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Evaluating Federal Information Technology Program Success Based on Earned Value Management

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This is to certify that the doctoral study by

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has been found to be complete and satisfactory in all respects,
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Abstract

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Doctoral Study Submitted in Partial Fulfillment

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Abstract

Despite the use of earned value management (EVM) techniques to track development progress, federal information (IT) software programs continue to fail by not meeting identified business requirements. The purpose of this logistic regression study was to examine, using IT software data from federal agencies from 2011 to 2014, whether a relationship between schedule variance (SV), cost variance (CV), and actual cost (AC) could predict the success of IT software program, as operationalized by meeting the identified business requirements. The population of interest was 132 IT software programs developed between 2011 and 2014 for federal agencies. The sample source was an archival database located at ITdashboard.gov. The theoretical framework for the study was earned value (EV) project management theory. The EV project management theory is a project performance measurement system that involves integrating cost, schedule, and performance elements for planning and control. EVM contributes to project success by providing early warnings when programs deviate from cost and schedule plans. This study found that only SV was significant (SV days, p = .002). The null hypothesis was rejected, suggesting that a relationship exists between IT program success and the SV, CV, and AC. This study may contribute to social change by increasing the program managers' understanding of EV in federal project management and by decreasing federal spending through successful programs and more cost-efficient use of taxpayers' money.

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Table of Contents

List of Tables

List of Figures

Section 1: Foundation of the Study

Even though U.S. federal agency administrators modified the earned value management (EVM) policy, researchers at the U.S. Government Accountability Office (GAO) revealed that federal information technology (IT) programs' schedule delays and cost overruns worsened between 2000 and 2013 (Cantwell, Mazzuchi, & Sarkani, 2013). The EVM triangle consists of project scope, schedule, and cost (Kwak & Anbari, 2012). The project scope refers to the requirements of a program (Cantwell et al., 2013) and is critical to the concept of employing earned value (EV) (Kwak & Anbari, 2012). Scope management is vital to the efficient management of any program (Farmer, Mazzuchi, & Sarkani, 2014). Because a program's scope affects EVM use, program managers must measure performance from the program's beginning until the program's closeout (Cantwell et al., 2013; Kwak & Anbari, 2012; Plumer, 2010).

EVM is a program management technique with the EV, or the completion of authorized work and budget, as its focus (Plumer, 2010). Program managers use EV to monitor performance and predict the final required costs and time necessary to finish programs (Hunter, Fitzgerald, & Barlow, 2014). U.S. federal agency administrators designed the federal IT Dashboard, ITDashboard.gov, to monitor spending to ensure federal agency administrators appropriately use their budgets (GAO, 2013). The U.S. Office of Management and Budget requires program managers to use EVM for all contracts valued equal to or greater than $20 million (E. Kim, 2000; U.S. Department of Defense [DoD], 2006).

Background of the Problem

U.S. federal agency administrators face difficulties such as cost overruns and schedule delays in IT software programs while managing investments (Cantwell et al., 2013). Agency administrators should plan and manage IT software programs more efficiently (GAO, 2014c). The EV program is a management technique based on EV, or the completion of authorized work and budgets. Program managers use EV to monitor performance and predict the final required costs and time necessary to finish a program (Hanna, 2012).

EV provides an early warning signal to program managers and to customers (Byung-Cheol, 2015; Fleming & Koppelman, 2005). If there is a schedule delay or cost overrun, program managers needed to reduce the program scope and address the risks (Kwak & Anbari, 2012; E. Kim, 2000). Numerous widespread deficiencies exist in using EVM schedule variance (SV) and cost variance (CV) (GAO, 2012). Therefore, federal contractors must learn to use the EVM tool correctly to improve federal IT program success (Kwak & Anbari, 2012).

Problem Statement

Although program managers use EVM, many federal IT software programs fail because the programs were unable to meet business requirements (Hunter et al., 2014; Jørgensen, 2014; Whitney & Daniels, 2013). From 2009 to 2012, the percentage of failed IT software increased from 68% to 84%, as federal contractors were unable to meet programs’ requirements, deadlines, and budgets while using EVM (Altuwaijri & Khorsheed, 2012). The general problem was that federal contractors use EVM without understanding how to monitor project costs and schedules. The specific problem was that federal contractors lack the understanding of the relationship between SV, CV, and actual cost (AC) could predict the success of IT software program.

Purpose Statement

The purpose of this quantitative logistic regression study was to examine the relationship that an understanding of SV, CV, and AC could predict the success of IT software programs in federal agencies completed between 2011 and 2014. The independent variables were SV, CV, and AC. The dependent variable was federal IT program success.

The population included U.S. Department of Defense, U.S. Department of Homeland Security, and the U.S. Department of Veterans Affairs contract data from IT software programs completed between 2011 and 2014. The geographic location of the study was in the United States. The study may contribute to social change by decreasing the federal budget by creating successful software programs (Kumhof & Laxton, 2013; Natvik, 2013).

Nature of the Study

I chose a quantitative method, which involves gathering and analyzing numerical data relating to the hypotheses. The quantitative method is used to examine the relationships between independent and dependent variables, and to predict the likelihood of reaction between two variables (Daigneault, 2014; Venkatesh, Brown, & Bala, 2013; Wisdom, Cavaleri, Onwuegbuzie, & Green, 2012). The quantitative method was appropriate for this study because I wanted to understand the relationship between EVM SV, CV, AC, and federal IT program success in order to understand if EVM helped create successful federal IT programs. The qualitative research method was not appropriate for this study because I studied relationships based on numerical values and I did not need to explore and understand the phenomenon of EVM.

Researchers can use three design options for the quantitative method: (a) correlational, (b) experimental, and (c) quasi-experimental (Leech & Onwuegbuzie, 2009). The correlational design was suitable for examining the relationship between this study's independent variables (EVM SV, CV, and AC) and dependent variable (federal IT program success). The experimental design was not appropriate for this study because I could not study the independent and dependent variables in a laboratory setting. Laboratory studies include clinical, scientific, and assessment studies, which are beyond the scope of this study. The quasi-experimental design was also not appropriate for this study because I did not need to establish a cause-and-effect relationship between the variables.

Research Question

The research question of this study was as follows: What is the relationship of SV, CV, and AC could predict the success of federal IT software programs?

Hypotheses

H_0: SV, CV, and AC have no relationship with federal IT program success for IT software programs completed in the U.S. Department of Defense, U.S. Department of Homeland Security, and U.S. Department of Veterans Affairs between 2011 and 2014.

H_a: SV, CV, and AC have a relationship with federal IT program success for IT software programs completed in the U.S. Department of Defense, U.S. Department of Homeland Security, and U.S. Department of Veterans Affairs between 2011 and 2014.

Theoretical Framework

The theoretical framework for this study was EV project management theory. EV project management theory is a respected tool that program managers use in maintaining projects (Hanna, 2012). The EV project management theory is a project performance measurement system that involves integrating cost and schedule aspects (Cerreta, 2012; Jeyakumar, 2013). The key variables for this study were the independent variables, which were SV, CV, and AC, and the dependent variable, which was federal IT project success.

Completed work packages are the basic building blocks for cost-schedule measurement and performance reporting (Hunter et al., 2014). Analysts at the U.S. Department of Defense developed the EVM system as cost/schedule control system criteria (C/SCSC) to control major projects (Acebes, Pajares, Galán, & López-Paredes, 2014). EV project management was applicable to this study because the EV metrics are suitable for evaluating federal IT program success.

