level asserted by the 2004 focus group. Thus, this topic received considerable attention during the 2005 focus group meeting. Those FINDER users affirmed that they continued to experience consistent “success” with the system, but only sporadically submitted success tagging reports. The users (in this group, six line-level detectives) gave a number of explanations for the gap between actual and reported successes. These included:

- “I’m not sure what kinds of things you want us to report.”
- “I didn’t know what the success tag button was supposed to be for.”
- “No one told me that [success tagging] is important.”
- “I’m too busy to use [success tagging]. You guys should know that, the fact is, I use FINDER all the time, and that’s proof that it’s successful for me.”
- “A lot of times I get a hit [data match] and I keep on going to make my case. Then, by time I finish my case, I forget to do the [success] tag.”
- “Everyone on my squad uses it [FINDER] all the time. It works great, but I guarantee you none of them took the time to make a success report.”

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4 The focus group recommended that success tagging incentives be offered to FINDER users. Suggestions included entry in a gift card lottery, celebratory computer sound effects, and computer animation upon reporting a success. These recommendations were not implemented.
• “I wouldn’t do it [success tagging] because I’m busy. But [names another detective] is always giving me [expletive] about it, so sometimes I go back and try and do the [success] tags when I’m not too busy.”

Third, between December 2005 and February 2006, roughly 731 successes were reported relative to 1.8 million queries; or about one success per 2,500 queries. The successes were claimed by approximately 115 (7%) of the system’s estimated 1,600 users during the period (FINDER, 2006). It is possible that these 115 success-reporting users were the only users having success. This seemed unlikely in light of the focus groups’ experiences and anecdotal success reports.

Thus, success tagging records were suspected to be incomplete and, alone, not logically or statistically sufficient to support hypotheses testing. However, surrogate success measures were considered. These included:

• Through a user survey, capture success (or performance) *expectations* as a proxy for actual successes.

• Through a user survey, attempt to determine the relationship of actual successes reported to actual successes experienced, and weight reported successes accordingly.

• Create a composite success measure using a combination of reported successes, user expectations, and actual usage data.

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5 The author handwrote focus group comments during the session and confirmed accuracy of the transcription with those making the comments.

6 The author and FINDER staff were frequently informed of successes that were not reported via the success tagging feature.
- Develop a success construct through a confirmatory factor analysis using reported successes, user expectations (or estimates) of success, and actual usage data as the component indicators.

These four, surrogate (or proxy) measures are not all-inclusive. However, they did provide a foundation to consider alternatives to the objectively-measured success tagging reports.

The first option is suggested by Goodhue (1995) in conjunction with TTF measurements that capture the user’s expectation of success. Goodhue explicitly recognizes the weaknesses inherent in substituting the user’s performance expectations as a “surrogate” for actual performance (p. 105) but notes that there is often no other option in applied research.

The second option encompasses both an objective measure of success and the user’s recall of unreported successes. If users (via survey) generally recall, say, five unreported successes for every one success they reported, the objective (success-tagging) measure could be multiplied by five to estimate a success level. While this option incorporates some degree of objectivity, the use of subjective, user-recall data may produce questionable results (e.g., Zaworski, 2004).

The third option incorporates known levels of reported successes, known levels of usage, and/or other factors into a summative index. Summative indices are mathematically convenient when based on solid measurement criteria; scales require substantial theoretical, logical or expert grounding (Babbie, 1995). However, some researchers have suggested that a combination of scaled or indexed measures may be the best way to get at a valid (but not entirely objective) technology performance metric. For example, intended use and/or actual usage data has considerable support as valid proxy measure for user-level performance (e.g., Legris et al, 2003) and could be conceptually defended as a component of a success scale. However, scales built on
cumulative values of different components do not necessarily capture the relative importance of its components (Babbie, 1995). Finally, no validated scale was identified that could be directly applied to this study.

The fourth option incorporates confirmatory factor analysis (CFA). CFA appears appropriate in this context since it is intended to “confirm” a theory-driven analysis (Kline, 2005; Maruyama, 1998; Thompson, 2005; Wan, 2002). User-level success can be conceptualized as a theoretically-supported construct that is measured through indicators including actual success, usage, user intentions, and user expectations.

The CFA approach has the advantage of assigning standardized coefficient estimates to the indicator variables. The standardized estimates report the relative magnitude of the indicators’ influence on the success construct. For example, Goodhue (1998) employed CFA in his examination of TTF factors across a wide domain of business technologies, but he did not address a performance metric in that analysis. However, some researchers believe that factor analyses are frequently misapplied and misinterpreted (Hurley et al, 1997). The TTF theory and FINDER task-fit measure required further investigation and analysis to support a CFA (Goodhue & Thompson, 1995; Goodhue, 1998).

The potential weaknesses associated with success tagging as an exclusive, empirical measure were carefully considered in the design of this study. Alternative success measure items were incorporated in the user survey instrument (see Chapter 3) with the intent that a credible success measure could be constructed should success tagging, alone, not be adequate.
Finder task-fit

Goodhue (1995, 1998) and Goodhue and Thompson (1995) developed an instrument intended to measure twelve dimensions that capture how a specific technology fits the user’s task needs and environment. The measure of task-fit in this study, which was borrowed from Goodhue’s model and was influenced by Zaworski’s (2004) expansion of that model, was labeled "FINDER task-fit." The FINDER task-fit label was intended to clarify that it is a measurement representing a distinct adaptation of Goodhue’s instrument; specifically modified for the FINDER-based study. Goodhue acknowledged that such adaptations of TTF would be necessary in different information system domains, and Zaworski used a TTF adaptation in his comparative study of police information sharing.

Goodhue’s (1995) twelve TTF dimensions include (broadly) ease of use, value to user, compatibility to user needs, flexibility, and system reliability. While Goodhue (1998) found the TTF measure a valid predictor of users’ expected system use and performance gains, he did not link expectations to actual performance. Further, Goodhue noted that validity-testing was limited to a corporate environment and was not necessarily generalizable.

The FINDER task-fit measure was conceptualized as a numerical value derived from a summative index of component, task-fit indicators. The index’s components and conceptual relationships of FINDER task-fit dimensions to Goodhue’s (1995) TTF dimensions are discussed in detail in the “Instrument” section of Chapter 3.

Usage rate

Goodhue’s (1995) TTF model seeks to explain performance in terms of task fit and system use (see Figure 3, p. 34). In the TTF model, system use is presented as intended use and
as being positively related to expected performance. As previously noted, intended or expected system use is frequently used as a surrogate measure for performance or success (Davis, 1989; Goodhue & Thompson, 1995; Nunn & Quinet, 2002). Logically, if users have a choice, why would they use a technology system that did not generate some form of success?

However, assuming a positive relationship between usage and success could be misleading. For example, a user who is required to use a specific system may, effectively, have no technology options, or a user may have access to only one system. Alternatively, the user may have the choice between many similar or complementary technologies. If there are no alternative technology choices available to the user, or use of a particular system is required, usage levels of that system may be high, even if success with that system is low. If multiple systems are available, use in any one system might be low depending on that user’s task needs relative to the task needs of and systems available to other users. In addition, high levels of usage may indicate the user is untrained and inefficient, or that the system is inefficient. Conversely, low levels of usage may indicate very effective users and a very efficient system (e.g., Goodhue, 1995, 1998; Goodhue & Thompson, 1995).

On the other hand, police users consistently report they would use a system, if it enabled success, regardless of system difficulty or complexity (e.g., Colvin & Goh, 2005; Lin, 2004). Essentially, and importantly, a complex mix of contextual factors appears to be important to the interpretation of system use. These factors include the user environment, technology, and pragmatic results of system use. This mix of factors affecting system use is modeled, but not explained, in the TTF framework (Goodhue, 1995, 1998; Goodhue & Thompson, 1995).

Another aspect of assessing system use relative to performance may be related to the cross-sectional approach used in prior research (Goodhue & Thompson, 1995; Nunn & Quinet,
FINDER focus groups asserted that their continued use of the system reflects their success experience and expectations. This suggested a time-variant approach to usage that is logical and supported by research (Venkatesh & Davis, 2000; Venkatesh et al, 2003).

A simple measure of usage is the number of FINDER queries made by the user during a given time period. However, query volume alone lacks face validity as a measure. For example, two users might have each made one hundred queries during a six-month period after joining FINDER. Thus, a resultant cross-sectional analysis would find these two users were not different. However, if one user initiated all one hundred queries in the first week and not thereafter, it might be concluded that this user experimented with the system and, finding it unhelpful, never used it again. Alternatively, if the second user queried FINDER at a steadily increasing rate over the six-month period, it would seem this user’s needs were being met – evidenced by continuing and increasing use – and a stronger claim of the usage/user-level success relationship might be supported.

All other influences held constant, the TTF framework suggested the best system use measure as usage rate over time versus a cross-sectional “snapshot.” Further, as the examples above indicate, the change in usage rate over time could be important (i.e., is usage increasing, stable, or decreasing?) Therefore, in order to capture usage as a meaningful measure, usage rate was conceptualized as a mathematical function of individual user query volume, time period, and change over time. With the potential of confounding effects in mind, and with the support of the literature and FINDER users’ input, the usage rate was proposed as being positively related to user-level success.
**Computer expertise**

The TTF model (Goodhue, 1995) suggests “individual characteristics” are important in considering task fit. Goodhue described individual characteristics, conceptually, as the user’s familiarity with basic computer functions, or “computer literacy” (p 1836). Computer literacy is, presumably, indirectly captured in TTF instrument questions that relate to perceived ease of use or usability, but Goodhue used just a single survey item (familiarity with word processing and spreadsheets) as a computer literacy indicator.

In addition, the author’s experience and focus group observations suggested that the computer expertise influence on usage and success might be important. Some users just seem to embrace and successfully use technology much more quickly than others. Thus, this study used a **computer expertise** measure. The measure is informed by the TTF instrument, Davis’ (1989) Technology Acceptance Model (TAM), Venkatesh and Davis’ (2000) TAM II, and a review of the computer literacy literature. Zaworski’s (2004) computer expertise terminology was borrowed for its existing use in the police information sharing context. This term is used in place of “computer literacy,” which encompasses a large body of study (e.g., Kim & Keith, 1994; Smith, Caputi, & Rawstorne, 2000). The computer expertise measure was conceptualized as a numerical value derived from a summative index of items collected by the user survey.

**Job assignment**

The TTF model incorporates “task characteristics” into the task technology fit construct. Goodhue and Thompson (1995) assessed the effect of task characteristics on the task technology fit by classifying users into broad job-assignment categories (e.g., administrative, managerial, executive). Clearly, “tasks” are an important component of a model that considers the
relationship between technology and its fit to the user’s tasks. This relationship has been empirically validated, but tests of TTF have been across dissimilar business environments, and the instrument was developed with diverse business applications in mind. Goodhue notes the lack of job-specificity in the TTF instrument as a limiting factor in its application elsewhere (Goodhue, 1998).

The FINDER context provided an opportunity to focus the task characteristics construct. FINDER’s relatively homogenous, police context permitted greater specificity in defining task characteristics. Rather than incorporating generalized task sets in the analysis, task characteristics were operationalized by identifying the user’s job assignment.

Assessing and understanding the influence of the FINDER user’s job assignment on that user’s success level was extremely important. For example, does FINDER help resolve large volumes of barking dog complaints (by identifying dog owners) but not provide much value in homicide investigations? Does FINDER help solve child rape offenses and identify emerging terrorist organizations while lending little value to investigating people who make-off with grocery shopping carts?

If the policy goal is to fight terrorism, then FINDER (and similar systems) must be designed to support the needs of intelligence officers. If the goal is to enhance sex crimes investigations, then FINDER (and similar systems) must also be designed to meet sex crimes detectives’ needs. Because information sharing has not generally been available to either intelligence officers or sex crimes detectives in the past (or to any other officers), the kinds of information they need, the form of the information, and how (and if) they can use the information successfully has not been established (BJA, 2005).
Two challenges were anticipated in the inclusion of a job assignment variable in this study. First, capturing “job assignment” in an empirical analysis was expected to be problematic. There were hundred of possible job titles among FINDER’s users that the user survey would capture as nominal data. However, the literature provided guidance in cataloging police job titles into sets that lend themselves to analysis (Fyfe et al, 1997; Commission on Accreditation of Law Enforcement Agencies [CALEA], 1998). It was anticipated that FINDER users’ job titles could be collapsed into meaningful sets suited to empirical analysis.

Second, the TTF model does not specify a direct effect of task characteristics on success or system use. As the TTF model reflects (Figure 3, p. 34), task characteristics have a hypothesized, direct effect on task-fit; task-fit then has a direct effect on both system use and individual performance. Thus, strictly construed, the TTF framework does not predict the effect of job assignment on the performance measures. However, neither does TTF assume that actual successes, actual usage, or specific job assignments are being measured. In addition, other researchers have demonstrated a direct effect of users’ tasks on intended use or expected performance gains (Colvin & Goh, 2005; Lin, 2004; Zaworski, 2004). Thus, the FINDER user’s job assignment was conceptualized as an independent variable, with direct effects predicted on the FINDER task-fit measure, system usage, and user-level success.

**FINDER training**

The influence of user training on TTF, system use, or performance is not specifically addressed in the TTF model. The literature (Goodhue, 1995, 1998; Goodhue & Thompson, 1995; Davis, 1989; Legris et al, 2003) suggests that user training may be encompassed by technology acceptance and usability measures, but Zaworski (2004) found that several user-
Training indicators were independently significant to technology fit. Technology fit was expected to help predict both success and system usage.

The training variable in this study proposal was conceptualized as having a direct effect on both usage rates and user-level success. The indirect effect, as noted above, is supported by the Goodhue (1995) model. The direct effect was indicated by FINDER-specific anecdotal evidence in combination with a preliminary analysis of use and success data.

The anecdotal evidence arose from a training program that was developed for FINDER users. The trainers, who informally monitored usage and success data, perceived that both usage and reported successes rose almost immediately after users attended the training (J. McClure, personal communication, December 2005). A preliminary review of the query log and success-tag data suggested this perception was accurate, and data was available that outlined if, and when, specific groups of users received training. However, the FINDER training curriculum emphasized success tagging and innovative use of the FINDER system. Thus, it was not known whether training actually influenced usage and success versus simply influencing the users’ probability of reporting successes. In addition, it was not known whether any gains in success experience due to training were sustained over time.

Regardless, the literature supported FINDER-user training as an independent variable that might indirectly influence both system use and success. The best objective evidence (query logs and success reports) suggested a direct effect as well. Thus, FINDER training was included in the research model. Training was operationalized as a dichotomous variable reflecting whether the user had received the training.
Control Variables

The literature suggests several variables that are not of primary interest for predictive value in the proposed framework, but they must be considered in order to help control for confounding effects or assist in identifying spurious relationships (Senese, 1997). The control variables in this study were identified as the user’s law enforcement experience (Zaworski, 2004), the user’s time as a FINDER user, the user’s agency name and agency size (Davis, 1989; Goodhue, 1995, 1998; Legris et al, 2003; Zaworski, 2004), the user’s workload, and the user’s access to other technology (Goodhue, 1995, 1998; Goodhue & Thompson, 1995).

Experience

Zaworski’s (2004) study found that users’ law enforcement tenure was significantly related to their task-fit measures in an information sharing environment. However, while the users’ task-specific experience levels might be considered part of the “other factors” or “individual characteristics” constructs of the TTF framework, TTF does not specifically link a user’s experience (tenure on the job) to the interaction of technology and task. In other words, the influence of the user’s job experience on task-fit, use, or performance is not specifically hypothesized by TTF.

Logically, in the FINDER and police contexts, an experienced police officer should have higher levels of success than the inexperienced officer; with or without FINDER. However, studies of the relationship between law enforcement experience and technology have shown mixed results (e.g., Danziger & Kraemer, 1985; Zaworski, 2004). Thus, law enforcement tenure (years of law enforcement-related experience) was incorporated as a control variable in this study’s design. The inclusion of this variable was believed necessary to control for differences
in user-level success that could be attributed to user-level proficiencies that were not related to FINDER.

**Time as user**

The inclusion of a time-as-user control was based on the same logic as the law enforcement tenure control variable. Logically, users with more experience using FINDER should have higher levels of success. However, Goodhue and Thompson (1995) and Venkatesh and Davis (2000) found negative relationships with system use from users who, they speculated, were more experienced with the technology or, due to reliance on the technology, more sensitive to any system shortcomings. These findings suggest it is possible that the more seasoned or sophisticated technology users are more difficult to satisfy. Thus, the user’s time as a FINDER user was considered important to control for variances (in either direction) in task fit, usage, or success.

The “time as FINDER user” variable was operationalized as a scale measure. The measure was proposed as the number of weeks since the user first logged-into the FINDER system. These data were available through the FINDER query logs.

**Agency name**

The user’s agency (identified by agency name) was included to represent the user’s general task environment. This variable was envisioned as indirectly capturing the subjective norms and other contextual influences suggested by the TTF model. As a practical matter, it was recognized as unlikely that the agency name could be used in a parametric analysis. This is a nominal variable and there were at least 120 agencies involved in FINDER. However, agency
name was expected to have value in non-parametric analyses. A preliminary review of usage and success data suggested that certain agencies produced high levels of both use and success reports. The author’s observations suggested that these high levels of usage and success reporting were due to the presence of a FINDER “advocate” in those agencies. Thus, exploratory value was associated with capturing the user’s agency name and, potentially, controlling for unique contextual influences associated with the agency.

**Agency size**

The user’s agency size (number of sworn officers) can be linked to the availability of technology resources and support in police agencies (Nunn, 2001). IT resources and support are believed to influence task-fit perceptions (Goodhue, 1995), and any influence on task-fit were important to recognize in the design of this study.

The inclusion of an agency size variable as an indicator of IT resources and support was expected to help control for related variances in task-fit measures. In addition, information about the user’s agency size was used to help assess the representativeness of user survey responses. This assessment was to be based on survey response rates that were proportional to the agency size distribution of those agencies involved with FINDER.

**Number of agencies sharing information**

In the TTF model, Goodhue (1995, 1998) discusses the effect of information from multiple systems on individual performance. In the corporate context studied by Goodhue, the multiple systems were intra-organizational (such as systems in different divisions of the same corporation) versus inter-organizational. The availability of information from a variety of
sources was considered particularly relevant to the non-routine users. Non-routine users were those who had the most complex task set and could require multiple technologies to satisfy task needs.

Although FINDER shares information inter-organization, there are clear parallels to Goodhue’s (1995, 1998) consideration of multiple systems and non-routine information use. By Goodhue’s definition, detectives and analysts would be non-routine users; clerks or data entry personnel would be routine users.

Given the distributed nature of FINDER’s Query Logs, the number of agencies sharing information can have a direct effect on Query Log reports of system usage. If a FINDER user makes a single query to \( x \) number of FINDER agencies, the Query Logs count that as \( x \) queries, because each agency is queried. If the number of FINDER agencies sharing information increases, then the value of \( x \) queries might increase equivalently; assuming that FINDER users always query all available agencies (FINDER, 2006).

However, it was not known whether FINDER users do, in fact, always query all agencies. The Query Logs did not provide an ability to determine the scope (number of agencies queried) of individual user queries, and casual discussions with users about this topic suggested considerable variance between and within users. Some users indicated they always query all agencies; some users indicated their query style is contingent on the information being sought in individual cases; and others described expanding, repeated queries until the needed information is found.

The variety of query styles combined with growing numbers of query potentials (the number of FINDER agencies) could skew user activity reports acquired from the Query Logs. The inclusion of a variable to control, at least, for the number of agencies available for queries
during a given time period was expected to reduce this skew. Thus, the number of agencies available to share information was incorporated as a continuously-measured control variable.

*User workload*

The tasks associated with a specified assignment can vary greatly in terms of workload volume (Fyfe et al, 1997; CALEA, 1998). A burglary detective may be assigned 300-400 cases a month; a homicide detective may have a single case a month. Further, a detective in a small agency may investigate all kinds of crime and have the general job assignment of “detective” versus specialized investigative assignments in a larger agency. The job assignment label does not necessarily reflect workload. Certainly, the same situation exists among workers with similar job titles outside of policing, but no consideration of workload *volume* differences has been found in the general literature. Thus, workload was included in this study for exploratory purposes.

The incorporation of a workload control measure in this study’s design was based on the logic that a user’s task-set or related behaviors are influenced by the user’s workload. It was believed that a workload influence might be particularly important in the relationship of task-fit indicators (job assignment and FINDER task-fit) to usage rates. In practical terms, a very busy detective might rely more on FINDER (in absolute terms of usage) for assistance than a less-busy detective. Alternatively, a detective who solves 10% of 400 cases assigned every month will potentially have many more chances for “success” than a detective who investigates and solves a much lower number of cases each month.

The job assignment and task-fit variables do not specifically capture task volume; nor is workload identified in Goodhue’s (1995) model. However, police literature has recognized that
police are inclined to record activities (tickets, calls for service, reports) as surrogates for productivity measures (Fyfe et al, 1997). The author’s observations supported this; it was expected that FINDER users would have reasonably-detailed workload (or caseload) data at hand. The availability of this kind of data was to be established through the user survey. If workload data were readily available, they could be collected for exploratory analysis in the TTF framework.

User technology options and voluntariness

The final control variable related to whether other information sharing technology was available to the user, and whether the user voluntarily engaged in FINDER use. The TTF model specifies a technology construct as predicting task fit. Technology, in this context, was proposed by Goodhue (1995) as the existence of technology options or the influence of voluntary (versus mandated) technology use. However, Goodhue offered few specifics about the theoretical technology link. The literature is vague as to the influence of either voluntariness or multiple technology options on user expectations, behavior, or performance. This is a complex issue with little understanding of its dynamics (also see Goodhue, 1998; Goodhue & Thompson, 1995).

When the influences of alternative technologies and voluntariness were considered in this study’s design, it was believed that the vast majority of FINDER users were voluntary users. Further, it was believed that no technology similar to FINDER was available, and that there were therefore no viable options to FINDER. However, it was recognized that users might believe FINDER to be interchangeable with other systems, and this could affect their use or task-fit perceptions. In addition, it was considered that a user survey could reveal that FINDER users believe FINDER is used most effectively in conjunction with or to complement other systems.
Multiple technologies have been compared elsewhere (e.g., Bharati & Chaudhury, 2004) but no research has been found that studies interaction effects in the type of context encountered with FINDER. Furthermore, Goodhue (1995) suggests the TTF analysis across multiple technologies is even more complex when the user is engaging in non-routine tasks. These are analytical tasks that require the use of inter-dependent information sources and are directed to diverse user objectives. On its face, the non-routine task definition seems applicable to the task-sets of FINDER’s police users.

In a multiple-technology study across different companies, Goodhue & Thompson (1995) employed a technology weight. The weight was simply one divided by the number of available technologies. The logic of this method was that the more technologies available, the lower the influence of any one technology. Goodhue and Thompson found this weight was statistically significant in that particular context, but suggested only that the inter-dependence of multiple technologies might be important.

Thus, absent clarifying theory or research about this topic, the direct influence of voluntariness or multiple technologies on either FINDER use or user-level success was dropped from the predictive model suggested by TTF. Two, exploratory measures were retained as controls. The first is a dichotomous measure of voluntariness (yes/no). The second was conceptualized as a weighted technology-option adapted from Goodhue’s (1998) user evaluation instrument and modified to the FINDER context. Table 4 on the next page describes each of the study variables discussed above.
<table>
<thead>
<tr>
<th>Variable Name/Type</th>
<th>Variable Type</th>
<th>Description</th>
<th>Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>User-Level Success/Dependent</td>
<td>Continuous</td>
<td>Number of successes reported by an individual user.</td>
<td>FINDER logs &amp; User Survey</td>
</tr>
<tr>
<td>Usage Rate/Dependent &amp; Independent (mediating)</td>
<td>Continuous</td>
<td>Individual user’s average number of FINDER queries per day during specified time period.</td>
<td>FINDER logs</td>
</tr>
<tr>
<td>FINDER Task-fit/Independent</td>
<td>Continuous</td>
<td>Scale value derived from modified TTF instrument. (Goodhue, 1995, 1998; Goodhue &amp; Thompson, 1995)</td>
<td>User survey</td>
</tr>
<tr>
<td>Computer Expertise/Independent</td>
<td>Continuous</td>
<td>Scale value derived from adapted from Goodhue (1995) and Zaworski (2004).</td>
<td>User survey</td>
</tr>
<tr>
<td>Job Assignment/Independent</td>
<td>Categorical</td>
<td>User-reported primary job assignment.</td>
<td>User survey</td>
</tr>
<tr>
<td>Workload/Control</td>
<td>Continuous</td>
<td>User-reported average monthly “workload” or “caseload” volume.</td>
<td>User survey</td>
</tr>
<tr>
<td>Training/Independent</td>
<td>Dichotomous</td>
<td>Yes/No whether user has received training from the FINDER staff.</td>
<td>User survey &amp; PSTC training records</td>
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<tr>
<td>Agency/Control</td>
<td>Categorical</td>
<td>Name of user’s employing police agency.</td>
<td>User survey</td>
</tr>
<tr>
<td>Time as LEO/Control</td>
<td>Continuous</td>
<td>Number of years user has been employed as a sworn law enforcement officer</td>
<td>User survey</td>
</tr>
<tr>
<td>Time as user/Control</td>
<td>Continuous</td>
<td>Period of time elapsed between first log-in as FINDER user (measured in days, weeks or months)</td>
<td>FINDER query logs &amp; User survey</td>
</tr>
<tr>
<td>Number of Agencies Sharing Info</td>
<td>Continuous</td>
<td>Number of police agencies sharing information via FINDER</td>
<td>PSTC &amp; FINDER Query Logs</td>
</tr>
<tr>
<td>Technology/Control</td>
<td>Categorical (possibly scale or ratio)</td>
<td>Other information sharing technology available to user (i.e., other system name). Alternatively, weighted value of technologies</td>
<td>User survey</td>
</tr>
</tbody>
</table>
Hypotheses

The primary research question was posed as: *What factors influence user-level success for FINDER’s users?* The Task Technology Fit (TTF) model (Goodhue, 1995) has been offered as the theoretical framework. Table 3 presented hypothetical relationships derived from the framework that can be explored in the FINDER context. These relationships provided the bases for testable hypotheses.

The variable of primary interest was user-level success. Thus, the preliminary set of hypotheses were oriented to independent variables that were proposed to have either a direct influence on success, or an indirect effect on success that is mediated by usage rates.

The theoretical framework and literature suggested that FINDER’s user-level success might be positively predicted by four variables. These variables were the user’s FINDER task-fit measure, the user’s FINDER usage rate, the user’s computer expertise measure, and the user’s receipt of FINDER training. The predicted effect of a fifth variable, the user’s job assignment, was non-directional. It was therefore hypothesized that:

- **H₁:** A FINDER user’s task-fit measure will be positively and significantly related to the number of successes reported by that user.
- **H₂:** A FINDER user’s usage rate will be positively and significantly related to the number of successes reported by that user.
- **H₃:** A FINDER user’s computer expertise measure will be positively and significantly related to the number of successes reported by that user.
- **H₄:** A FINDER user’s receipt of FINDER training will be positively and significantly related to the number of successes reported by that user.
• H₅: A FINDER user’s job assignment will be positively and significantly related to the number of successes reported by that user.

The theoretical framework and the literature also predicted that the FINDER task-fit measure, FINDER training, and computer expertise measure positively and directly predict usage rate. Job assignment, a categorical variable, was also proposed to have a significant relationship with the usage rate. Therefore:

• H₆: A user’s FINDER task-fit measure will be positively and significantly related to that user’s usage rate.

• H₇: A user’s receipt of FINDER training will be positively and significantly related to that user’s usage rate.

• H₈: A FINDER user’s computer expertise measure will be positively and significantly related to that user’s usage rate.

• H₉: A FINDER user’s job assignment, a FINDER user’s usage rate will be significantly related to that user’s.

Figure 5 depicts the conceptual relationships of these hypotheses in the TTF framework (the path arrows designate the relevant hypothesis).
Summary

This chapter has elaborated on the definition of low-level police information sharing and the importance of this type of information sharing to public safety goals. The paucity of police information sharing research has been explained, and the limited research available about this topic has been reviewed. Goodhue’s (1995) Task-Technology Fit theory has been described and its applicability as the framework for this study has been justified. The study variables, informed by TTF and other research, have been defined and generally operationalized. These variables were then incorporated into nine hypotheses.

Chapter 3 will explain the methods employed by this study to test the offered hypotheses. These methods include the design and execution of a FINDER user survey and, prospectively, how survey responses will be analyzed in combination with data from Query Logs, success reports, and other sources.
CHAPTER 3: METHODOLOGY

This chapter describes the methods employed to gather data for testing the hypotheses that were developed in Chapters 1 and 2. Nine hypotheses were offered with regard to relationships suggested by the Task-technology Fit (TTF) framework (Goodhue, 1995, 1998; Goodhue & Thompson, 1995). Empirical tests of these hypotheses required measurement data for the twelve study variables (see Table 4, p. 61). Seven of the study variables were to be measured exclusively through a FINDER user survey (discussed in the next section). The remaining five study variables were to be measured through a combination of sources.

The five variables whose measurements were derived either in combination with or from sources other than the survey were:

1. Usage rate
2. Number of agencies sharing information
3. Time as user
4. User-level success
5. Training

This section describes how data for those measurements were acquired from Query Logs, PSTC records, and success-tagging reports.

Query Logs

It has been previously noted that FINDER’s Query Logs capture detailed information about each query made by FINDER’s users. Access to FINDER was achieved through a police
agency computer that had been configured for that purpose. FINDER is available only via Florida’s law enforcement intranet and is not accessible to the public (PSTC, 2006c). The author’s role in the Florida Law Enforcement Data Sharing Consortium and sworn status with a Florida law enforcement agency enabled access to FINDER system logs and reports. Access for purposes of this study was endorsed by the Florida Law Enforcement Data Sharing Consortium (PSTC, 2006d).

FINDER connects police agencies via designated computer servers that are referred to as “FINDER nodes.” The node permits an agency or agencies to both contribute data to FINDER and retrieve data from other FINDER nodes. The node may provide information sharing capacity for a single agency or multiple agencies. Multiple agencies can share a node to reduce per-agency costs (PSTC, 2006c).

As of April 2006, there were 40 FINDER nodes providing *bi-directional* information sharing among 47 agencies. An additional 15 agencies were known to have “guest accounts.” Guest accounts are *not* bi-directional; that is, guest users can query FINDER, but their agencies are not contributing data to the system. Thus, a total of 62 agencies were known to have users making FINDER queries. An additional 59 agencies (for a total of 121) were involved with FINDER, but it was not known what role – if any – those 59 agencies had in terms of query activity (PSTC, 2006b). ¹

It is in the FINDER nodes that Query Logs are collected and stored. Each of the nodes records details about each query *into* that node. The nodes do not record information about queries going *out*. Each node stores this information apart from the other nodes. In other words,

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¹ At any given time, many agencies were in transition from conceptually agreeing to join FINDER, to formally agreeing to join, to actually sharing information. The number and status of involved agencies changed on an almost-daily basis and were reflected on the FINDER website.
there is not a central collection point for all FINDER query information. Thus, Query Log data for this study had to be extracted from each of the 40 FINDER nodes.²

The Query Log data were collected in the following fashion:

1. Each of the 40 FINDER nodes’ Query Log files were accessed through a FINDER administrative function.

2. The Query Log files were downloaded to display within the FINDER application. Each node, for each month between December 2004 and February 2006, required a separate download to the FINDER display.

3. Each downloaded display for the period was then copy-and-pasted into an Excel spreadsheet. This process created 600 Excel files (40 nodes x 15 months) that reflected a total of 1,836,236 query records. Query volume for the period, by node, is shown in Table 5 beginning on the next page. Those numbers shown in italics were believed to be inaccurate due to system corruption at the node level and will be discussed in detail in Chapter 4.

² The author is indebted to Mr. Kunal Motwani (kmotwani@mail.ucf.edu), FINDER’s lead software developer, for providing information about the FINDER system nodes and Query Logs. This information was provided by Mr. Motwani via numerous emails and conversations between October 2005 and April 2006.
### Table 5: FINDER Node Query Activity December 2004-February 2006

<table>
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<tr>
<th>FINDER NODES</th>
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<th>Jan-05</th>
<th>Feb-05</th>
<th>Mar-05</th>
<th>Apr-05</th>
<th>May-05</th>
<th>Jun-05</th>
<th>Jul-05</th>
<th>Aug-05</th>
<th>Sep-05</th>
<th>Oct-05</th>
<th>Nov-05</th>
<th>Dec-05</th>
<th>Jan-06</th>
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69
4. Each of the 1.8 million query records provided the following information:
   a. Internet Protocol (IP) address of the node originating the query
   b. Day of query
   c. Time of query
   d. User name
   e. Type of query (e.g., person, property, vehicle)
   f. Type of query subset (e.g., person/victim, property/pawned, vehicle/towed)
   g. Query parameters (the specific information sought)

5. The Query Log data were organized to identify each user’s FINDER usage volume per month for December 2004 to February 2005. During this process, 1,603 user names were identified and enabled measurement of the Usage Rate and Time as User variables.

A descriptive analysis of the Query Log data will be provided in Chapter 4.

Other PSTC Records

An examination of Table 5 demonstrates that many nodes reported no queries for long periods of time. The zero-query activity periods indicate that the node had not yet joined FINDER during the period for which the zeroes appear. For instance, Table 5 shows that the Leesburg PD node had no activity from December 2004 until December 2005, because the node did not become active until December 2005.

PSTC staff also record information related to the level and timing of FINDER agencies’ involvement in the system. One such record incorporates a list of FINDER nodes and the date that the node was enabled for FINDER access (K. Motwani, personal communication, March 14, 2006). When the PSTC node records are combined with the node-level Query Log data, the
necessary information for the *Number of Agencies Sharing Information* variable was confirmed.

The PSTC staff also maintained records reflecting the dates and locations of FINDER training sessions. Training records listed eight training sessions conducted throughout Florida, beginning September 2005 and ending February 2006 (J. McClure, personal communication, April 25, 2006). These records, in combination with related survey items, provided the data necessary for measurement of the *FINDER Training* variable.