Definition of Terms

Actual cost: AC, as used with EVM, refers to the costs expended and incurred that relate to a project's budgeted costs (Defense Contract Management Agency [DCMA], 2012).

American National Standards Institute/Electronic Industries Association (ANSI-EIA) 748: The document that represents the industry rewrite of the original 35 C/SCSC (Kwak & Anbari, 2012).

Cost performance index (CPI): The relationship between performed physical work and the management's budget for the completed work in relation to the AC or budget spent to complete the work (Hunter et al., 2014).

Cost variance: Represents the difference between the EV and ACs (Hanna, 2012).

Earned value: The summation of the accomplished authorized work and the management's completed work budget (Acebes, Pajares, Galán, & López-Paredes, 2013).

Earned value management (EVM): A program management technique that involves monitoring program performance and predicting final cost and time required to complete the program based on the EV of the program (Hanna, 2012; Hazır, 2015).

EV management metric: Refers to CV percentages, CV, SV percentages, and SV (DCMA, 2012).

Schedule performance index (SPI): A measurement of the efficiency of the baseline schedule, which represents the relationship between the achieved EV and the planned value (Hunter et al., 2014).

To-complete performance index (TCPI): The measure of the forecasted future performance levels required to meet the managerial and financial goals (DCMA, 2012).

Work breakdown structure: A tree diagram that displays deliverables of software, hardware, services, and program-unique tasks (DCMA, 2012).

Assumptions, Limitations, and Delimitations

Assumptions

Assumptions are facts a researcher considers true without verification (Marshall & Rossman, 2011). This study included two assumptions involving the successful implementation of the EVM tool for program management of U.S. federal agency contracts. The first assumption was that the identification and discussions of EVM are transferable and applicable across all U.S. federal agency contracts required to use EVM.

A second assumption was that program managers use EVM to help manage and complete the program on cost and on schedule.

Limitations

Limitations are possible weaknesses of the study (Cunha & Miller, 2014). Cunha and Miller (2014) reported that there are challenges to measuring value added in the domain of higher education, and that there are limitations to using commonly available administrative data as the basis for the measures. The sample set of my study included IT software programs in the U.S. Department of Defense, U.S. Department of Homeland Security, and U.S. Department of Veterans Affairs. This study included programs completed between 2011 and 2014 with expenditures of at least $20 million per year and with contracts administered by the U.S. Department of Defense, U.S. Department of Homeland Security, or the U.S. Department of Veterans Affairs administrations.

Delimitations

Delimitation is an established limit or boundary of a study (Domingos et al., 2014). This study involved examining the relationship between EVM SV, CV, AC, and program success for the U.S. Department of Defense, U.S. Department of Homeland Security, and U.S. Department of Veterans Affairs administrations’ IT software programs completed between 2011 and 2014. Thus, the target for this study was EVM for IT software program contracts. I limited the scope of this study to completed IT software programs with contracts administered by the U.S. Department of Defense, U.S. Department of Homeland Security, and U.S. Department of Veterans Affairs administrations.

Significance of the Study

This study may be valuable to business because the implementation of EVM SVs and CVs can improve IT software program development in U.S. federal agencies and save taxpayer money (E. Kim, 2000). This study may also be valuable to agencies beyond those in my study. EVM is applicable to different types of U.S. federal agency contracts that are equal to or more than $20 million (DoD, 2006).

Contribution of Business Practice

This study may contribute to effective business practices by demonstrating the effectiveness of using EVM to control the outcome of software products (Hunter et al., 2014). By improving EVM SVs and CVs, U.S. federal agency administrators can improve the delivery of U.S. federal agency IT software contracts to be on time and within cost (Kwak & Anbari, 2012; Plumer, 2010). U.S. federal agency program managers can help save taxpayers money by developing successful IT software programs instead of wasting money on failing programs (Savolainen, Ahonen, & Richardson, 2012). The results of my study may contribute to business practice by improving how program managers implement business practices for developing software programs that might, in turn, improve the programs' likelihood for success (Voss, 2012). In addition, the findings of my study might contribute to customers' satisfaction with the final products because program managers could use them to improve business effectiveness and efficiency (Voss, 2012). Indeed, to have a successful program, program managers must complete the IT software program within cost, on schedule, and in accordance with customer requirements (Batselier & Vanhoucke, 2015c; Cantwell et al., 2013; Fu, Li, & Chen, 2012).

This study focused on U.S. federal agency IT software programs that require EVM. Research on software program implementation has revealed that program managers prematurely cancelled 18% of the programs and completed 53% of the IT software programs in federal agencies, which indicated an over-cost and behind-schedule status (Plaza & Turetken, 2009). U.S. federal agency administrators can save taxpayers money by improving business practices employing EVM during the development and execution of IT software programs (Plumer, 2010).

Implications for Social Change

Budget deficits in recent years have increased the federal debt to the point where the debt is greater than economic growth (Kumhof & Laxton, 2013; Lin & Chu, 2013). The federal debt can have serious negative consequences on U.S. society, such as restraining economic growth (Kumhof & Laxton, 2013; Yoon, 2012). After a slow recovery from the recession of 2007 to 2009, the economic growth rate has started to improve (Marri, Crocco, Shuttleworth, Gaudelli, & Grolnick, 2012; Natvik, 2013; Yoon, 2012). The intent of this study was to increase the awareness of how program management tools such as EVM can help create successful programs and reduce costs (Acebes et al., 2013). Program managers should become well versed program management tools, such as EVM, in order to create successful programs to help save taxpayers' money (Murphy & Cormican, 2012).

A Review of the Professional and Academic Literature

The purpose of this quantitative logistic regression study was to examine the relationship of SV, CV, and AC could predict the success of IT software programs in federal agencies completed between 2011 and 2014. In the remainder of this section, I offer a review of the professional and academic literature that I used to inform my study. I gathered 229 peer-reviewed references, 176 of which were published from 2012 to 2015. The 166 peer-reviewed references that I discuss in this review section exceed the requirement for 60 peer-reviewed references published between 2012 and 2015. The references section contains 88% peer-reviewed journal articles published between 2012 and 2015. The remaining 12% includes peer-reviewed journal articles published before 2012, government websites, and contemporary books.

Initial search results included 2,000 articles, dissertations, books, and materials related to EVM, program success, and the quantitative research process. In my Boolean search strings, I included combined subject terms and dates of publication, which narrowed the search results. The search parameters included recent publication dates and scholarly sources to reduce the search results. Further adjustments in the criteria for results resulted in 300 sources directly related to the study. The types of academic material reviewed for the literature review appear in Table 1.

The theoretical framework for this study was EV project management theory, which is a project performance measurement system that integrates cost and schedule aspects. Scope management is vital to the effective management of any program (Acebes et al., 2013). Understanding the scope of a program may be of even greater importance when employing EV; program managers must measure program performance throughout the life of the program, from implementation until program closeout (Fleming & Koppelman, 2005).

Table 1

Synopsis of Sources in the Literature Review

References type	Total	References from 2012 to 2015	References prior to 2012
Research-based peer reviewed journal (Literature review section)	166	161	5
Research-based peer reviewed journal (Section 2)	52	51	1
Contemporary books	7	0	7
Government websites	12	12	0
Dissertations	11	5	6

The independent variables in my study were SV, CV, and AC. The dependent variable was federal IT program success. A federal IT program is successful if the SV and CV percentage is between -5% and 10% (DCMA, 2012). These topics include program management information systems, successful IT software programs, and IT software program management failures.