**Success-Tagging Data Collection**

Success tagging data was more readily available than Query Logs. Success tag reports from all FINDER nodes were available on a month-by-month basis beginning in December 2004. These reports were downloaded to a FINDER display, and then copy-and-pasted to Excel spreadsheets. Reports were acquired for the December 2004 to February 2006 period. Each success tag report contains fields for the following information:

1. Report number (automatically populated reference number for the report that is the subject of the success)
2. Report date (automatically populated date of the report that is the subject of the success)
3. User’s phone number
4. Report Type (automatically populated type of report that is subject of success)
5. User’s name (not the system user name)
6. User’s email address
7. User’s comments/description of success
8. Date of success tagging
9. FINDER module used (i.e., pawn, persons, vehicles)
10. Data source (which node provided the “successful” data)

A total of 731 success reports were filed by 115 different FINDER users for the fifteen-month period. A descriptive analysis of these reports will be provided in Chapter 4.

**Instrument**

Eleven of the twelve study variables were captured either fully or partially through a self-report, web-based, FINDER user survey. This section will describe and justify the development of the user survey instrument. First, the general design and layout of the instrument will be discussed and supported. Second, the theory, concepts and principles employed in the construction of items and their response scales will be offered. Third, instrument pre-testing will be described.

**General Design and Layout Considerations**

Instrument design was based on guidance from faculty advisors, subject matter experts, a review of survey methodology literature, and the instruments used in related research efforts. In particular, Babbie’s (1995), Alreck and Settle’s (1995) and Dillman’s (2000) survey methodology work provided significant support in the instrument’s design. Also, Goodhue’s (1995,1998) TTF, Davis’ (1989) TAM, and Venkatesh and Davis’ (2000) TAM II instruments were important to informing the design. Finally, Ioimo’s (2000) and Zaworski’s (2004) TTF police-based surveys helped guide TTF-related adaptations to the FINDER user survey.
**The Web medium**

The research design for this project incorporated a web-based user survey for distribution to all FINDER users. The web-based approach was chosen as the sole method of administration (as opposed to paper or interview-based administration) for several reasons. First, and foremost, the identities and physical locations of the user population were not known. This, alone, precluded direct mailing or individually contacting potential respondents either initially or for follow-up reminders. Second, the “blind” distribution of paper surveys to all FINDER agencies was not viable. Such a procedure would have required distributing roughly 8,000 copies of the survey to the agencies (enough copies to distribute to, potentially, each employee of the FINDER member agencies) with the hope that FINDER users would somehow acquire a copy and respond. Third, FINDER users were known users of web-based applications (i.e., FINDER). It was therefore assumed that FINDER users would be comfortable with a web-based survey, and respondents’ comfort with the survey medium helps produce higher response rates (Babbie, 1995; Dillman, 2000).

**Survey introduction and access**

Dillman (2000) emphasizes the importance of immediately capturing a potential respondent’s attention and cooperation via an effective introduction to the instrument. This can be achieved by persuading the respondent that the rewards associated with completing the instrument outweigh any costs. Rewards can be self-serving or other-serving; costs include time, effort, and perceived risks of participation. Thus, a one-page survey cover letter was composed with the intended effect of convincing potential respondents that their “rewards” would exceed their “costs.”
The cover letter advised potential respondents that completing the survey would be very helpful in developing FINDER to better serve the respondent’s information sharing needs, and that a response would help the FINDER research team. The response of all FINDER users was asserted to be valuable, regardless of the respondent’s level of FINDER use or affinity. It was also noted that a survey response was estimated to take fewer than ten minutes of the respondent’s time. No tangible compensation was provided or offered to respondents. The cover letter addressed Informed Consent requirements and provided contact information for both the researcher and the Institutional Review Board. (see Appendix A for the cover letter, informed consent, and instrument).

Respondents were directed to the website where the FINDER on-line survey was located. The website could be accessed by clicking on a hyperlink contained in the cover letter. Alternatively, directions were provided for cutting-and-pasting the link to an Internet browser if the respondent’s computer, network or firewalls prevented direct access to the survey website.

Upon linking to the web survey, the respondent was asked to Login using his/her FINDER User Name. Each person authorized access to FINDER has a self-assigned user name. It is this User Name that links each user to specific system activity that is tracked through the FINDER Query Logs. However, because of FINDER’s distributed technology, there is no central database of FINDER users that directly links the User Name either to an identifiable individual or specific agency. ¹ Thus, the User Name login criteria protected against multiple survey responses by one individual and permitted linkage of the user names to their actual system use. The use of a control mechanism to prevent multiple responses from single individuals is standard survey protocol (Alreck & Settle, 1995; Dillman, 2000).

¹ Some users choose a variation of their actual name, or their agency email address, as their FINDER user name. In these cases, the user could be identified.
**Item layout and ordering**

Upon login, the respondent was automatically directed to the first web page containing survey items. The first set of items were intended to be “easy” response items that would apply to all respondents. One key to encouraging respondents to complete a survey is to initially engage them by soliciting responses to items that require a minimum of mental effort. The first set of questions may be the most important to achieving this (Dillman, 2000). Subsequent survey web pages were designed with a minimum of visual clutter and relatively small groupings of similarly formatted items. The groupings were composed either by the subject matter of the group, or the response style (e.g., agree/disagree or multiple choice), or both.

The grouping, or clustering, technique of similar subjects or response styles permits the respondent to focus more on the question asked than the presentation (Alreck & Settle, 1995; Babbie, 1995; Dillman, 2000). These style groupings also permit a minimal use of instructions to the respondent. The “cost” of mental energy to read lengthy or repeated instructions can cause respondents to quit before the survey is completed (Dillman, 2000).

The order of items in a survey can influence responses due to the respondent’s initiation, routine, and fatigue (Alreck & Settle, 1995). Each of these effects can cause the respondent to answer survey items in a programmed fashion without actually reading the question and considering the response. The initiation effect is attributed to the respondent “learning” how to respond through the first items. The bias is created when the respondent applies this learned response to later items. Bias due to routine can occur when similar-looking items appear together and the respondent answers them similarly. Respondent fatigue can occur when the number of items is too large. In this case, the respondent simply wants to be finished with the survey and answers questions without consideration of their content.
To avoid bias and error associated with item order in terms of overall layout, items were grouped (as noted above) by style and content. These groups were distributed within the instrument with the goal of achieving a balance between consistency of styles and variety of content. This balance was intended to maintain the respondent’s interest by avoiding a “routine” and minimizing the mental energy necessary to differentiate between response modes (e.g., check boxes, agree/disagree, drop-down windows). The FINDER instrument incorporated the liberal use of point-and-click responses and drop-down selections to minimize respondent effort and encourage survey completion. The flowchart in Figure 6 depicts the conceptual ordering of item groups in the FINDER instrument.

The ordering of items within the item groups is also important. Dillman (2000) notes that items should be ordered to improve recall by leading the respondent through a sequence of questions that help the respondent build an accurate recollection of the desired event. This cognitive and time-referent order of items helps prevent the type of respondent recall error that has been discussed relative to other police-user surveys (e.g., Zaworski, 2004). The FINDER user instrument employed cognitive design techniques in an effort to build greater accuracy in respondents’ recall of their successful FINDER experiences. In addition, within-group ordering incorporated a mix of positively and negatively-worded stems. A mix of positive/negative is desirable to help prevent bias or error caused by a routine of all-positive or all-negative questions (Alreck & Settle, 1995; Dillman, 2000).

The survey items were not numbered. Numbering is unnecessary and potentially distracting in the web format (the items have been formatted and numbered in Appendix A for convenience). Some of the items involved “skips.” Skips are branched or contingency questions that, in a paper survey, might appear as: “If you answered ‘No’ to Question 3, please skip to
question 9.” In paper instruments, skip questions require careful design to ensure that the respondent understands the directions (Alreck & Settle, 1995; Dillman, 2000). However, the FINDER instrument incorporated “auto-skips” that were performed automatically by the web survey software. These auto-skips were not visible to the respondents.
Figure 6: FINDER Survey Instrument Conceptual Flowchart
Web-based appearance

Dillman (2000) cautions against the overuse of graphics, animation, and sound in web-based surveys. Excessive web graphics distract the respondent from the task of focusing on answering questions. Further, some respondents may access the web survey via slow Internet connections. Graphics, animations and sounds consume considerable bandwidth and can cause malfunctions in the survey software for respondents who use dial-up or other low-bandwidth Internet access methods. Thus, graphics and animation were avoided or minimized throughout the instrument.

Dillman (2000) also warns that web surveys can take on different appearances between computers, computer monitors, and network operating systems. Problems such as misaligned columns and headings, word wrapping failures, and partial page displays due to different screen resolutions can frustrate the user. Thus, the survey cover letter and FINDER instrument were accessed and tested with a variety of email, browser, and hardware configurations to ensure proper presentation and display across the potentially disparate network domains.

Response styles and scales

The FINDER instrument contained 85 items. The response styles for the items were comprised of:

- 14 dichotomous check boxes
- 7 multiple choice check boxes (4 nominal & 3 ordinal)
- 5 drop down selections (3 nominal & 2 ratio)
- 56 agree/disagree (all 7-point Likert scales)
3 open-ended text
85 total items

As noted above, some of the items involved skips or branches. Depending on responses to the branched items, respondents were presented with a minimum of 49 items to a maximum of 75 items. The branched items are discussed in more detail beginning on page 84.

The FINDER instrument made considerable use of agree/disagree, 7-point Likert scales as in the example in Figure 7 below:

<table>
<thead>
<tr>
<th>Strongly Disagree</th>
<th>Moderately Disagree</th>
<th>Disagree</th>
<th>Neither Agree nor Disagree</th>
<th>Agree</th>
<th>Moderately Agree</th>
<th>Strongly Agree</th>
<th>Not Applicable</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>FINDER helps me do my job more efficiently.</strong></td>
<td>☐️</td>
<td>☐️</td>
<td>☐️</td>
<td>☐️</td>
<td>☐️</td>
<td>☐️</td>
<td>☐️</td>
</tr>
</tbody>
</table>

Figure 7: Example of Agree/Disagree Scale

Likert scales are frequently used in social science research because they are powerful and easy for respondents to understand (Alreck & Settle, 1995; Gliem & Gliem, 2003). Babbie (1995) notes the value of Likert-type scales as their “unambiguous ordinality” that reflects the respondent’s “relative intensity” of feelings about the topic (p 177). Gliner and Morgan (2000) assert that agree/disagree formats are suitable for social science research because they permit summated values of multiple items. Summated values are used as indicators to measure attitudes or perceptions about a theorized construct. Hasson and Arnetz (2005), however, warn that care must be taken in the development of Likert scale summated values, and it is important that the number of scale choices must be neither too little nor too much.
Since the FINDER instrument was intended to measure FINDER users’ perceptions about FINDER’s role in achieving user-level successes, the agree/disagree scale was indicated as the appropriate, dominant scale format. The 7-point, agree/disagree scale was reliably employed by both Ioimo (2000) and Zaworski (2004) in the police technology environment. In addition, the seven-point format is consistently supported by the literature. The respondent has enough scale-response choices to be reasonably selective, but will not be overwhelmed by too many choices as in a 1 to 10 or 1 to 100 scale (e.g., Cox, 1980; Hasson & Arnetz, 2005).

The scale in the FINDER instrument provided a midpoint choice of “neither agree nor disagree” rather than “neutral” or “no opinion” or “undecided.” Dillman (2000), particularly, advocates the use of the “neither agree nor disagree” as the midpoint label and suggests that “no opinion,” “neutral,” or “undecided” labels, where applicable, should be attached to the end of the scale.

Initial drafts of the FINDER instrument did not include “not applicable” in the Likert scales. Pre-testing these initial drafts established that, in the absence of a “not applicable” choice, respondents would choose the midpoint value (neither agree nor disagree) – even when the item was not applicable to them – rather than skip the item. There is a distinct difference, both conceptually and in terms of coding scale values, between neutrality regarding an item versus lack of applicability of that item. Because so little was known about the assignments and interests of FINDER users, it was not possible to design an instrument in which each item could be reasonably assumed to be applicable to every user. Thus, “not applicable” was placed as the end-point selection in the Likert scaled items.
Survey Items

The research question asks: What factors influence user-level success in the FINDER system? Goodhue’s (1995) Task Technology Fit theory has been employed to frame the research design and helped identify twelve variables of interest. Only one variable of the twelve, the number of FINDER agencies involved in information sharing, was not addressed by the survey instrument. Seven variables were measured entirely from survey response; the measures for the other four variables were derived from a combination of survey responses, automated FINDER logs, and various PSTC records. Appendix B shows the relationships between the study variables and specific survey items. These relationships are further discussed below.

User-level success (36 items)

User-level success was the outcome variable of primary interest and, thus, received considerable attention in the survey. The FINDER success tagging feature was described as the mechanism by which FINDER users reported FINDER-driven outcomes that were perceived as “successes.” It was noted that only about 7% of FINDER’s known users had reported successes, and that success reports were made in less than .05% of all FINDER queries. Several possible explanations were offered about the seemingly low rate of reported successes. However, the key issue was whether the reported successes represented all successes experienced by FINDER users, or just a subset of actual successes. The best pre-survey evidence (focus groups and observations) suggested the latter; that only a portion of actual successes had been reported via the success tagging feature.

The possibility of success under-reporting was believed to be the result of several factors. These included vague definitions of “success;” lack of familiarity with the success tagging
function; time lags between FINDER use and the success experience; inconvenience to and time required of the user to complete a success tag; and a perceived lack of user benefit from completing a success tag. With these factors in mind, survey items were constructed to establish whether success tagging data represented all successes and, if not, both the degree and causes of under-reporting.

The degree of success under-reporting, if any, was critical to this study (no evidence of success over-reporting had been found). Clearly, if this study employed an inaccurate measure of user-level success, it would be difficult to defend any assertion about factors influencing that measure. Therefore, a variety of items was composed with the intent to extract from FINDER users the information needed to compose credible measures of actual user-level success. These measures would be based on a combination of existing data and the survey responses.

To that end, a total of 33 user-success items were incorporated into the FINDER user survey (six additional success-tagging usability items were incorporated as controls related to FINDER Task Fit indicators). These items were tailored – with considerable overlap – to three success-reporting classes of FINDER users:

1. Users who were not familiar with the success tagging function and, thus, had not reported a success;
2. Users who were familiar with the success tagging feature but had not reported a success; and,
3. Users who had reported successes via the success tagging feature.

The survey flow chart in Figure 6 depicts item branching between the three success-reporting classes of users. Thirteen success-related items were addressed to users in all three classes, including the first seven items of the survey that sought a yes/no response to whether the
user had experienced any one of seven common, police success measures (e.g., arrest, case clearance, recovered property). As noted above, these seven items were believed to be “easy” responses that would quickly convince respondents that the survey addressed realistic policing outcomes. In addition, if a respondent other than the 115 or so who had completed success tags answered “yes” to any of the first seven success measures, the belief that successes had been under-reported would be immediately confirmed.

Five additional success-related items were provided to all users. These items queried user experience in terms of performance gain, efficiency, and user recall as to specific successes. A sixth item initiated the first branch by asking respondents if they were familiar with FINDER success tagging feature. If the answer was “no,” the respondent would be skipped to the end of the survey. Respondents who answered “yes” were then asked if they had used the success tagging feature, and the response to this question initiated the second branch of items.

Respondents who were familiar with success tagging but had not used it were automatically skipped to a set of six additional items. These items sought to determine why the respondent had not used success tagging and, if applicable, the level of reported/unreported success. Respondents who had used success tagging were automatically skipped to fourteen additional items. Since this class of respondents was known to have reported successes, several items focused on their definitions of success and sought to determine if their successes were under-reported. In addition, the effect of training on their success reporting was addressed, and an exploratory question was asked to get a sense of whether this success-reporting class believed that other users were experiencing successes that were not reported.
**FINIDER task-fit (20 items)**

The literature review described Goodhue’s (1995, 1998) and Goodhue and Thompson’s (1995) development of the Technology Task-Fit theory and measurement instruments. It was noted that TTF instrument validation has taken place in corporate environments using broad, user task-set categories. Importantly, Goodhue (1995) noted that the TTF instrument described a link between technology, task-fit, and *expected* performance gains. Goodhue suggested that future research should look at *actual* performance gains in relationship to task-fit measures.

Ioimo (2000) and Zaworski (2004) modified items from the TTF instrument for application in a police technology environment. Their evaluation of objectively-measured performance gains, however, focused on aggregate, versus individual, objective performance measures. This study had the advantage over prior research in that a set of individual, actual performance data was available via success tagging logs. Thus, the FINDER survey instrument modified Goodhue’s (1995, 1998) instruments to a greater degree than those of Ioimo and Zaworski. The availability of objective performance (user-level success) data enabled tighter focus on task-fit issues. This focus was intended to develop task-fit measures for the users of a specific technology – FINDER – as opposed to Goodhue’s approach to technology, generally.

The FINDER Task-Fit items are loosely designed around Goodhue’s (1995) original task-fit dimensions. However, it is explicitly noted that the FINDER study uses TTF as a guiding framework and is not intended to either test or empirically validate Goodhue’s work. Thus, only a subset of Goodhue’s (1995, 1998) theorized task-fit dimensions are addressed in the FINDER items. The primary dimensions of interest are usability, ease of use, and usefulness of data. Secondary measurement dimensions are locatability of data, level of detail, accessibility, reliability and the distinction between routine and non-routine use.
As noted above, survey items were tailored to respondents in three success-reporting classes. In terms of FINDER task-fit, respondents in all three classes were presented with 13 items. Respondents in the class of users familiar with success tagging, but who had not reported any successes, were branched to an additional four items that relate ease of use to success. Respondents in the class of users who had reported successes were branched to three additional items that relate ease of use to success. The task-fit dimensions addressed by each item are depicted in Appendix C.

**Computer expertise (3 items)**

Technology users who are able to use their computers to complete their job tasks can be considered computer literate (Kim and Keith 1994). Zaworski (2004) operationalized computer literacy in the police information sharing environment as “computer expertise” (p 117) and incorporated related items in his survey instrument. Zaworski’s items were borrowed, with minor modification, for the FINDER survey. These three items assessed the respondent’s general comfort with learning new computer programs, and whether the respondent is treated as an informal computer trainer or expert by co-workers.

**Usage rate (1 item)**

The single survey item associated with the usage rate variable is exploratory. As noted earlier, objective usage information was extracted from FINDER User Logs. The exploratory item will enable comparison of actual usage rates to the user’s self-reported usage level.
**Job assignment (6 items)**

The nature of the user’s job assignment was captured by several nominal response items (sworn/non-sworn, job title, rank, function). The multi-item approach to job assignment was necessary because nothing was known about the composition of job assignments among FINDER users (other than they worked for police agencies). Absent prior knowledge about job assignments, these items collected task-set indicators from the broad (title) to the dichotomous (sworn/non-sworn). The intent of these items was to develop as narrow a definition of job assignment as the user composition and data permitted. The absence of narrowly-focused task-set or job assignment data has limited the value of prior task-fit research (Goodhue, 1995).

In addition, these items included a search for indicators of the user’s mix of routine and non-routine tasks. The information technology needs of users with routine task sets is believed to be different from those with non-routine task-sets. “Non-routine” users are envisioned as having greater analytical (versus administrative) tasks that increase or complicate information sharing needs (Goodhue, 1998; Goodhue & Thompson, 1995; Zaworski, 2004).

**Workload (3 items)**

The research model conceptualizes the user’s workload as a control variable. It has been posited that individual workload could influence task-fit, usage, and success independently of the theoretically-predicted effects. Further, it was proposed that law enforcement employees are likely to maintain personal workload records that are relevant to their assignments.

Workload data was sought via three, branched survey items. The first item asked if workload data was maintained; if yes, the second item classified the type of data; and the third
item asked the user to estimate monthly workload in terms of the user’s workload measure. These items were exploratory.

**FINDER training (2 items)**

The user’s completion of FINDER training was a “yes/no” item. An additional agree/disagree item (whether more training is needed) was included for exploratory purposes.

**Agency (4 items)**

The TTF model predicts that un-specified “other” user characteristics influence technology use and individual performance. The literature indicates that these other characteristics can be related to the user’s work environment and normative influences (e.g., Davis, 1989; Dishaw & Strong, 1999; Goodhue, 1995; Goodhue & Thompson, 1995). Normative influences may be time-sensitive (Venkatesh & Davis, 2000) and anecdotal evidence indicates that the presence of a FINDER “advocate” in specific agencies may influence user behavior. Further, it has been suggested that police agency size and resources can affect the viability, technological and management support, and user acceptance of technology (e.g., Nunn, 2001).

The four survey items related to the Agency variable sought to identify the name of the user’s agency, the type of agency (e.g., police, sheriff, state), and the influence of a FINDER advocate (if any). The agency name (many categories of nominal data) was not suitable for inferential analyses, but agency size can be derived from the agency name.
**Time as law enforcement officer (1 item)**

Prior research has found different effects of users’ law enforcement experience on their perception of police technology systems (Ioimo, 2000; Zaworski, 2004). This variable was included as a control in the research model. A single item captured the respondents’ number of years of law enforcement-related experience.

**Time as FINDER user (1 item)**

The literature contains a variety of findings about the influence of a user’s experience (in terms of time as user) on that user’s evaluation of and expected performance gains from that specific technology (e.g., Goodhue, 1998; Venkatesh & Davis, 2000). In this study, user experience – or time as a FINDER user – has been modeled as a control variable. Objective, user experience data was available through FINDER’s automated Query Logs. A single survey item asked the respondents when they began using FINDER. This item was exploratory (i.e., user recall versus objective data) but also served as a redundant check against the possibility of the user having been a FINDER member under multiple user names.

**Technology (5 items)**

It has been previously noted that the user’s access to alternative (or competing) technologies can influence that user’s perception of the value of any given technology. In this study, the availability of alternate technology is incorporated as a control variable that also offers some exploratory potential. Goodhue (1995) included the alternate-technology variable in the expanded TTF model that has been used as the framework for this research, but noted that the influence of alternate technologies is a complex and poorly understood component of the model.
Goodhue accounted for alternate technology simply by counting the number of software applications available to the users in his study. However, this method was applied in just a few homogenous organizations where, plausibly, the count of available technologies was consistent across the user group. In comparison, the FINDER context is much different since it studies over 120 organizations that have disparate technologies. In fact, FINDER was created to help bridge these disparities (PSTC, 2006c).

Zaworski (2004) reported that police users (regardless of access to an information sharing system) sought information from a variety of automated sources. The author’s experience also suggested that police agencies have a wide variety of stand-alone information systems. These systems serve specific purposes for limited access by specific user groups (e.g., gang database, domestic violence injunctions, and drug intelligence). Thus, the concept of alternate technology is *user-specific*. A gang crimes investigator may not know about nor have access to the domestic violence database and vice versa. Therefore, the survey items related to the availability and value of technologies other than FINDER are specific to that user’s perception.

The five survey items related to alternate technology sought to identify whether the user believed alternate technologies were available; whether the user employed alternate technologies; the value of FINDER relative to alternate technologies; and whether the user’s FINDER use was voluntary or mandated.

*Miscellaneous items (3 items)*

Three survey items address administrative and follow-up issues. One item controlled for the existence of multiple user names by the same respondent, one item asked whether the
respondent would be agreeable to follow-up contact by the researcher, and one item permitted open-ended, text comment.

**Instrument Pre-testing**

Pre-testing surveys can provide information that helps increase the survey response rate and ensure that the survey obtains the information it is intended obtain. If the survey instructions are too difficult for respondents to understand, or if the survey questions are open to misinterpretation, the response rate will suffer and the actual responses may not answer the necessary questions (Alreck & Settle, 1995; Babbie, 1995). Survey pre-testing can help avoid these types of problems.

Dillman (2000) provides a four-stage guide for survey pre-testing. These four stages are:

1. Review by knowledgeable colleagues and analysts;
2. Interviews to evaluate cognitive and motivational qualities;
3. A pilot study; and,
4. A final check of the instrument.

Dillman’s recommendations, with the exception of the pilot study, were used to pre-test the FINDER user survey instrument.

First drafts of the FINDER instrument were provided to a review group that included faculty advisors, graduate students, and law enforcement practitioners. The members of this review group were familiar with FINDER and the purpose of this study. A number of suggestions resulted from this review and changes were made to survey layout, instructions, wording, content, and scales.
The revised instrument was then presented to ten law enforcement practitioners who were familiar with FINDER but had not had prior exposure to the survey. A paper version of the survey was handed to this group of ten respondents with the simple request to “please take it.” The group complied and suggested additional revisions; primarily revisions to ensure applicability across sworn and non-sworn users. In addition, the observation of this group indicated that the survey could be completed in less than ten minutes.

The subsequent revisions were then incorporated into the web-based version of the survey that would be taken online. The online survey was then provided, on a person-by-person basis, to two new groups of five people each. Members in both groups were familiar with FINDER (or actual users) and were generally familiar with the purpose of this study.

The five members of the first group were asked to take the online survey either with the author present or in constant telephone communication as part of a “think-aloud” interview (Dillman, 2000, p. 142). As these five respondents went through the survey, they vocalized their thought about format, style, instructions, and each item. Dillman describes this as part of the cognitive interviewing pre-test stage.

The five members of the second group were asked to take the survey without interruption. Immediately upon completion, they were asked for their perceptions about format, style, instructions, and the clarity or content of the items. This process is the retrospective technique and is believed to have particular value in assessing the ease with which the survey can be taken (Dillman, 2000; Fowler, 1993).

The ten members of the second pre-test group offered valuable feedback; particularly with regard to the visual layout of scales and lists of items. In addition, this group observed that two of the items encompassed multiple topics and suggested that these items be separated into
five, distinct items. All of the second group’s recommendations were implemented.

The final review of the instrument was conducted by eight new reviewers. Five of these reviewers had no prior experience with either FINDER or the survey. These five reviewers were used primarily as proofreaders; Dillman (2000) suggests that a fresh review such as this is critical in catching typographical and formatting errors. The final three reviewers were FINDER practitioners who had participated in the review of earlier instrument versions and provided the final, pre-distribution evaluation of the survey.

A pilot study was not used to pre-test the instrument. It is noted, however, that the FINDER instrument was reviewed and/or pre-tested by more than forty people. Generally, pilot studies are administered to a sample of 100 or more respondents believed to be representative of the larger study’s sample population. The pilot study provides the survey to the pilot sample in the same fashion intended for the main survey. Pilot survey responses can be statistically analyzed to help uncover any problems before administration of the main survey (Dillman, 2000).

However, pilot surveys can be expensive and time consuming, and Dillman (2000) notes that the type of full-scale pre-testing suggested by the pilot survey is rarely completed in practice (also see Alreck & Settle, 1995; Fowler, 1993). Most important to the pilot study concept, this study did not have the ability to identify a pre-test, pilot survey sample. Sampling limitations will be more fully discussed in the next section.

Sample

A frequent goal in research projects is the attempt to gain understanding about some aspect of a larger population (whether a population of people, organizations, or any other unit of
study) by studying a subset of the larger population. Theoretically, conclusions about the larger group (populations) can be made based on observations of the smaller group (the subset). This subset is characterized as a “sample” of the population of interest (Alreck & Settle, 1995; Babbie, 1995; Fowler, 1993; Morgan & Gliner, 2000; Senese, 1997).

The definitions of terms used in the sampling discussion are borrowed from Morgan and Gliner (2000, chap. 10). The theoretical or target population includes all participants of interest and represents the group to which the researcher hopes to generalize research findings. The accessible population or sampling frame incorporates those members of the target population to whom the researcher has access. The selected sample is a subset of the sampling frame and represents members (or units) of the sampling frame that are selected to participate in the study. The actual sample is comprised of the members (or units) of the selected sample from which, ultimately, the study data is acquired.

The cases, participants, or elements of a sample are the individual people, objects or events that are being studied. These are also referred to as the units of analysis (Babbie, 1995). The units of analysis in this study were the individual FINDER users. The target population was all FINDER users. The sampling frame was all FINDER users who had used the system between December 2004 and February 2006; this was the period for which Query Logs and success tagging reports were available. The selected sample was equivalent to the sampling frame; it included all users of record for the fifteen-month period. The relationships of population, sampling frame, selected sample and actual sample are depicted in Figure 8. The actual sample results are reported in Chapter 4.

The critical factor in choosing a valid sample is that the sampling frame group must be representative of the relevant characteristics, or parameters, of the target population. Therefore,
the researcher must identify the population parameters that are relevant to the study and build a sampling method to capture these parameters within the sample. This can be accomplished through probability theory, logic, or research expertise (Alreck & Settle, 1995; Babbie, 1995; Fowler, 1993; Morgan & Gliner, 2000; Senese, 1997).

The use of a web-based survey instrument was identified as a critical data collection tool in this study. This sampling methodology addresses the distribution of the survey to FINDER users who are believed to be representative of all FINDER users. This Section will address the development of a probability sample from the population of FINDER users. First, the target population will be described and its relevant, known parameters will be described. Second, the sampling frame will be identified. The sampling frame will be shown as equivalent to the selected sample. Third, the execution of the sampling process – the actual distribution of surveys to the selected sample – will be outlined.
**Target Population and Relevant Parameters**

Researchers frequently fail to specify their target populations and the research reader must try to infer the subject of generalizations from the sample (Babbie, 1995; Morgan & Gliner, 2000). In this study, the target population was all users of record of the FINDER police information sharing system between December 2004 and February 2006. It has been noted in prior pages that generalizations arising from this study are limited to FINDER users. Non-users
are not being studied, and no comparison is being made between FINDER and any other information sharing system.

When clearly defined, relevant population parameters can be compared with like parameters in the actual sample drawn from the population (Morgan & Gliner, 2000). The known parameters in this study have been previously described as FINDER users and their agencies, system use, and reported successes. The characteristics of these parameters are elaborated below.

An analysis of FINDER Query Logs identified 1,603 user names that had been used for login to FINDER during the specified period. In addition, the Query Logs associate the user name with a FINDER agency via the FINDER agency’s unique IP (Internet Protocol) Address. Success Tagging logs identify the users (and their agencies) that have reported FINDER successes. Technically, the user name and IP associations should form a conclusive list of users and agencies that comprise the target population. However, some obstacles to the formation of the user list became apparent during this study. Problems with sampling lists used in applied research are a frequent occurrence (e.g., Babbie, 1995; Morgan & Gliner, 2000).

Four obstacles affected the ability to accurately define the FINDER target population and its relevant parameters. First, the technology architecture of FINDER places control of FINDER access at the agency level. A FINDER Administrator at each agency determines who will be authorized access to FINDER via that agency’s network. Local agency network security processes aside, since FINDER is a web-based technology, anyone with law enforcement clearance, Internet access, and authorization from a FINDER agency’s administrator could
obtain FINDER access. Thus, responsibility for the composition of the user population rests almost entirely at the local agency level.  

Second, FINDER users might share their user name with other law enforcement personnel and a single user name could actually represent many users. Third, users can change their user names. These changes would not be known to anyone but the FINDER Administrator in that user’s agency. In this case, multiple user names might actually represent a single user. Fourth, Query Logs are a product of each FINDER agency’s local network. If that network has technical problems, the Query Logs can become corrupted. When this happens, the logs might not accurately reflect user and usage activity during the problem period (K. Motwani, personal communication, December 14, 2005).

The author’s inquiry about dramatic variations in node-level query activity provide an example of the interplay between these four obstacles. Agency X was interested in FINDER but wanted an opportunity to evaluate it before officially joining the system. Agency Y, already a FINDER member, offered Agency X a guest account. The guest account permitted members of Agency X to experiment with FINDER via Agency Y’s network. In addition, because Agency X was not a member of FINDER, Agency X was provided only a few user names for a trial run. Queries by Agency X guest users appeared in the Query Logs as activity originating in Agency Y. Over a two-month period, Agency Y’s network caused corruption of the Query Logs files. This file corruption caused between 50 and 90% of both agencies’ query data to be lost (FINDER, 2006; K. Motwani, personal communications).

The guest users at Agency X liked FINDER and used it with high frequency. However, officers at Agency X shared user names until their agency formalized participation in FINDER.

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2 Access to FINDER must be made through a secure intranet. Internet access to FINDER is only possible via a police agency’s network system (PSTC, 2006c).
Once Agency X joined FINDER, some users changed user names while others kept the guest names. Since Agencies X and Y were involved in this host/guest arrangement; none of the other FINDER agencies had any technical or practical need to know about the guest-user agreement.

This example is offered to qualify reliance on Query Logs to establish the theoretical parameters of FINDER’s targeted user population. However, the complexities of guest accounts and query log corruption aside, a review of Query Logs and user behavior (based on the logs) suggested that, in the balance, there were about 1,600 FINDER users for the period of interest. Also, an examination of Query Logs for the period indicated that less than 15% of the Query Log information showed signs of data corruption. There did not appear to be any data corruption issues with the success tagging logs. With these qualifications in mind, the parameters of the target population relevant to the sampling methodology, for the period of December 2004 through February 2006, were identified as:

- Known FINDER users
- Per-user FINDER activity
- Per-agency FINDER activity
- Distribution of Success Tagging among users and agencies

Two additional population parameters were identified that were not reliant on FINDER’s logs. They were:

- Agency type (police, sheriff, other)
- Agency size

These six parameters were developed to compare against the like parameters of the actual
sample: those FINDER users who responded to the user survey. The comparison was planned to help assess representativeness of the sample and the effect of any non-response bias on survey results (Morgan & Gliner, 2000).

**Sampling Frame and Selected Sample**

It was noted that the sampling frame and the selected sample were equivalent. The FINDER sample was a probability sample in which all known FINDER users had an equal chance of participating in the survey.

FINDER users in the accessible population were visible through the query logs, but they could not be individually identified or contacted. Rather, it was intended that the accessible population of users would be contacted about the survey through their agency’s FINDER administrator. In plain language, “access” to the accessible population relied on forty-seven different administrators publishing the survey notice to their respective node’s FINDER users. Thus, access to users was indirect and dependent on the good-faith efforts of agency-level administrators.

**Survey Distribution**

The distribution of the survey instrument was electronic, via a website designed exclusively for the FINDER survey. The survey distribution, obstacles to distribution, response rate, and findings are discussed in Chapter 4.
Summary

This chapter has described the development of the FINDER survey instrument, the sampling plan, and the plan for distribution of the survey to FINDER users. Chapter 4 will describe the data used in this study; both those acquired through FINDER’s automated logs and those acquired through the user survey. In addition, Chapter 4 will report on the analyses of these data in the empirical tests of this study’s hypotheses.
CHAPTER 4: ANALYSIS AND FINDINGS

This chapter describes and analyzes the data that were collected to test hypotheses about the research question. The data was acquired from three sources: FINDER’s Query Logs, FINDER’s Success Tag reports, and the user survey. In addition, qualitative information was obtained from follow-up inquiries is examined. These inquiries were conducted in an effort to understand issues and relationships that emerged both within and between the primary datasets. The qualitative information is offered, where applicable, to inform and enhance the empirical perspective.