EVM is an irreplaceable tool for any type of program management (Acebes et al., 2014). EVM has 32 guidelines that provide a developmental approach for monitoring program performance (Hunter et al., 2014). Program managers employ program management information systems during the decision-making process, in which the program managers organize, plan, and control programs (Caniëls & Bakens, 2012; Colin & Vanhoucke, 2015).

History of EVM

U.S. federal agency administrators recognized the problem of poor performance because of cost overruns and underperformance (Hunter et al., 2014). Program managers once referred to EVM as Program Evaluation Review Technique/Cost (PERT/Cost) (Trietsch & Baker, 2012). However, EVM developers changed the name of the principle because they concluded that contractors would not adapt well to the principle because multiple versions of PERT/Cost existed within various procurement programs (Trietsch & Baker, 2012).

In the 1960s, U.S. federal agency administrators started using EVM for financial analysis of specialty programs (Kwak & Anbari, 2012). Researchers started to investigate the influence of EVM regarding program success and found that a relatively strong correlation existed between EVM use and program success. They thus concluded that program managers could scale EVM use to fit programs varying in size and complexity (E. Kim, 2000). In 1967, U.S. federal agency administrators adopted EVM by creating the C/SCSC (Fleming & Koppelman, 2005).

In the 1970s, U.S. federal agency administrators developed a program measurement system called C/SCSC to create a solution for poor performance (Hsu, Shih, Chiang, & Lui, 2012; Kwak & Anbari, 2012). From the 1970s to the early 1980s, subcultures of C/SCSC continued to develop, even though program managers in private industry and U.S. federal agency administrators refused to use C/SCSC (Fleming & Koppelman, 2005).

By 1989, the U.S. federal agencies administrator started to use EVM because it was mandated by the undersecretary of defense for acquisition, which made EVM essential for program management and procurement (E. Kim, 2000). From the late 1980s to the early 1990s, EVM emerged as a program management methodology that managers and executives could use and understand (Mortaji, Bagherpour, & Noori, 2013). In the 1990s, program managers adopted and integrated EVM into programs (Gershon, 2013).

In the mid-1990s, leaders in private industry requested a revision to the system to make EVM easier to use in private industry (Kwak & Anbari, 2012). In 1995, U.S. federal agency administrators reduced the EVM criteria to 32 (De Marco & Narbaev, 2013). Advocates of EVM use in private industry transferred the changes U.S. federal agency administrators made to EVM to private industry by adopting the ANSI EIA 748-A standard (Fleming & Koppelman, 2005). In 1996, leaders at the Project Management Institute published the first edition of the Program Management Body of Knowledge (PMBOK) guide, which includes an overview of EVM, and continued to publish information on EVM in each edition (Fleming & Koppelman, 2005). In the construction industry, program managers became early commercial adopters of EVM (Batselier & Vanhoucke, 2015a; Doloi, Iyer, Rentala, & Sawhney, 2012). In 1998, U.S. federal agency administrators adjusted the requirements to the ANSI/EIA-748-1998, which is the ANSI guideline for EVM (Mortaji et al., 2013).

On large programs, U.S. federal agency administrators require private governmental contractors to use EVM (Plumer, 2010). U.S. federal agency program managers found that EVM improved control features and began to apply EVM to nongovernmental work (De Marco & Narbaev, 2013). The U.S. federal agency administrators and private sector leaders started to use EVM because program managers accepted EVM as a methodology for program management (E. Kim, 2000).

EVM is an important subject in U.S. federal agency administration and the defense industry for many reasons (Cerreta, 2012; GAO, 2012). To improve the federal acquisition regulation, U.S. federal agency administrators added EVM as a requirement for the U.S. Office of Management and Budget (GAO, 2014a, 2014b, 2014e). U.S. federal agency administrators made important modifications to the key program management process policy used since the 1960s in the defense acquisition processes (Fleming & Koppelman, 2005).

The 32 EVM guidelines stimulated the development of approaches for monitoring program performance (Hunter et al., 2014). The guidelines used by the program managers predict the program's final cost and time requirements based on a program's performance record at a given point in time (Kwak & Anbari, 2012). With 20% or more of a new program completed, program managers can predict a program's final cost by using the EVM performance results (Gershon, 2013). Program managers must successfully complete programs on schedule, with high quality, and within budget (Murphy & Cormican, 2012). Program management is risky because federal government may cancel programs before completion or programs may exceed the budget, fail to meet the delivery dates, or perform poorly and lack the expected quality (Shah, 2014; Uzzafer, 2013).

My study focused on information pertaining to program management, U.S. federal agency administrations' requirements for scheduling, and EVM as outlined in the *Defense Acquisition Guidebook* and the Defense Acquisition Instruction 5000.2 (Kwak & Anbari, 2012). Even with the extensive research published on the issue of cost overruns, the root causes of cost overruns and how implementing EVM helps alleviate the issue remains unknown (Meng, 2012). To succeed, program managers must complete programs on time to take advantage of marketing and other windows of opportunity (Jørgensen, 2014). However, public reports of program results are generally not encouraging, and reporters frequently write about failed programs (Savolainen et al., 2012; Young, Young, Jordan, & O'Connor, 2012). Further, the programs are at risk for large cost overruns and delays, and the final product of the programs may lack some of the planned requirements or have unexpected performance failures (Hsu et al., 2012; Wnuk, Gorschek, & Zahda, 2013).

Researchers have documented the history of program management, performance measurement, and program control (Vanhoucke, 2012). U.S. federal agency administrators developed EVM methodology specifically for U.S. Department of Defense programs and expanded the methodology to include extensions, such as earned schedule (Naeni et al., 2014). The developers of EVM made EVM user friendly, but they need to improve it (Ben-David, Gelbard, & Milstein, 2012). The developers created EVM from a cost management tool for monitoring large-scale high-risk systems (Fleming & Koppelman, 2005; Kwak & Anbari, 2012). As a result, the developers of EVM transformed a federal agency contractual requirement into a national standard for program management (De Marco & Narbaev, 2013).

Program Management

As company managers continue to rely on IT to achieve success, companies must have an IT system that can deliver information efficiently (Acebes et al., 2013). Program management must implement IT systems correctly for organizations to gain any value from the IT efforts (Caniëls & Bakens, 2012). Some organizations did not gain significant improvement from using program management because organizational leaders did not train the program management team to implement program management properly (Córdoba & Piki, 2012).

Program managers use program management information systems during the decision-making process when organizing, planning, and controlling programs (Caniëls

& Bakens, 2012; Colin & Vanhoucke, 2015). Program team members are becoming educated in program work as the team better defines program objectives (Córdoba & Piki, 2012). However, programs have not been performing to expected standards (J. Kim, Kang, & Hwang, 2012). Program managers can improve stakeholders' acceptance by using better decision processes, leadership, and management while closely collaborating with stakeholders (Beringer, Jonas, & Kock, 2013).

Program managers must balance three objectives to achieve program success, which are cost, schedule, and performance (Cantwell et al., 2013; Lech, 2013). Program managers use cost, schedule, and performance as program constraints since the three objectives represent the interdisciplinary nature of program management (GAO, 2014a; Hunter et al., 2014; Webb, 2012). In most programs, the program team needs several different areas of specialized technical and managerial knowledge and skills to meet the cost, schedule, and performance objectives (Drury-Grogan, 2014).

Program management information systems. Since 2000, program management information systems have changed drastically (Caniëls & Bakens, 2012; Gannon, 2013). Information system program managers no longer focus on resource management and scheduling (Caniëls & Bakens, 2012). To help program-oriented organizations, leaders at the Program Management Institute formed an organization to enhance the recognition, training, and career development of IT software program managers (Bátiz-Lazo & Krichel, 2012; Gannon, 2013; Kauffman, Techatassanasoontorn, & Wang, 2012).

The critical factors for the pre-acquisition phase of the acquisition cycle include technology, advocacy, readiness level, requirements maturity, schedule detail, life-cycle cost, trade studies, acquisition and contract strategy, risk management, system engineering, and program office personnel tenure and experience (Chennakrishnan & Srinath, 2014; Puus & Mets, 2010; Smartt & Ferreira 2014; Wicht & Crawley, 2012). L. Davis (2014) and Shah (2014) incorporated data from U.S. federal agencies and industry executive interviews. Townsend (2013) and Webb (2012) indicated pre-acquisition activities reduced the risk of schedule growth and cost within organizations. Mishra, Mishra, and Ostrovska (2012) described the main cause for schedule and cost growth and ways to improve program performances.

As a standalone system or component of an embedded system, software is an important acquisition in U.S. federal agencies (Wicht & Crawley, 2012). When using embedded systems, organizational leaders must have more functionality in software than in hardware (Jarke et al., 2011). As a result, the cost of software, including maintenance costs, exceeded the relative cost of hardware (Altuwaijri & Khorsheed, 2012).

Plumer (2010) provided evidence of existing difficulties in managing the development of software systems. In a 1979 report, the GAO administrator found more than 50% of U.S. federal agency contracts for software development had cost overruns, and more than 60% of U.S. federal agency contracts had schedule overruns (Cantwell et al., 2013). Additionally, U.S. federal agency administrators could not use more than 45% of the completed software (GAO, 2014b), did not receive more than 29% of software, and could use less than 2% of the software without additional work (Plumer, 2010).

Organizational leaders must initiate a sustained program management effect throughout the organization’s structure and culture to implement program management successfully (Acebes et al., 2013). Difficulties exist in the management of software system development (Cantwell et al., 2013; Silva et al., 2015). The condition of software development management is in crisis (Silva et al., 2015).

Successful IT software program management. Program managers should focus on having transformational leadership training within the organization during the course of the program (Boonstra, 2013; Verburg, Bosch-Sijtsema, & Vartiainen, 2012). Program managers can use transformational leadership to achieve IT approval while influencing individual IT success and enhancing the system users' perception of the organization support and system efficiency (Verburg et al., 2012). Li, Tan, and Teo (2012a) noted transformational leadership works by enhancing system users' perception of an organization's system and support self-efficiency.

Top management support's top concern is often the program context because the program's context is one of the factors affecting the probability of program success (Boonstra, 2013; De Bakker, Boonstra, & Wortmann, 2012; Young & Poon, 2013). During the span of the program, sponsors provide a critical link between the program and corporate governance while confirming the program fulfills the program requirements (Unger, Kock, Gemünden, & Jonas, 2012). Sheffield and Lemétayer (2013) noted timing, human resources, scope, and risks have the greatest impact on program success.

Researchers in industries and academia started to study the sources of program success because of the development of program management, along with the collapse of program budgets, increased risk of high-cost program failure, and shorter deadlines (Mir & Pinnington, 2014; Ramos & Mota, 2014; Stoica & Brouse, 2014). Scholars have chosen from either process or system approaches while emphasizing either the human characteristics or the construct for achieving success (L. Davis, 2014; Seiler, Lent, Pinkowska, & Pinazza, 2012; Verner, Babar, Cerpa, Hall, & Beecham, 2014). Most organizational leaders use programs to accomplish business objectives, but many still failed to meet the program requirements (Cserháti & Lajos Szabó, 2014; DCMA, 2012; DoD, 2006). To address the gap between the set goal and the results of the program the organizational leaders created to meet the goal, the leaders have formal standards for improving program management (Ancosky, 2013; Shah, 2014; Townsend, 2013). The formal standards produced mixed results in the few studies researchers conducted (Córdoba & Piki, 2012). Unger, Gemünden, and Aubry (2012) found that the level of program manager practice is proportional to program success, even though the program managers in industry do not widely use the program manager practices that improved program success the most. Organizational leaders must give a sustained effort to implement program management throughout the organization’s structure and culture to be successful (Unger et al., 2012a). Researchers have gathered an abundant amount of evidence that indicates the existence of difficulties in management software program development (De Bakker et al., 2012; Mazur, Pisarski, Chang, & Ashkanasy, 2014; Raheem, Olawale, & Olawale, 2012).

IT software program management failures. Academic researchers have not defined software development program failure (Molloy & Stewart, 2013). Savolainen et al. (2012) sampled articles from several different journals and found an overall lack of knowledge on software development suppliers’ perspective on program success. The lack of knowledge impedes the growth of knowledge on program management failures (Altuwaijri & Khorsheed, 2012).

Researchers, organizational leaders, and customers studied successful programs to develop better practices and standards for project management (Sheffield & Lemétayer, 2013). However, program failures are common (Ali, Soomro, & Brohi, 2013; Savolainen et al., 2012). Organizations tend to fail because of decision-making practices and management (Giezen, 2012). Young et al. (2012) noted researchers should study the sets of systematic biases to understand, diagnose, and prevent failures from occurring in future programs. Savolainen et al. (2012) created the framework for identifying elements to influence program outcomes, defining systematic biases that have the potential to disrupt the program, and summarizing the eight most common program failures.

Hwang and Low (2012) observed cost overruns despite differences in program types or location. Program managers contended there was no evidence of improvement of forecasting accuracy since 1941 (De Souza, Da Rocha, & Dos Santos, 2015; Kwak & Anbari, 2012). Program managers attributed the estimated cost escalation of programs at approval and the AC of the program at completion to internal and external factors such as failure to account for risk, error of omission, complexity, optimism bias, schedule changes, scope changes, and scope creep (Flyvbjerg, 2012). Without knowing the root cause of the overrun, the program cost overruns can lead to program termination and disruptions in future programs because of the increased costs of the current programs (Lehtinen, Mäntylä, Vanhanen, Itkonen, & Lassenius, 2014). The program manager must have the ability to predict program costs with higher accuracy to have a realistic financial plan (Y. Wang, Yu, & Chan, 2012). The conventional approach to forecasting the program cost is to use detailed information specifically established for the program to support the cost (Hunter et al., 2014; Jørgensen, Halkjelsvik, & Kitchenham, 2012).

The media has given a considerable amount of attention to large-scale IT program failures since businesses waste billions of dollars each year on developing new IT software programs that end up failing (Savolainen et al., 2012). Requirements and analysis are critical factors in determining software development success (Dargan, Campos-Nanez, Fomin, & Wasek, 2014; Zwikael, Pathak, Singh, & Ahmed, 2014). Program manager must manage the cost, schedule, and performance to have a successful program (Cantwell et al., 2013; J. Kim, Koo, C. Kim, Hong, & Park, 2015). For a successful program, the program manager must monitor the performance, completion cost, and program duration (Byung-Cheol & Seong-Jin, 2015; Y. Wang et al., 2012). Incomplete or changing program requirements due to a lack of customer input or absence of executive support cause program failure (Islam, Mouratidis, Edgar, & Weippl, 2014; Mehta, Hall, & Byrd, 2014).