A variety of parametric and non-parametric tests was used to analyze data and test the hypotheses. These tests, their applicability, and reference sources are detailed in Appendix D. In addition, several conventions were adopted by which both parametric and non-parametric statistics could be described (e.g., “strongly correlated” or “very weakly associated”). These conventions and their sources are also detailed in Appendix D.

This chapter first describes, analyzes and discusses the primary datasets. That process revealed several previously unidentified, alternative measures for user-level success and system use. These additional measures were included in a final set of study variables that were used to test hypotheses. Second, the additional variables required that the original hypotheses be modified and expanded to test newly-identified measures of user-level success and system use. This resulted in the development of an expanded set of twenty-six hypotheses. These hypotheses were then tested using seven multiple regression models. The results are discussed. Finally, an exploratory, nonrecursive structural equation model was used to consider the relationship between user-level success and information system use.
Query Log Data

Query Log information representing 1.8 million user queries between December 2004 and February 2006 were collected from FINDER’s 40 nodes. These Query Log data were collected to construct a measure of “System Use.” This measure was conceptualized as an individual’s rate of use over the 15 month study period. However, examination of the Query Logs and the processes by which their data were created compelled the development of four system use measures intended to reflect different dimensions of system use. This section discusses and describes the development logic of those four measures.

Some important characteristics of the Query Log data that helped frame their analysis include:

- The Query Logs represented activity at the node level. A node is a computer server that resides at an agency and provides and receives FINDER information via the State of Florida Intranet dedicated for criminal justice system use known as CJNET. One node can be affiliated with one or several agencies. Agencies could formally share a node or informally permit guest users to access FINDER through the node.

- Each query counted represented a query received by a node and did not represent a single query sent by the user. For example, if a user was trying to find a stolen Rolex watch and sent a query about the watch to all 40 nodes, that single query topic (the Rolex) would be counted as 40 queries (one query per node). ¹

- User queries of their own nodes were counted in the Query Logs.

¹ As noted earlier, information concerning Query Logs and FINDER server functions was provided by FINDER’s lead developer, Mr. Kunal Motwani.
• Users affirmatively selected which nodes were queried; the user could query a single node or every node available as a matter of user preference or practicality.

• The Query Logs were maintained at each node’s computer server and some node’s Query Log files were corrupted. Analysis of the logs suggested that 5.6% did not contain full data during certain months.

• Each node had to authorize access to each of the other available nodes. Users at a given node could not query other nodes until the other nodes were authorized. As of August 2006, twenty-two nodes had not activated full access to all other available nodes. The number of nodes *not* activated (out of forty possible nodes) ranged from one to fifteen. ²

The Query Log structure created a substantial measurement problem. A valid measure was required to indicate the individual user frequency of use without over or under-estimating the activity. This problem was compounded by the dynamic changes in agency participation. The number of agencies was not static over the fifteen month observation period. Therefore, a measurement indicator was required that compensated for the Query Log limitation. The following discussion describes the logic and method used to provide a reliable user frequency measure.

**Individual User’s Query Activity and Weighting**

Each Query Log event record provided the Internet Protocol (IP) address of the originating node, the day and time the query was received, the user’s Username, and the leading

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² Detective Jim McClure, of the FINDER staff, is credited with discovering and reporting un-activated nodes following the author’s inquiry about irregularities in query activity.
query parameters (e.g., name of a person or a type of property). To determine system use rates by individual users, the Query IP and Username were extracted from each query event, for each node, on a monthly basis, for the period of December 2004 (the first month that Query Logs became available) through February 2006. This process identified 1,603 FINDER users who had made queries at any time during the fifteen-month period. Of these users, 253 were eliminated from the analyses because they were administrative, system anomalies (such as an invalid IP address), development, testing, or group accounts. This left valid Query Log data for 1,352 users.

The month-by-month node data was combined and initially sorted to identify, for each user who had queried a node, the following information:

1. The user’s query IP address (the user’s home node)
2. The user’s Username
3. Number of months as a user, calculated from first appearance in the Query Logs through February 2006. A user first appearing in December 2004 would have fifteen months as a user; a user beginning in February 2006 would have one month as a user.
4. Total number of queries December 2004 – February 2006
5. Average number of queries per month as a user

A review of these initial data revealed the influence of the number of available FINDER nodes on users’ query volume. In December 2004 there were only twelve FINDER nodes; by February 2006 there were thirty-eight nodes active (and two, inactive nodes). Thus, if in

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3 Query volume at each node, derived from the Query IP, was described in Table 5.

4 More specifically, 1,603 user names which did not accurately reflect the true number of users.
December 2004 a user had made a single query to all nodes, the Query Logs would have recorded twelve queries. If the same, single query to all FINDER nodes was made in February 2006, the Query Logs would have counted thirty-eight queries.

The effect of the number of FINDER nodes on raw query volume is demonstrated in the example of Table 6. User A of the example is a fifteen-month user, having appeared in the Query Logs in December 2004. Comparing User A’s raw query volume suggests sporadic, but increasing query frequency over the fifteen month period. However, recalling that query volume is measured by the receiving nodes, the increasing availability of nodes also increases reported query volume even when the user’s FINDER use is constant. Thus, when User A’s raw query volume is divided by the number of nodes available each month, it appears that User A’s FINDER use has been decreasing since January 2005.
Table 6: User Query Volume Standardization Example

<table>
<thead>
<tr>
<th>Month</th>
<th>User A (raw query volume)</th>
<th>Number of Nodes Active by Month</th>
<th>User A (raw query volume/ nodes)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dec-04</td>
<td>258</td>
<td>12</td>
<td>21.5</td>
</tr>
<tr>
<td>Jan-05</td>
<td>386</td>
<td>13</td>
<td>29.7</td>
</tr>
<tr>
<td>Feb-05</td>
<td>125</td>
<td>14</td>
<td>8.9</td>
</tr>
<tr>
<td>Mar-05</td>
<td>312</td>
<td>16</td>
<td>19.5</td>
</tr>
<tr>
<td>Apr-05</td>
<td>284</td>
<td>17</td>
<td>16.7</td>
</tr>
<tr>
<td>May-05</td>
<td>170</td>
<td>21</td>
<td>8.1</td>
</tr>
<tr>
<td>Jun-05</td>
<td>447</td>
<td>24</td>
<td>18.6</td>
</tr>
<tr>
<td>Jul-05</td>
<td>370</td>
<td>27</td>
<td>13.7</td>
</tr>
<tr>
<td>Aug-05</td>
<td>471</td>
<td>27</td>
<td>17.4</td>
</tr>
<tr>
<td>Sep-05</td>
<td>17</td>
<td>30</td>
<td>0.6</td>
</tr>
<tr>
<td>Oct-05</td>
<td>303</td>
<td>33</td>
<td>9.2</td>
</tr>
<tr>
<td>Nov-05</td>
<td>78</td>
<td>37</td>
<td>2.1</td>
</tr>
<tr>
<td>Dec-05</td>
<td>403</td>
<td>38</td>
<td>10.6</td>
</tr>
<tr>
<td>Jan-06</td>
<td>136</td>
<td>37</td>
<td>3.6</td>
</tr>
<tr>
<td>Feb-06</td>
<td>26</td>
<td>38</td>
<td>0.7</td>
</tr>
<tr>
<td>Grand Total</td>
<td>3786</td>
<td>-</td>
<td>180.9</td>
</tr>
</tbody>
</table>

The influence of the increasing number of FINDER nodes would not be important if all FINDER users were active for the entire study period (December 2004 to February 2006). However, users entered the Query Logs at different times during the period, so the raw query data required standardization based on node availability. The histogram in Figure 9 reflects the staggered times of user entry during the study period.

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5 This entry month is estimated and limited by the interrupted use complications discussed beginning on page 115.
The potential influence of changes in the number of participating FINDER agencies had been recognized earlier (pages 56-57) and resulted in the inclusion of “Number of Agencies Sharing Information” as a control variable. The weighting convention described above – dividing query volume for each month by the number of available nodes in that month – standardized the volume data and eliminated the need for a separate, “Number of Agencies Sharing Information” variable.

These weighted query values were used for the balance of this study. Thus, the initial system use measures were identified as:

- **User Months**: Number of months as a user (calculated from first appearance in the Query Logs through February 2006)
• Query Volume: Average query volume per month as user based on weighted query data
• Total Queries: Total number of weighted queries made by the user between December 2004 and February 2006

The summary statistics for these three measures are provided in Table 7.

**Query Volume**

Query Volume statistics suggested, and a plot of the data confirmed, positive skew in its distribution. Additional analyses were conducted in an effort to identify sources and causes of the skew. These analyses revealed influences that required further investigation: query scope, repeated queries, and interrupted use. Examination of these influences provided a deeper understanding of query behavior and was both conceptually and mathematically important in developing valid system use measures. These influences are discussed below.

**Query scope**

Implicit to the logic of weighting raw system use by the number of active nodes was the assumption that, on average, users directed queries to all nodes available to them, or that the increasing availability of nodes encouraged users to seek information more frequently. In either case, the increased availability of information was expected to increase query volume. The Task-Technology Fit model (Goodhue, 1995) supports this logic and suggests that system use is positively influenced by the availability of additional, useful information.

However, there is little empirical evidence supporting the relationship between more-information and more-use. Thus, an effort was made to determine specifically whether FINDER
users’ *query scope* (the number of FINDER nodes from which information was sought) was related to the increased availability of information (i.e., more FINDER nodes).

Query scope can be compared to casting a net. Broad query scope in FINDER casts the net over both a wide geographical area and a wide set of data sources. Narrow query scope is like dipping a small net in a fish tank to catch one fish; a small, defined area and target are the objectives. Query events, or the frequency of queries, are comparable to each cast or dip of the net.

To understand the query scope employed by FINDER users, a secondary survey was conducted (the “FINDER User” survey administered in this study is discussed beginning on page 131). A random sample of ninety users was drawn from respondents to the primary survey who had provided an email address for follow-up inquiries. These users were sent an email request to classify their typical FINDER query behavior in terms of query scope. Eighty-five email addresses were valid; fifty-six (66%) responses were returned. Of those responses, 76.8% reported: “I usually query all available agencies, and then I drill-down in those results to find what I need.”

Limitations to the query scope response data were recognized: although randomly selected, the responses were from primary survey respondents who offered their email address for follow-up questions, and who took the time to answer the query scope question. However, their response to the query scope question is decisive with 76.8% of the respondents reporting “query all agencies” behavior.

A number of respondents to the query scope question who reported that they “query all agencies” included comments with their replies. Representative comments (copied and pasted from respondents’ emails) include:
• Detective Sergeant: It makes no sense to keep expanding searches when it only takes a couple of minutes for the system to run everything. Especially if you are looking for general information about someone. Which is what I am usually doing if on Finder. However, if I am trying to locate a certain item or person that I know is local, then of course I save the time and just run a local check.

• Detective: Great question, I tried for a while to just look close by but once I know the name of a bad guy I want to know how big his turf is so I will check everywhere. It is amazing how often some people show up.

• Homicide Detective Sergeant: Obviously, in a homicide you query for as much information that you can and then begin the process of paring it down to your specific needs.

• Detective: I usually query all available agencies. I particularly like to read the narratives of prior contacts when they are available. Yesterday, I ran tags from traffic stops on one of numerous tags in a condo community trying to find an occupied burglary suspect. My third tag gave me my suspect and I await the line up for charges.

• HIDTA Analyst: Actually, I don't drill down once I find a hit, I just use all the information I receive.

• State Attorney’s Investigator: I go straight to ALL AGENCIES because I usually have no idea where the information may come from. This has proven to be very useful as there may be several agencies that have info on the same person.

• State Law Enforcement Analyst: The cases I work usually involve individuals that have traveled and/or resided in various counties/cities within the state; thus, I always start my queries with the largest net available before narrowing down the generated output.
• Violent Crimes Detective: I select [query all available agencies]… Data Sharing [FINDER] is the most valuable tool that I use. It has solved numerous cases for me and my co-workers.

These users suggested that a search for information initially includes all FINDER nodes. This behavior further supported the query volume weighting convention as a more precise reflection of system use within the user’s context of available information. Conceptually, it is system use relative to available information that is proposed in the task-fit model.

**Repeated queries**

As noted above, the Query Logs captures the user’s query parameters. Parameters are the topic of the query; the names of people, descriptions of property, and other information of interest to the user. During the collection and sorting of the Query Logs, it was observed that certain users were repeating query topics – evidenced by repeated appearance of the parameters – throughout the month of activity visible in each set of logs. In other words, if a user were searching for “John Smith,” the query for John Smith from that user would be seen many times over the month-long Query Log file. In addition, users would sometimes make the same query two or three times throughout a single day.

Repeated query behavior is not surprising. Police information users recognize that new information is always becoming available; a suspect who is not “in the system” today could very well appear in the system at a later time. Lin (2004) documented this practice in his study of detectives’ use of an information system. Lin found that police users placed strong value on a “monitoring” system (p. 61) that checked databases repeatedly for newly-arriving information.
In addition, FINDER’s agency representatives to the Law Enforcement Data Sharing Consortium have called for a monitoring (or subscription) functionality to be built into FINDER (PSTC, 2006).

The FINDER architecture and construction of the Query Logs precluded an empirical measure of repeated queries. However, some understanding of the repeated query influence was desirable. If high levels of system use were associated with high levels of user success, understanding the relationships between scope, volume and repeated queries would be informative.

An exploratory effort was made to determine the prevalence of repeated queries by conducting a detailed examination of ten FINDER users’ queries. These ten users were selected randomly selected from a pool of 110 users who made queries on November 1, 2005 to the most active node. The individual queries made by each of the ten users, for November 2005, were sorted to check for exact matches in the query parameters. In other words, if User 1 made a query for “John Smith,” the data were searched for additional queries on “John Smith” by that user at any other point during November 2005. Alternative queries, such as “Jon Smith,” “J. Smith,” “Smythe,” etc. were not matched.

This analysis revealed repeated query behavior among seven of the ten users. The percentage of repeated queries to total queries on a per-user basis ranged from 0% to 50%. Repeat queries accounted for 23% of the total queries by the ten users, and the count of repeated queries was not consistently reflected in total queries (users with high rate of repeated queries were not necessarily the users with highest total queries).

An additional step was taken to gauge the prevalence of repeated queries beyond the limited data shown above. A secondary survey was conducted with a random sample of one-
hundred users drawn from respondents to the primary, user survey. These users were sent an email request to classify their typical FINDER query behavior in terms of repeated queries. Ninety-four email addresses were valid; sixty-seven valid (71.3%) responses were returned. The responses are summarized below.

- When you make a FINDER query about a person, property, or vehicle and don’t get any matching information, do you try the same query again? (n=67)
  - Yes, I usually try the query again at a later time. (34%)
  - No. If I don't find information the first try I move on to something else (22%).
  - It really depends on the case or situation I'm making the query about. (43%)

- When you do find it necessary to make repeated queries on the same subject, is it usually because: (n=62)
  - I am hoping new information about the subject will become available. (66%)
  - Some of the FINDER agencies were "unavailable" on my first try. (26%)
  - “Both” or “it depends” [respondent write-in] 8%

These data and responses suggested that repeated queries could have a significant influence on the measure of system use and any analysis of user-level success that is associated with system use. The limited data indicated that a high rate of repeated queries is not necessarily related to a high volume of use. The repeated query rate could be a better predictor of success than volume alone. However, as noted, repeated query data was not available in the FINDER logs, and the effect of repeated queries could only be a matter of speculation relative to its role in system use or user-level success.
**Interrupted use**

Query Log data revealed that 975 (77%) of the 1,266 users with at least two months of FINDER activity had months of zero query activity, or “interrupted use.” The widespread occurrence of interrupted use was not expected. Figure 10 graphically represents the nature of interrupted use among ten, randomly selected users. Shaded months indicate use during that month; un-shaded months indicate zero-query level.

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<tr>
<th>User</th>
<th>Dec-04</th>
<th>Jan-05</th>
<th>Feb-05</th>
<th>Mar-05</th>
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</table>

Figure 10: Examples of Interrupted Use

As the examples above suggest, the interruptions appeared random. The interrupted use data was extensively explored in an effort to detect any relationships with other Query Log parameters. The interruptions were not due to Query Log corruption; that would require each node to be completely out of service. An examination was conducted of both the sequence and incidence of interrupted queries by IP address, the month, the timing of first interruption after the start date, the length of interruptions, and query behavior in the month. Comparison of means and correlation tests were conducted for relationships between interrupted use and user months,
query volume, and total query volume. None of these efforts identified patterns or relationships that helped explain interrupted use.

The analysis was expanded to consider whether users might have “dropped-out” of FINDER based on their number of consecutive months of zero query activity leading up to February 2006. This possibility was explored through a proposition that users would not return to an active status after two or more consecutive months of no activity. However, a detailed examination of 1,027 users with two or more consecutive months of interrupted activity found that users could take breaks from FINDER of up to twelve months before returning to active use. Thus, no convention for “dropout” could be established.

An understanding of interrupted use was desirable for both mathematical and conceptual reasons. Mathematically, the repeated presence of zero values in the queries prevented construction of moving averages or indices that could have reflected trends in use (zeros in the denominators). Conceptually, interrupted use was important in considering the influence of system use on user-level success. A high level of interrupted use might identify a user who received little value from FINDER. Alternatively, interrupted use might demonstrate excellent task-fit; the user only needed to make a FINDER query to locate very specific, non-routine information.  

The presence of interrupted use was measured by “Active Months,” the number of months a user conducted queries of that user’s total months visible in the FINDER Query Logs between December 2004 and February 2006. Summary statistics for the Active Months measure

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6 Later interviews with users suggested the latter. Some users employed FINDER sporadically for very specific information tasks.
are presented in Table 7. This measure is based on the 1,266 users who had at least two months as a user (a one-month user could not have interrupted use).

**Usage Rate**

Usage Rate was initially conceptualized as a measure reflecting changes in the user’s query volume over time. It was hypothesized that a consistent or increasing rate of FINDER use over time would be positively related to user-level success.

The widespread presence of interrupted use precluded the use of moving averages or baseline indices to compute a rate measure. Efforts to adapt a trend measure, such as the Cox-Stuart test using midpoint values (Sprent & Smeeton, 2001), also failed. The slope of trendlines, fit to each user’s monthly query volume, was computed but was not correlated to any other system use measures. After extensive experimentation with rate and trend statistics, the Query Log data proved unsuitable for the calculation of a meaningful “usage rate.” Consequently, the hypothesized relationship of a system use trend was eliminated from empirical tests.

**Outlier Data and Tests for Normality**

Descriptive analyses identified the presence of outlier data in the Query Volume distribution. Outliers can disproportionately influence analyses and should be examined to determine if the outlier data are the result of inaccurate data collection or otherwise anomalous to the research context. However, outlier data should not be eliminated from the analyses unless it is believed to be either inaccurate or misrepresentative of the phenomenon being studied (Gujarati, 2003).

The Query Log data, the source data, were examined for users classified as outliers and
who each averaged more than fifty (weighted) queries per month. No irregularities were observed in the source data for these users.

Four of the outlier users had returned user surveys in which they identified themselves as high-volume users. Three additional outlier users (although they had not returned surveys) were identified as users assigned to a specific detective squad. The members of that squad were high-volume FINDER users and represented the single greatest source of “success tags” among all FINDER’s nodes. Thus, the outlier cases were accepted as accurate measurements and relevant to the study’s objectives.

Tests for the normal distribution of the Query Log data were conducted against each variable: User Months, Query Volume, and Active Months. The distributions of each these datasets were estimated to be significantly different from the normal distribution (p<.000).

Discussion

There is little value in conducting refined analyses with source data that is unrefined or inaccurate (e.g., Babbie, 1995). Therefore, the preceding pages in this section have described the Query Log source data to provide an appropriate context for their analyses. The objective measures supplied by raw Query Log data offered an excellent opportunity to explore and understand “system use” in the sense offered by the theoretical framework. However, these data must be considered from the perspective of their limitations and un-measured, underlying influences:

- Some FINDER servers were unreliable in reporting system use

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7 While these users were not personally identified, their supervisors and co-workers – who were involved in follow-up interviews – outlined the frequent use of FINDER and high success rate by all members of their detective squad.
• Users may have had FINDER experience prior to December 2004 that is not reported by User Months

• System use measures may be poor indicators of underlying behaviors related to query scope, repeated queries, and interrupted use

• The assumption that, most of the time, FINDER users query all available sources was supported, but not proven

• The existence of repeated query behavior was identified but not measured

• The assumption that volume weighting by node is appropriate was supported, but not proven

One objective of this study was to build performance metrics for the FINDER system. The availability of objective system use data, the Query Logs, initially suggested a convenient metric. However, the longitudinal evaluation of the Query Logs highlighted complexities in the data that precluded a single measure. These complexities would have likely gone unnoticed in a cross sectional analysis.

Subject to the expressed limitations, the Query Log data produced four measures related to system use:

• Query Volume: each user’s average monthly FINDER use for the period beginning with the user’s first appearance in the Query Logs and ending in February 2006, weighted for the number of available FINDER agencies in each month

• User Months: the measure of each user’s FINDER tenure based on the number of months from the user’s first appearance in the Query Logs through February 2006

• Months Active: the percentage of months in which the user had query activity compared to total user months
These data, operationalized as the variables described above, are summarized in Table 7.

Table 7: Summary Descriptive Statistics for Query Log Variables

<table>
<thead>
<tr>
<th></th>
<th>N</th>
<th>Mean</th>
<th>Median</th>
<th>Std. Deviation</th>
<th>Minimum</th>
<th>Maximum</th>
</tr>
</thead>
<tbody>
<tr>
<td>All Valid Users between Dec 04 - Feb 06</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Total Queries</td>
<td>1352</td>
<td>45.7</td>
<td>13.0</td>
<td>107.7</td>
<td>0</td>
<td>1615.0</td>
</tr>
<tr>
<td>Query Volume</td>
<td>1352</td>
<td>4.888</td>
<td>1.75</td>
<td>9.872</td>
<td>0.00</td>
<td>132.79</td>
</tr>
<tr>
<td>User Months</td>
<td>1352</td>
<td>8.560</td>
<td>9.00</td>
<td>3.982</td>
<td>1</td>
<td>15</td>
</tr>
<tr>
<td>All Valid Users &gt; 2 or More User Months between Dec 04 - Feb 06</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Query Volume</td>
<td>1266</td>
<td>4.796</td>
<td>1.630</td>
<td>9.922</td>
<td>0.00</td>
<td>132.79</td>
</tr>
<tr>
<td>User Months</td>
<td>1266</td>
<td>9.08</td>
<td>9.00</td>
<td>3.574</td>
<td>2</td>
<td>15</td>
</tr>
<tr>
<td>Months Active</td>
<td>1266</td>
<td>.563</td>
<td>.545</td>
<td>.333</td>
<td>0.067</td>
<td>1.0</td>
</tr>
</tbody>
</table>

Success Tag Data

“Success tag” reports were user-initiated, self reports of user-defined successes arising from their FINDER use. The success tag information was highly subjective, with case-specific details submitted in a free-text format, and the success tags were not consistently linked to the reporting user’s Query Log activity. Consequently, the success tag data offered little empirical value. The success tag data did, however, help inform interpretation of the Query Logs, the analysis of user survey responses, and guided follow-up interviews with users.
Success Tag Description, Volume, and Distributions

A total of 734, valid success tags total were identified out of the 889 submitted by users between December 1, 2004 and July 30, 2006. The 155 success tags that were excluded did not contain enough information to determine the nature of the success. Most of excluded success tags appeared to be the result of user error or experimentation.

The success tag process links the user’s self-reported success to a source document provided by a FINDER node. Success Tags included the following data fields:

- The report number provided by the originating agency for the tagged, source document.
- The report type classifying the nature of the source document (e.g., traffic citation, pawn ticket, incident report, field contact information)
- The date the source document was made available to the FINDER system.
- The date that the user executed the success tag.
- Free-text comments in which the user describes the successful event.
- The name of the police agency that provided the source report. Some FINDER nodes encompass several agencies; the data source permits specific follow-up on tagged, source information.
- Contact information for the FINDER user making the success tag report.

Success tags were submitted by users in thirty-nine agencies, representing thirty-four FINDER nodes. Eighteen successes could not be linked to a submitting user or agency. The distribution of success tags across these agencies was highly skewed. Of these thirty-nine
agencies, five were responsible for 80% (585) of all reported successes. Of these top five agencies, two submitted 53% (387) of all success tags.

A rough calculation was conducted to determine the rate of success tags per node compared to the number of known users per node. Known users were identified via the Query Log analysis through February 2006; success tag data extended through July 2006, so the true number of users per node could not be established. This calculation reflected wide disparity in the ratio of reported successes to known users: the range was 12% to 367%. A figure in excess of 100% means that the number of successes reported at that node exceeded the number of known users at that node (more than one success per known user). When only the top five success reporting agencies were considered, the success/users range was 33% to 367% and represented four nodes. Then, the success tagging methodology is seriously broken…

The distribution of successes among the 159 users who reported successes was also examined. The top four users, all from the same node, were responsible for 44% (317) of all reported successes; the top 10% of the users (16 users) were responsible for 62% of all reported successes. The range of successes reported per user was from one success (78 users) to 172 successes (one user). The median number of successes was 2.0; the average was 4.5.

Successes were also considered for their distribution in time across the study period. Table 8 reflects this distribution. The average reported successes per month was 37; the median was 28. November 2005 and July 2006 suggest outlier data at 136 and 110 reported successes during those months, respectively.
Table 8: Distribution of Success Tags by Month: Dec 04 – Jul 06

<table>
<thead>
<tr>
<th>Dec-04</th>
<th>Jan-05</th>
<th>Feb-05</th>
<th>Mar-05</th>
<th>Apr-05</th>
<th>May-05</th>
<th>Jun-05</th>
<th>Jul-05</th>
<th>Aug-05</th>
<th>Sep-05</th>
<th>Oct-05</th>
<th>Nov-05</th>
<th>Dec-05</th>
<th>Jan-06</th>
<th>Feb-06</th>
<th>Mar-06</th>
<th>Apr-06</th>
<th>May-06</th>
<th>Jun-06</th>
<th>Jul-06</th>
</tr>
</thead>
<tbody>
<tr>
<td>31</td>
<td>15</td>
<td>8</td>
<td>16</td>
<td>10</td>
<td>12</td>
<td>38</td>
<td>18</td>
<td>17</td>
<td>20</td>
<td>48</td>
<td>136</td>
<td>58</td>
<td>25</td>
<td>30</td>
<td>49</td>
<td>24</td>
<td>36</td>
<td>34</td>
<td>110</td>
</tr>
</tbody>
</table>

Distance between the Success and Source Data

The success tag data provided an opportunity to estimate the geographical or jurisdictional distance between the successful user’s agency and the agency that provided the source data. The distance measure was ordinal and specified as:

- 0 = Data acquired from within user’s own agency led to success.
- 1 = Data acquired from another agency within user’s county led to success.
- 2 = Data acquired from another agency in an adjoining county led to success.
- 3 = Data acquired from another agency in a non-adjoining county led to success.

Of the 734 success reports, the agency location of both the reporting user and data source could be established in 641 cases. The distribution of successes based on distance in these cases is shown in Table 9.
Table 9: Distance between Successful Users and Source Data

<table>
<thead>
<tr>
<th>Data Source</th>
<th>Number of Success Reports</th>
<th>Percent of Success Reports</th>
</tr>
</thead>
<tbody>
<tr>
<td>Within user’s agency</td>
<td>309</td>
<td>48.2%</td>
</tr>
<tr>
<td>Within user’s county</td>
<td>239</td>
<td>37.3%</td>
</tr>
<tr>
<td>Adjoining county</td>
<td>57</td>
<td>8.9%</td>
</tr>
<tr>
<td>Non-adjoining county</td>
<td>36</td>
<td>5.6%</td>
</tr>
<tr>
<td>Total</td>
<td>641</td>
<td>100.0%</td>
</tr>
</tbody>
</table>

Classification of Successes

Success tag details, derived from the “Comments” portion of the data, were highly variant in composition and detail. Several depersonalized examples (copied and pasted from the Success Tags) are provided below.
Table 10: Examples of Success Tag Details

<table>
<thead>
<tr>
<th>PROPERTY TAKEN IN BURGLARY ON 11/03/04</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ref an investigation I was looking for updated info ref this subject.</td>
</tr>
<tr>
<td>Capias requested for Burglary, Grand Theft, Violation of Pawn Brokers Act. Admission and confession gained from suspect, Michael xxxxx. Dollar amount recovered was $100.00.</td>
</tr>
<tr>
<td>No arrest, searching one subjects name assisted me in locating a person that I only had the first name of that is possibly a subject of interest in my case.</td>
</tr>
<tr>
<td>Investigation on-going for petit theft. 05-xxxxxx</td>
</tr>
<tr>
<td>Arrest made/property recovered</td>
</tr>
<tr>
<td>Witness located in drug case for State Attorney's Office. No arrest or property recovered.</td>
</tr>
<tr>
<td>An arrest warrant was obtained for xxxxx for Murder. We only knew his first name at the onset of the investigation but later learned his girlfriend's name. Searching her name provided a report filed listing her boyfriend's full name.</td>
</tr>
</tbody>
</table>

A review of the success tag comments suggested a classification convention that was subjective, but permitted a rudimentary sorting of the data. The comments were scored across five dimensions and property value. A value of “1” was assigned if the dimension applied; a value of “0” if not.
Table 11: Success Tag Rating Dimensions

<table>
<thead>
<tr>
<th>Dimension</th>
<th>Criteria</th>
</tr>
</thead>
<tbody>
<tr>
<td>Arrest</td>
<td>Arrest stated, arrest pending, warrant or capias obtained/being obtained</td>
</tr>
<tr>
<td>Case Cleared</td>
<td>Case clearance specified without indication of arrest or case cleared with prosecution declined or waived.</td>
</tr>
<tr>
<td>Property</td>
<td>Stolen property (other than vehicles) recovery identified or pending.</td>
</tr>
<tr>
<td>Vehicle</td>
<td>Stolen vehicle recovered or vehicle of interest identified or located</td>
</tr>
<tr>
<td>Investigative Lead</td>
<td>Information acquired without indication of arrest, case clearance, property, or vehicle recovery.</td>
</tr>
<tr>
<td>Value</td>
<td>When indicated, value of stolen property recovered or located.</td>
</tr>
</tbody>
</table>

Arrest and Case Clearance were mutually exclusive. Investigative Lead was exclusive to all other categories. A property recovery was not assumed to reflect a case clearance. Each comment could receive a score of one in up to three categories (although none did) in addition to a property value. For example, a comment noting an arrest combined with recovery of stolen property and a vehicle with a stated value would be scored positive (“1”) for the first three dimensions and include the property value.

Based on this subjective scoring convention, all 734 success tags were reviewed and scored. The results of that process are reflected in Table 12 on the next page.
Table 12: Frequency of Success Tag Dimensions in 734 Cases

<table>
<thead>
<tr>
<th>Success Dimension</th>
<th>Frequency</th>
</tr>
</thead>
<tbody>
<tr>
<td>Arrests</td>
<td>384</td>
</tr>
<tr>
<td>Case Clearance</td>
<td>34</td>
</tr>
<tr>
<td>Property</td>
<td>537</td>
</tr>
<tr>
<td>Vehicle</td>
<td>3</td>
</tr>
<tr>
<td>Investigative Lead</td>
<td>142</td>
</tr>
<tr>
<td>Property Value</td>
<td>$192,581</td>
</tr>
</tbody>
</table>

Nearly one-third (31.6%) of these success tags were different only in their source reports. These tags reflected cases where a single suspect, group of suspects, or investigation was associated with multiple source reports, and a success tag was generated for each source report. For example, several cases were observed that reflected identical suspects and cases numbers with the only difference in the success tags being the Report Number of the associated pawn tickets and incident reports. These multiple-success investigations were the source of outlier data for November 2005 and July 2006.

**Interviews with Success Tag Users**

Eleven of the FINDER users who had submitted success tags were interviewed in person, by telephone, or through email. These users had provided consent for follow-up contact in their responses to the user survey. Included in these eleven interviews were three of the four high-volume success taggers. The interviews are summarized below.
These three, high-volume success-tag users were responsible for 41% of all tags reported. Each of these users was assigned to a property investigations squad; each of them also was heavily involved in pawnshop investigations. Two of these users were also outlier cases in the Query Volume measure.

The three users described using FINDER as a routine part of their workdays. They ran queries on suspects and property from hundreds of reports that were forwarded to them by other detectives. The query routine was mechanical versus selective or based on a priori hunches or information. One user articulated that he had no “assigned” caseload; he would just adopt cases for which he found information in FINDER and through other sources. Essentially, his case clearance rate was 100% because he only took cases that he had “already solved” through FINDER queries. Each of these investigators identified themselves as “the FINDER person” for his squad or district. Each was also an enthusiastic FINDER member, having been part of the “original” group of detectives who pushed for the formation of the Data Sharing Consortium.

Three other success-tag users were interviewed who were assigned to analyst positions. One was a pawnshop analyst, one was an intelligence analyst, and one was a crime and intelligence analyst for a state agency. Each had submitted one success tag.

The pawnshop analyst described a routine of mechanical FINDER queries based on reports she received from detectives. She related that although she frequently found valuable information in FINDER, she typically forwarded the information to detectives and did not claim a “success.” This analyst was also an outlier user in the Query Log data. The intelligence analyst and state analyst described selective use of FINDER that was dependent on specific assignments. The intelligence analyst related that she could go for “a month or two” without using FINDER at all; this was a reflection of her information needs versus disenchantment with
the FINDER system. The state analyst thought she would go no longer than a few weeks without using FINDER, and she relied on sworn personnel to make success tags on any information she provided.

Of the remaining five success tag users interviewed, two were human resources background investigators. They related routine, mechanical FINDER queries based entirely on their applicant workload. A third user was a homicide investigator who labeled herself as the “FINDER person” for her squad and who had made several success tags. She noted that when she located “successful” information, she might make the success tag, but any case clearances or arrests would be attributed to the detective for whom she had made the query. The homicide detective related that her (and her partner’s) FINDER activity was sporadic and based on their need to look for information that was not readily available in their “normal” systems. It was possible for them to go more than a month without accessing the system.

The two final users interviewed were both general crimes investigators from small police departments. Both related that FINDER gave them newfound access to their local Sheriff’s data and that this represented a huge step forward in meeting their information sharing needs. In addition, both related that their agencies were unable to afford alternative information resources (such as privately-run databases), and FINDER was their only information source outside of FCIC/NCIC. One detective said he used FINDER almost daily; the other said he might go for “several weeks” without using FINDER because he had a very small caseload.