EV project management theory. There are four dissertations written about EV project management. The title of the first dissertation, written by E. Kim (2000) was *A Study on the Effective Implementation of Earned Value Management Methodology*. In the 1960s, federal government agency administrators applied EVM in their large acquisition programs (Cantwell et al., 2013). Due to increasing global competition and advanced technological developments, many organizational leaders have increased the use of EVM as a way to achieve better control of their projects and better performance (Kwak & Anbari, 2012). To apply EVM to projects in various industries and government agencies, E. Kim addressed the following questions: (a) How might implementing EVM methodology within private and public industry be design and (b) what modifications, if any, did public and private industries make to employ the EVM methodology? The findings from E. Kim’s study were as follows: (a) Current EVM methodology is changing and the existing scholarly literature is not current within the EVM methodology area; (b) an approach to consider is to use four factor groups which are EVM users, EVM methodology, implementation process, and project environment as shown in the model developed during E. Kim's research can improve the acceptance and performance of EVM; (c) no difference in applying EVM in projects of private or public industries or small or large projects.

The title of the second dissertation, written by Makar (2008), was *Assessing Critical Success Factors in Earned Value Management*. EVM has received recognition within the project management community as an effective cost and risk management technique (De Marco & Narbaev, 2013). Individuals within some organizations are not ready to implement EVM due to their lack of project management maturity and organization readiness (Gershon, 2013). Makar aimed to develop an assessment instrument that could accurately measure organizational skills, capabilities, and critical success factors required to implement EVM successfully (Makar, 2008). The research indicated the assessment model was a valid tool in helping organizational leaders determine their EV readiness and identified gaps within their current project management maturity and organizational readiness based on E. Kim's EV implementation model (Makar, 2008).

The title of the third dissertation, written by Plumer (2010), was *The Relationship between Earned Value Management Metrics and Customer Satisfaction*. Information technology projects have a high failure rate (Altuwaijri & Khorsheed, 2012). Federal government contractors complete only 25% of IT projects within budget and on schedule, and 15% of completed project are not operational (Altuwaijri & Khorsheed, 2012). In the quantitative study, Plumer examined levels of satisfaction of IT projects in customers, developed through the use of the EVM System, which is a project management system in widespread use in IT applications since 2006 (Plumer, 2010). The result of Plumer's study did not show any correlation between customer satisfaction and EVM use. Customer satisfaction is one dimension of project success (Kwak & Anbari, 2012). The other three dimensions are meeting schedule and budget goals, commercial success, and preparing for the future (Gershon, 2013; J. Kim et al., 2015).

The title of the fourth dissertation, written by Cerreta (2012), was *Exploring Performance Based Logistics Predictors of Earned Value Management Outcomes: A Quantitative Study*. The purpose of the quantitative correlation study was to examine relationships between performance-based logistics metrics of operational readiness rate, reliability growth rate, and depot mean downtime with the EVM metrics of the SPI and the CPI (Cerreta, 2012). A three-predictor multiple linear regression model using operational readiness rate, reliability growth rate, and depot mean downtime was suitable for examining the relationships with all three predictors as analyzed concurrently with the outcome variables (Starkings, 2012). The results of the research study showed a significant interaction effect existed between schedule and cost performance indices (Cerreta, 2012; J. Kim et al., 2015).

Researchers at the GAO (2012) produced a report titled *NASA: Earned Value Management Implementation across Major Spaceflight Projects Is Uneven*. Some of the findings from the report were as follows: (a) more than half of the projects did not use an EVM system that was fully certified as compliant with the industry EVM standards and (b) only four of the 10 projects had formal surveillance reviews that ensured key data produced by the system were reliable (GAO, 2012). National Aeronautics and Space

Administration (NASA) researchers have a limited ability to conduct a sound analysis of the EVM data and they have not conducted a gap analysis to determine the extent of their workforce needs (Hunter et al., 2014). NASA has experienced cost growth and schedule slippage in its portfolio of major projects and leaders have taken actions to improve in this area, including the implementation of EVM. EVM is a tool developed to help program managers monitor risks (GAO, 2012). Researchers at GAO recommended that NASA analysts establish a time frame for requiring new spaceflight projects to implement its new EVM system, conduct an EVM skills gap analysis, a change management plan for EVM, and strengthen their EVM requirements by requiring projects to include formal EVM surveillance (Hunter et al., 2014).

Researchers at the GAO (2014a) also wrote a report titled, *Department of Defense Business Systems Modernization: Additional Enhancements Are Needed for Army Business System Schedule and Cost Estimated to Fully Meet Best Practices*. Leaders in the U.S. Department of Defense invest billions of dollars annually to develop and implement enterprise resource planning systems, which they consider critical to transforming the department’s business operations and addressing some of their long-standing weaknesses, including those related to financial management and business systems modernization (Cantwell et al., 2013). Army personnel made progress in incorporating schedule best practices, such as capturing and sequencing all activities and integrating activities horizontally and vertically, but GAO researchers identified other deficiencies in schedule and cost best practices (Cantwell et al., 2013).

EVM is a management methodology for integrating scope, schedule, and resources and for measuring project performance and progress (Pajares & López-Paredes, 2011). Although the understanding of the determinants of success, increasing maturity, and a stream of successful programs and projects is increasing, project failures continue at a disturbing rate (Altuwaijri & Khorsheed, 2012). There are noticeable examples of failures in major public programs and projects (Mortaji et al., 2013). Office of Management and Budget administrators reported that of the 840 major IT investments in the U.S. federal IT portfolio in fiscal year 2008, which cost approximately $65 billion, there were 346 major IT investments that cost approximately $27 billion and that were not well planned and managed, which reflected investments on the management watch list as well as those rated unacceptable (Kwak & Anbari, 2012). The leaders of these projects needed to address performance measures, the implementation of EVM, security, or other issues before obligating funding in Fiscal Year 2008 (Kwak & Anbari, 2012).

An exploration of EVM practices at NASA revealed emerging performance measurement trends, needed improvements, and suggested recommendations for applying EVM practice to other government programs and projects (Hunter et al., 2014). The results of the research contributed to the management of future projects and encouraged the project management community to review and advance the application of project management and EVM to government (Cantwell et al., 2013). NASA is a project-driven organization whose staff members apply project management to all their projects and apply EVM effectively to enhance the success of their projects and programs (Hunter et al., 2014). Therefore, NASA receives substantial value from the implementation of EVM, promotes consistent practices across the agency, and provides effective training for all staff members involved in project management processes (Kwak & Anbari, 2012). Increased economic pressure and competition for budgets among federal agencies has resulted in the implementation of new program management requirements in an attempt to limit cost and schedule delays (Hunter et al., 2014).

Half of the major defense acquisition programs are not meeting cost goals, and 80% have increasing unit costs (GAO, 2011b). Between 2008 and 2010, the budgets for 98 major defense acquisition projects increased 9% (GAO, 2011b). In the Fiscal Year 2012 budget request, the U.S. Department of Defense comptroller asked for $85.3 billion of the $553.1 billion budget, or approximately 15.4%, for major defense acquisition projects (Kwak & Anbari, 2012).

Project management has existed since humans began building things (Eweje, Turner, & Müller, 2012). A close connection exists between U.S. Department of Defense projects and formal project management, but not all project management is the same (Eweje et al., 2012). Problems with defense acquisition include poor cost estimates, development delays, changing requirements, and excessive oversight (Cantwell et al., 2013). Many U.S. Department of Defense program managers underestimate cost and schedule because they fail to understand the complexities involved and their efforts to correct an underperforming project are unsuccessful (Cantwell et al., 2013).

The implementation of EVA in the Malaysian construction industry is not widespread (Batselier & Vanhoucke, 2015a; Hunter et al., 2014). The four major project performance monitoring methods used in the Malaysian construction industry are stochastic methods, EVA, fuzzy logic model, and miscellaneous method (Hunter et al., 2014). Compared to stochastic methods and the fuzzy logic model, EVA has notable advantages in accuracy and flexibility (Mortaji et al., 2013). An EVA working flowchart developed by Hunter et al. (2014) led to more detailed project performance and more accurate future performance of the project so that the project management quality and efficiency in the Malaysian construction industry could be brought to a higher level.

The purpose of De Marco and Narbaev’s (2013) research study was to contribute to the distribution of EVM as a practicable methodology to monitor facility construction and renovation projects within the perspective of the European industry. The primary purpose of managing a facility construction project is to complete the project on time and within the budget while conforming to established requirements and specification (Hunter et al., 2014). The practice of EVA in the European construction industry lags behind other experienced countries and industries, although EVM emerged as applicable, adaptable, and predictive of integrated final cost and schedule of facility construction projects (De Marco & Narbaev, 2013). A simple CPI forecasts cost estimate at completion, while the earned schedule concept is an accurate predictor for the time estimate at completion (Fleming & Koppelman, 2005).

In many cases, unsystematic cost and schedule tracking practices, as well as inaccurate data collection, cause projects to experience profit loss (Hanna, 2012). An EVM system allows electrical contractors to monitor construction progress, perform forecasts on the project, uncover problems occurring on site, and respond to problems in projects as early as possible (Hanna, 2012). Early warning signs exist (Acebes et al., 2014; Byung-Cheol, 2015). Using an EVM system can also help detect cost overruns and schedule slippages early in the project, which allows the project team to take corrective action in a timely manner (Hunter et al., 2014).

The implementation of large information systems is a complex and risky exercise that leads to several problems concerning budgets, quality, and time schedules (Acebes et al., 2014). The failure rate of information systems projects is 84% in the public sector (Plumer, 2010). The financial loss due to information systems project failures in the United States is approximately $150 billion annually and is similar in the European Union (Altuwaijri & Khorsheed, 2012). InnoDiff is a new model proposed for the successful implementation of IT projects (Altuwaijri & Khorsheed, 2012). InnoDiff supports establishing a program management office to implement corporate strategy for project management and to transform an organization into a learning organization (Altuwaijri & Khorsheed, 2012). Sharing information is important because organization cannot improve project knowledge without experience from other projects (Kwak & Anbari, 2012).

EVM is one of the most widely used and known methodologies for project control and monitoring (Colin, Martens, Vanhoucke, & Wauters, 2015; Kwak & Anbari, 2012; Willems, & Vanhoucke, 2015). An innovative and simple graphical framework for project control and monitoring could integrate the dimensions of project cost and schedule with risk management, therefore extending the EVM (Acebes et al., 2014; Colin et al., 2015). EVM allows program managers to know whether the project has cost or time overruns, but program managers do not know when deviations from planned values are so important that they should take corrective actions or, in the case of a good performance, when they should detect sources of improvement (Naeni et al., 2014; Salari, Bagherpour, & Kamyabniya, 2014). To implement this framework, program managers need the data provided to EVM traditional analysis and Monte Carlo simulation (Acebes et al., 2014; Acebes, Pereda, Poza, Pajares, & Galán, 2015).

Cost overruns to projects are frequent, regardless of project type and location

(Hanna, 2012). Reliable cost estimates are essential for effective project control and the management of cash flows within a project and at the company level (Acebes et al., 2014; Willems, & Vanhoucke, 2015). During project execution, a Bayesian adaptive forecasting method incorporates into the predictions the actual performance data from EVM and revises pre-project cost estimates, making full use of the available information (Caron, Ruggeri, & Merli, 2013; B. Kim, (2015); Kwak & Anbari, 2012; Mortaji, Noorossana, & Bagherpour, 2015).

EVM is a well-known project management method to measure project performance (Mortaji et al., 2013; Salari, et al., 2014). The EVM serves to monitor and manage scope, schedule, and cost status using an integrated system (Hanna, 2012). Researchers formulated EVM using L-R fuzzy numbers (Mortaji et al., 2013). The model improves applicability of the EVM under uncertain conditions and leads to better planning and taking more appropriate managerial decisions (Mortaji et al., 2013).

The EV method is useful for analyzing and controlling the performance of a project, which allows a more accurate measurement of both the performance and the progress of a project (Gershon, 2013). A new fuzzy-based EV model has the advantage of developing and analyzing the EV indices and the time and cost estimates at completion under uncertainty (Naeni et al., 2014). The model is useful in evaluating the progress of projects where uncertainty is present (Naeni et al., 2014).

Two new metrics combine EVM and project risk management for project controlling and monitoring (Fleming & Koppelman, 2005). The proposed model involves comparing EVM CV and SV with the deviation the project should have under risk analysis expected conditions (De Marco & Narbaev, 2013). The two indexes allow program managers to analyze whether the project overruns are within expected variability or there are structural and systemic changes over the project life cycle (Gershon, 2013). The new monitoring indexes are the cost control index and the schedule control index (Fleming & Koppelman, 2005).

The prediction of project duration has undergone an investigation in EVM using three EV methods: planned value method, earned duration method, and earned schedule method (Batselier & Vanhoucke, 2015b; Elshaer, 2012; Mortaji et al., 2015). Earned schedule method outperforms the other two methods on average and fails in the case of wrong warnings coming from noncritical activities that suffer from delays or are ahead of schedule (Elshaer, 2012). Activity-based sensitivity measures serve as weighted parameters of the activities to improve the schedule performance of a project by removing or decreasing the negative effect of wrong warnings of noncritical activities (Gershon, 2013). The computation results of a simulation study on big benchmark projects reveal that sensitivity information is capable of improving the forecasting accuracy of the earned schedule method (Acebes et al., 2014).

While all the performance indicators planned value, EVM, AC, SV, SPI, CV, CPI, Budget at completion, estimate at completion, and TCPI) can have value to any project, two EVM metrics in particular are critical to project which are TCPI and CPI (Fleming & Koppelman, 2005). Program managers must meet 10 key requirements to implement EVM successfully:

1. EVM requires that program managers must fully understand, define, and scope the project, including 100% of the project efforts.

2. EVM requires that program managers decompose the defined scope, break it down into major management tasks selected as points of management control and planned and scheduled down to the detailed work package level.
3. EVM requires authorization of an integrated and measureable project baseline relating the scope of work directly to an achievable budget and then locking into a specific time frame for performance measurement.
4. EVM requires the accomplishment of only authorized and budgeted work.
5. EVM requires measuring physical performance (the EV) using previously defined schedule metrics.
6. EVM requires that program managers relate the values earned to the planned values to reflect performance against the project baseline.
7. EVM requires the ACs reported to be consistent with the EV measured to allow for an accurate portrayal of cost performance.
8. EVM requires period forecasts (weekly, monthly) to determine how much time and money it took to complete 100% of the project.
9. EVM requires that a full disclosure of actual results to all persons who have an interest in the project.
10. EVM requires that project management, in conjunction with management at all levels, and customer stakeholders decide on the appropriate actions to take to stay within authorized project expectations (Elshaer, 2012; Gershon, 2013; Naeni et al., 2014; Pajares & López-Paredes, 2011).