Discussion

The original research plan for this study incorporated a longitudinal analysis that would have examined the relationship of system use to success tagging data over a fifteen-month
period. However, the analysis of the success tag information demonstrated that these success data were too subjective to be used in an empirical analysis. Thus, these data were used primarily to inform the analyses of information from both Query Logs and the user survey.

Unstructured interviews with FINDER users who had completed success tags were very informative. These interviews described two types of use that helped explain the Query Log data. The first type of user employed FINDER on a daily basis in a mechanical fashion. This type of use generated high query volume and, in some cases, a very high level of demonstrated success. The high-volume, mechanical users were those associated with property and pawnshop investigations or background investigations.

The second type of user was a more selective and less frequent FINDER user. These users described case-specific needs that arose infrequently; they could have months-long gaps in FINDER use that did not reflect any dissatisfaction with the system. These users included the intelligence and state crime analyst as well as a general crimes detective with a light caseload.

The interviews also revealed an unexpected consideration in the search for an appropriate success metric. Several of these users described being the FINDER source for co-workers who would claim case clearance or arrest credit for those cases aided by FINDER data. In other words, although the interviewed users generated the FINDER successes, the traditional success measures (arrests and case clearances) would not be credited to them.

The user interviews and the success tag data also revealed the importance of information sharing within the user’s own agency. Several users commented that FINDER gave them access to data in their own agency that they could not acquire through their resident RMS. The examination of “distance” demonstrated the validity of their claim; almost half of the success tags employed data from the users’ own agencies.
A final point of success tag interest was the low number (three) of vehicle-related successes. A homicide detective, who had located a murder suspect through vehicle information, noted that vehicle information was efficiently available through the FCIC and NCIC. FINDER was useful for vehicle information when nothing was known about the vehicle except color and general description, or when a vehicle’s association with a person (a non-owner) was of interest. Typically, where a person was identified through vehicle information, that person was the “success;” the vehicle was just part of the search.

**Survey**

This section describes and discusses user survey results and the adoption of the results as empirically and conceptually sound variables. First, adequate survey sample size is estimated in a statistical power analysis. Second, the survey distribution, response, and representativeness of the response are discussed. Third, responses to the survey items are described and analyzed to assess their reliability and validity as measures for empirical testing.

**Power Analysis and Estimated Sample Size**

This section discusses the power analysis used to estimate the number of survey responses required to conduct statistical analyses using the survey data. A minimum of eighty-four survey responses was calculated to be necessary to achieve desired statistical power. This minimum sample requirement was identified prior to survey distribution. Ultimately, 402 valid survey responses comprised the final sample and satisfied statistical power needs.

Statistical power relates to the probability of committing Type I and Type II errors. Power, generally, is a function of the significance level, the effect size, and the sample size. If
two of these values are known, the third can be determined with a power table. In this study, the
significance level was set by convention at \( p < .05 \) and, as described below, the effect size was
estimated. Thus, adequate sample size could be determined through the power analysis.\(^8\)

The effect size estimates the degree of influence that the independent variable(s) have
on the dependent variable(s). A large effect is more easily detected in a small sample and vice
versa (Cohen, 1977; Morgan & Gliner, 2000). Effect size can be estimated by theory, expert
opinion, or effect size findings in prior research. For the statistical power analysis in this study,
effect size was estimated through an evaluation of prior research. Specifically, the correlation
coefficients (\( r \)) from prior task-fit and technology-acceptance research were roughly averaged to
estimate effect size. Cohen (1977) asserts that this “soft” approach to estimating effect size is
valid; no two studies are exactly alike, and \( r \)-values are, of themselves, estimates (p. 79). The
existing research used to estimate effect size for this study is described in Appendix E.

Prior research reflected a range of approximate effect size from \( r = .32 \) to \( r = .85 \), or
medium to large effect size. The lowest effect size estimates were reported by Goodhue (1995)
and Goodhue and Thompson (1995). They used an adjusted \( r \)-square which is a more
conservative approach in multivariate analyses (e.g., Kachigan, 1991). Their estimate, rounded
down to \( r = .30 \), was adopted as the most conservative for use in this study.

With a known significance level (\( p < .05 \)) and estimated effect size based on \( r = .30 \), the
statistical power tables were consulted to establish the sample size required at the ideal power
level of .80 (Gliner & Morgan, 2000). The necessary sample sizes for significance testing are

source in the discussion of statistical power. Thus, while the others offer insight to the power issue, Cohen is cited
here as the leading source.
n = 68 for directional hypotheses and n = 84 for non-directional hypotheses (Cohen, 1977, pp. 101-102, Table 3.4.1).

**Representativeness of Sample and Non-response Bias**

Notice of the user survey and a request to distribute it to FINDER users was sent by email to all FINDER administrators, beginning May 24, 2006. Data did not exist that enabled contacting users directly. Initial response to the notice was lackluster; it was determined that over one-half of the administrators of record were no longer serving in that capacity or did not know they had been designated as their agency’s FINDER administrator. An assortment of technology, operational, and management personnel were eventually identified as *de facto* representatives to the Data Sharing Consortium. These representatives were reminded between three and six times each – by a combination of email, telephone, and personal contacts – to provide the survey information to all personnel at their node who had current or past FINDER access.

Of the forty nodes that had formalized their FINDER participation by June 2006, affirmative responses were received from thirty-eight that the survey had been received and would be distributed to users. A total of 430 survey responses were received by August 7, 2006. Of this number, 28 were excluded due to duplications, inability to confirm a valid username, or the respondent’s failure to answer any questions. Thus, 402 valid surveys were retained for analysis.

From the pool of 402 survey respondents, 252 were matched with their Query Log data. The remaining 150 respondents were validated as users among a group of 173 who were recently-active by June 2006, but for whom detailed Query Log data were not available. Of the
803 FINDER users who were active in the Query Logs by February 2006 or visible as “new” or recently-active users by June 2006, the 402 surveys represented a 50.1% response rate.9

Several parameters of the respondents were compared against known parameters of the FINDER user population. The purpose of these comparisons was to assess whether those responding to the survey differed in some fashion from those who did not respond. Non-response bias is the biggest threat to the validity of survey research (e.g., Babbie, 1995; Dillman, 2000). The comparisons included response by agency type and size, and the parameters derived from the Query Logs (Query Volume, Months Active, and User Months). The agency size comparison was based on the Consortium’s size convention (PSTC, 2006), and response by node was influenced to an unknown degree by the presence of guest accounts. In some cases, the Query Logs failed to provide information about the user/agency association.

Generally, survey representation was consistent across the agencies by type and size. Statistical testing for differences in representation between the agency and agency size groups was not conducted because the reliability of source data (users per agency) was roughly estimated. Some under-representation was indicated for medium-size Police Departments (between 100 and 249 sworn) and Sheriff’s Offices (between 250 and 499 sworn). These groups were comprised of six police and seven Sheriff’s agencies.

An assessment was also conducted at the user level for the 252 survey respondents who were matched with Query Log data. The Query Volume, User Months, and Active Months data were compared between the survey respondents (n=252), all non-responding users known to be

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9 The 402 responses represent 23.6% of the 1,698 usernames that were identified as using FINDER at least one time between December 2004 and June 2006. The response rate cited above is based on users who were active in the six months leading up to the survey.
active in 2006 (n=474), and the population of all non-responding known users for whom Query Log data was available (n=1,022).

A comparison of the descriptive statistics for these three groups suggested differences in the enumerated parameters; particularly in Query Volume where the average, median, and standard deviation were higher for the respondents when compared to the full population of non-respondents.

Query Log-based data for all three groups were non-normal but generally passed tests for homogeneity in variance. The t-tests and Mann-Whitney U tests were used, as appropriate to the data set, to statistically test for differences between the groups. The comparison tests found the expected, statistically significant difference between the survey response group and all non-responders (n=1,022) in the Query Log parameters. No statistical difference was found in the parameters between survey responders and active non-responding users (n=474), except in the User Months parameter.

The difference in User Months was further examined. A comparison of the mean and median values between responders and active non-responders indicated that those responding to the survey had a longer, known FINDER tenure. Boxplots of the data confirmed this. The seventy-fifty percentile for responders was fourteen months as opposed to eleven months for non-responders. The interquartile range for responders was seven months compared to six months for non-responders.

**Discussion**

The “representativeness” issue in this study is both complicated and enhanced by considering response to a cross-sectional survey compared to longitudinal data. The Query Log
parameters were established from data originating as many as twenty months prior to the survey, and there is a complete gap of up to five months (March to August 2006) between Query Logs and the survey. As the analyses of Query Log data reflected, the widespread occurrence of interrupted use and possibility of user dropout complicates assumptions about even defining the difference between a FINDER “user” and a “non-user.”

However, the tests of group differences suggest that non-response bias should not affect using survey responses to generalize Query Log data (with the exception of User Months) to users who were active by February 2006. The difference in the User Month distribution among those responding and those who did not indicates that survey respondents, as a group, had a greater length of FINDER tenure than non-responders; at least as of February 2006.

In perspective, however, the evaluation of non-response bias on Query Log data only applies to 252 of the 402 survey respondents. The absence of user-level information attendant to FINDER’s structure precluded examining user characteristics for indications of bias beyond what was available in the Query Log data. In the aggregate, 50.1% of all known, active users responded to the survey, and the distribution of responses appears reasonably representative of the user population as distributed by agency type and agency size. Further, the known user-level parameters of survey responders (Query Log data) are, with exception of FINDER tenure, not statistically different from the known user-level parameters of the equivalent (active) non-responding population.

Thus, while non-response bias is the biggest threat to any survey research (Dillman, 2000), the survey responses in this study were believed to be adequate in both sample size and representativeness of the study population. The use of data acquired through the survey is subject to the limitations noted above.
Survey Data

Eighty-nine items from the user survey were available for empirical analysis. In preparation for item analyses, items were re-coded to exclude “Not Applicable” responses. The Not Applicable option was provided primarily to prevent non-sworn respondents from being scored on topics outside their authority (such as arrests or property recovery). In addition, thirty items had been constructed to evaluate the use of the Success Tagging feature and the reliability of success tags as an empirical user-level success measure. However, the analysis of Success Tag data demonstrated that these data were not suitable for empirical use. These thirty survey items were excluded from further consideration. Thus, fifty-nine survey items remained available for analyses. These items, and the percentage distribution of responses to each item, are presented in Appendix E.

The survey items or their indices were compared to the Query Log data through correlation matrices that were repeatedly updated during the survey analysis. The correlation data provided important information about both expected and unexpected relationships and were used to understand and refine variable measures. In that regard, the first effort towards understanding the survey data required modifying or collapsing nominal data so it could be meaningfully used in the matrices. The first survey items addressed were the nominal measures for agency affiliation and job assignment, job function, and user rank.

Agency

The Agency variable was described as a control for the user’s environmental context. Two survey items addressed the respondent’s agency name and type (items 8 and 9) and asked
the respondent to select the agency name from a dropdown list of all Florida law enforcement agencies.

A total of 393 respondents from 56 different agencies answered these items; nine did not identify their agency. The response total was distributed to 119 (30.3%) from Police Departments, 265 (67.4%) from Sheriff’s Offices, and 9 (2.3%) from state agencies. No federal agency users responded.

Of these agencies, forty had fewer than five responses, and nineteen had a single survey response. The range of responses per agency was 1 to 89; the mean was 7.05; the median was 2, and the standard deviation was 12.9 responses. The low level of responses from some agencies should not be interpreted as a poor response rate; some small agencies only had a few users.

An additional, agency-context item (item 38) was included in the survey and inquired about the presence of a FINDER “advocate.” This item and its mean score (1= strongly disagree to 7= strongly agree) was:

<table>
<thead>
<tr>
<th>Item 38</th>
<th>Mean</th>
</tr>
</thead>
<tbody>
<tr>
<td>I work with someone who is always encouraging me to use FINDER.</td>
<td>3.83</td>
</tr>
</tbody>
</table>

**Discussion**

The Agency Type variable remained nominal at three levels: Police, Sheriff, and State.

---

10 Agency-level responses are different than the node-level analysis discussed earlier.

11 There are no federal agency nodes in FINDER. It is not known whether there were non-responding federal law enforcement employees who could access FINDER through guest accounts.
However, the agency names were not suited for empirical application (fifty-five dummy variables would have been required). Both logic and the literature suggested that size reflects differences in the user environment, agency culture, and resources (e.g., Fyfe et al, 1997; CALEA, 1998), so a refined agency size measure was used to represent the agency control variable.

The agency size measure was different than the pseudo-interval measure supplied by FINDER convention. Those un-equivalent intervals (0-99, 100-249, 250-499, and more than 500 sworn) were too broad, and a number of agencies’ sworn strength fell at interval borders. Therefore, the actual number of sworn officers (FDLE, 2006) in the agencies represented by survey respondents was used as the scale level measure for agency size. The histogram in Figure 11 reflects the distribution of survey respondents by agency size.
When the Agency Type and re-coded Agency Size measures were used in a secondary correlation analysis, Agency Size was associated with change in other items including: users’ level of experience, availability of technology, and job assignment varieties (these relationships will be explored in later pages). However, no correlations of interest were found for Agency Type.

Item 38, the FINDER advocate item, was initially intended for use in the construction of an “advocate” index to reflect agency-specific norms. However, other advocacy-related items
had been dropped due to the exclusion of Success Tag sections. The use of single, Likert Scale items is discouraged, so item 38 was not included in the hypothesis-testing models.12

**Job assignment**

Job Assignment was identified as a critical variable in the task-fit framework. Four survey items were designed to measure the respondent’s task set. These four, nominal items (items 11 through 14) asked for the respondent’s sworn status, job function, rank, and job title.

The rank (item 13) and job title (item 14) responses cannot be summarily described; there were eleven response levels for rank and thirty response levels for job title. Full results on these items are reported in Appendix E. Response to the sworn/non-sworn item (item 11) was 326 (81.5%) sworn and 74 (18.5%) non-sworn among the respondents. Response to the job function item (item 12) reflected assignments of 61 (15.2%) to patrol, 242 (60.2%) to investigations, 40 (10%) to administrative jobs, and 58 (14.4%) to analysis jobs.

**Discussion**

The challenge of collapsing job titles into a manageable data set was anticipated. The job function item was included in the survey to help catalog job titles and serve as the four-level default measure for job assignment. The relationships between job function, sworn/non-sworn, title, and rank were examined with lambda (directional) and Cramer’s V (symmetric) statistics.

Very strong, statistically significant relationships were identified among the sworn/non-sworn, job function, and job title items. The relationship between those items and rank was

---

12 Post-hypothesis testing, the effect of item 38 was explored on regression models. The item tested as significant in Model 4 (see Table 27) in the prediction of perceived performance and efficiency gains, but had no effect in the models of specific outcomes or system use.
The collective statistical relationships between the items helped guide their reclassification into a manageable set of categories.

First, additional examination of rank data revealed that 78.4% of the respondents reported line-level ranks (i.e., sergeant or supervisor, corporal or officer/deputy/agent/analyst). Twenty-nine respondents (7.1%) reported higher ranks. Cross-tabulation analyses of the higher ranks with their function and titles (where reported) revealed that twenty-eight of the high-rank respondents were administrators of broad investigative functions. These twenty-eight respondents were therefore classified to an “administrative” job title that was expected to be a reliable proxy for rank.

Second, of the forty-seven non-sworn respondents who provided their job title, forty-two (89.4%) identified themselves as analysts. Thus, the analyst title or job classification was expected to serve as a reliable proxy for the respondent’s sworn status.

Third, specific job titles were reported by 341 (85%) of the respondents while job function was reported by all but one respondent. Guided by the both users’ reports of job function relative to job title and the classifications suggested by the statistical tests, a set of seven job functions was created. These seven functions, and their distribution among survey respondents, are shown in Table 14 on the next page. The frequency of patrol and analytical job assignments -- comprising 26% of the responding users – was higher than expected. The prevalence of property investigators as the largest group of users was expected due to FINDER’s property-based origins.
Table 14: Variables for Job Assignment Measure

<table>
<thead>
<tr>
<th>Variable</th>
<th>Frequency</th>
<th>Percent</th>
</tr>
</thead>
<tbody>
<tr>
<td>Patrol</td>
<td>64</td>
<td>16.0%</td>
</tr>
<tr>
<td>All Investigations</td>
<td>48</td>
<td>12.0%</td>
</tr>
<tr>
<td>Property Investigations</td>
<td>121</td>
<td>30.3%</td>
</tr>
<tr>
<td>Persons Investigations</td>
<td>32</td>
<td>8.0%</td>
</tr>
<tr>
<td>Other Investigations</td>
<td>33</td>
<td>8.3%</td>
</tr>
<tr>
<td>Analysis</td>
<td>43</td>
<td>10.8%</td>
</tr>
<tr>
<td>Admin/Other</td>
<td>61</td>
<td>15.1%</td>
</tr>
<tr>
<td>Total</td>
<td>402</td>
<td>100.0%</td>
</tr>
</tbody>
</table>

*User-level success*

The survey included twelve items designed to measure different dimensions of user-level success. These dimensions included specific outcomes, perceived changes in user performance, and perceived changes in user efficiency. Items one through seven captured specific outcome information. Those items and their results are shown below.
Table 15: Items Comprising User-level Success Index

<table>
<thead>
<tr>
<th>Have you:</th>
<th>Yes</th>
<th>Yes%</th>
<th>No</th>
<th>No%</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. Made an arrest?</td>
<td>148</td>
<td>45.7%</td>
<td>176</td>
<td>54.3%</td>
</tr>
<tr>
<td>2. Solved a case?</td>
<td>172</td>
<td>51.8%</td>
<td>160</td>
<td>48.2%</td>
</tr>
<tr>
<td>3. Recovered property?</td>
<td>140</td>
<td>43.9%</td>
<td>179</td>
<td>56.1%</td>
</tr>
<tr>
<td>4. Identified a suspect?</td>
<td>217</td>
<td>63.6%</td>
<td>124</td>
<td>36.4%</td>
</tr>
<tr>
<td>5. Located a person?</td>
<td>203</td>
<td>60.2%</td>
<td>134</td>
<td>39.8%</td>
</tr>
<tr>
<td>6. Recovered a vehicle?</td>
<td>14</td>
<td>4.8%</td>
<td>275</td>
<td>95.2%</td>
</tr>
<tr>
<td>7. Discovered a crime?</td>
<td>91</td>
<td>29.1%</td>
<td>222</td>
<td>70.9%</td>
</tr>
</tbody>
</table>

Five items were related to changes in user performance and efficiency. These items and their mean scores (1= strongly disagree to 7= strongly agree) were:

Table 16: Items Comprising Performance/ Efficiency Index

<table>
<thead>
<tr>
<th>Item</th>
<th>Mean</th>
</tr>
</thead>
<tbody>
<tr>
<td>28 FINDER has helped me improve my job performance. n=355</td>
<td>5.28</td>
</tr>
<tr>
<td>36 FINDER has helped me solve or prevent crimes. n=306</td>
<td>4.93</td>
</tr>
<tr>
<td>45 It is easy for me to give specific examples of how FINDER has helped me do my job. n=346</td>
<td>4.69</td>
</tr>
<tr>
<td>21 FINDER helps me do my job more efficiently. n=356</td>
<td>5.64</td>
</tr>
<tr>
<td>42 FINDER saves me a lot of time. n=357</td>
<td>4.86</td>
</tr>
</tbody>
</table>

These twelve items were examined through a correlation analysis (Cramer’s V). As expected,
with the exception of ‘recovered a vehicle’ (item 6), all items strongly or very strongly correlated at p<.001. Item 6 (‘vehicle’) was weakly correlated at p<.05 with some items, and not significantly correlated with other items.

**Discussion**

The twelve items described above reflect the theoretically and logically supported construct of “user-level success” across distinct dimensions. Items 1 through 7 are dichotomous (yes/no) measures of specific outcomes. Items 28, 36, 45, 21, and 42 are scaled items of performance perceptions. The scale and conceptual differences between the two sets of items prevented their combination into a combined measure. Thus, they will be discussed separately.

Items 1 through 7 were identified as the best measure of the level of user-level success although it provides no measure of frequency in the items. The use of these items for the success measure required that they reflect the success construct in both a reliable and valid manner. Reliability refers to the consistency of the items, taken together, in representing the idea of success. In other words, the measure of each item (yes/no) relative to the others, should remain consistent among users who report similar levels of success.

Reliability of items 1 through 7 was tested with the Cronbach’s Alpha statistic. An Alpha value greater than .70 indicates acceptable reliability; greater than .80 is good or very good; values approaching or exceeding .90 are excellent in terms of indicating reliability among the items (Gliem & Gliem, 2003; Gliner & Morgan, 2000; Kline, 2005). The initial Alpha value was good, but improvement in reliability was predicted with the removal of item 6 (“recovered a vehicle”). With item 6 removed, the Alpha value for the remaining six items was .882, indicating very good reliability.
The validity of the items as a success measure was also considered. The removal of item six was supported statistically and through evidence offered by the review of the Success Tag data. The Success Tags had very few reports of vehicle “successes” and a user had suggested that “vehicle recoveries” were typically achieved through systems like the NCIC. The validity of the remaining six items in a success measure were supported by the task-fit framework and prior research and literature (e.g., BJA, 2005; Zaworski, 2004).

The remaining six items required transformation to a single measure, an index, to be suitable for hypothesis testing (e.g., Babbie, 1995). A summative index, adding-up responses where “Yes”=1 and “No” =0, was not feasible because some of the items were not applicable to some users (e.g., non-sworn users can’t make arrests). Thus, the measure had to reflect the success level relative to each user’s success capacity. This was achieved by measuring success as the ratio (percentage) of reported successful outcomes to successful outcomes possible (excluding “Not Applicable” responses). This ratio, the Success Index, provided a scale measure (0.0 to 1.00) that represented the level of success reported by the survey respondent.

The histogram in Figure 12 illustrates the distribution of the Success Index values among the respondents. The mean index value was .4495 and median index value was .330 with a standard deviation of .393. These statistics indicate that half of the survey users experienced success in less than one-third of the dimensions applicable to them and, on average, users experienced success in about one-half (45%) of the dimensions applicable to them. Of the 402 respondents, 83 (20.6%) reported 100% success across applicable items, and 127 users (31.6%) reported no success.
Items 28, 36, 45, 21, and 42 report users’ perceptions about changes in their performance and task efficiency attributed to FINDER. These items were all very strongly associated with rho values ranging from 0.535 to 0.707 and p<.001 in all relationships. The strength of these relationships indicated that these five items represented a performance and efficiency construct within the general concept of user-level success. The items were tested for reliability, using Cronbach’s Alpha, in the same fashion as items 1 through 7. The Alpha value for the five items was .876, indicating very good reliability in their measurement of the construct. No improvement in the Alpha value was accomplished by eliminating any of the items.
These five items were also evaluated for their validity in representing a construct of performance and efficiency. All of the items are well-grounded in the Task-technology Fit model (Goodhue, 1995) and in parallel items validated in Zaworski’s (2004) study of police information sharing. Consequently, these items were considered to be reliable and valid indicators of FINDER users’ perceptions of changes in individual performance and efficiency attributed to their FINDER use.

Since items 28, 36, 45, 21, and 42 were identically scaled and conceptually similar (on a seven-point, agree/disagree scale), they were suitable for inclusion in an index (e.g., Babbie, 1995). The index value was created for each user by averaging that user’s response across the items. This index was labeled the Performance / Efficiency Index. As expected, this index was strongly correlated to the User-level Success measure ($r = 0.661$, $p < .001$). The strength of this correlation indicates that users’ perceptions about increases in individual performance and efficiency are highly related to their level of successful outcomes.

The Success Index was conceptualized to be a subset of the Performance/Efficiency Index. The Success Index measures outcomes; the Performance/Efficiency Index measures general performance perceptions that (at a minimum) include successful outcomes and efficiency. This suggests that combining the two is “double counting.” Therefore, the two indices were considered mutually exclusive as dependent variables, and would require separate models to test for user-level success.

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13 A Confirmatory Factor Analysis model was tested to fit these items to separate constructs of Performance and Efficiency. The data did not fit the model.
**Frequency of use**

Item 19 was the single item used to measure respondents’ frequency of FINDER use. The item and its results are shown below.

<table>
<thead>
<tr>
<th>19. How often do you use FINDER?</th>
<th>Frequency</th>
<th>Percent</th>
</tr>
</thead>
<tbody>
<tr>
<td>Almost never</td>
<td>91</td>
<td>22.9%</td>
</tr>
<tr>
<td>Few times a month</td>
<td>122</td>
<td>30.7%</td>
</tr>
<tr>
<td>About once a week</td>
<td>37</td>
<td>9.3%</td>
</tr>
<tr>
<td>Few times a week</td>
<td>68</td>
<td>17.1%</td>
</tr>
<tr>
<td>Almost every day</td>
<td>80</td>
<td>20.1%</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td><strong>398</strong></td>
<td><strong>100.0%</strong></td>
</tr>
</tbody>
</table>

**Discussion**

The initial study proposal did not envision that a significant number of survey respondents would be new users or users not visible in the Query Logs. However, the frequency of use measure acquired from item 19 was the only system use measure available for 150 (37%) of those responding to the survey.

The responses to item 19 were compared to the objective data from the Query Logs to help determine whether they were comparable measures. Item 19 was significantly (p<.01) and positively correlated to Total Queries (r=.468), Query Volume (r=.473), and Active Months.
Further, item 19 was positively and significantly correlated \((p<.01)\) to both the Success Index \((r=.616)\) and the Performance/Efficiency Index \((r=.637)\). The moderate or strong correlations of item 19 responses to the Query Log measures suggested that item 19 offered an alternative system use measure to the objective data; particularly with regard to the Active Months measure.

The Query Log data were manipulated to determine if a composite measure would gain associational value with item 19. Several combinations were tried, but the product of Active Months and Total Queries achieved the best correlation value with item 19 responses \((r=.462, p<.01)\) which was less than the \(r\) value of item 19 to Active Months \((r=.604)\). Conceptually, item 19 was a better representation of Active Months (frequency) versus volume (Total Queries and Query Volume), and appeared to represent a viable proxy to the Active Months measure.

**FINDER Task-fit**

The FINDER Task-fit variable was conceptualized along theory and research-based dimensions of system usefulness and usability (see Appendix C). These dimensions were measured through fifteen survey items that were conceptualized as providing a measure of the FINDER Task-fit construct. The fifteen items are presented in two groups. The first group (items 30, 31, and 34) were excluded from the FINDER Task-fit Index discussed below. The second group of twelve items was used to construct the index. The items and their mean scores \((1=\text{strongly disagree to } 7=\text{strongly agree})\), are:
Table 18: Items Excluded from FINDER Task-fit Index

<table>
<thead>
<tr>
<th></th>
<th>Description</th>
<th>Mean</th>
</tr>
</thead>
<tbody>
<tr>
<td>30</td>
<td>I use FINDER to search for property more than I use it to search for people.</td>
<td>4.48</td>
</tr>
<tr>
<td></td>
<td>n=338</td>
<td></td>
</tr>
<tr>
<td>31</td>
<td>In my job I have to use multiple computer systems to assemble the information I need.</td>
<td>5.47</td>
</tr>
<tr>
<td></td>
<td>n=376</td>
<td></td>
</tr>
<tr>
<td>34</td>
<td>I only use FINDER if I am looking for a person or property outside of my jurisdiction.</td>
<td>3.53</td>
</tr>
<tr>
<td></td>
<td>n=357</td>
<td></td>
</tr>
</tbody>
</table>

Table 19: Items Comprising FINDER Task-fit Construct

(Cronbach’s Alpha = .824)

<table>
<thead>
<tr>
<th></th>
<th>Description</th>
<th>Mean</th>
</tr>
</thead>
<tbody>
<tr>
<td>22</td>
<td>FINDER is easy to use. n=374</td>
<td>5.82</td>
</tr>
<tr>
<td>23</td>
<td>I use FINDER only as a last resort. n=354</td>
<td>2.56</td>
</tr>
<tr>
<td>25</td>
<td>I use FINDER to locate information about people. n=360</td>
<td>5.78</td>
</tr>
<tr>
<td>27</td>
<td>FINDER provides me information that I cannot get from any other source. n=361</td>
<td>5.33</td>
</tr>
<tr>
<td>29</td>
<td>FINDER has helped me locate people that I couldn’t find through other techniques. n=349</td>
<td>4.91</td>
</tr>
<tr>
<td>33</td>
<td>Most of the time, FINDER provides information that is useful to me. n=362</td>
<td>5.43</td>
</tr>
</tbody>
</table>
Table 20: Items Comprising FINDER Task-fit Construct

<table>
<thead>
<tr>
<th></th>
<th>Description</th>
<th>n</th>
<th>Mean</th>
</tr>
</thead>
<tbody>
<tr>
<td>35</td>
<td>I use FINDER’s “Link Analysis” to get the information I need.</td>
<td>309</td>
<td>4.40</td>
</tr>
<tr>
<td>37</td>
<td>I have to make a lot of queries on FINDER to get the information I need.</td>
<td>350</td>
<td>3.63</td>
</tr>
<tr>
<td>40</td>
<td>I would use FINDER more often if it did not take so long to get a response to my queries.</td>
<td>354</td>
<td>3.70</td>
</tr>
<tr>
<td>43</td>
<td>I think FINDER is poorly designed.</td>
<td>364</td>
<td>2.76</td>
</tr>
<tr>
<td>47</td>
<td>FINDER would be more useful to me if it had analytical tools.</td>
<td>349</td>
<td>4.11</td>
</tr>
<tr>
<td>48</td>
<td>The best thing about FINDER is I can get information that I was not able to get before.</td>
<td>359</td>
<td>5.35</td>
</tr>
</tbody>
</table>

**Discussion**

Reliability testing used Cronbach’s Alpha and produced an initial Alpha value of .715, or an acceptable level of reliability for all fifteen items (e.g., Kline, 2005). The Cronbach’s Alpha test suggested that reliability could be improved by dropping some of the items. Two of these items, 30 and 34, addressed specific FINDER search behaviors versus usefulness or usability. These two items were logically justified for being excluded from the task-fit construct. A third item, 31, asked about the availability of systems other than FINDER. This item, on its face, reflects a different concept than usefulness or usability, and also was dropped from the task-fit construct.¹⁴

The remaining twelve items were re-tested using Cronbach’s Alpha and produced an Alpha statistic of .824. This Alpha value suggests a good level of reliability among the items.

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¹⁴ Item 31 was later considered for suitability as a component of the Technology construct.
No significant increase in the reliability coefficient would have been achieved by eliminating additional items.

Since all twelve items were identically scaled and conceptually similar (on a seven-point, agree/disagree scale), they were suitable for inclusion in an index (e.g., Babbie, 1995). The index value was created for each user by averaging that user’s response across the items. Five of the items (23, 37, 40, 43, and 47) had been reverse coded because they were negatively worded; their mean values were adjusted accordingly. The resulting index value was used as the measure for the FINDER Task-fit variable.

**Computer expertise**

The Computer Expertise variable was conceptualized through theory and research that suggested a FINDER user’s level of computer expertise would positively influence that user’s level of success. Computer expertise was to be measured by three survey items (26, 32, and 39). The reliability and validity of these items in their representation of Computer Expertise is discussed below. These three items, and their mean scores (1= strongly disagree to 7= strongly agree), are:
Table 21: Items Comprising Computer Expertise Construct

<table>
<thead>
<tr>
<th></th>
<th>Item</th>
<th>Mean</th>
</tr>
</thead>
<tbody>
<tr>
<td>26</td>
<td>I am usually comfortable with learning new computer programs.</td>
<td>5.88</td>
</tr>
<tr>
<td></td>
<td>n=379</td>
<td></td>
</tr>
<tr>
<td>32</td>
<td>My co-workers often ask me to help them with computer problems.</td>
<td>5.01</td>
</tr>
<tr>
<td></td>
<td>n=368</td>
<td></td>
</tr>
<tr>
<td>39</td>
<td>My co-workers often ask me to help teach them how to use software.</td>
<td>4.53</td>
</tr>
<tr>
<td></td>
<td>n=353</td>
<td></td>
</tr>
</tbody>
</table>

**Discussion**

Reliability testing of the items was conducted using Cronbach’s Alpha and produced an Alpha value of .760, or an acceptable level of reliability (e.g., Kline, 2005). However, the Cronbach’s Alpha analysis indicated that reliability would be increased to .842 (good or very good reliability) if item 26 were dropped.

The Cronbach’s Alpha analysis suggested the presence of a different dimension being measured by item 26 when compared to items 32 and 39. While item 26 deals exclusively with the user’s level of comfort (or computer expertise) with new programs, items 32 and 39 expand computer expertise to the dimension of helping co-workers. In other words, the concept of measuring any one user’s level of “computer expertise” is diluted in items 32 and 39 by also measuring that user’s status (or willingness) as the go-to computer person for co-workers.

The mix of helping co-workers and computer expertise is not specifically validated within the task-fit framework employed by this study. Zaworski (2004, pp. 116-117) found no
significant relationship between “assists co-workers with computer problems” and “computer knowledge,” but he did not otherwise test the items.

The question in terms of the User Expertise construct was whether to accept the three-item construct (with an adequate reliability coefficient); drop item 26 to increase reliability (but lose the user’s self-assessment of expertise); or employ a single item (item 26) as the User Expertise measure. The decision was made to use the three-item construct. This decision was justified for two reasons. First, there are statistical risks associated with use of Likert-scaled, single-item measures (e.g., Gliem & Gliem, 2003). Second, a user’s willingness to assist others may be important to this study (see the earlier discussion about squad-level FINDER experts). Further, and by definition, “expertise” is a relative term of perceived ability between people that is independent of the “expert’s” self-assessment.

Since the three items were identically scaled and conceptually similar, they were suitable for inclusion in an index (e.g., Babbie, 1995). The Computer Expertise index value was created for each user by averaging that user’s response across the three items. Any interpretation of this index’s influence on user-level success or system use must recognize that “computer expertise” captures both the user’s self-assessment of skill and that user’s status as a computer “expert” within his or her work environment.

**Workload**

The Workload variable was conceptualized through theory and research that suggested a FINDER user’s workload would be useful as a control for that user’s level of system use. Workload was to be measured by a single survey item (item 52). This item was answered in a three-step process that first identified whether the respondent tracked workload, then the
respondent’s type of workload, and finally asked the respondent to characterize monthly workload in approximate intervals.