These 10 requirements are necessary to implement EV on any project successfully (Fleming & Koppelman, 2009).

EV analysis is a method for managing the work during the execution phase of a project (Hunter et al., 2014; Maes, De Haes, & Van Grembergen, 2015). This is a control method used to help the program manager keep the project on track and headed toward project success (Acebes et al., 2014). Three major methods are necessary for major projects: the work breakdown structure, critical path method scheduling, and EV analysis (Elshaer, 2012). EV analysis is not a planning method (Gershon, 2013). This is a method for managing the work during the execution phase of a project (Naeni et al., 2014). Using the method allows the program manager to control the work that takes place during the execution phase (Gershon, 2013; Maes et al., 2015). Most program managers, and most organizational leaders, do not use EV analysis (Kwak & Anbari, 2012).

Federal information technology dashboard. The Obama administration implemented the federal IT Dashboard on June 1, 2009 (GAO, 2013). With the federal IT Dashboard, both federal agency personnel and the public can view and track federal IT investment data online (GAO, 2011c; Linders, 2012; Nam, 2014). The federal IT Dashboard incorporates data gathered from the agencies' Exhibit 53 and Exhibit 300 reports, which include general information on more than 7,000 federal IT investments and detailed information on over 700 major agencies (IT Dashboard, 2014). Agency chief information officers are responsible for maintaining the federal IT Dashboard by evaluating and updating the data with the federal IT Dashboard interface (IT Dashboard, 2014).

The Obama administration developed the federal IT Dashboard to reveal the federal government's performance and expenditures on IT investments (GAO, 2011c). The federal IT Dashboard is a website containing details on federal IT investments so that federal agency personnel, business leaders, the public, and stakeholders can monitor the progress of investments (GAO, 2013). With the federal IT Dashboard, the public can determine the amount of money and time spent, as well as the personnel responsible for the federal government IT programs (Linders, 2012; Nam, 2014). Additionally, the public can access the same data that government employees use to determine the performance of federal IT investments (GAO, 2011b). By making the federal IT Dashboard available to the public, government leaders made the data transparent so that the government could attend to underperforming programs before the programs fail (Plumer, 2010).

The federal IT Dashboard contains agencies' Exhibit 53 and Exhibit 300 report data, information, updated activity, chief information officer evaluations, and other investment information reported by the agencies (IT Dashboard, 2014). The federal IT Dashboard contains data from the 27 federal government agencies and departments' Exhibit 53 and Exhibit 300, which consist of four parts and two parts, respectively (IT Dashboard, 2014). The federal departments are the U.S. Departments of Agriculture, Commerce, Defense, Education, Energy, Health and Human Services, Homeland Security, Housing and Urban Development, Interior, Justice, Labor, State, Transportation, Treasury, and Veteran Affairs (GAO, 2011b). The federal government agencies are U.S. Agency for International Development, U.S. Army Corps of Engineers, Environmental Protection Agency, General Services Administration, NASA, National Archives and Records Administration, National Science Foundation, Nuclear Regulatory Commission, Office of Personnel Management, Small Business Administration, Smithsonian Institution, and Social Security Administration (GAO, 2013). The four parts of Exhibit 53 are Exhibit 53A (Agency IT investment portfolio), Exhibit 53B (Agency IT security portfolio), Exhibit 53C (Agency cloud computing portfolio), and Exhibit 53D (Agency IT reductions and reinvestments) (IT Dashboard, 2014). The two parts of Exhibit 300 are Exhibit 300A (IT capital asset summary) and Exhibit 300B (Performance measurement report) (GAO, 2011c).

Customer Satisfaction

EVM addresses only the quality of work completed (De Marco & Narbaev, 2013). Customers give approval when the program team completes all product requirements and the expected quality (Fleming & Koppelman, 2005). A program manager must use other means to control the technical and quality content of the performed work (Molloy & Stewart, 2013). Thus, suppliers may seem to abide by the EVM guidelines and receive positive results from EVM, even though the program fails to meet the product requirements (Plumer, 2010). With performance-based EV, program managers can integrate the program’s technical performance with the use of examining cost and schedule performance by linking work packages to milestones for meeting the product requirements (Acosta, 2015; Naeni et al., 2014; Townsend, 2013). Program managers can use PBEV to incorporate the outcome of risk management into revised plans and the estimate at completion (Shah, 2014). Although program managers consider EVM a risk-management tool, EVM is not helpful for risk management (Fleming & Koppelman, 2005).

U.S. federal agency administrations’ IT software program success is a concept program managers use to estimate how well the program meets the customer needs (Dorey, Oehmen, & Valerdi, 2012). The perceived quality is the difference between the program quality and the quality defined by customer needs (Jarke et al., 2011). Program managers influence the program quality by influencing the technical and functional quality, which affects the service results and the service delivery, respectively (Giezen, 2012). The customer needs are used to define the quality the customers want from the product (Peled & Dvir, 2012). Thus, program managers use IT management success to determine the program quality (Sheffield & Lemétayer, 2013).

Companies strive to achieve high economic returns by working toward obtaining high levels of customer satisfaction (Plumer, 2010). Program managers can use a variety of customer satisfaction level measuring techniques to monitor service offerings and products (Voss, 2012). By measuring levels of customer satisfaction, organizations can improve communication with other parties to create mutual agreements, recognize demands for process improvement, understand problems that need addressing, evaluate program progress, and monitor and report changes within the program (Colin & Vanhoucke, 2015; Hsu et al., 2012).

In the software development industry, organizational leaders have to emphasize the importance of understanding users' requirements to maximize the levels of customer satisfaction (Da Silva, Da Mota Silveira Neto, O'Leary, De Almeida, & De Lemos Meira, 2014; Plumer, 2010). When considering a new IT software program, organizational leaders must consider the likelihood of success that comes with investing in IT software programs and the expensive installation (Sheffield & Lemétayer, 2013). Additionally, organizational leaders need to have close customer relations when developing innovative products to have quick customer feedback on the product development (Voss, 2012).

Cost/schedule indexes CPI, SPI, TCPI, variances SV and CV. The SPI and CPI measure cost and schedule deviations from the planned baseline, where both indices incorporate the EVM metrics (Acosta, 2015; Fleming & Koppelman, 2005). Program managers' benefit from using a performance measurement system because program managers can use the system to determine the originally scheduled work accomplished (E. Kim, 2000; Townsend, 2013). The CPI is important in determining the resources used on the program and if the program is within budget (Acebes et al., 2014). The TCPI is an index focused on the future of the program by determining the performance level the program team needs to achieve to meet the managerial financial commitment (Fleming & Koppelman, 2005). When using TCPI and CPI, program managers can use the two indices as managerial tools for a single program or portfolio of programs (Naeni et al., 2014).