Of 402 respondents, 330 reported a workload measure. The item and the frequency of responses were:

Table 22: Workload Measure (Survey Item 52)

| Item 52. On average, how many [calls, cases, projects, meetings] do you handle each month? |
|-----------------------------------------------|------------------|
| Frequency | Percent |
| Fewer than 10 | 28 | 8.5 |
| Between 10 and 50 | 185 | 56.1 |
| Between 51 and 100 | 76 | 23.0 |
| More than 100 | 41 | 12.4 |
| Total Responses | 330 | 100.0 |

**Discussion**

The workload item responses were reviewed in correlation and covariance analyses. No significant relationships were found between Workload and the other variables or items of interest. The correlation coefficient for workload compared to Query Volume, Total Queries, Agency Size, Success, Success Tags and Job Assignment were less than $r = 0.10$ and not statistically significant. It is noted that no conceptual argument is made that “between 10 and 50” cases is a workload equivalent to “between 10 and 50” projects, or any other workload type. The workload item was exploratory.
Training

The Training variable was conceptualized through theory and research that suggested users who had received FINDER training would be more successful than those who had not. Two survey items were designed to build a measure of each user’s level of FINDER training. The first (item 20) related to types of training received; the second (item 46) considered the user’s perceived need for additional training. The items and responses are detailed below.

Table 23: FINDER Training Received (Survey Item 20)

<table>
<thead>
<tr>
<th>20. What kind of FINDER training have you received?</th>
<th>Frequency</th>
<th>Percent</th>
</tr>
</thead>
<tbody>
<tr>
<td>Co-worker or supervisor, UCF, and agency training</td>
<td>3</td>
<td>0.8%</td>
</tr>
<tr>
<td>Co-worker or supervisor and UCF training</td>
<td>10</td>
<td>2.5%</td>
</tr>
<tr>
<td>Co-worker or supervisor and agency training</td>
<td>10</td>
<td>2.5%</td>
</tr>
<tr>
<td>Agency training and UCF training</td>
<td>7</td>
<td>1.8%</td>
</tr>
<tr>
<td>Co-worker or supervisor training only</td>
<td>150</td>
<td>38.1%</td>
</tr>
<tr>
<td>UCF training only</td>
<td>35</td>
<td>8.9%</td>
</tr>
<tr>
<td>Agency training only</td>
<td>56</td>
<td>14.2%</td>
</tr>
<tr>
<td>No training</td>
<td>123</td>
<td>31.2%</td>
</tr>
<tr>
<td>Total</td>
<td>394</td>
<td>100.0%</td>
</tr>
</tbody>
</table>

Table 24: Value of FINDER Training (Survey Item 46)

<table>
<thead>
<tr>
<th>Item 46 (1 to 7 agree/disagree scale)</th>
<th>Mean</th>
</tr>
</thead>
<tbody>
<tr>
<td>I could get better results from FINDER if I were provided more training about how to use it. n=361</td>
<td>4.10</td>
</tr>
</tbody>
</table>
Discussion

The training received item (20) was re-coded into four dummy variables: no training, co-worker/supervisor training, agency training, and UCF training. Of the three training types, the UCF training was the only type to have an established curriculum that would have been presented in a consistent fashion, regardless of the respondent’s agency affiliation.

The responses to item 46 (need more training) were checked for relationships to the training variables. Cramer’s V (nominal to nominal) and Spearman rank (ordinal to ordinal) methods found item 46 significantly and negatively related to the UCF training variable, and positively related to the No Training variable. The relationships to co-worker/supervisor and agency training were negative, but not statistically significant.

These relationships indicated that item 46 accurately reflected the intent of the question. In terms of users’ satisfaction with training received, the strongest relationship (more satisfied) was with the formalized UCF/FINDER curriculum, and the least satisfaction was associated with no training at all.

The four dichotomous training variables (training dummies) were retained for empirical testing. Item 46 was cautiously retained with recognition that the use of a single, Likert-scale item poses measurement risks (e.g., Gliem & Gliem, 2003).

Law enforcement experience and FINDER experience

Both law enforcement experience and Time as FINDER User were proposed in the research framework as controlling for the user’s law enforcement and FINDER experience against other factors influencing user-level success. They are both discussed here.

Law enforcement experience was measured by a single item (item 15) that reflected from
less than one year of experience to more than twenty years of experience. The mean number of years of experience was 13.27 years, the median years of experience was 14 years, and the standard deviation of the years of experience distribution was 5.78. The mode of the distribution was 20 years or more of experience; this group represented 25% of all respondents.

FINDER experience was computed from the Query Logs as User Months (when the survey respondent was matched with query data). It is important to note that User Months were calculated only for the 252 respondents who were visible in the Query Logs between December 2004 and February 2006.

Item 16 asked respondents to report when they first began using FINDER. These responses were not usable. Nearly half of the respondents failed to recall either the year or month (or either) that started their FINDER use. For those respondents who did complete the item and whose answer could be checked with Query Log data, the self-report data was generally inaccurate. Consequently, the User Months data was the only reliable data available to represent FINDER experience, and it was limited to 252 (63%) of the respondents. These data were reported and discussed in the Query Log analysis (Table 7).

**Discussion**

The senior status of many respondents (twenty-five percent with twenty or more years of service) was not expected. Correlation analysis indicated that years of law enforcement experience was weakly, but significantly correlated with agency size, Sheriff’s Offices, User Months, and “other” investigative positions. The strongest correlation ($r=.204$, $p<.01$) was with User Months. This suggested a relationship between FINDER and general law enforcement seniority.
The failure of item 16 to accurately report respondents’ time in the FINDER system was not unexpected. The potential for respondent recall problems was anticipated. The risk of relying on self-report recall information was verified by the ability to compare the recall responses to the objective data from the Query Logs.

Technology

Goodhue’s (1995) Task-technology Fit model and subsequent research suggest that competing technologies and voluntariness of use have some unknown degree of impact on the use of the system being studied. If users are required to use a particular technology, then system use could be inflated, regardless of the system’s value to the user. If the user has multiple technology options, then system use can be diluted in the system being studied. The Technology construct of this study was intended to measure both the voluntariness and technology-option dimensions.

Voluntariness was addressed by a single item (item 17) asking the respondents whether they were required to use FINDER. Of the 402 responses, 352 (87.6%) said “no” and 46 (11.4%) answered “yes.”

Technology options were to be measured by three items (31, 44, and 49). The initial reliability test of the three items produced a Cronbach’s Alpha value of .462 that indicated the three items did not provide a reliable measure of the Technology construct. When item 31 was dropped (“In my job I have to use multiple computer systems to assemble the information I need”), the Alpha value increased to .648 for items 44 and 49. These two items, and their mean scores (1= strongly disagree to 7= strongly agree), are shown below.
Table 25: Items Comprising Technology Index

<table>
<thead>
<tr>
<th>Item</th>
<th>Description</th>
<th>Mean</th>
</tr>
</thead>
<tbody>
<tr>
<td>44</td>
<td>I have computer tools other than FINDER to help me get information from outside of my jurisdiction. n=370</td>
<td>4.41</td>
</tr>
<tr>
<td>49</td>
<td>FINDER is the only computer tool I have to get information from other police agencies. n=369</td>
<td>3.90</td>
</tr>
</tbody>
</table>

Discussion

Responses to item 17 reflected that the great majority (87.6%) of respondents’ FINDER use was voluntary. This was important because Goodhue (1995) posited that non-voluntary system use would complicate any analyses of the effect of system use on individual performance (user-level success). The presence of some non-voluntary users in the response group permitted a statistical assessment of this effect.

The relatively low Cronbach’s Alpha of .648 for the two, technology options items (44 and 49) could not be explained. The questions were, essentially, mirror images, and were posed in both the positive and negative context to protect against response bias (Dillman, 2000). Responses to these two items were reviewed, case-by-case, to check for coding errors; none were found. An examination of correlations between the two items and other items and indices was also conducted. The items were identical in terms of significant correlations, but item 44 had slightly stronger correlation values with other items and constructs of interest. It is possible that responses to item 49 were biased because of its close proximity to item 44 (‘routine’ bias) or because it was the last in the series of twenty-nine agree/disagree items (‘fatigue’ bias).

In the initial development of variables for this study, the Technology variable was identified as exploratory. The use of items with Cronbach’s Alpha values less than .70 and as
low as .50 has been supported when the items represent exploratory concepts (Hair et al, 1998; McMillan & Schumacher, 1993). Thus, response to items 44 and 49 were averaged and adopted as a measure of Technology (alternative technologies).

**Final Study Variables**

The initial and final variables derived from both Query Logs and the user survey are presented in Table 26.

Table 26: Final Study Variables

<table>
<thead>
<tr>
<th>Initial Variable (Name/Type)</th>
<th>Final Measures</th>
<th>Level</th>
<th>Description</th>
<th>Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>User-Level Success/Dependent</td>
<td>Scale</td>
<td>Number of successes reported by an individual user.</td>
<td>FINDER logs &amp; User Survey</td>
<td></td>
</tr>
<tr>
<td>Success Index</td>
<td>Scale</td>
<td>Percentage of six, applicable, successful outcomes reported by users.</td>
<td>Survey Items 1-5, &amp; 7</td>
<td></td>
</tr>
<tr>
<td>Performance/Efficiency Index</td>
<td>Scale</td>
<td>Average of five, 7-point scale items.</td>
<td>Survey Items 21, 28, 36, 42, &amp; 45</td>
<td></td>
</tr>
<tr>
<td>Usage Rate/Dependent &amp; Independent (mediating)</td>
<td>Scale</td>
<td>Individual user’s average number of FINDER queries per day during specified time.</td>
<td>FINDER Query Logs</td>
<td></td>
</tr>
<tr>
<td>Total Queries</td>
<td>Scale</td>
<td>Total FINDER queries by user between Dec 04 &amp; Feb 06. Weighted by number of available FINDER nodes by month.</td>
<td>FINDER Query Logs</td>
<td></td>
</tr>
<tr>
<td>Query Volume*</td>
<td>Scale</td>
<td>User’s average FINDER queries per month following user’s first appearance in Query Logs. Weighted by number of available FINDER nodes by month.</td>
<td>FINDER Query Logs</td>
<td></td>
</tr>
<tr>
<td>Active Months</td>
<td>Scale</td>
<td>Percentage of User Months with query activity following user’s first appearance in Query Logs (active mos. /total mos. In FINDER) between Dec 04 &amp; Feb 06.</td>
<td>FINDER Query Logs</td>
<td></td>
</tr>
<tr>
<td>Initial Variable (Name/Type)</td>
<td>Final Measures</td>
<td>Level</td>
<td>Description</td>
<td>Source</td>
</tr>
<tr>
<td>----------------------------------------------</td>
<td>---------------------------------</td>
<td>---------------</td>
<td>----------------------------------------------------------------------------</td>
<td>-----------------------------------------</td>
</tr>
<tr>
<td>Frequency of Use</td>
<td>Ordinal</td>
<td>Approximate-interval scale of user’s frequency of use during month or week.</td>
<td>User Survey item 19</td>
<td></td>
</tr>
<tr>
<td>FINDER Task-fit/ Independent</td>
<td>Scale</td>
<td>Scale value derived from modified TTF instrument. (Goodhue, 1995, 1998; Goodhue &amp; Thompson, 1995)</td>
<td>User survey</td>
<td></td>
</tr>
<tr>
<td>FINDER Task-fit Index</td>
<td>Scale</td>
<td>Average of twelve, 7-point scale items measuring FINDER usefulness &amp; usability.</td>
<td>User survey items 22, 23, 25, 27, 29, 33, 35, 37, 40, 43, 47, &amp; 48</td>
<td>User survey items 22, 23, 25, 27, 29, 33, 35, 37, 40, 43, 47, &amp; 48</td>
</tr>
<tr>
<td>Computer Expertise/ Independent</td>
<td>Scale</td>
<td>Scale value derived from adapted from Goodhue (1995) and Zaworski (2004).</td>
<td>User survey</td>
<td></td>
</tr>
<tr>
<td>Computer Expertise Index</td>
<td>Scale</td>
<td>Average of three, 7-point scale items. (Exploratory variable)</td>
<td>User survey items 26, 32, &amp; 39</td>
<td></td>
</tr>
<tr>
<td>Job Assignment/ Independent</td>
<td>Nominal</td>
<td>User-reported primary job assignment.</td>
<td>User survey</td>
<td></td>
</tr>
<tr>
<td>Primary Job Function</td>
<td>Nominal</td>
<td>Patrol, Investigations, Analysis/Support, Administrative (4 categories)</td>
<td>User survey item 12</td>
<td></td>
</tr>
<tr>
<td>Job Title*</td>
<td>Nominal</td>
<td>Patrol, All Investigations, Property Investigations, Persons Investigations, Other Investigations, Analysis, Other (seven categories)</td>
<td>User survey items 12 &amp; 14</td>
<td></td>
</tr>
<tr>
<td>Sworn Status*</td>
<td>Nominal</td>
<td>Sworn or non-sworn status</td>
<td>User survey item 11</td>
<td></td>
</tr>
<tr>
<td>Workload/ Control</td>
<td>Scale</td>
<td>User-reported average monthly “workload” or “caseload” volume.</td>
<td>User survey</td>
<td></td>
</tr>
<tr>
<td>Average Monthly Workload</td>
<td>Ordinal</td>
<td>Approximate interval measure of average number of user-relevant workload events per month. (Exploratory variable)</td>
<td>User Survey item 52</td>
<td></td>
</tr>
<tr>
<td>Training/ Independent</td>
<td>Nominal</td>
<td>Yes/No whether user has received training from the FINDER staff.</td>
<td>User survey &amp; PSTC training records</td>
<td></td>
</tr>
<tr>
<td>Training Yes/No*</td>
<td>Nominal</td>
<td>Whether user reports receiving any type of FINDER training.</td>
<td>User survey item 20</td>
<td></td>
</tr>
<tr>
<td>Initial Variable (Name/Type)</td>
<td>Final Measures</td>
<td>Level</td>
<td>Description</td>
<td>Source</td>
</tr>
<tr>
<td>-----------------------------</td>
<td>----------------</td>
<td>--------</td>
<td>-----------------------------------------------------------------------------------------------------------------------------------------------</td>
<td>-----------------------------</td>
</tr>
<tr>
<td>FINDER Training Yes/No</td>
<td>Nominal</td>
<td>Whether user reports receiving formal training provided by FINDER staff.</td>
<td>User survey item 20</td>
<td></td>
</tr>
<tr>
<td>Training Need*</td>
<td>Ordinal</td>
<td>Response to survey item addressing need for more training.</td>
<td>User survey item 46</td>
<td></td>
</tr>
<tr>
<td>Agency/Control</td>
<td>Nominal</td>
<td>Name of user’s employing police agency.</td>
<td>User survey</td>
<td></td>
</tr>
<tr>
<td>Agency Type*</td>
<td>Nominal</td>
<td>Police or Sheriff</td>
<td>User survey item 8</td>
<td></td>
</tr>
<tr>
<td>Agency Sworn*</td>
<td>Scale</td>
<td>Number of sworn personnel in user’s employing agency.</td>
<td>User survey item 9 &amp; FDLE report</td>
<td></td>
</tr>
<tr>
<td>Agency Advocate*</td>
<td>Ordinal</td>
<td>Response to survey item (exploratory)</td>
<td>User survey item 38</td>
<td></td>
</tr>
<tr>
<td>Time as LEO/Control</td>
<td>Scale</td>
<td>Number of years user has been employed as a sworn law enforcement officer</td>
<td>User survey</td>
<td></td>
</tr>
<tr>
<td>Law Enforcement Experience</td>
<td>Scale</td>
<td>Number of years of law enforcement experience.</td>
<td>User survey item 15</td>
<td></td>
</tr>
<tr>
<td>Time as user/Control</td>
<td>Scale</td>
<td>Period of time elapsed between first log-in as FINDER user (measured in days, weeks or months)</td>
<td>FINDER query logs &amp; User survey</td>
<td></td>
</tr>
<tr>
<td>User Months</td>
<td>Scale</td>
<td>Constrained to number of months measured from user’s first login after December 1, 2004 and measured to February 28, 2006 (maximum 15 months)</td>
<td>FINDER Query Logs</td>
<td></td>
</tr>
<tr>
<td>Number of Agencies Sharing Info</td>
<td>Scale</td>
<td>Number of police agencies sharing information via FINDER</td>
<td>PSTC &amp; FINDER Query Logs</td>
<td></td>
</tr>
<tr>
<td>None</td>
<td>Scale</td>
<td>Number of agencies sharing information was incorporated into measures of query volume.</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Technology/Control</td>
<td>Nominal</td>
<td>Other information sharing technology available to user (i.e., other system name). Alternatively, weighted value of technologies</td>
<td>User survey</td>
<td></td>
</tr>
<tr>
<td>Initial Variable (Name/Type)</td>
<td>Final Measures</td>
<td>Level</td>
<td>Description</td>
<td>Source</td>
</tr>
<tr>
<td>-----------------------------</td>
<td>----------------</td>
<td>-------</td>
<td>-------------</td>
<td>--------</td>
</tr>
<tr>
<td>Required Use</td>
<td>Nominal</td>
<td>Whether user is required to use FINDER. (Exploratory variable)</td>
<td>User Survey item 17</td>
<td></td>
</tr>
<tr>
<td>Technology Options</td>
<td>Scale</td>
<td>Average of two, 7-point scale items. (Exploratory variable)</td>
<td>User Survey items 44 &amp; 49</td>
<td></td>
</tr>
</tbody>
</table>

* Indicates variables that did not contribute to explanatory power of regression models.

**Final Hypotheses and Hypothesis Testing**

The analysis of the data available for this study described the emergence of two, distinct measures for user-level success (the Success Index and the Performance/Efficiency Index). Also described were objective measures for system use (Total Queries, Query Volume, and Active Months) and FINDER Experience (User Months). These objective data were available for only 252 of the 402 survey respondents, but an additional measure of system use (Frequency of Use) was available for all survey respondents.

The initial hypotheses conceptualized user-level success and system use as single measures versus the multiple measures from the valid data set. Therefore, the hypotheses required expansion to test for predicted relationships across the combinations of success and system use measures. Hypothesis testing across the combinations of measures could help identify “best” measures of the constructs and be used to build related metrics. In addition, if the several outcome measures were individually reliable and valid, hypothesis testing across the combinations of measures was expected to produce consistent results in terms of the explanatory variables.
First, an expanded set of twenty-three hypotheses was developed and tested using multivariate regression (“regression”) techniques. Four regression models were constructed to test predictions on the two, user-level success measures with the two sets of system use measures. Three, additional models were required to test predictions on three system use measures.\(^{15}\) Third, a structural equation model (“SEM”) was used to explore the nonrecursive relationship between system use and user-level success that Goodhue’s (1995) Task-technology Fit Model proposes. The refined hypotheses are presented below.

**Final Hypotheses**

The first set of five, initial hypotheses predicted relationships of the independent variables (including system use) to user-level success. Each of these hypotheses was expanded to test for both measures of user-level success (Success Index and Performance/Efficiency Index) and, specifically in H\(_2\), three system use measures (Total Queries, Active Months, Frequency of Use) as predictors of success.

Initial hypotheses H\(_6\) though H\(_9\) predicted a single measure of system use as a mediating variable. Each of these hypotheses was expanded to test for relationships of the independent variables to each of the three, system use measures. In sum, the nine, initial hypotheses were refined and expanded to twenty-six hypotheses. Both the initial hypotheses and the expanded set are shown below. The expanded set has been stated in the null.

- Initial H\(_1\): A FINDER user’s task-fit measure will be positively and significantly related to the number of successes reported by that user.

\(^{15}\) Some variables were excluded from models because correlation analyses and model-building suggested they offered no explanatory power and did not contribute to this discussion. These variables were marked with an asterisk in Table 26.
• Final H0_1A: A user’s FINDER Task-fit does not influence that user’s Success Index.

• Final H0_1B: A user’s FINDER Task-fit does not influence that user’s Performance/Efficiency Index.

• Initial H2: A FINDER user’s usage rate will be positively and significantly related to the number of successes reported by that user.
  
  o Final H0_2A: A user’s Total Queries does not influence that user’s Success Index.
  
  o Final H0_2B: A user’s Active Months does not influence that user’s Success Index.
  
  o Final H0_2C: A user’s Frequency of Use does not influence that user’s Success Index.
  
  o Final H0_2D: A user’s Total Queries does not influence that user’s Performance/Efficiency Index.
  
  o Final H0_2E: A user’s Active Months does not influence that user’s Performance/Efficiency Index.
  
  o Final H0_2F: A user’s Frequency of Use does not influence that user’s Performance/Efficiency Index.

• Initial H3: A FINDER user’s computer expertise measure will be positively and significantly related to the number of successes reported by that user.
  
  o Final H03A: A user’s Computer Expertise does not influence that user’s Success Index.
  
  o Final H03B: A user’s Computer Expertise does not influence that user’s Performance/Efficiency Index.
• Initial H₄: A FINDER user’s receipt of FINDER training will be positively and significantly related to the number of successes reported by that user.
  o Final H₀₄A: A user’s receipt of FINDER training does not influence that user’s Success Index.
  o Final H₀₄B: A user’s receipt of FINDER training does not influence that Performance/Efficiency Index.

• Initial H₅: A FINDER user’s job assignment will be positively and significantly related to the number of successes reported by that user.
  o Final H₀₅A: A user’s Job Assignment does not influence that user’s Success Index.
  o Final H₀₅B: A user’s Job Assignment does not influence that user’s Performance/Efficiency Index.

• Initial H₆: A user’s FINDER task-fit measure will be positively and significantly related to that user’s usage rate.
  o Final H₀₆A: A user’s FINDER Task-fit does not influence that user’s Total Queries.
  o Final H₀₆B: A user’s FINDER Task-fit does not influence that user’s Active Months.
  o Final H₀₆C: A user’s FINDER Task-fit does not influence that user’s Frequency of Use.

• Initial H₇: A user’s receipt of FINDER training will be positively and significantly related to that user’s usage rate.
  o Final H₀₇A: A user’s receipt of FINDER Training does not influence that user’s Total Queries.
• Final H07B: A user’s receipt of FINDER Training does not influence that user’s Active Months.
• Final H07C: A user’s receipt of FINDER Training does not influence that user’s Frequency of Use.

• Initial H8: A FINDER user’s computer expertise measure will be positively and significantly related to that user’s usage rate.
  • Final H08A: A user’s Computer Expertise does not influence that user’s Total Queries.
  • Final H08B: A user’s Computer Expertise Training does not influence that user’s Active Months.
  • Final H08C: A user’s Computer Expertise does not influence that user’s Frequency of Use.

• Initial H9: A FINDER user’s job assignment, a FINDER user’s usage rate will be significantly related to that user’s.
  • Final H09A: A user’s Job Function does not influence that user’s Total Queries.
  • Final H09B: A Job Function does not influence that user’s Active Months.
  • Final H09C: A user’s Job Function does not influence that user’s Frequency of Use.

Regression Models and Results

SPSS 13.5, was used for the regression analyses. SPSS provides “automatic” model building algorithms, but the algorithms were not used because they do not necessarily build conceptually sound models. In addition, the algorithms (such as the “stepwise” method) do not
recognize dummy variables (dichotomously-coded, nominal variables) in their groupings (Norusis, 2005). Since the independent variables in this study incorporated several nominal measures (e.g., job assignment, required use) coded as group dummies, the regression models were manually constructed.

The addition of variables to a regression model increases $R^2$ values, even if those variables are not important to the model (Gliner & Morgan, 2000; Kachigan, 1986; Kline, 2005). Thus, the manual model-building included a test for statistical significance for the change in $R^2$ as variables were added. Variables that did not contribute a statistically significant amount of explanatory power to the model were excluded.

Where alternative measures for the same concept were available (e.g., training, agency, job assignment) the measure used in the models was that which contributed the most to explanatory power. In this fashion, combinations of variables were added and excluded from the model to find the best, explanatory “fit” of the variables to the success and system use measures. This manual process approximates that used by the SPSS algorithms, but allowed control over the conceptual validity of the models (Norusis, 2005).

Residual data and partial coefficient plots and statistics were examined after each of the seven models was refined. These examinations helped confirm the linear relationships of the study variables and the predictive validity of the models (e.g., Gliner & Morgan, 2000; Norusis, 2005; van Belle, 2002). The residual data are not discussed unless they were remarkable in some fashion.

Seven regression models were constructed to test hypotheses. The first four models predict user-level success. The final three models predict system use. The study variables used
in the models are discussed relative to their model results and hypotheses. Control variables and other relationships that were not hypothetically posed are also addressed.

Models 1 through 4 were constructed to test $H_{01}$ through $H_{05B}$. The first model regresses the objective, Query Log-based measures on the Success Index. The second model uses the survey-based Frequency of Use data to predict the Success Index. The third model regresses the objective, Query Log data on the Performance/Efficiency Index. The fourth model predicts the Performance/Efficiency Index using survey-based Frequency of Use data. The results for these four models are shown in Table 27.
Table 27: Results of Regression Testing for User-level Success Measures

<table>
<thead>
<tr>
<th>Independent Variables</th>
<th>Success Index</th>
<th>Performance/Efficiency Index</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Model 1 (n=252)</td>
<td>Model 2 (N=402)</td>
</tr>
<tr>
<td>Total Queries</td>
<td>.132*</td>
<td>-</td>
</tr>
<tr>
<td>Active Months</td>
<td>.290***</td>
<td>-</td>
</tr>
<tr>
<td>Frequency of Use</td>
<td>-</td>
<td>.441***</td>
</tr>
<tr>
<td>FINDER Task-fit</td>
<td>.367***</td>
<td>.232***</td>
</tr>
<tr>
<td>Computer Expertise</td>
<td>.002</td>
<td>.024</td>
</tr>
<tr>
<td>Investigative Assignment</td>
<td>.124*</td>
<td>.172***</td>
</tr>
<tr>
<td>Avg. Monthly Workload</td>
<td>.089</td>
<td>.053</td>
</tr>
<tr>
<td>FINDER Training</td>
<td>-.139**</td>
<td>-.035</td>
</tr>
<tr>
<td>Law Enforcement Experience</td>
<td>-.049</td>
<td>-.042</td>
</tr>
<tr>
<td>User Months</td>
<td>.118*</td>
<td>-</td>
</tr>
<tr>
<td>Required Use</td>
<td>-.078</td>
<td>-.077*</td>
</tr>
<tr>
<td>Technology Options</td>
<td>.035</td>
<td>.019</td>
</tr>
<tr>
<td>R²</td>
<td>.489</td>
<td>.456</td>
</tr>
</tbody>
</table>

*p<.05  **p<.01  ***p<.001  Standardized Coefficient Values (Beta) Displayed

**Discussion**

Table 28 reflects the acceptance or non-acceptance of the alternative hypotheses across the four regression models. First, the findings will be discussed regarding the success and system use measures. Second, the findings will be discussed in terms of each group of hypotheses.
Table 28: Summary of Hypothesis Testing for User-level Success Measures

<table>
<thead>
<tr>
<th>Alternative Hypothesis</th>
<th>Success Index</th>
<th>Performance/Efficiency Index</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Model 1</td>
<td>Model 2</td>
</tr>
<tr>
<td>$H_{a1A} &amp; H_{a1B}$</td>
<td>FINDER Task Fit $\rightarrow$</td>
<td>Yes</td>
</tr>
<tr>
<td>$H_{a2A} &amp; H_{a2D}$</td>
<td>Total Queries $\rightarrow$</td>
<td>Yes</td>
</tr>
<tr>
<td>$H_{a2B} &amp; H_{a2E}$</td>
<td>Active Months $\rightarrow$</td>
<td>Yes</td>
</tr>
<tr>
<td>$H_{a2C} &amp; H_{a2F}$</td>
<td>Frequency of Use $\rightarrow$</td>
<td>-</td>
</tr>
<tr>
<td>$H_{a3A} &amp; H_{a3B}$</td>
<td>Computer Expertise $\rightarrow$</td>
<td>No</td>
</tr>
<tr>
<td>$H_{a4A} &amp; H_{a4B}$</td>
<td>FINDER Training $\rightarrow$</td>
<td>Yes*</td>
</tr>
<tr>
<td>$H_{a5A} &amp; H_{a5B}$</td>
<td>Job Function $\rightarrow$</td>
<td>Yes</td>
</tr>
</tbody>
</table>

* Negative relationship

**User-level Success and System Use**

Optimally, a single, reliable and valid measure of user-level success could be developed for gauging the value of police information sharing to its users. The regression models suggest that while *both* the Success Index and Performance/Efficiency Index are good measures of user-level success, the models incorporating the Performance/Efficiency Index offer higher explanatory power. As noted earlier, the Success Index was considered a subset of the Performance/Efficiency Index. The regression models support the proposition that the Performance/Efficiency Index reflects both the successful outcomes captured by the Success Index and additional gains in user-level success through increased efficiency.
In terms of R² value, these two success measures are consistently predicted by both objective and survey-based system use data. This suggests that the survey-based measure of system use, Frequency of Use, is a valid surrogate for the objective, Query Log-based measures. This is an important finding. Given the time and resources that were necessary to collect the Query Log Data, the survey-based estimation of system use was a much more efficient way to represent system use in its relationship to user-level performance (at least in the context of FINDER’s distributed architecture). The system use measures are discussed at greater length below.

- **H₀₁A:** A user’s FINDER Task-fit does not influence that user’s Success Index. The null is rejected; FINDER Task-fit was found to be a positive, statistically significant predictor of the Success Index across all four models.

- **H₀₁B:** A user’s FINDER Task-fit does not influence that user’s Performance/Efficiency Index. The null is rejected; FINDER Task-fit was found to be a positive, statistically significant predictor of the Performance/Efficiency Index across all four models.

Three of the four regression models found the task-fit measure to be the most important predictor of user-level success. These findings were expected; the relationship of task-fit to individual performance is the foundation of the Task-technology Fit model (Goodhue, 1995) used to frame this study. In practical terms, the importance of task-fit means that users who reported high levels of the *usefulness* and *usability* of FINDER were also likely to report high levels of success. Usefulness items in the survey assessed the value of FINDER data to the user’s task-set. Usability items addressed ease of use and functionality.
• **H0_2A**: A user’s Total Queries does not influence that user’s Success Index. The null is rejected; Total Queries was found to be a positive, statistically significant predictor of the Success Index.

• **H0_2B**: A user’s Active Months does not influence that user’s Success Index. The null is rejected; Active Months was found to be a positive, statistically significant predictor of the Success Index.

• **H0_2C**: A user’s Frequency of Use does not influence that user’s Success Index. The null is rejected; Frequency of Use was found to be a positive, statistically significant predictor of the Success Index.

• **H0_2D**: A user’s Total Queries does not influence that user’s Performance/Efficiency Index. The null is not rejected; the relationship of Total Queries to the Performance/Efficiency Index was not statistically significant (p<.173).

• **H0_2E**: A user’s Active Months does not influence that user’s Performance/Efficiency Index. The null is rejected; Active Months was found to be a positive, statistically significant predictor of the Performance/Efficiency Index.

• **H0_2F**: A user’s Frequency of Use does not influence that user’s Performance/Efficiency Index. The null is rejected; Frequency of Use was found to be a positive, statistically significant predictor of the Performance/Efficiency Index.

Hypotheses H0_2A through H0_2F collectively predict the influence of different system use variables on the two user-level success measures. With one exception (H0_2D), both the objective and survey-based measures of system use were significant predictors of user-level success. This exception is discussed first.
The non-significant result for Total Queries in Model 3 can be approached by comparing it to the statistically significant result for Total Queries in Model 1. Only one variable differs between the models: user-level success. Model 1 uses the Success Index (success-as-performance outcomes) and Model 3 uses the Performance/Efficiency Index (success as performance outcomes and efficiency). The apparent difference between the measures is the inclusion of an unspecified efficiency dimension in the latter. It is the presence of “efficiency” in the success variable that offers an explanation for the statistical non-significance of Total Queries in Model 3.

Conceptually, increasing the level of queries to achieve success becomes inefficient at some point. It is unlikely that a linear relationship between queries and success extends across the possible range of either. The data used for the Performance/Efficiency Index were constrained to a value of 7.0 by their item scales. The Total Query measure was not constrained. Non-linearity and a diminishing return on Total Queries was assured at some point in their relationship.

Although the effect of dissimilar ranges in the variable measurements was shared by the models, Model 1 did not measure efficiency; it measured only whether certain outcomes had occurred, and it did not capture frequency of those outcomes. In other words, given an X value of Total Queries in Model 1, the Success Index would be the same for X Total Queries whether the user had made 1 arrest or 100 arrests. Clearly, 100 arrests for X Queries is more efficient than 1 arrest; but Model 1 does not measure efficiency, and Total Queries is shown as a statistically significant influence on success regardless of implicit efficiency or inefficiency.

Model 2, however, did measure efficiency. The statistical insignificance of Total Queries in that model affirms that, all other things held constant, an increase in Total Queries does not
contribute to efficiency. Further, during the iterative model-building process described above, it was noted that when the Workload control was excluded from Model 4, Total Queries became statistically significant (p<.045). This suggested that the Workload control offers an anchor (reference) point from which an “efficient” volume of queries can be estimated relative to the user’s workload.

Alternatively, the model could be flawed, or the relationship of Total Queries to success could be spurious. However, the evidence indicates that a volume-based measure of system use—such as Total Queries—can be used to estimate both outcomes and efficiency if the proper controls and scaling are in place.

The measures of frequency of use (Active Months and Frequency of Use) were statistically significant in all four models. Further, as noted above, it appeared the Frequency of Use survey measure was as good a predictor of success as were the combined data (Active Months and Total Queries) from the Query Logs. During the model-building process, it was observed in Models 1 and 3 that the exclusion of Total Queries resulted in significantly reduced effect in the Active Months variable. This produced a question about why Frequency of Use in Models 2 and 4, alone, offered as much predictive power as Active Months and Total Queries combined. In pragmatic terms, why would a five-point, rough interval scale from the survey emerge as a viable predictor with as much—or more—predictive power as the laboriously constructed, objective Query Log measures?

An explanation is offered. The Active Months variable measures frequency of use by months. The Frequency of Use variable from the survey, while limited to five intervals, is a finer measure by which the user estimates frequency on what is, effectively, a daily basis. Thus, Active Months is a specific measure of broad frequency periods (months), and Frequency of Use
is a rough measure of narrow frequency periods (days). The findings of the four models suggest that measuring frequency of use within short periods of time may be the simplest way to estimate system use.

- H\textsubscript{03A}: *A user’s Computer Expertise does not influence that user’s Success Index.* The null is not rejected; the relationship of Computer Expertise to the Success Index was not statistically significant.

- H\textsubscript{03B}: *A user’s Computer Expertise does not influence that user’s Performance/Efficiency Index.* The null is not rejected; the relationship of Computer Expertise to the Performance/Efficiency Index was not statistically significant.

The significance values for Computer Expertise ranged from p<.454 to p<.628 across all four models. The inclusion of this variable in the models was supported by the significance tests for changes in the R\textsuperscript{2} values, but the inclusion or exclusion of Computer Expertise did not move any other variables into or out of significance. These findings indicate that a FINDER user’s self-reported level of computer literacy have no significant power in predicting that user’s success level.

One explanation for the statistical insignificance of the computer expertise measure is that FINDER was designed by its users to be user friendly and require little, if any, training. If this is true, then computer expertise would not play a significant role in successful FINDER use. Alternatively, the Computer Expertise measure may not be valid. This measure was generated through three, self-report survey items, and there may be dimensions of computer literacy not captured by the small set of items.

It is possible that some baseline level of computer literacy is a necessary constant for
contemporary law enforcement employees, regardless of their self-assessments of computer expertise. In this study, respondents were, at a minimum, capable of locating and responding to the online survey. The core computer skills necessary to complete the survey may have been, in and of themselves, also adequate for achieving success with FINDER. If so, increases in computer expertise beyond a core skill set would have had no significant effect in the statistical analyses.

- H_{04A}: *A user’s receipt of FINDER training does not influence that user’s Success Index.*
  Mixed results. The null cannot be rejected.
- H_{04B}: *A user’s receipt of FINDER training does not influence that Performance/Efficiency Index.*
  Mixed results. The null cannot be rejected.

The results for the FINDER Training variable (whether training was provided by members of the FINDER staff), showed a mixed, negative relationship with the success variables. These results were not expected nor readily explained. The model findings reflect that when the Query Log data are used in the models (Models 1 and 3), FINDER Training is statistically significant in predicting a *reduction* in success. This negative relationship is also evident (though not significant) in the other two models. Substituting the Frequency of Use data for Query Log data in those models eliminated the statistical significance of FINDER Training, but not the negative relationship. It appeared that the control for User Months (an indicator of
FINDER experience) was the most important influence in moving FINDER Training in and out of statistical significance.

Conceptually, these data suggest that FINDER users become less successful after receiving the training, or that the users who attended FINDER training were different in some aspect that is not accounted for in the data and that is not directly related to their receipt of the training. For example, those users who attended the training may have sought training in an (unsuccessful) effort to improve weak investigative skills. Conversely, those users who did not seek training may have possessed a core set of skills or abilities that enhanced their success. It was also possible that the training curriculum was counterproductive to successful FINDER use.

Four steps were taken in an effort to explain these findings. First, the data were exhaustively re-examined to ensure that no coding errors had taken place. Second, the survey responses were reviewed to look for any patterns among those fifty-two survey respondents who had received FINDER training; particularly with regard to characteristics that were not included in the models. Third, the correlations and partial regression plots between the Training variables and other variables were reviewed for evidence of the negative relationships. None of these steps produced information to explain either the negative relationships or differences in significance between the models.

The fourth step was interviews with the FINDER staff’s trainer and an agency-level FINDER administrator who had conducted training at his agency. Both advised that training sessions were provided both to inform personnel about FINDER’s existence and to teach them how it is used. The FINDER trainer noted that “fifty or sixty” new users could be “signed-up” at a training session. The agency trainer reported that he had “signed-up” seventy new users.
through his training sessions. The FINDER trainer advised that “some” experienced users had attended his sessions, but new users were the target.

The agency-level trainer expressed frustration that few of his new users were actually using the system. He reported ninety-one registered users in his agency, but Query Logs only reflected activity by eleven users (four surveys were returned from his agency in which the registered users claimed they were not familiar with FINDER).

The FINDER trainer was perplexed when asked specifically about the negative relationship between system use, success, and FINDER training. He suggested that one explanation is “the training guy [himself] needs to be fired.” Otherwise, he could not offer a viable explanation and reiterated that FINDER agencies were asking for repeat training engagements because of the system’s popularity and user successes.

- H₀₊₅A: A user’s Job Assignment does not influence that user’s Success Index. The null is rejected; the Investigative job title classification was found to be a positive, statistically significant predictor of the Success Index in three of the four models.

- H₀₊₅B: A user’s Job Assignment does not influence that user’s Performance/Efficiency Index. The null is rejected; the Investigative job title classification was found to be a positive, statistically significant predictor of the Performance/Efficiency Index in three of the four models.

The Investigative Function dummy variable that tested as statistically significant in three of the four models was the job function (item 12) category selected by survey respondents. This variable provided the most explanatory power in the models. Although Model 4 did not find Investigative Function as statistically significant, significance was approached (p<.067).
All combinations of the various job assignment variables were tested in the models. The seven job classifications (patrol, property investigations, persons investigations, etc.) identified Property Investigations as significant in two of the models, but more explanatory power was achieved through the broader Investigative Function measure. Also noted was the consistent, negative relationship between the Patrol Function and the success measures. Although Patrol Function did not achieve statistical significance and did not contribute to the power of the models, it was clear that respondents in patrol assignments were reporting lower levels of success than their counterparts in investigative, analytical, and administrative positions.

The general finding that users in investigative job assignments experienced higher levels of success was expected. FINDER was created by and for investigators. Its origins as a pawn data sharing application were evident in the large proportion of survey respondents who were assigned to property crime investigations (see Table 14). The negative relationship of patrol assignments to success (though not statistically significant) was also expected. FINDER has not been widely deployed for wireless applications (i.e., in patrol cars) and, as Zaworski (2004) found, patrol officers are disinclined to routinely leave their patrol duties to use a desktop computer.

Neither the data nor other evidence gathered during this study provided clues as to why the Investigative Function was not statistically significant in the fourth model, or why the level of significance differed between the models. It was noted that as the negative influence of FINDER Training decreased, the positive influence of the Investigative Function increased. Given the poorly understood role of FINDER Training relative to success, the inverse relationship between FINDER Training and the Investigative Function could be spurious.

Three regression models were constructed to test the system use hypotheses $H_{06}$ through
The first model predicts Total Queries; the second model predicts Active Months; and the third model predicts Frequency of Use. The results for these three models are shown in Table 29.

Table 29: Results of Regression Testing for System Use Measures

<table>
<thead>
<tr>
<th>Independent Variables</th>
<th>Total Queries</th>
<th>Active Months</th>
<th>Frequency of Use</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Model 5 (n=252)</td>
<td>Model 6 (N=252)</td>
<td>Model 7 (n=402)</td>
</tr>
<tr>
<td>FINDER Task-fit</td>
<td>.166**</td>
<td>.281***</td>
<td>.428***</td>
</tr>
<tr>
<td>FINDER Training</td>
<td>.067</td>
<td>.001</td>
<td>-.015</td>
</tr>
<tr>
<td>Computer Expertise</td>
<td>-.081</td>
<td>-.153*</td>
<td>-.098*</td>
</tr>
<tr>
<td>Investigative Assignment</td>
<td>.134*</td>
<td>.282***</td>
<td>.311***</td>
</tr>
<tr>
<td>Avg. Monthly Workload</td>
<td>.075</td>
<td>.115</td>
<td>.086*</td>
</tr>
<tr>
<td>Law Enforcement Experience</td>
<td>-.116</td>
<td>-.198**</td>
<td>-.042</td>
</tr>
<tr>
<td>User Months</td>
<td>.338***</td>
<td>-.013</td>
<td>-</td>
</tr>
<tr>
<td>Required Use</td>
<td>.037</td>
<td>.059</td>
<td>.051</td>
</tr>
<tr>
<td>Technology Options</td>
<td>-.002</td>
<td>-.092</td>
<td>-.029</td>
</tr>
<tr>
<td>R²</td>
<td>.183</td>
<td>.206</td>
<td>.320</td>
</tr>
</tbody>
</table>

*p<.05  **p<.01  ***p<.001  Standardized Coefficient Values (Beta) Displayed

**Discussion**

The relatively low R² values for the system use models and their rank order was expected. The statistical significance of User Months to Total Queries was expected and is not particularly informative. With other user characteristics held constant, the total query volume of
users should increase the longer they use the system. The results for the variables of hypothetical interest and their relationships with the control variables are discussed below. Table 30 reflects the acceptance or non-acceptance of the alternative hypotheses across the three, System Use regression models.

Table 30: Summary of Hypothesis Testing for System Use Measures

<table>
<thead>
<tr>
<th>Alternative Hypothesis</th>
<th>Model 5 (n=252)</th>
<th>Model 6 (N=252)</th>
<th>Model 7 (n=402)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Total Queries</td>
<td>Active Months</td>
<td>Frequency of Use</td>
</tr>
<tr>
<td>Hₐ-6A, B, C FINDER Task Fit →</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Hₐ 7A, B, C FINDER Training →</td>
<td>No</td>
<td>No</td>
<td>No</td>
</tr>
<tr>
<td>Hₐ 8A, B, C Computer Expertise →</td>
<td>Mixed</td>
<td>Yes*</td>
<td>Yes*</td>
</tr>
<tr>
<td>Hₐ 9A, B, C Job Function →</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
</tbody>
</table>

* Negative relationship

- **H₀₆A:** A user’s *FINDER Task-fit does not influence that user’s Total Queries*. The null is rejected; FINDER Task-fit was found to be a positive, statistically significant predictor of Total Queries.

- **H₀₆B:** A user’s *FINDER Task-fit does not influence that user’s Active Months*. The null is rejected; FINDER Task-fit was found to be a positive, statistically significant predictor of Active Months.
• **H_{06C}: A user’s FINDER Task-fit does not influence that user’s Frequency of Use.** The null is rejected; FINDER Task-fit was found to be a positive, statistically significant predictor of Frequency of Use.

The acceptance of the three, alternative hypotheses for the relationship of FINDER Task-fit to the system use measures was expected and unremarkable. Task-fit measures usefulness and usability; system use was expected to be a positive function of both of these task-fit dimensions.

• **H_{07A}: A user’s receipt of FINDER Training does not influence that user’s Total Queries.** The null is not rejected; the relationship of FINDER Training to Total Queries was not statistically significant.

• **H_{07B}: A user’s receipt of FINDER Training does not influence that user’s Active Months.** The null is not rejected; the relationship of Finder Training to Active Months was not statistically significant.

• **H_{07C}: A user’s receipt of FINDER Training does not influence that user’s Frequency of Use.** The null is not rejected; the relationship of FINDER Training to Frequency of Use was not statistically significant.

Although the system use regression models did not report training to be statistically significant, it was noted that the (very small) coefficients for FINDER Training were positive in their relationships to the objective system use measures of Models 5 and 6 (Total Queries and Active Months), but negative for the survey-based measure of system use (Frequency of Use).

The mixed and weak influence of training in these three models suggests that the negative influence of training on user-level success (Models 1-4) is not directly related to an interaction
between training and system use. In other words, the regression models indicate a direct effect of training on user-level success, but the training effect is not significantly mediated by system use.

- **H\textsubscript{08A}:** A user’s Computer Expertise does not influence that user’s Total Queries. The null is not rejected; the relationship of Computer Expertise to Total Queries was not statistically significant.
- **H\textsubscript{08B}:** A user’s Computer Expertise does not influence that user’s Active Months. The null is rejected; Computer Expertise was found to be a negative, statistically significant predictor of Active Months.
- **H\textsubscript{08C}:** A user’s Computer Expertise does not influence that user’s Frequency of Use. The null is rejected; Computer Expertise was found to be a negative, statistically significant predictor of Frequency of Use.

The possibility of a negative relationship between computer expertise and system use was noted in the development of the study variables. Researchers have proposed or found (Goodhue, 1995; Venkatesh & Davis, 2000) that more sophisticated or experienced system users may use their technology systems less than unsophisticated users. Reduced system use by expert users was posited as the result of either more efficient use or an expression of system dissatisfaction by more demanding, sophisticated users.

From this perspective, the findings were expected that Computer Expertise significantly and negatively influenced system use in the Active Months and Frequency measures (Models 6 and 7). This relationship supports expert users as being more efficient in their FINDER use than less expert users; at least in terms of the frequency reflected by the measures in Models 6 and 7.

Alternatively, the negative relationship might reflect FINDER dissatisfaction (and
reduced use) among the more sophisticated users. However, if this were the case, Computer Expertise should have been negatively related to the FINDER Task-fit measure and the success measures in Models 1 through 4. It is possible that the relationship between Computer Expertise and system use was spurious in these models, and it is recalled that the Computer Expertise index may have measured more dimensions than computer literacy.

Of interest was why Computer Expertise was not significant in only one of the three models, the Model 5 prediction of Total Queries (p<.185). This issue was considered in terms of the system use measures: Models 6 and 7 predicted system use as frequency (Frequency of Use and Active Months) while Model 5 predicted system use as volume (Total Queries).

A review of partial correlation plots for the models suggested an explanation. The frequency of use variables were constrained (0.0 to 1.0 for Active Months and 1 to 5 for Frequency of Use) while Total Queries data was not. Outlier cases were visible in the Total Queries plot and were posited as “cancelling” the controlling effect of Computer Expertise on use. In other words, the outlier data for Total Queries could statistically overpower the controlling effect of Computer Expertise on “normal” (non-outlier) users’ query volume (Gujarati, 2003; Norusis, 2005). These outlier cases were discussed in the Query Log analysis.

To test this proposition, eight cases of outlier data were removed and the remaining data were tested in a revision (Model 5a) to Model 5. With outliers excluded, both Computer Expertise and Law Enforcement Experience became statistically significant, and the $R^2$ improved to .233. These changes brought Model 5 into consistency with Models 6 and 7 across all measures. The change is shown in Table 31 where Model 5 (with outliers) is compared to Model 5a (without outliers).
Table 31: Revised Model 5: Excluding Outliers in Prediction of Total Queries

<table>
<thead>
<tr>
<th>Independent Variables</th>
<th>Model 5 (N=252)</th>
<th>Model 5a (n=244)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Total Queries</td>
<td>Total Queries</td>
</tr>
<tr>
<td></td>
<td>With Outliers</td>
<td>With Outliers</td>
</tr>
<tr>
<td></td>
<td>Removed</td>
<td>Removed</td>
</tr>
<tr>
<td>FINDER Task-fit</td>
<td>.166**</td>
<td>.234***</td>
</tr>
<tr>
<td>FINDER Training</td>
<td>.067</td>
<td>.007</td>
</tr>
<tr>
<td>Computer Expertise</td>
<td>-.081</td>
<td>-.121*</td>
</tr>
<tr>
<td>Investigative Assignment</td>
<td>.134*</td>
<td>.179*</td>
</tr>
<tr>
<td>Avg. Monthly Workload</td>
<td>.075</td>
<td>.101</td>
</tr>
<tr>
<td>Law Enforcement Experience</td>
<td>-.116</td>
<td>-.152*</td>
</tr>
<tr>
<td>User Months</td>
<td>.338***</td>
<td>.351***</td>
</tr>
<tr>
<td>Required Use</td>
<td>-.037</td>
<td>.017</td>
</tr>
<tr>
<td>Alternative Technology</td>
<td>-.002</td>
<td>-.054</td>
</tr>
<tr>
<td>R²</td>
<td>.183</td>
<td>.233</td>
</tr>
</tbody>
</table>

*p<.05  **p<.01  ***p<.001  Standardized Coefficient Values (Beta) Displayed

The statistical effect of excluding Total Query outliers is conceptually important. Model 5a – like Models 6 and 7 – affirms that higher levels of computer expertise can reduce levels of system use. However, Model 5a also suggests an important exception to the controlling effect of Computer Expertise. This exception was linked to interview information obtained through Success Tagging interviews (pp. 125-127).

Six of the outlier users that were removed from Model 5a were identified as detectives or
analysts assigned to pawnshop investigations. Interviews with these users had revealed mechanical, or non-targeted system use that produced high query volumes. Relying on an earlier analogy, these users cast a large net – repeatedly and indiscriminately – without a specific target in mind, and are successful.

This type of high volume user is not concerned with efficiency and confounds the presumed efficiency-gain effect of computer literacy. Consequently, this type of query behavior could confound other analyses that rely on system use measures to predict or serve as proxy for user-level success. In this study, there was not a control for “pawn shop investigator.” The job assignment variables used in the models did not discriminate between this group (and perhaps other unidentified groups of high-volume users) and other users.

- H₀⁹A: A user’s Job Function does not influence that user’s Total Queries. The null is rejected; Investigative Function was found to be a positive, statistically significant predictor of Total Queries.
- H₀⁹B: A Job Function does not influence that user’s Active Months. The null is rejected; Investigative Function was found to be a positive, statistically significant predictor of Active Months.
- H₀⁹C: A user’s Job Function does not influence that user’s Frequency of Use. The null is rejected; Investigative Function was found to be a positive, statistically significant predictor of Frequency of Use.

Based on the results of Models 1 through 4 that reflected Investigative Function as a

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¹⁶ Background investigators also reported mechanical query behavior, but they were not identified in the outlier cases.
significant predictor of success, the results for Hypotheses H09A, H09B, and H09C were expected in Models 5 through 7 and were unremarkable.

**Relationships in the Control Variables**

There were five control variables incorporated in the seven regression models: Technology Options, Workload, Required Use, Law Enforcement Experience, and User Months. As Tables 27 and 29 reflect, the control variables were, generally, not statistically significant in predicting user-level success or system use, but they each added statistically significant explanatory power to the models. The first three control variables will be discussed separately; the two indicators of experience are considered together.

The Technology variable was not statistically significant in its relationship to either success or system use measures. However, of interest was its relationship to system use (negative) compared to user-level success (positive). The direction of these statistically insignificant relationships suggests that users who have more alternatives to FINDER use FINDER less, but also have (relatively speaking) more success with FINDER.

Conceptually, and recognizing that the technology variable was not significant in the models, a negative relationship between Technology Options and FINDER system use is expected. The unexpected relationship is the possibility that a user who has more technology options is more successful with FINDER than users with fewer options. A check of the relationship between alternative technologies and computer expertise was conducted to consider whether users who have more available technology are more successful because they have more computer experience. However, the correlation between Technology Options and Computer Expertise was very weak and insignificant (r= -.019, p<.709).
It also possible that a complementary or synergistic effect occurs when FINDER and other systems are used in combination. For instance, it is recalled that almost half of the success tagging users achieved success with data from within their own agencies. These data were technically available through their agency RMS as a technology option. The limited findings here suggest that the interaction of multiple technologies in police information systems is a ripe research topic.

The Workload measure was statistically insignificant in six of the seven models; it was statistically significant in predicting frequency of use in Model 7. Workload was conceived as an exploratory variable to control for difference in system use that might be attributed to differences in the user’s workload. The Workload survey item was scaled in un-equivalent intervals and asked respondents for a workload estimate based on each respondent’s workload type (calls for service, cases, projects). It’s reliability and validity are questionable. However, the model building process identified the Workload measure it as a statistically important explanatory variable. Further, as noted earlier, the importance of the workload measure might be related to its providing a baseline by which efficiency is assessed or perceived.

The Required use variable was also a statistically insignificant predictor in six of the seven models, found significant only in its prediction of the Success Index in Model 2. This result was not expected. Any significance in the Required Use measure was expected in the system use outcomes; not in predicting user-level success, and not without a parallel result for system use.

Additional study of the Required Use survey responses found that twenty-two (48%) of those users reporting that they were required to use FINDER were from only three agencies. The five supervisors of those twenty-two “required use” respondents were known due to their
involvement and responses to other components of this study. Each of these supervisors was asked, within a series of general questions about FINDER, whether they or their agencies required its use. Four of the five supervisors advised that no one in their agency or command were required to use the system. The fifth supervisor advised that background investigators (representing two of the twenty-two “required use” users) were required to incorporate a FINDER search into background checks on law enforcement applicants. Of the five supervisors, three were direct supervisors of the users in question; two were indirect supervisors in the users’ chains of command.

This issue was explored further to consider whether workplace norms might have influenced users to (apparently) incorrectly report they were required to use FINDER. Those who reported required use were compared against those who did not report required use for their response to survey item 38: “I work with someone who is always encouraging me to use FINDER.” The Cramer’s V test was used to conduct this comparison and found a statistically significant difference between the groups on their responses (Cramer’s V = .261, p<.01). A crosstab evaluation of the data reflected that responses to item 38 in the agreement range were much higher for the required use respondents; 45% of those who reported required use also agreed with item 38, compared to 26% of the users who reported voluntary use.

These findings suggested that the validity of the Required Use variable was questionable. However, it can be argued that if users believe they are required to use the system, then perhaps that is more important than whether they are actually required to use it. Thus, the required use variable remained as a control for system use in the regression models, but its significance in Model 2 was not considered important. Perhaps more importantly, while Goodhue (1995) proposed an unspecified relationship between voluntariness and system use, the definition of
voluntary use did not consider *perceived* voluntariness (or perceived requirement) as found in this study. Future studies could be improved by considering workplace norms in the development of voluntary-use/required-use variables.

Law Enforcement Experience and Time as FINDER User were conceived as controls for user-level success that might be attributed to experience-based proficiencies rather than FINDER use. Law enforcement experience was measured as the user’s number of years of law enforcement experience, and the user’s time as a FINDER user was measured as User Months. The User Months data were available only for the 252 respondents who were matched with Query Log activity.

These experience measures are considered jointly because of their divergent results throughout the seven models. Law enforcement experience was found to be a statistically significant negative predictor of system use in Models 6 and 7; an insignificant negatively-signed control in Models 1, 2, and 4; an insignificant, positively-signed influence in Model 3. User Months, which was included only in Models 1, 2, 5, and 6, also had divergent results. User Months was significant in predicting the Success Index but insignificant (with a Beta of .000; p<.993) in its relationship with the Performance/Efficiency Index. User Months was highly significant in positively predicting Total Queries, but negatively-signed and insignificant in predicting Active Months. In effect, the only consistent finding about FINDER users’ experience was that system use, generally, was negatively related to law enforcement experience. The data provided no clues as to whether this relationship might be due to experienced users’ sophistication and efficiency or those senior users’ discomfort or dissatisfaction with technology in general.

An examination of the experience variables revealed they were significantly correlated to
agency size (number sworn) and Sheriff’s Offices, with a significant and negative correlation to Police Departments. In other words, the most experienced respondents in terms of law enforcement and FINDER experience tended to be members of the larger Sheriff’s Offices.

FINDER originated largely through efforts to share pawn data led by personnel in five of the state’s larger Sheriff’s Offices. Users from those five agencies comprised forty-one of the fifty-two (72%) survey respondents with at least fifteen User Months. Eighteen of these users were interviewed during the course of this study.

These interviews, conducted as-needed between January and August 2006, addressed the several Query Log and Success Tag questions discussed earlier in this chapter. A common theme expressed by these senior FINDER users was their commitment to information sharing. These users repeatedly expressed their enthusiasm for the information exchange and that it was long overdue as a tool for Florida law enforcement. Several of them expressed hope that this study would help “prove” the value of information sharing to their Sheriffs.

Conversely, the newer FINDER users who were contacted during the course of the study were not aware of FINDER’s origins or development. Many were unaware of UCF’s role and required an explanation of that role before providing interview information. These users perceived FINDER as a useful tool (like NCIC), but did not express a commitment to information sharing or an understanding of FINDER’s development through a Consortium effort.

The proposition that “experience,” at least in the context of FINDER’s unique origin, might reflect a dimension of commitment to information sharing is not without support. The concept of information sharing champions being necessary for success has been discussed

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17 It was discovered during the survey and follow-up interview process that “FINDER” had to be explicitly associated with other system labels such as “Pawn System,” or “UCF System,” or “Data Sharing Consortium”.
elsewhere in terms of agency-level participation (e.g., BJA, 2002). An unmeasured dimension, commitment to information sharing, may be associated with the most senior FINDER users. If so, then that unmeasured dimension may explain the divergent results for Law Enforcement Experience and User Months that are found in the regression models.

**Exploration of Relationship between Success and System Use**

The Task-technology Fit framework (Goodhue, 1995) used in this study conceptualized – but did not explain – the relationship between user-level success and system use. The logical relationship describes system use being required to generate success, but success is likely to generate additional system use. A better understanding of this relationship is important because system use frequently serves as a surrogate measure for information system success. The surrogate measure is accepted under the assumption that increases in system use reflect increases in success. The important, unanswered question is how much additional success (if any) is being reflected by increases in system use. If the answer to that question is better understood, system use may be useful as a reliable success metric.

This section uses a nonrecursive structural equation path model (SEM) to explore the relationship between user-level success and system use. Nonrecursive models estimate simultaneous relationships between endogenous (dependent) variables and their shared exogenous (independent) predictor variables. In this study, User-level Success and System Use were the endogenous variables proposed by the task-fit framework to have a feedback relationship.

Table 32 considers the relationship between user-level success and system use by reporting $R^2$ values from regressions (Models 4 and 7) modified to include or exclude success or
system use appropriately. The $R^2$ values indicate that User-level Success is less dependent on System Use ($R^2$ decreasing 8.9% when System Use is dropped) than System Use is dependent on User-level Success ($R^2$ decreasing 24.2% when User-level Success is dropped).

Table 32: Changes in $R^2$ Values in User-level Success and System Use Relationships

<table>
<thead>
<tr>
<th>Inclusion/Exclusion of Exogenous Variable</th>
<th>Endogenous Variable</th>
<th>$R^2$</th>
</tr>
</thead>
<tbody>
<tr>
<td>System Use included as exogenous variable → User-level Success as endogenous variable</td>
<td>User-level Success as endogenous variable</td>
<td>.665</td>
</tr>
<tr>
<td>System Use excluded as exogenous variable</td>
<td>System Use as endogenous variable</td>
<td>.606</td>
</tr>
<tr>
<td>User-level Success included as exogenous variable → System Use as endogenous variable</td>
<td>System Use as endogenous variable</td>
<td>.422</td>
</tr>
<tr>
<td>User-level Success excluded as exogenous variable</td>
<td></td>
<td>.320</td>
</tr>
</tbody>
</table>

Conceptually – not statistically, and with scaling differences in mind – these $R^2$ data suggest that an additional increment of “success” produces more increments of “system use” than system use produces of success. Thus, conceptually, there is a relationship of diminishing returns. If a single success produces 100 more queries, those 100 queries will not reciprocally produce another success; perhaps 300 more queries will be required to accomplish that, with all other things (such as caseload, computer expertise, job assignment, etc.) held constant.

The potential of a diminishing-returns (or increasing-returns) relationship poses a challenge to using system use as a surrogate measure for success. For example, if it is found at a given time that a given number of successes are reported based on a given level of system use, it
cannot be assumed that a twofold increase in system use reflects a twofold increase in successes. Some grasp of the *relative* relationship between the two measures is necessary.

**Conceptual Model**

A nonrecursive SEM path diagram was constructed to explore this relationship. The conceptual model is shown in Figure 13 mirrors Goodhue’s (1995) task-fit framework.
Nonrecursive models present a variety of challenges in their design and interpretation, and it is difficult to satisfy their assumptions. Some of the key assumptions, and implications of their violation, are discussed here.

This study was initially proposed to consider the longitudinal relationship between user-level success and system use, but a cross sectional analysis was mandated because the Success Tag-based data was not reliable. Logically, the validity of a nonrecursive model is questionable when cross sectional data are used. The nonrecursive model is based on a feedback relationship that, by definition, measures change over time versus the cross sectional snapshot. Maruyama notes that the difficulty in satisfying assumptions may cause researchers to wonder “whether there really are nonrecursive models” (p. 101) that can be validly constructed with cross sectional data. Thus, absent longitudinal data, results from a nonrecursive model should be cautiously considered (Kline, 2005; Maruyama, 1998).

The nonrecursive model also assumes that equilibrium has been achieved in the relationship between the endogenous variables. The equilibrium assumption means that the relationship is stable; that there are no influences that cause the relative relationship between the endogenous variables to change. Equilibrium is difficult to argue in applied study; any number of influences can affect a claimed state of equilibrium. However, a stability index, produced by SEM software, provides an indication of equilibrium that can be considered with the model’s results (Kline, 2005; Maruyama, 1998). 18

It is difficult to identify a nonrecursive model. Identification means that there are enough degrees of freedom in the model to estimate the unknown parameters. By their nature, most

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18 Kline (2005) reports studies indicating that the stability index does not adequately reflect equilibrium-based bias, but use of the stability index as a guide is not dismissed.
nonrecursive models are unidentified and modifications are required to achieve identification.

Two, general methods can be used to achieve identification: constraining parameters or re-
specifying the model with instrumental variables or otherwise removing relationships that
require estimation. Kline notes that such procedures can “seem like a shell game: add this path,
drop another, and – voila’! – the model is identified” (2005, p. 249). Thus, modifications should
be true to a model that has been logically or theoretically supported.

The models shown Figure 13 (above) and Figure 14 (below) were not re-specified. All
relationships proposed by Goodhue (1995) were retained in the final model. However, to obtain
identification, the parameter for the relationship of success to system use was set to a reference
value of one, as generally suggested by Kline (2005). The constraint on the success parameter
enhanced model fit and produced logical results that were consistent with underlying theory and
regression findings. The data used for the SEM analysis were those from Model 2 in the
regressions. These data were used because of the available sample size (N=402) and the use of
the Success Index rather than the Performance/Efficiency Index. Conceptually, the influence of
the efficiency dimension in the Performance/Efficiency Index was expected to confound the
nonrecursive relationship through an unspecified influence of efficiency on system use.

**Nonrecursive Model Results**

The graphic results of the final model, with standardized coefficient values, are shown in
Figure 14. The related statistics are provided in Table 33.

**Discussion**

The Stability Index and Goodness of Fit measures indicate that the final model was
reasonably fit by the data. The results suggest the expected, statistically significant relationship between user-level success and system use. The magnitude of the direct effect for Success $\rightarrow$ System Use is the largest; it estimates that a level of User-level Success one standard deviation above the mean will produce an increase in System Use .267 standard deviations above its mean. The indirect effect on User-level Success via System Use is estimated as .267 x .157 or .042.

Figure 14: Final Nonrecursive SEM Results

$^{19}$ A Stability Index< 1.0; $X^2 > .05$; GFI>.900; AGFI>.900 and RMSEA<.05 indicate good model fit (Kline, 2005; Maruyama, 1998; Wan, 2002)
Table 33: Table of Statistics for Final Nonrecursive Model

<table>
<thead>
<tr>
<th>Exogenous Variable</th>
<th>User-level Success</th>
<th>System Use</th>
</tr>
</thead>
<tbody>
<tr>
<td>User-level Success</td>
<td>-</td>
<td>.267 ***†</td>
</tr>
<tr>
<td>System Use</td>
<td>.157**</td>
<td>-</td>
</tr>
<tr>
<td>FINDER Task-Fit</td>
<td>.405***</td>
<td>.350***</td>
</tr>
<tr>
<td>Investigative Function</td>
<td>.212***</td>
<td>.183***</td>
</tr>
<tr>
<td>Computer Expertise</td>
<td>.003</td>
<td>-.107**</td>
</tr>
<tr>
<td>Workload</td>
<td>.064</td>
<td>.065</td>
</tr>
<tr>
<td>Required Use</td>
<td>.053</td>
<td>-.067</td>
</tr>
<tr>
<td>FINDER Training</td>
<td>-.061</td>
<td>-.027</td>
</tr>
<tr>
<td>Law Enforcement Experience</td>
<td>-.042</td>
<td>-.035</td>
</tr>
<tr>
<td>Alternative Technology</td>
<td>.006</td>
<td>-.045</td>
</tr>
<tr>
<td>R²</td>
<td>.423</td>
<td>.443</td>
</tr>
<tr>
<td>Stability Index =</td>
<td>.042</td>
<td></td>
</tr>
</tbody>
</table>

Goodness of Fit Measures

\[ X^2 = 23.153, df= 22, p>.393 \]

GFI = .987

AGFI = .968

RMSEA = .012

**p<.01  ***p<.001  † Estimated significance
In other words, an increase in User-level Success one standard deviation above its mean produces an indirect effect – through System Use – of an increase in User-level Success .042 standard deviations above its mean (Kline, 2005).

These findings, subject to the limitations and cautions expressed above, support the proposition that success achieved by FINDER users results in additional system use, but the additional system use does not produce commensurate increases in success, with all other influences held constant. As noted above, the value of this finding is that it offers limited empirical evidence that using system use measures as surrogates for user-level success should acknowledge differences in the relative magnitudes of the feedback relationship. Given the data available through FINDER and its users, success predicts system use better than system use predicts success.
CHAPTER 5: CONCLUSIONS, RECOMMENDATIONS, LIMITATIONS

This study has looked at a combined set of data that depicted how law enforcement officers successfully achieve their task objectives through the use of shared, low-level police information. The study included 1,352 police users of the Florida Integrated Network for Data Exchange and Retrieval (FINDER), their 1.8 million FINDER system data records, 741 specific reports of FINDER “successes,” survey responses from 402 active users, and interviews with users who collectively represented nearly 120 Florida police agencies.

FINDER provides low-level information to its users. This information is routinely collected by police agencies’ records managements systems (RMS) and includes details from traffic citations, field contact cards, criminal and non-criminal police reports, pawnshop records, and calls-for-service records. Low-level information has not been widely shared in the past.

FINDER offered a unique opportunity to identify the benefits of sharing low-level police information and explore how these benefits could be increased. Systems like FINDER have been proposed as an important piece of America’s efforts to fight both traditional crime and terrorism. This study was envisioned as supporting those efforts.

Conclusions

This study produced findings that are important to understanding the dynamics and value of police information sharing. Value was conceptualized as “user-level success,” or outcomes attributed to FINDER that satisfied the individual user’s task needs. Some key conclusions about user-level success are reported below and contribute to the development of performance metrics.
**User-level Success**

1. *Sharing low-level police information produces successful policing outcomes.*

   Specific success reports submitted by 159 users included details about 384 arrests and 537 stolen property recoveries attributed to FINDER information. A survey of 402 users found that 68.4% had used FINDER information to make arrests, clear cases, develop investigative leads, discover a crime, or locate or identify a person of interest.

2. *Sharing low-level police information produces gains in individual performance and efficiency.* Of the 402 FINDER users responding to the survey, 71.6% reported that FINDER had helped improve their job performance. Gains in efficiency attributed to FINDER were reported by 82.6% of the users.

3. *The importance of sharing information within one’s own agency may be underestimated.*

   Specific success reports reflected that 48.2% of successes were based on FINDER’s extraction of information from within the reporting user’s own agency. User interviews indicated that FINDER acquired information from within the users’ agency RMS that they could not otherwise access.

4. *Sharing information with both local and distant agencies produces success.* Specific success reports reflected that 37.3% of successes were based on information acquired from other, local agencies. Distant agencies provided information leading to 14.5% of reported successes.

**Discussion**

The combined data strongly support the value of sharing low-level police information. These data affirmed that user-level success or performance measures in police information
sharing should encompass a range of positive outcomes broader than arrests or case clearances. FINDER’s police users reported that investigative leads, property recoveries, discovery of crime, and contact or background information about both offending and non-offending subjects are important to achieving performance and efficiency objectives.

This study also found contextual factors that can influence efforts to measure user-level value of information sharing. Prolific users were identified who served as their squad-level “FINDER person.” These users found information that produced arrests and case clearances for non-users. In addition, users were identified who had no assigned caseload and who identified crimes and offenders by mining FINDER’s data. These investigators adopted only those cases that they had already “solved” and reported a 100% clearance rate. These findings suggest that “objective” arrest and case clearance measures of success must consider the user’s context.

An unexpected finding was the prevalence of successes attributed to FINDER’s extraction of data from the users’ own agencies. These users reported that they were unable to access or efficiently gain access to important data via their agency RMS. FINDER provided an efficient method of getting this information. In addition, users in Police Departments reported that FINDER gave them access to critical data held by their local Sheriff’s Office. They had previously been unable to acquire these data. These findings indicate that information sharing is important intra-agency and inter-agency, both locally and with distant information sources.

A key objective of this study was to determine what factors influence user-level success. If these factors can be identified, then strategies can be developed to optimize them and thereby increase success levels. The Task-Technology Fit (TTF) framework (Goodhue, 1995) was used to guide research aimed at identifying these factors. One of the two major TTF components was system use. Goodhue proposed that a technology user’s system use predicts changes in that
user’s performance. However, this relationship was not specified and was acknowledged as complex and contextual. Conclusions related to the system use construct as applied to FINDER are reported below.

**System Use**

1. *Frequency of use was the best measure for “system use” in terms of predicting user-level success.* Data that reported each FINDER user’s specific system activity over a fifteen-month period were analyzed during this study. These data represented 1.8 million specific queries for information by 1,352 users. Of the variety of system use measures that were extracted from or computed with these data and survey responses, the frequency of use measures best predicted user-level success.

2. *Users search for information from all available sources.* Most users, 76.8% in a secondary survey, reported that they usually search all FINDER agency data sources rather than selectively or incrementally search. Users were not dissuaded by the additional time required for broad searches.

3. *Many users conduct repetitive searches to locate newly-available information.* Repetitive searches constituted 23% of FINDER’s system activity in a random sample of query logs. A secondary survey of users found that 34% “usually” conduct repetitive searches for new information; an additional 43% reported that they conduct repetitive searches “depend[ing] on the case or situation.”

4. *System use behaviors vary with user job tasks.* Some users engaged in routine, high volume, mechanical FINDER searches for any useful information. Others used FINDER to selectively search for specific information. While these methods produced divergent
measures of system use, both also produced successes. The method chosen appeared
dependent on the user’s job assignment.

Discussion

Information systems research consistently postulates that unspecified measures of
“system use” predicts users’ satisfaction or successes with the system. This study had
FINDER’s objective system data (the Query Logs) from December 2004 to February 2006 to
compare with user-level success. A number of objective measures were extracted or computed
from the data and considered for their reliability and validity in reflecting the system use
construct. User query volume – the number of inquiries each user made to each FINDER agency
– was evaluated through several measures. These measures included users’ average monthly
query volume, total query volume over fifteen months, fifteen-month query volume indices,
fifteen-month averages and moving averages, and query volume trends. None of these query
volume measures was independently valid in predicting user-level success.

The objective Query Log data also provided a frequency of use measure. This was the
percentage of months that each user made queries during that user’s FINDER tenure. The
frequency-by-month measure, when combined with the user’s total query volume, was
statistically significant in predicting success. In addition, survey respondents estimated their
system use through a rough, days-of-use-per-week measure. That measure, which was
independent of query volume, was the most powerful “system use” predictor of user-level
success. A statistical control variable was used for the 11.4% of users who reported that they
were required to use FINDER.

These findings suggest that the frequency of system logins may be the best system use
metric when considering user-level performance. The volume of activity (query volume) following the login was not a good system use measure. The failure of volume measures to predict success might be due to differences in individual user’s workloads, query methods, or job assignment. Those differences were revealed in system use behaviors that included repeated queries, mechanical queries, and targeted queries.

Of users responding to a secondary survey about query behaviors, 77% reported that they repeated queries in an effort to find newly-available information about their topic of interest. An exploratory examination of their repeated query behavior indicated that repeated query behavior does not necessarily result in high query volume. Data were not available to estimate the effect of repeated queries on user-level success, but the prevalence of repeated query behavior suggests that it rewards users. This behavior also suggests that FINDER’s functionality could be improved with the inclusion of monitoring or subscription routines that automatically check for new information on subjects of interest.

Mechanical, or indiscriminate, high-volume query behavior was also identified as affecting the measurement of system use. This type of behavior was primarily attributed to pawnshop and background investigators. Generally, they executed queries on every person, address, or piece of property listed in case files and waited to see if any information of interest was returned. Essentially, they engaged in high query volume, exploratory searches and were rewarded with high levels of success. This query behavior both allowed them to solve reported crimes and discover unreported crimes such as dealing in stolen property or violations of probation.

Conversely, other successful users reported that they used FINDER selectively when they had investigative leads that led them to target their searches for information. This type of user
exhibited consistent frequency of use but a low volume of use. However, whether targeted or mechanical, most users (76.8%) reported that they executed searches against all available FINDER agencies. They did not typically query only a few agencies or start with local searches and expand the search incrementally.

These system use findings are important for three reasons. First, they identify a system use metric – frequency of use – that was valid in the FINDER analysis and can be considered for application elsewhere. The validity of this metric is supported by an understanding of user behaviors that can confound system use measures that are based on activity or volume. Second, an understanding of system use behaviors and the difference between frequency of use and volume of use can assist software developers with system design. System functionalities should include the capture of users’ login activity and automated routines to eliminate the need manually executed repeat queries. Third, system designers should recognize that users will probably seek all available information in their queries. Both system architecture and bandwidth requirements are likely to be affected by user demands.

The second major component of the TTF framework is task-technology fit. TTF proposes that information system users will have greater gains in performance when the system is usable (ease of use) and provides information that is useful in meeting the user’s task needs. Task needs are affected by user characteristics including the user’s work and technology experience, environment, and job functions. Conclusions about FINDER’s task-technology fit and related user characteristics are provided below.
Task-Technology Fit

1. * Users’ who positively assessed FINDER’s usefulness and ease of use experienced higher levels of success. Empirical analyses consistently found that the user’s assessment of system usefulness and usability was the most powerful predictor of user-level success. Usefulness addresses the value of the information provided by FINDER to meeting user task needs. Usability refers to the system’s ease of use.

2. * Users assigned to investigative functions were most likely to report user-level success. FINDER users assigned to investigative functions achieved higher levels of success than those assigned to patrol, analytical, or administrative functions.

3. * A FINDER user’s level of computer expertise did not significantly influence the likelihood of achieving user-level success. Users’ computer expertise (computer literacy) was not a statistically significant influence in predicting user-level success. The computer expertise measurement was exploratory.

4. * The user’s type of agency and agency size did not influence the likelihood of achieving user-level success. Users from Police Departments, Sheriff’s Offices, and state law enforcement agencies were included in this study. The sizes of these agencies ranged from six to 1,600 sworn officers. Neither the agency type nor the agency size statistically contributed to predictions of user-level success.

5. * The influence of users’ law enforcement experience, FINDER experience, and FINDER-related training on user-level success was not clarified with empirical tests. Mixed results were produced in the empirical models that estimated the influence of experience and training on user-level success. Factors such as the commitment to information sharing by
senior FINDER members who helped found the system, and the selection of disengaged
users for FINDER training were believed to have confounded the analyses.

Discussion

Task-fit was consistently found to be a significant and highly influential predictor of
user-level success. Task-fit measures included the users’ job functions and assessments of
FINDER’s usefulness and usability in their task context. Controlling influences, such as the
user’s technology environment, agency type, and agency size did not have significant
explanatory power in the empirical models.

Measures of the effect of law enforcement experience and length of FINDER experience
were mixed in their prediction of both system use and user-level success. Interviews with users
suggested that the “experience” measures in the FINDER context might have been confounded
by an unmeasured user dimension characterized as “commitment to information sharing.” A
number of FINDER’s most successful and senior users were involved in founding, designing,
and implementing the system. The presence of a “commitment” dimension could have created
spurious empirical relationships in the experience data.

The appearance of a negative relationship between users’ who received FINDER training
and their level of success was unexpected. The negative effect of training on success did not
appear to be mediated through the frequency of system use, and none of the empirical data
available suggested an explanation. One explanation of the relationship is that FINDER training
is, of itself, somehow counterproductive. A second explanation – supported by limited,
qualitative evidence – is that many users who received FINDER training were “signed-up” as
users at the same time they received the training. Some – perhaps many – of these new users did
not demonstrate an interest in or need for FINDER. Consequently, their FINDER use and successes were limited. Specific data were not available to link newly-recruited users to FINDER training and their system use. The training topic remains unresolved.

A FINDER user’s assignment to an investigative function was statistically significant in predicting that user’s level of success. This finding was expected. FINDER was conceived by investigators and most of its users are investigators. FINDER has not been widely deployed in a wireless environment available to patrol officers. The data sets and software interface were designed and specified by investigators who founded the system. In this context, the task-fit of FINDER to investigators was assured, but the important finding is that good task fit does predict user-level success.

Further, usability (ease of use) and usefulness of data were jointly reported as dimensions that reflect of task-fit. Some researchers have suggested that ease of use is not particularly important to police users. However, based on the data gathered from FINDER users, ease of use appears to be an important dimension of task-fit and, consequently, ease of system use is important to user-level success.

Recommendations

The conclusions outlined above support the value of sharing low-level police information as evidenced by user-level success in the FINDER system. Several evidence-based recommendations are offered that can be used to enhance other information sharing efforts.

1. User-level success with police information sharing includes outcomes beyond traditional measures of arrests and case clearances. System metrics should be designed to efficiently
capture success events that include investigative leads, property recovery, locating or identifying people, the discovery or prevention of crimes, and efficiency gains.

2. Police information sharing successes can be increased by improving the task-technology fit. Task-fit can be enhanced by relying on users to specify data needs, functionality, and the user interface. Ease of use appears to be important to end users.

3. The design of police information sharing systems should provide monitoring functionality to alert users to newly-arriving information about subjects of interest.

4. Police agency leaders and technology managers should recognize that sharing information within their own agency could produce success. As a first step to advancing information sharing objectives, agencies should examine their resident records management system to determine whether valuable, low-level information is readily available to their own agency members.

5. Police information sharing systems rely on the coordinated efforts of technology managers at each participating agency. User-level success can be inhibited by the failure of these managers to ensure the availability of and access to timely and complete data. The governance structure of the information sharing project should clearly identify agency-level technology managers and routinely verify their continued support of the system. Quality assurance processes should be in place for both data accuracy and security control.

Implications for Additional Research

Findings emerged during the course of this study that could not be adequately explored or explained. These findings suggest topics for additional research. These topics include:
1. Data from user-reported Success Tags – while informative – was empirically unreliable. Additional research could identify better processes for reliably reporting success data.

2. Improved efficiency was indicated to be an important dimension of user-level success. This study did not collect data to measure changes in efficiency attributed to police information sharing. Additional research could clarify the role of efficiency to improvements in user-level performance.

3. Different, user-level information-seeking techniques were identified in this study. They included mechanical queries, targeted queries, and repeated queries. Neither the value of these techniques towards achieving user-level success nor their effect on system use measures could be established with the available data. Additional research may reveal if query techniques are embedded in system use data and whether specific techniques produce higher levels of success.

4. Because reliable longitudinal data were not available in this study, the relationship of system use and other explanatory variables to user-level success was considered in a cross sectional approach. Additional research using reliable data in a longitudinal design would help identify time-variant dimensions of the information sharing process.

5. It is extremely important to note that this study examined how FINDER users acquired the data and the outcomes that resulted from the data acquisition, but did not look at how the users analyzed or applied the data to achieve those outcomes. FINDER users, generally, discounted the need for automated “analytical tools.” This is an area ripe for additional research. Analytical styles and methods employed to different ends by different users is a likely source of unexplained variance in the regression models.
Limitations

- This study is expected to add to the limited body of knowledge about the dynamics and value of police information sharing. Data and methodological limitations were discussed in context as they appeared in the research process. Limitations include:

- This study focused on a single police information sharing system functioning in Florida’s unique law enforcement and technology environments.

- The user survey was administered as a probability sample. However, data collected through the survey remains subject to unidentified non-response or response biases.

- The survey found that 88% of FINDER’s users are voluntary users. These voluntary users may be more comfortable with technology than the general law enforcement population.

- At least 5% of the objective Query Log data were missing or inaccurate.

- Success Tag reports were highly subjective.

- Exploratory measures for computer expertise, technology options, and required use were employed in empirical analyses.
APPENDIX A: FINDER USER SURVEY
May 24, 2006

Greetings:

As a FINDER user, you probably know that FINDER was built as a collaborative effort between Florida’s law enforcement community and the University of Central Florida (UCF). This survey is being conducted by members of the FINDER team at UCF and is very important in helping us understand how we can make FINDER best suit your needs.

You may use FINDER every day or you may use it very rarely. In either case, your perspective on how FINDER fits into your job tasks will help us build a better information sharing system that may help you perform your duties more efficiently and effectively. Therefore, we would greatly appreciate your taking a few minutes to complete this on-line survey.

Participation in this survey is voluntary. You do not have to answer any questions that you do not wish to answer, and you may discontinue participation at any time. Although you will use your FINDER User Name to login to the survey, the researchers will not know who you are unless your User Name is also your real name. There is no central registry of FINDER users and there is minimal risk that you can be identified by your survey response. In any event, your responses are confidential, and your identity will not be divulged in any reports or discussions.

The results of this survey will be made available upon request. There are no direct benefits or compensation to participants; you must be at least 18 years old to participate in the survey.

If you have any questions about this research, please contact Dr. Mike Reynolds, at (407) 882-1592. Questions or concerns about research participants' rights may be directed to the UCFIRB Office, University of Central Florida Office of Research, 12201 Research Parkway, Suite 501, Orlando, Florida 32826-3246. The phone number is (407) 823-2901.

You may take this survey by CTRL + clicking on the link http://infosharingsurvey.com and logging-in with your FINDER User Name. Your agency’s computer firewall may prevent this link from working. If that is the case, you can copy and paste this link into your Internet-access browser.

Pre-testing of this survey indicates that it should take you less than 10 minutes to complete. We would greatly appreciate your response by June 15, 2006.

Sincerely,

Dr. Mike Reynolds
Associate Professor
University of Central Florida
(407)882-1592
FINDERSurvey@mail.ucf.edu
As a result of your use of FINDER, have you:

<table>
<thead>
<tr>
<th></th>
<th>Yes</th>
<th>No</th>
<th>Not Applicable</th>
</tr>
</thead>
<tbody>
<tr>
<td>1.</td>
<td>Made an arrest?</td>
<td>☐</td>
<td>☐</td>
</tr>
<tr>
<td>2.</td>
<td>Solved a case?</td>
<td>☐</td>
<td>☐</td>
</tr>
<tr>
<td>3.</td>
<td>Recovered property?</td>
<td>☐</td>
<td>☐</td>
</tr>
<tr>
<td>4.</td>
<td>Identified a suspect?</td>
<td>☐</td>
<td>☐</td>
</tr>
<tr>
<td>5.</td>
<td>Located a person?</td>
<td>☐</td>
<td>☐</td>
</tr>
<tr>
<td>6.</td>
<td>Recovered a vehicle?</td>
<td>☐</td>
<td>☐</td>
</tr>
<tr>
<td>7.</td>
<td>Discovered a crime?</td>
<td>☐</td>
<td>☐</td>
</tr>
</tbody>
</table>

8. For what type of law enforcement agency do you work?
   - [ ] Police Department
   - [ ] Sheriff’s Office
   - [ ] State Agency
   - [ ] Federal Agency
   - [ ] Other

9. What agency is your primary employer? (optional) __________________________________________________________

9a. What is your FINDER User Name? __________________________________________________________

10. Some FINDER users have used more than one User Name or shared a User Name with others. If you have used a FINDER User Name(s) other than the one above, please enter it below. If you have shared a User Name, please mark “This name has been shared.”
    
    Please enter any other User Name you have used. ____________________________________________
    
    [ ] This name has been shared
11. Are you a sworn law enforcement officer or non-sworn employee?
   
   ☐ Sworn   ☐ Non-sworn

12. Which of the following best describes your primary job function?
   
   ☐ Patrol   ☐ Investigations   ☐ Administrative   ☐ Analysis or support

13. What is your rank? ________________________________________________  ☐ Not applicable

14. What is your job title? ____________________________________________

15. What is your total number of years of law enforcement-related experience? ________ years

16. When did you begin using FINDER?   Month_______   Year ________  ☐ I don’t remember

Please continue to the next page
17. Are you **required** by your agency or supervisor to use FINDER

☐ No  ☐ Yes

18. Has your job assignment changed since you began using FINDER?

☐ No  ☐ Yes

19. How often do you use FINDER?

☐ Almost never  ☐ A few times a month  ☐ About once a week  ☐ A few times a week  ☐ Almost every day

20. What kind of FINDER training have you received? (please select all that apply)

☐ A co-worker or supervisor showed me how to use FINDER

☐ I attended a training session presented by the University of Central Florida or the Law Enforcement Consortium.

☐ My agency provided a FINDER training class.

☐ I did not receive any FINDER training.

**Please continue to the next page**
Please indicate your level of agreement or disagreement with the following statements:

<table>
<thead>
<tr>
<th></th>
<th>Strongly Disagree</th>
<th>Moderately Disagree</th>
<th>Disagree</th>
<th>Neither Agree nor Disagree</th>
<th>Agree</th>
<th>Moderately Agree</th>
<th>Strongly Agree</th>
<th>Not Applicable</th>
</tr>
</thead>
<tbody>
<tr>
<td>21</td>
<td>FINDER helps me do my job more efficiently.</td>
<td>☐</td>
<td>☐</td>
<td>☐</td>
<td>☐</td>
<td>☐</td>
<td>☐</td>
<td>☐</td>
</tr>
<tr>
<td>22</td>
<td>FINDER is easy to use.</td>
<td>☐</td>
<td>☐</td>
<td>☐</td>
<td>☐</td>
<td>☐</td>
<td>☐</td>
<td>☐</td>
</tr>
<tr>
<td>23</td>
<td>I use FINDER only as a last resort.</td>
<td>☐</td>
<td>☐</td>
<td>☐</td>
<td>☐</td>
<td>☐</td>
<td>☐</td>
<td>☐</td>
</tr>
<tr>
<td>24</td>
<td>I use FINDER to locate missing or stolen property.</td>
<td>☐</td>
<td>☐</td>
<td>☐</td>
<td>☐</td>
<td>☐</td>
<td>☐</td>
<td>☐</td>
</tr>
<tr>
<td>25</td>
<td>I use FINDER to locate information about people.</td>
<td>☐</td>
<td>☐</td>
<td>☐</td>
<td>☐</td>
<td>☐</td>
<td>☐</td>
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</tr>
<tr>
<td>26</td>
<td>I am usually comfortable with learning new computer programs.</td>
<td>☐</td>
<td>☐</td>
<td>☐</td>
<td>☐</td>
<td>☐</td>
<td>☐</td>
<td>☐</td>
</tr>
<tr>
<td>27</td>
<td>FINDER provides me information that I cannot get from any other source.</td>
<td>☐</td>
<td>☐</td>
<td>☐</td>
<td>☐</td>
<td>☐</td>
<td>☐</td>
<td>☐</td>
</tr>
<tr>
<td>28</td>
<td>FINDER has helped me improve my job performance.</td>
<td>☐</td>
<td>☐</td>
<td>☐</td>
<td>☐</td>
<td>☐</td>
<td>☐</td>
<td>☐</td>
</tr>
<tr>
<td>29</td>
<td>FINDER has helped me locate people that I couldn’t find through other techniques.</td>
<td>☐</td>
<td>☐</td>
<td>☐</td>
<td>☐</td>
<td>☐</td>
<td>☐</td>
<td>☐</td>
</tr>
<tr>
<td>30</td>
<td>I use FINDER to search for property more than I use it to search for people.</td>
<td>☐</td>
<td>☐</td>
<td>☐</td>
<td>☐</td>
<td>☐</td>
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</tbody>
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Please continue to the next page
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<th>Strongly Agree</th>
<th>Not Applicable</th>
</tr>
</thead>
<tbody>
<tr>
<td>31</td>
<td>In my job I have to use multiple computer systems to assemble the information I need.</td>
<td>☐</td>
<td>☐</td>
<td>☐</td>
<td>☒</td>
<td>☐</td>
<td>☐</td>
<td>☐</td>
</tr>
<tr>
<td>32</td>
<td>My co-workers often ask me to help them with computer problems.</td>
<td>☐</td>
<td>☐</td>
<td>☐</td>
<td>☐</td>
<td>☒</td>
<td>☑</td>
<td>☐</td>
</tr>
<tr>
<td>33</td>
<td>Most of the time, FINDER provides information that is useful to me.</td>
<td>☐</td>
<td>☐</td>
<td>☐</td>
<td>☒</td>
<td>☐</td>
<td>☐</td>
<td>☐</td>
</tr>
<tr>
<td>34</td>
<td>I only use FINDER if I am looking for a person or property outside of my jurisdiction.</td>
<td>☐</td>
<td>☐</td>
<td>☐</td>
<td>☒</td>
<td>☐</td>
<td>☐</td>
<td>☐</td>
</tr>
<tr>
<td>35</td>
<td>I use FINDER’s “Link Analysis” to get the information I need.</td>
<td>☐</td>
<td>☐</td>
<td>☐</td>
<td>☒</td>
<td>☐</td>
<td>☐</td>
<td>☐</td>
</tr>
<tr>
<td>36</td>
<td>FINDER has helped me solve or prevent crimes.</td>
<td>☐</td>
<td>☐</td>
<td>☐</td>
<td>☐</td>
<td>☒</td>
<td>☐</td>
<td>☐</td>
</tr>
<tr>
<td>37</td>
<td>I have to make a lot of queries on FINDER to get the information I need.</td>
<td>☐</td>
<td>☐</td>
<td>☐</td>
<td>☐</td>
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<tr>
<td>38</td>
<td>I work with someone who is always encouraging me to use FINDER.</td>
<td>☐</td>
<td>☐</td>
<td>☐</td>
<td>☐</td>
<td>☒</td>
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</tr>
<tr>
<td>39</td>
<td>My co-workers often ask me to help teach them how to use software.</td>
<td>☐</td>
<td>☐</td>
<td>☐</td>
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<tr>
<td>40</td>
<td>I would use FINDER more often if it did not take so long to get a response to my queries.</td>
<td>☐</td>
<td>☐</td>
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<td>☐</td>
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</tr>
<tr>
<td>41</td>
<td>My job requires me to do a lot of data analysis.</td>
<td>☐</td>
<td>☐</td>
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Please continue to the next page
Please indicate your level of agreement or disagreement with the following statements:

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<th>Moderately Agree</th>
<th>Strongly Agree</th>
<th>Not Applicable</th>
</tr>
</thead>
<tbody>
<tr>
<td>42</td>
<td><strong>FINDER saves me a lot of time.</strong></td>
<td></td>
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<td>43</td>
<td>I think <strong>FINDER is poorly designed.</strong></td>
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<tr>
<td>44</td>
<td>I have computer tools other than <strong>FINDER</strong> to help me get information from outside of my jurisdiction.</td>
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<tr>
<td>45</td>
<td>It is easy for me to give specific examples of how <strong>FINDER</strong> has helped me do my job.</td>
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</tr>
<tr>
<td>46</td>
<td>I could get better results from <strong>FINDER</strong> if I were provided more training about how to use it.</td>
<td></td>
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<tr>
<td>47</td>
<td><strong>FINDER</strong> would be more useful to me if it had analytical tools.</td>
<td></td>
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</tr>
<tr>
<td>48</td>
<td>The best thing about <strong>FINDER</strong> is I can get information that I was not able to get before.</td>
<td></td>
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</tr>
<tr>
<td>49</td>
<td><strong>FINDER</strong> is the only computer tool I have to get information from other police agencies.</td>
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</tr>
</tbody>
</table>

Please continue to the next page
50. Which of the following best represents the workload measure that you use in your job?

- [ ] Number of calls for service that I respond to
- [ ] Number of cases I receive to investigate
- [ ] Number of projects that are assigned to me
- [ ] Number of reports that I write
- [ ] Number of people I am supposed to contact, or brief, or make presentations to
- [ ] None of these reflect the workload measure that I use.

51. In your current job assignment, do you maintain some measure, statistic, or record of your workload?

- [ ] No
- [ ] Yes

If “No” skip to #53 on next page

If “Yes” please continue to #52

52. On average, how many calls, or cases, or projects, or reports, or contacts do you handle each month?

- [ ] Fewer than 10
- [ ] Between 10 & 50
- [ ] Between 51 & 100
- [ ] More than 100

Please continue to #53 on next page
53. Did you know that FINDER has a “Success Tagging” feature?

☐ Yes  ☐ No

If “No,” please go to # 83 on the last page

54. Have you ever used the “Success Tagging” feature?

☐ Yes  ☐ No

If “Yes,” please go to #64 on the next page

If “No,” please go to #55 on page 11
My perceptions about “success tagging” include:

<table>
<thead>
<tr>
<th></th>
<th></th>
<th>Strongly Disagree</th>
<th>Moderately Disagree</th>
<th>Disagree</th>
<th>Neither Agree nor Disagree</th>
<th>Agree</th>
<th>Moderately Agree</th>
<th>Strongly Agree</th>
<th>Not Applicable</th>
</tr>
</thead>
<tbody>
<tr>
<td>64</td>
<td>I do a “success tagging” every time FINDER helps me perform my job.</td>
<td></td>
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</tr>
<tr>
<td>65</td>
<td>I only do a “success tagging” when FINDER information directly helps me solve a case.</td>
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</tr>
<tr>
<td>66</td>
<td>I'm not sure what a &quot;success&quot; is supposed to be.</td>
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<tr>
<td>67</td>
<td>I would only report a “success” if I arrested someone specifically because of FINDER.</td>
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<tr>
<td>68</td>
<td>I believe that my continued use of FINDER proves that I am having success.</td>
<td></td>
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<tr>
<td>69</td>
<td>I don’t see any real value with “success tagging.”</td>
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</tr>
<tr>
<td>70</td>
<td>FINDER has not helped me perform my job.</td>
<td></td>
<td></td>
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<td></td>
</tr>
<tr>
<td>71</td>
<td>It takes too much time to do a &quot;success tagging.&quot;</td>
<td></td>
<td></td>
<td></td>
<td></td>
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<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>72</td>
<td>FINDER has brought me more success than the other computer systems I have available.</td>
<td></td>
<td></td>
<td></td>
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</tr>
<tr>
<td>73</td>
<td>The actual &quot;success&quot; happens after I log-off from FINDER and I may forget to report it.</td>
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<tr>
<td>74</td>
<td>I use “success tagging” if FINDER helps me make an arrest.</td>
<td></td>
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Please continue to the next page
My perceptions about “success tagging” include:

<p>| | | | | | | | | | |</p>
<table>
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<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>75</td>
<td>I use “success tagging” if FINDER helps me locate or recover stolen property.</td>
<td>Strongly Disagree</td>
<td>Moderately Disagree</td>
<td>Disagree</td>
<td>Neither Agree nor Disagree</td>
<td>Agree</td>
<td>Moderately Agree</td>
<td>Strongly Agree</td>
<td>Not Applicable</td>
</tr>
<tr>
<td>76</td>
<td>I use “success tagging” if FINDER provides me information from other agencies that I could not have discovered without FINDER.</td>
<td>Strongly Disagree</td>
<td>Moderately Disagree</td>
<td>Disagree</td>
<td>Neither Agree nor Disagree</td>
<td>Agree</td>
<td>Moderately Agree</td>
<td>Strongly Agree</td>
<td>Not Applicable</td>
</tr>
<tr>
<td>77</td>
<td>I started using “success tagging” only after I received FINDER training.</td>
<td>Strongly Disagree</td>
<td>Moderately Disagree</td>
<td>Disagree</td>
<td>Neither Agree nor Disagree</td>
<td>Agree</td>
<td>Moderately Agree</td>
<td>Strongly Agree</td>
<td>Not Applicable</td>
</tr>
<tr>
<td>78</td>
<td>Other people I know who use FINDER have successes that they don’t report.</td>
<td>Strongly Disagree</td>
<td>Moderately Disagree</td>
<td>Disagree</td>
<td>Neither Agree nor Disagree</td>
<td>Agree</td>
<td>Moderately Agree</td>
<td>Strongly Agree</td>
<td>Not Applicable</td>
</tr>
<tr>
<td>79</td>
<td>I use “success tagging” because people I respect have encouraged me to do so.</td>
<td>Strongly Disagree</td>
<td>Moderately Disagree</td>
<td>Disagree</td>
<td>Neither Agree nor Disagree</td>
<td>Agree</td>
<td>Moderately Agree</td>
<td>Strongly Agree</td>
<td>Not Applicable</td>
</tr>
<tr>
<td>80</td>
<td>Other computer systems I use bring me more success than FINDER.</td>
<td>Strongly Disagree</td>
<td>Moderately Disagree</td>
<td>Disagree</td>
<td>Neither Agree nor Disagree</td>
<td>Agree</td>
<td>Moderately Agree</td>
<td>Strongly Agree</td>
<td>Not Applicable</td>
</tr>
<tr>
<td>81</td>
<td>The most “successful” thing about FINDER is it saves me time.</td>
<td>Strongly Disagree</td>
<td>Moderately Disagree</td>
<td>Disagree</td>
<td>Neither Agree nor Disagree</td>
<td>Agree</td>
<td>Moderately Agree</td>
<td>Strongly Agree</td>
<td>Not Applicable</td>
</tr>
</tbody>
</table>

82. When you think about all the successes you have had using FINDER, approximately what percentage of those successes have you reported using the “success tagging” feature?

- [ ] Less than 10%
- [ ] 11-25%
- [ ] 26-50%
- [ ] 51-75%
- [ ] 76-100%

Please go to # 83 on the last page
I have not used FINDER’s “Success Tagging” because:

<table>
<thead>
<tr>
<th></th>
<th>Strongly Disagree</th>
<th>Moderately Disagree</th>
<th>Disagree</th>
<th>Neither Agree nor Disagree</th>
<th>Agree</th>
<th>Moderately Agree</th>
<th>Strongly Agree</th>
<th>Not Applicable</th>
</tr>
</thead>
<tbody>
<tr>
<td>55</td>
<td>I have not had any successes using FINDER.</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>56</td>
<td>I don't know how to use the &quot;Success Tagging&quot; feature.</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>57</td>
<td>I'm not sure what a &quot;success&quot; is supposed to be.</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>58</td>
<td>It takes too much time to do a &quot;success tagging.&quot;</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>59</td>
<td>The actual &quot;success&quot; happens after I log-off from FINDER and I may forget to report it.</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>60</td>
<td>I would only report a “success” if I arrested someone specifically because of FINDER.</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>61</td>
<td>I believe that my continued use of FINDER proves that I am having success.</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>62</td>
<td>I don’t see any real value with “success tagging.”</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>63</td>
<td>FINDER has not helped me perform my job.</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Please continue to the next page
83. May we contact you if we have any follow-up questions about your survey responses?

☐ Yes Please provide your email address ________________________________

☐ No

Thank you for taking the time to complete this confidential survey. Your FINDER opinions and experiences are very important in helping us build FINDER so it best meets your needs.

You can send this survey back to us with the attached, postage-paid envelope.

If you have any additional comments or suggestions about FINDER or this survey, please write them below. Also, you may contact us directly through escottjr@mail.ucf.edu or (407)882-1592.

Comments:

____________________________________________________________________

____________________________________________________________________

____________________________________________________________________

____________________________________________________________________

____________________________________________________________________
APPENDIX B: IRB APPROVAL
THE UNIVERSITY OF CENTRAL FLORIDA
INSTITUTIONAL REVIEW BOARD (IRB)

IRB Committee Approval Form

PRINCIPAL INVESTIGATOR(S): Ernest Scott Jr. IRB#: 06-3420
Supervisor: K. Michael Reynolds, Ph.D.

PROJECT TITLE: FINDER User Survey

[X] New project submission [ ] Resubmission of lapsed project #
[ ] Continuing review of lapsed project # [ ] Continuing review of #
[ ] Study expires: [ ] Initial submission was approved by expedited review
[ ] Initial submission was approved by full board review but continuing review can be expedited
[ ] Suspension of enrollment email sent to PI, entered on spreadsheet, administration notified

Chair

[X] Expedited Approval

Dated: 4/4/06
Cite how qualifies for expedited review: minimal risk and #7

[ ] Exempt

Dated:
Cite how qualifies for exempt status: minimal risk and

[X] Expiration
Date: 4/4/07

IRB Reviewers:

Signed: ____________________________
Dr. Jacqueline Byers, Chair

Signed: ____________________________
Dr. Sophia Dziegielewski, Vice-Chair

Signed: ____________________________
Dr. Tracy Dietz, Vice-Chair

Complete reverse side of expedited or exempt form

[ ] Waiver of documentation of consent approved
[ ] Waiver of consent approved
[ ] Waiver of HIPAA Authorization approved

NOTES FROM IRB CHAIR (IF APPLICABLE):
APPENDIX C: RELATIONSHIPS OF INSTRUMENT ITEMS TO STUDY VARIABLES
<table>
<thead>
<tr>
<th>Variable</th>
<th>FINDER User Survey Item Number(s)</th>
<th>Description/Comments</th>
</tr>
</thead>
<tbody>
<tr>
<td>Respondent aware of success tagging but who have not used it</td>
<td></td>
<td>Level of success (specific policing outcomes)</td>
</tr>
<tr>
<td>Responder aware of success tagging but who have not used it</td>
<td>1-7</td>
<td>User efficiency</td>
</tr>
<tr>
<td>Respondents who have used success tagging</td>
<td>21</td>
<td>Change in performance</td>
</tr>
<tr>
<td>Respondents who have used success tagging</td>
<td>26</td>
<td>Level of success (solving or preventing crimes)</td>
</tr>
<tr>
<td>Respondents who have used success tagging</td>
<td>28</td>
<td>User efficiency</td>
</tr>
<tr>
<td>Respondents who have used success tagging</td>
<td>36</td>
<td>User has examples of success</td>
</tr>
<tr>
<td>Respondents who have used success tagging</td>
<td>42</td>
<td>ID whether user knowledgeable about “success tagging” (if no, end of survey)</td>
</tr>
<tr>
<td>Respondents who have used success tagging</td>
<td>45</td>
<td>ID whether user has used success tagging</td>
</tr>
<tr>
<td>Respondents who have used success tagging</td>
<td>53,63</td>
<td>Definition of success (continued use)</td>
</tr>
<tr>
<td>Respondents who have used success tagging</td>
<td>60,62</td>
<td>Definition of success (what is it)</td>
</tr>
<tr>
<td>Respondents who have used success tagging</td>
<td>60,62</td>
<td>Definition of success (includes arrests)</td>
</tr>
<tr>
<td>Respondents who have used success tagging</td>
<td>75,76</td>
<td>Definition of success (arrests only)</td>
</tr>
<tr>
<td>Respondents who have used success tagging</td>
<td>75,76</td>
<td>Definition of success (property recovery)</td>
</tr>
<tr>
<td>Respondents who have used success tagging</td>
<td>78</td>
<td>Definition of success (info other agency)</td>
</tr>
<tr>
<td>Respondents who have used success tagging</td>
<td>81</td>
<td>Use of tagging after training (control)</td>
</tr>
<tr>
<td>Respondents who have used success tagging</td>
<td>82</td>
<td>Exploratory: unreported successes other users</td>
</tr>
<tr>
<td>Respondents who have used success tagging</td>
<td>65</td>
<td>User efficiency</td>
</tr>
<tr>
<td>Respondents who have used success tagging</td>
<td>62,69</td>
<td>Level of success (unreported/reported)</td>
</tr>
<tr>
<td>Respondents who have used success tagging</td>
<td></td>
<td>Definition of success, direct solve only</td>
</tr>
<tr>
<td>Respondents who have used success tagging</td>
<td></td>
<td>Reporting success, value of report</td>
</tr>
<tr>
<td>Variable</td>
<td>FINDER User Survey Item Number(s)</td>
<td>Description/Comments</td>
</tr>
<tr>
<td>-------------------------------</td>
<td>-----------------------------------</td>
<td>--------------------------------------------------------------------------------------</td>
</tr>
<tr>
<td>Items for all respondents</td>
<td>Respondent aware of success tagging but who have not used it</td>
<td></td>
</tr>
<tr>
<td>FINDER Task-fit</td>
<td>22, 23, 25, 27, 29, 48, 30, 31, 33, 34, 35, 37, 40, 31, 43, 47</td>
<td>Ease of use, Useful data, Useful data, locatability, level of detail, Useful data, not prev available, Useful data, property, Useful data, most of time, Useful data outside jurisdiction, Useful data, link analysis, Ease of use, Usability (negative) too long of time, Routine/non-routine, multiple systems, Usability (negative), Usability (negative) analytical tools, Ease of use (negative, reporting success), Ease of use (negative, time to report success), Usability (success after logoff)</td>
</tr>
<tr>
<td>Computer Expertise</td>
<td>26, 32, 39</td>
<td>Computer expertise, new software, Computer literacy, assisting others, Computer literacy, assisting others</td>
</tr>
<tr>
<td>Usage Rate</td>
<td>19</td>
<td>Users’ recall of usage rate</td>
</tr>
<tr>
<td>Job Assignment</td>
<td>11, 12, 13, 14, 18, 41</td>
<td>Sworn or non-sworn, Job function, Job rank, Job title, Control for changes in job assignment, Routine/non-routine tasks</td>
</tr>
<tr>
<td>Variable</td>
<td>FINDER User Survey Item Number(s)</td>
<td>Description/Comments</td>
</tr>
<tr>
<td>--------------------------------</td>
<td>----------------------------------</td>
<td>----------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------</td>
</tr>
<tr>
<td></td>
<td>Items for all respondents</td>
<td><strong>Respondent aware of success tagging but who have not used it</strong></td>
</tr>
<tr>
<td><strong>Workload</strong></td>
<td>50</td>
<td>First item in branch to determine type of workload.</td>
</tr>
<tr>
<td></td>
<td>51</td>
<td>Second item in branch; asks if workload records are kept</td>
</tr>
<tr>
<td></td>
<td>52</td>
<td>Third item in branch; user recall of workload volume</td>
</tr>
<tr>
<td><strong>Training</strong></td>
<td>20 46</td>
<td>Type of FINDER training recvd</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Whether more training desired</td>
</tr>
<tr>
<td><strong>Agency</strong></td>
<td>8 9 38</td>
<td>Type of agency</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Name of agency</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Normative influence (advocate)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Normative influence (social)</td>
</tr>
<tr>
<td><strong>TL Time in Law Enforcement-related job</strong></td>
<td>15</td>
<td>Years</td>
</tr>
<tr>
<td><strong>Time as FINDER User</strong></td>
<td>16</td>
<td>User recall relative to data available in FINDER query logs.</td>
</tr>
<tr>
<td><strong>Technology</strong></td>
<td>17 44 49</td>
<td>Voluntariness of FINDER use</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Access to multiple police systems</td>
</tr>
<tr>
<td></td>
<td></td>
<td>No access to other info sharing systems</td>
</tr>
<tr>
<td></td>
<td></td>
<td>FINDER success relative to other technology available (positive)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>FINDER success relative to other technology available (negative)</td>
</tr>
</tbody>
</table>
APPENDIX D: STATISTICAL TESTS AND CONVENTIONS
Table 34: Statistical Tests

<table>
<thead>
<tr>
<th>Statistical Test</th>
<th>Data Type</th>
<th>Comments</th>
<th>Sources</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cramer’s V (“phi”)</td>
<td>Nominal</td>
<td>Chi-square based</td>
<td>Aldridge, 2001; Norusis, 2005</td>
</tr>
<tr>
<td>gamma</td>
<td>Ordinal</td>
<td>Asymmetric associations (directional)</td>
<td>Babbie, 1995; Weisberg et al, 1996</td>
</tr>
<tr>
<td>Independent Samples t-Test</td>
<td>Scale</td>
<td>Comparison of means between two independent samples</td>
<td>Gliner &amp; Morgan, 2000; Kachigan, 1986; Norusis, 2005</td>
</tr>
<tr>
<td>Kendall’s tau (“tau”)</td>
<td>Ordinal</td>
<td>Symmetric associations tau-b for 2x2 comparisons; tau-c for others</td>
<td>Weisberg et al, 1996; Norusis, 2005</td>
</tr>
<tr>
<td>lambda</td>
<td>Nominal</td>
<td>PRE-based</td>
<td>Norusis, 2005</td>
</tr>
<tr>
<td>Levene Test for Homogeniety of Variance</td>
<td>Scale</td>
<td>Checks for equal variance between samples for ANOVA</td>
<td>Norusis, 2005</td>
</tr>
<tr>
<td>Mann-Whitney</td>
<td>Ordinal</td>
<td>Comparison of means for two-sample, unpaired data</td>
<td>Gliner &amp; Morgan, 2000; Liao, 2002</td>
</tr>
<tr>
<td>Multiple Regression</td>
<td>Scale &amp; dichotomous</td>
<td>Predictive relationship of multiple Variables on single outcome variable (single path)</td>
<td>Gliner &amp; Morgan, 2000; Kachigan, 1986; Norusis, 2005</td>
</tr>
<tr>
<td>One-way ANOVA</td>
<td>Scale</td>
<td>Comparison of means between three or more groups</td>
<td>Norusis, 2005; Gliner &amp; Morgan, 2000</td>
</tr>
<tr>
<td>Pearson Product-moment coefficient</td>
<td>Scale</td>
<td>Bivariate correlation</td>
<td>Babbie, 1995; Gliner &amp; Morgan, 2000; Norusis, 2005</td>
</tr>
<tr>
<td>Spearman’s rho (“rho”)</td>
<td>Ordinal &amp; non-normal scale</td>
<td>Association where both variables rank ordered</td>
<td>Weisberg et al, 1996; Aldridge, 2001; Norusis, 2005</td>
</tr>
<tr>
<td>Structural equation modeling</td>
<td>Scale &amp; dichotomous</td>
<td>Simultaneous predictive relationship of multiple variables on one or more outcomes (multiple paths)</td>
<td>Kline, 2005; Maruyama, 1998; Wan, 2002</td>
</tr>
</tbody>
</table>
Table 35: Convention Used for Interpreting Correlation Coefficient

<table>
<thead>
<tr>
<th>Correlation Value</th>
<th>Verbal Designation</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.0</td>
<td>No relationship</td>
</tr>
<tr>
<td>0.1 to .10</td>
<td>Very Weak</td>
</tr>
<tr>
<td>.11 to .25</td>
<td>Weak</td>
</tr>
<tr>
<td>.26 to .50</td>
<td>Moderate</td>
</tr>
<tr>
<td>.51 to .75</td>
<td>Strong</td>
</tr>
<tr>
<td>.76 to .99</td>
<td>Very Strong</td>
</tr>
<tr>
<td>1.00</td>
<td>Perfect association</td>
</tr>
</tbody>
</table>

Source: Losh (2002)

Table 36: Convention Used for Cramer’s V Statistic

<table>
<thead>
<tr>
<th>Cramer’s V Statistic</th>
<th>Verbal Designation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Less than .10</td>
<td>Weak</td>
</tr>
<tr>
<td>.10 to .29</td>
<td>Moderate</td>
</tr>
<tr>
<td>.30 or higher</td>
<td>Strong</td>
</tr>
</tbody>
</table>

Source: Standard table and graph format and interpretation (2004).
Table 37: Convention Used for lambda Statistic

<table>
<thead>
<tr>
<th>lambda Statistic</th>
<th>Verbal Designation</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.0</td>
<td>No relationship</td>
</tr>
<tr>
<td>0.0 to 0.2</td>
<td>Very weak</td>
</tr>
<tr>
<td>0.2 to 0.4</td>
<td>Weak</td>
</tr>
<tr>
<td>0.4 to 0.6</td>
<td>Moderate</td>
</tr>
<tr>
<td>0.6 to 0.8</td>
<td>Strong</td>
</tr>
<tr>
<td>0.8 to 1.0</td>
<td>Very strong</td>
</tr>
<tr>
<td>1.0</td>
<td>Perfect relationship</td>
</tr>
</tbody>
</table>

Source: Schwab (2004)
APPENDIX E: CORRELATION COEFFICIENTS (r) IN PRIOR RESEARCH
<table>
<thead>
<tr>
<th>Author(s)</th>
<th>Description</th>
<th>Approximate r value *</th>
</tr>
</thead>
<tbody>
<tr>
<td>Goodhue (1995)</td>
<td>Used Task-technology fit (TTF) instrument with 259 technology users in 9 companies. Significant variables related to system usefulness &amp; usability related to user tasks ranged from adj r-square .11 to .30</td>
<td>.33-.55</td>
</tr>
<tr>
<td>Colvin &amp; Goh (2005)</td>
<td>Used Technology Acceptance Measure (TAM) with 430 patrol officers in one city. r-squared =.22 for ease of use and .22 for usability of technology systems.</td>
<td>.47</td>
</tr>
<tr>
<td>Dishaw &amp; Strong (1999)</td>
<td>Used combination of TTF and TAM instruments across 60 IT projects in 3 corporations. The combined effect of TTF and TAM was r-squared=.51</td>
<td>.71</td>
</tr>
<tr>
<td>Legris et al (2003)</td>
<td>Reviewed use of TAM across multiple research domains and concluded that TAM consistently predicts about 40% of system use.</td>
<td>.63</td>
</tr>
<tr>
<td>Davis (1989)</td>
<td>Developed TAM and tested across organizations in 3 studies (combined n=300). r values from .45 to .85</td>
<td>.45-.85</td>
</tr>
<tr>
<td>Danziger &amp; Kraemer (1985)</td>
<td>Studied 374 detectives in 40 agencies &amp; influence of technology on performance. r values of influence of IT on performance ranged from .34-.56</td>
<td>.34-.56</td>
</tr>
<tr>
<td>Venkatesh &amp; Davis (2000)</td>
<td>Extended TAM to TAM II and tested longitudinally across 4 systems and 156 users with sub-groups of voluntary and mandatory users. In the voluntary use group, r-square across 3 time period ranged from .44-.60</td>
<td>.66-.77</td>
</tr>
<tr>
<td>Goodhue &amp; Thompson (1995)</td>
<td>Used TTF instrument on 600 users in 2 companies. Adjusted r-square across relevant TTF dimensions ranged from .10 to .25</td>
<td>.32-.50</td>
</tr>
</tbody>
</table>

* For purpose of estimation, the square root of both r-square and adjusted r-square is used.
### Have you:

<table>
<thead>
<tr>
<th>Have you:</th>
<th>Yes</th>
<th>Yes%</th>
<th>No</th>
<th>No%</th>
<th>Total Response</th>
<th>N.A./No answer</th>
<th>Applicable Responses</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. Made an arrest?</td>
<td>148</td>
<td>45.7</td>
<td>176</td>
<td>54.3</td>
<td>396</td>
<td>78</td>
<td>324</td>
</tr>
<tr>
<td>2. Solved a case?</td>
<td>172</td>
<td>51.8</td>
<td>160</td>
<td>48.2</td>
<td>402</td>
<td>70</td>
<td>332</td>
</tr>
<tr>
<td>3. Recovered property?</td>
<td>140</td>
<td>43.9</td>
<td>179</td>
<td>56.1</td>
<td>402</td>
<td>83</td>
<td>319</td>
</tr>
<tr>
<td>4. Identified a suspect?</td>
<td>217</td>
<td>63.6</td>
<td>124</td>
<td>36.4</td>
<td>402</td>
<td>61</td>
<td>341</td>
</tr>
<tr>
<td>5. Located a person?</td>
<td>203</td>
<td>60.2</td>
<td>134</td>
<td>39.8</td>
<td>402</td>
<td>65</td>
<td>337</td>
</tr>
<tr>
<td>6. Recovered a vehicle?</td>
<td>14</td>
<td>4.8</td>
<td>275</td>
<td>95.2</td>
<td>402</td>
<td>113</td>
<td>289</td>
</tr>
<tr>
<td>7. Discovered a crime?</td>
<td>91</td>
<td>29.1</td>
<td>222</td>
<td>70.9</td>
<td>402</td>
<td>89</td>
<td>313</td>
</tr>
</tbody>
</table>

### For what type of law enforcement agency do you work?

<table>
<thead>
<tr>
<th></th>
<th>Police Department</th>
<th>Sheriff's Office</th>
<th>State Agency</th>
<th>Total Responses</th>
</tr>
</thead>
<tbody>
<tr>
<td>Police</td>
<td>120</td>
<td>273</td>
<td>9</td>
<td>402</td>
</tr>
<tr>
<td>Police%</td>
<td>29.9%</td>
<td>67.9%</td>
<td>2.2%</td>
<td></td>
</tr>
</tbody>
</table>

### Are you a sworn or non-sworn employee?

<table>
<thead>
<tr>
<th></th>
<th>Sworn</th>
<th>Non-sworn</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sworn</td>
<td>326</td>
<td>74</td>
</tr>
<tr>
<td>Sworn%</td>
<td>81.5%</td>
<td>18.5%</td>
</tr>
<tr>
<td>N</td>
<td>400</td>
<td></td>
</tr>
</tbody>
</table>
12. Which of the following best describes your job function?

<table>
<thead>
<tr>
<th></th>
<th>Frequency</th>
<th>Percent</th>
</tr>
</thead>
<tbody>
<tr>
<td>Patrol</td>
<td>61</td>
<td>15.2%</td>
</tr>
<tr>
<td>Investigations</td>
<td>242</td>
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</tr>
<tr>
<td>Administrative</td>
<td>40</td>
<td>10.0%</td>
</tr>
<tr>
<td>Analysis/Support</td>
<td>58</td>
<td>14.4%</td>
</tr>
<tr>
<td>Total</td>
<td>401</td>
<td>100.0%</td>
</tr>
</tbody>
</table>

13. What is your rank?

<table>
<thead>
<tr>
<th></th>
<th>Frequency</th>
<th>Percent</th>
</tr>
</thead>
<tbody>
<tr>
<td>Officer/Deputy/Agent</td>
<td>206</td>
<td>51.2%</td>
</tr>
<tr>
<td>Supervisor</td>
<td>12</td>
<td>3.0%</td>
</tr>
<tr>
<td>Corporal</td>
<td>30</td>
<td>7.5%</td>
</tr>
<tr>
<td>Sergeant</td>
<td>38</td>
<td>9.5%</td>
</tr>
<tr>
<td>Lieutenant</td>
<td>16</td>
<td>4.0%</td>
</tr>
<tr>
<td>Manager</td>
<td>1</td>
<td>0.2%</td>
</tr>
<tr>
<td>Captain</td>
<td>7</td>
<td>1.7%</td>
</tr>
<tr>
<td>Other Command</td>
<td>5</td>
<td>1.2%</td>
</tr>
<tr>
<td>Analyst</td>
<td>41</td>
<td>10.2%</td>
</tr>
<tr>
<td>Other</td>
<td>41</td>
<td>10.2%</td>
</tr>
<tr>
<td>No response</td>
<td>5</td>
<td>1.2%</td>
</tr>
<tr>
<td>Total</td>
<td>402</td>
<td>100.0%</td>
</tr>
<tr>
<td>Function</td>
<td>Frequency</td>
<td>Percent</td>
</tr>
<tr>
<td>-------------------------------</td>
<td>-----------</td>
<td>---------</td>
</tr>
<tr>
<td><strong>Patrol Functions</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Officer/Deputy</td>
<td>56</td>
<td>13.9%</td>
</tr>
<tr>
<td>Traffic Officer</td>
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<td>1.0%</td>
</tr>
<tr>
<td>Marine Officer</td>
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</tr>
<tr>
<td>Tactical Officer</td>
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<td>0.2%</td>
</tr>
<tr>
<td>School Officer/DARE</td>
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<td>0.2%</td>
</tr>
<tr>
<td><strong>Investigative Functions</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>All Crimes</td>
<td>48</td>
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</tr>
<tr>
<td>Property Crimes</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Detective- All Property Crimes</td>
<td>101</td>
<td>25.1%</td>
</tr>
<tr>
<td>Detective-Auto Theft</td>
<td>9</td>
<td>2.2%</td>
</tr>
<tr>
<td>Detective-White Collar Crimes</td>
<td>11</td>
<td>2.7%</td>
</tr>
<tr>
<td>Persons Crimes</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Detective- All Persons Crimes</td>
<td>2</td>
<td>0.5%</td>
</tr>
<tr>
<td>Detective-Violent Crimes</td>
<td>4</td>
<td>1.0%</td>
</tr>
<tr>
<td>Detective-Homicide</td>
<td>12</td>
<td>3.0%</td>
</tr>
<tr>
<td>Detective-Sex Crimes</td>
<td>2</td>
<td>0.5%</td>
</tr>
<tr>
<td>Detective-Child Abuse</td>
<td>5</td>
<td>1.2%</td>
</tr>
<tr>
<td>Detective-Robbery</td>
<td>7</td>
<td>1.7%</td>
</tr>
<tr>
<td>Other Investigations</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Detective-Computer Crimes</td>
<td>1</td>
<td>0.2%</td>
</tr>
<tr>
<td>Detective-Narcotics/Vice</td>
<td>7</td>
<td>1.7%</td>
</tr>
<tr>
<td>Agricultural Crimes</td>
<td>1</td>
<td>0.2%</td>
</tr>
<tr>
<td>Intelligence Officer</td>
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<td>3.2%</td>
</tr>
<tr>
<td>Background Investigator</td>
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<td>1.2%</td>
</tr>
<tr>
<td>State Attorney Investigator</td>
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<td>1.0%</td>
</tr>
<tr>
<td>Crime Scene Investigator</td>
<td>2</td>
<td>0.5%</td>
</tr>
<tr>
<td><strong>Analytical Functions</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Crime Analyst</td>
<td>35</td>
<td>8.7%</td>
</tr>
<tr>
<td>Research Analyst</td>
<td>6</td>
<td>1.5%</td>
</tr>
<tr>
<td>Investigative Assistant</td>
<td>2</td>
<td>0.5%</td>
</tr>
<tr>
<td><strong>Admin/Other</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>No Response</td>
<td>2</td>
<td>0.5%</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td>402</td>
<td>100.0%</td>
</tr>
</tbody>
</table>
15. What is your total number of years of law enforcement experience?

<table>
<thead>
<tr>
<th>Years of Experience</th>
<th>Frequency</th>
<th>Percent</th>
</tr>
</thead>
<tbody>
<tr>
<td>&lt;1 year</td>
<td>4</td>
<td>1.0%</td>
</tr>
<tr>
<td>1</td>
<td>2</td>
<td>0.5%</td>
</tr>
<tr>
<td>2</td>
<td>10</td>
<td>2.5%</td>
</tr>
<tr>
<td>3</td>
<td>12</td>
<td>3.0%</td>
</tr>
<tr>
<td>4</td>
<td>6</td>
<td>1.5%</td>
</tr>
<tr>
<td>5</td>
<td>16</td>
<td>4.0%</td>
</tr>
<tr>
<td>6</td>
<td>8</td>
<td>2.0%</td>
</tr>
<tr>
<td>7</td>
<td>15</td>
<td>3.7%</td>
</tr>
<tr>
<td>8</td>
<td>26</td>
<td>6.5%</td>
</tr>
<tr>
<td>9</td>
<td>19</td>
<td>4.7%</td>
</tr>
<tr>
<td>10</td>
<td>20</td>
<td>5.0%</td>
</tr>
<tr>
<td>11</td>
<td>19</td>
<td>4.7%</td>
</tr>
<tr>
<td>12</td>
<td>21</td>
<td>5.2%</td>
</tr>
<tr>
<td>13</td>
<td>12</td>
<td>3.0%</td>
</tr>
<tr>
<td>14</td>
<td>19</td>
<td>4.7%</td>
</tr>
<tr>
<td>15</td>
<td>15</td>
<td>3.7%</td>
</tr>
<tr>
<td>16</td>
<td>30</td>
<td>7.5%</td>
</tr>
<tr>
<td>17</td>
<td>25</td>
<td>6.2%</td>
</tr>
<tr>
<td>18</td>
<td>12</td>
<td>3.0%</td>
</tr>
<tr>
<td>19</td>
<td>11</td>
<td>2.7%</td>
</tr>
<tr>
<td>20+</td>
<td>97</td>
<td>24.1%</td>
</tr>
<tr>
<td>No response</td>
<td>3</td>
<td>0.7%</td>
</tr>
<tr>
<td>Total</td>
<td>402</td>
<td>100.0%</td>
</tr>
</tbody>
</table>

17. Are you required by your agency or supervisor to use FINDER?

<table>
<thead>
<tr>
<th>Frequency</th>
<th>Percent</th>
</tr>
</thead>
<tbody>
<tr>
<td>No</td>
<td>352</td>
</tr>
<tr>
<td>Yes</td>
<td>46</td>
</tr>
<tr>
<td>No answer</td>
<td>4</td>
</tr>
<tr>
<td>Total</td>
<td>402</td>
</tr>
</tbody>
</table>
18. Has your job changed since you began using FINDER?

<table>
<thead>
<tr>
<th></th>
<th>Frequency</th>
<th>Percent</th>
</tr>
</thead>
<tbody>
<tr>
<td>No</td>
<td>311</td>
<td>78.7%</td>
</tr>
<tr>
<td>Yes</td>
<td>84</td>
<td>21.3%</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td><strong>395</strong></td>
<td><strong>100.0%</strong></td>
</tr>
</tbody>
</table>

19. How often do you use FINDER?

<table>
<thead>
<tr>
<th></th>
<th>Frequency</th>
<th>Percent</th>
</tr>
</thead>
<tbody>
<tr>
<td>Almost never</td>
<td>91</td>
<td>22.9%</td>
</tr>
<tr>
<td>Few times a month</td>
<td>122</td>
<td>30.7%</td>
</tr>
<tr>
<td>About once a week</td>
<td>37</td>
<td>9.3%</td>
</tr>
<tr>
<td>Few times a week</td>
<td>68</td>
<td>17.1%</td>
</tr>
<tr>
<td>Almost every day</td>
<td>80</td>
<td>20.1%</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td><strong>398</strong></td>
<td><strong>100.0%</strong></td>
</tr>
</tbody>
</table>

20. What kind of FINDER training have you received?

<table>
<thead>
<tr>
<th>Training Type</th>
<th>Frequency</th>
<th>Percent</th>
</tr>
</thead>
<tbody>
<tr>
<td>Co-worker or supervisor, UCF, and agency training</td>
<td>3</td>
<td>0.8%</td>
</tr>
<tr>
<td>Co-worker or supervisor and UCF training</td>
<td>10</td>
<td>2.5%</td>
</tr>
<tr>
<td>Co-worker or supervisor and agency training</td>
<td>10</td>
<td>2.5%</td>
</tr>
<tr>
<td>Agency training and UCF training</td>
<td>7</td>
<td>1.8%</td>
</tr>
<tr>
<td>Co-worker or supervisor training only</td>
<td>150</td>
<td>38.1%</td>
</tr>
<tr>
<td>UCF training only</td>
<td>35</td>
<td>8.9%</td>
</tr>
<tr>
<td>Agency training only</td>
<td>56</td>
<td>14.2%</td>
</tr>
<tr>
<td>No training</td>
<td>123</td>
<td>31.2%</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td><strong>394</strong></td>
<td><strong>100.0%</strong></td>
</tr>
<tr>
<td>Question</td>
<td>SD</td>
<td>MD</td>
</tr>
<tr>
<td>--------------------------------------------------------------------------</td>
<td>----</td>
<td>----</td>
</tr>
<tr>
<td>FINDER helps me do my job more efficiently. N=356</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Freq.</td>
<td>3</td>
<td>0</td>
</tr>
<tr>
<td>%</td>
<td>0.8%</td>
<td>0%</td>
</tr>
<tr>
<td>FINDER is easy to use. N=374</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Freq.</td>
<td>3</td>
<td>1</td>
</tr>
<tr>
<td>%</td>
<td>0.8%</td>
<td>0.3%</td>
</tr>
<tr>
<td>I use FINDER only as a last resort. N=354</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Freq.</td>
<td>2</td>
<td>7</td>
</tr>
<tr>
<td>%</td>
<td>35.0%</td>
<td>6.5%</td>
</tr>
<tr>
<td>I use FINDER to locate missing or stolen property. N=305</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Freq.</td>
<td>12</td>
<td>2</td>
</tr>
<tr>
<td>%</td>
<td>3.9%</td>
<td>0.7%</td>
</tr>
<tr>
<td>I use FINDER to locate information about people. N=360</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Freq.</td>
<td>3</td>
<td>2</td>
</tr>
<tr>
<td>%</td>
<td>0.8%</td>
<td>0.6%</td>
</tr>
<tr>
<td>I am usually comfortable with learning new computer programs. N=379</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Freq.</td>
<td>6</td>
<td>1</td>
</tr>
<tr>
<td>%</td>
<td>1.6%</td>
<td>0.3%</td>
</tr>
<tr>
<td>FINDER provides me information that I cannot get from any other source. N=361</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Freq.</td>
<td>4</td>
<td>3</td>
</tr>
<tr>
<td>%</td>
<td>1.1%</td>
<td>0.8%</td>
</tr>
<tr>
<td>FINDER has helped me improve my job performance. N=355</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Freq.</td>
<td>4</td>
<td>1</td>
</tr>
<tr>
<td>%</td>
<td>1.1%</td>
<td>0.3%</td>
</tr>
<tr>
<td>FINDER has helped me locate people that I couldn’t find through other techniques. N=349</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Freq.</td>
<td>7</td>
<td>3</td>
</tr>
<tr>
<td>%</td>
<td>2.0%</td>
<td>0.9%</td>
</tr>
<tr>
<td></td>
<td>Question</td>
<td>SD</td>
</tr>
<tr>
<td>---</td>
<td>-------------------------------------------------------------------------</td>
<td>----</td>
</tr>
<tr>
<td>30</td>
<td>I use FINDER to search for property more than I use it to search for people. N=338</td>
<td>Freq.</td>
</tr>
<tr>
<td></td>
<td></td>
<td>%</td>
</tr>
<tr>
<td>31</td>
<td>In my job I have to use multiple computer systems to assemble the information I need. N=376</td>
<td>Freq.</td>
</tr>
<tr>
<td></td>
<td></td>
<td>%</td>
</tr>
<tr>
<td>32</td>
<td>My co-workers often ask me to help them with computer problems. N=368</td>
<td>Freq.</td>
</tr>
<tr>
<td></td>
<td></td>
<td>%</td>
</tr>
<tr>
<td>33</td>
<td>Most of the time, FINDER provides information that is useful to me. N=362</td>
<td>Freq.</td>
</tr>
<tr>
<td></td>
<td></td>
<td>%</td>
</tr>
<tr>
<td>34</td>
<td>I only use FINDER if I am looking for a person or property outside of my jurisdiction. N=357</td>
<td>Freq.</td>
</tr>
<tr>
<td></td>
<td></td>
<td>%</td>
</tr>
<tr>
<td>35</td>
<td>I use FINDER’s “Link Analysis” to get the information I need. N=309</td>
<td>Freq.</td>
</tr>
<tr>
<td></td>
<td></td>
<td>%</td>
</tr>
<tr>
<td>36</td>
<td>FINDER has helped me solve or prevent crimes. N=306</td>
<td>Freq.</td>
</tr>
<tr>
<td></td>
<td></td>
<td>%</td>
</tr>
<tr>
<td>37</td>
<td>I have to make a lot of queries on FINDER to get the information I need. N=350</td>
<td>Freq.</td>
</tr>
<tr>
<td></td>
<td></td>
<td>%</td>
</tr>
<tr>
<td>Question</td>
<td>SD</td>
<td>MD</td>
</tr>
<tr>
<td>--------------------------------------------------------------------------</td>
<td>----</td>
<td>----</td>
</tr>
<tr>
<td>I work with someone who is always encouraging me to use FINDER. N=329</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Freq.</td>
<td>35</td>
<td>12</td>
</tr>
<tr>
<td>%</td>
<td>10.6%</td>
<td>3.6%</td>
</tr>
<tr>
<td>My co-workers often ask me to help teach them how to use software. N=353</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Freq.</td>
<td>19</td>
<td>13</td>
</tr>
<tr>
<td>%</td>
<td>5.4%</td>
<td>3.7%</td>
</tr>
<tr>
<td>I would use FINDER more often if it did not take so long to get a response to my queries. N=354</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Freq.</td>
<td>21</td>
<td>17</td>
</tr>
<tr>
<td>%</td>
<td>11.6%</td>
<td>3.1%</td>
</tr>
<tr>
<td>My job requires me to do a lot of data analysis. N=364</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Freq.</td>
<td>26</td>
<td>8</td>
</tr>
<tr>
<td>%</td>
<td>7.1%</td>
<td>2.2%</td>
</tr>
<tr>
<td>FINDER saves me a lot of time. N=357</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Freq.</td>
<td>5</td>
<td>3</td>
</tr>
<tr>
<td>%</td>
<td>1.4%</td>
<td>0.8%</td>
</tr>
<tr>
<td>I think FINDER is poorly designed. N=364</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Freq.</td>
<td>2</td>
<td>2</td>
</tr>
<tr>
<td>%</td>
<td>20.9%</td>
<td>12.9%</td>
</tr>
<tr>
<td>I have computer tools other than FINDER to help me get information from outside of my jurisdiction. N=370</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Freq.</td>
<td>47</td>
<td>36</td>
</tr>
<tr>
<td>%</td>
<td>6.2%</td>
<td>5.4%</td>
</tr>
<tr>
<td>It is easy for me to give specific examples of how FINDER has helped me do my job. N=346</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Freq.</td>
<td>8</td>
<td>7</td>
</tr>
<tr>
<td>%</td>
<td>2.3%</td>
<td>2.0%</td>
</tr>
<tr>
<td>Question</td>
<td>SD</td>
<td>MD</td>
</tr>
<tr>
<td>----------</td>
<td>----</td>
<td>----</td>
</tr>
<tr>
<td>I could get better results from FINDER if I were provided more training about how to use it. N=361</td>
<td>22</td>
<td>19</td>
</tr>
<tr>
<td>%</td>
<td>6.1%</td>
<td>5.3%</td>
</tr>
<tr>
<td>FINDER would be more useful to me if it had analytical tools. N=349</td>
<td>17</td>
<td>18</td>
</tr>
<tr>
<td>%</td>
<td>3.2%</td>
<td>4.6%</td>
</tr>
<tr>
<td>The best thing about FINDER is I can get information that I was not able to get before. N=359</td>
<td>2</td>
<td>4</td>
</tr>
<tr>
<td>%</td>
<td>0.6%</td>
<td>1.1%</td>
</tr>
<tr>
<td>FINDER is the only computer tool I have to get information from other police agencies. N=369</td>
<td>47</td>
<td>22</td>
</tr>
<tr>
<td>%</td>
<td>12.7%</td>
<td>6.0%</td>
</tr>
</tbody>
</table>

50. Which of the following best represents the workload measure that you use in your job?

<table>
<thead>
<tr>
<th>Frequency</th>
<th>Percent</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of calls</td>
<td>42</td>
</tr>
<tr>
<td>Number of cases</td>
<td>211</td>
</tr>
<tr>
<td>Number of projects</td>
<td>60</td>
</tr>
<tr>
<td>Number of reports</td>
<td>3</td>
</tr>
<tr>
<td>Number of people met</td>
<td>7</td>
</tr>
<tr>
<td>None of the above</td>
<td>76</td>
</tr>
<tr>
<td>Total</td>
<td>399</td>
</tr>
</tbody>
</table>
51. In your current job assignment, do you maintain some measure, statistic, or record of your workload?

<table>
<thead>
<tr>
<th>Frequency</th>
<th>Percent</th>
</tr>
</thead>
<tbody>
<tr>
<td>No</td>
<td>70</td>
</tr>
<tr>
<td>Yes</td>
<td>330</td>
</tr>
<tr>
<td>Total</td>
<td>400</td>
</tr>
</tbody>
</table>

52. On average, how many [calls, cases, projects, meetings] do you handle each month?

<table>
<thead>
<tr>
<th>Frequency</th>
<th>Percent</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fewer than 10</td>
<td>28</td>
</tr>
<tr>
<td>Between 10 and 50</td>
<td>185</td>
</tr>
<tr>
<td>Between 51 and 100</td>
<td>76</td>
</tr>
<tr>
<td>More than 100</td>
<td>41</td>
</tr>
<tr>
<td>Total</td>
<td>330</td>
</tr>
</tbody>
</table>
REFERENCES


*Standard table and graph format and interpretation.* (2004). Retrieved April 6, 2006 from Rutgers, State University of New Jersey, Department of Sociology, Anthropology and Criminal Justice Web site: http://sociology.camden.rutgers.edu/curriculum/format.htm