Program managers must define the scope of the program effort (Elshaer, 2012). Additionally, the program managers have to decompose the scope of the program and separate the major management tasks to use as points for management control (Grzywaczewski & Iqbal, 2012). The program managers must authorize integrated and measurable program baselines related to the scope of work (Aliverdi, Naeni, & Salehipour, 2013; Batselier & Vanhoucke, 2015c). The relationship between the program baseline and scope of work must be within an achievable budget baseline (Shi & Blomquist, 2012). Program managers must make program forecasts periodically to determine the amount of time and money needed for program completion (Flyvbjerg, 2012). Investors and people who have worked on the program must make full disclosure of the actual results (Naeni et al., 2014). Program management from all levels and stakeholders must decide on the appropriate action to take while staying in the authorized program expectation (Fleming & Koppelman, 2005).

Depending on the amount of work accomplished, the work package may have a negative or unfavorable variance, no variance, or a positive or favorable variance (Townsend, 2013). The formula used to calculate SV is *SV = budget cost of work performed (BCWP) – budget cost for work scheduled (BCWS*) (Naeni et al., 2014). Thus, SV depends on budgetary terms (DCMA, 2012). Program managers use SV to indicate whether the contract tasks are on, behind, or ahead of schedule (GAO, 2014a; Townsend, 2013).

To determine contract cost performance, program managers use the AC of work performed (ACWP) (Hanna, 2012). For a work package, program managers use ACWP to determined costs of performing the work (De Marco & Narbaev, 2013). CV is the AC compared with the budgeted cost of work performed (Plumer, 2010). The formula for CV is *CV= BCWP – ACWP* (Kwak & Anbari, 2012). Program managers interpret CV as spending more or less money than budgeted for a specific task (Fleming & Koppelman, 2005). By using TCPI, program managers gain useful information for managing and controlling the program (Fleming & Koppelman, 2005). Program managers can use the methods for TCPI and apply the methods to schedule analysis (Naeni et al., 2014).

Though many performance indicators exist, only two EVM metrics are critical to programs (De Marco & Narbaev, 2013). The CPI and TCPI are crucial to program success (Naeni et al., 2014). If program managers calculate a negative value for CV, the program managers could react by making the necessary adjustments to the program because the CV serves as an early warning detector of problems that surface in any part of the contract (Byung-Cheol, 2015; Chengshuang, Qingpeng, & Yaowu, 2015; Fleming & Koppelman, 2005).

Program Management and Business Outlook

Since the initial conception, program management has become a set of practices, principles, and tools program managers use to gain precise results (Kroeger et al., 2014). Program management must be capable of strengthening the internal relationship between organizational business strategy and programs (Bernroider, Wong, & Lai, 2014). For most programs, the program managers conceive the program within a given business perspective, such as improving the company's market position or increasing company's profits (Sheffield & Lemétayer, 2013). Program managers determine the project's performance based on whether the program was within budget, on time, and of the desired quality (Savolainen et al., 2012).

Information technology software program customers have started to understand the complex issues that challenge IT software programs (Christoph & Konrad, 2014; Ramasesh & Browning, 2014). The IT software industry strongly depends on the performance of IT software program managers (Cantwell et al., 2013). As the importance of IT software program managers increases, more organizations are encouraged to embrace software program management practices and focus on developing personnel (Savolainen et al., 2012). Throughout the programs, organizational leaders need to develop the abilities of managers and team members to increase performance, motivation, and loyalty (Savolainen et al., 2012).

Both contractors and U.S. federal agency administrators have substantial losses from high employee turnover for several reasons: (a) loss of knowledge on the corporate program, (b) steep learning curve and time required for new personnel to adapt to the new environment, and (c) time required to re-establish trust between U.S. federal agency contractors and program managers (L. Davis, 2014). Critical personnel and program managers may be incapable of making optimal decisions because of the high turnover rates that result in higher costs with slower delivery (Nixon, Harrington, & Parker, 2012). Additionally, U.S. federal agency administrators have increasing senior management turnover that contributes to the increased program costs and longer program development periods (L. Davis, 2014).

Similar to other functional strategies in business, program management is a type of management designed for accomplishing set business goals, strategies, and work tasks within a set budget and schedule (Kroeger et al., 2014). Organizational leaders use program management to execute competitive strategies to achieve a given outcome (Yang, Huang, & Hsu, 2014). Because senior program managers change during the development of a program, the new program managers may change the organization's direction (L. Davis, 2014). Employing new program managers led to frequent program reviews because the new program manager may not be familiar with the program (Nixon et al., 2012). Ultimately, frequent program reviews resulted in program delays, which increase the final program cost (Cantwell et al., 2013). Because U.S. federal agency administrators function in a complicated environment, the U.S. federal agency acquisition program is different from most commercial businesses where success and failure relate to profit (K. Davis, 2014; Walker, 2013).

Transition and Summary

Program managers need to involve the final user throughout the development process (Nixon et al., 2012). To improve the success rate of the program, the team that formulated the program must guide program development (Lech, 2013). The program is successful only if both the SV and the CV percentages are between -5% and 10% (DCMA, 2012). The leading companies that have program managers capable of defining and measuring the success of the IT software program are likely to succeed (Lech, 2013).

The EVM is an objective measuring program management tool that program managers can use for measuring program progression (Kwak & Anbari, 2012). The EVM is an integrated tool capable of measuring the cost, scope, and schedule (De Marco & Narbaev, 2013). Studying program quality revealed quality was important for EVM and software program management (Sheffield & Lemétayer, 2013). Researchers can use EV SV and CV to show the success of a completed program (Fleming & Koppelman, 2005). The information and background in Section 1 provided the foundation for investigating the relationship between EVM SV, CV, AC, and federal IT program success within U.S. federal agencies (Shah, 2014). The concepts and theories represented in the literature review section support the need for EVM metrics based on U.S. federal agency IT software program management requirements for producing a successful program (De Marco & Narbaev, 2013).

The EV project management theory was applicable to my study because this study involved using the EV metric to evaluate EVM CV, EV SV, AC, and federal IT project success. The budget of the program relates to the CV measured as both a percentage and a value in the million dollar range (Sato, 2014). The schedule of the program relates to the SV measured as a percentage and in days (Townsend, 2013). The program was successful if both the CV and SV percentage was between -5% and 10% (DCMA, 2012). Thus, the research data relate to the EV project management theory used in this research study. Section 2 includes a description of the program, purpose statement, role of the researcher, participants, research method and design, population and sampling, ethical research, data collection, data analysis technique, reliability and validity, and transition and summary. Section 3 contains an overview of this study, presentation of the findings, applications to professional practice, implications for social change, recommendations for action, recommendations for further study, reflections, and conclusions.

Section 2: The Project

From 2009 to 2012, the percentage of failed IT software programs increased from 68% to 84% because federal contractors were unable to meet the programs’ requirements, deadlines, and budgets while using EVM (Altuwaijri & Khorsheed, 2012). The main reasons for the increasing IT software program failures are cost overruns and schedule delays (Cantwell et al., 2013). To alleviate the cost and schedule problems, U.S. federal agency administrators have enforced the use of EVM in monitoring IT software program contracts valued at $20 million or more (GAO, 2011a). This study involved examining the relationship of SV, CV, and AC could predict federal information software program success. A program is deemed successful if the customer is content with the final IT software program product (Voss, 2012).

Many organizational leaders face the challenge of executing IT software programs in an efficient and timely manner (Plumer, 2010). Programs for U.S. federal agencies are often late and over budget (GAO, 2014a, 2014d, 2014e). As the dependence on information systems increases, organizational leaders face the challenge of the increasing costs of IT software programs (Reich, Gemino, & Sauer, 2012). Information technology program success is a central reason to use EVM for U.S. federal agency IT software programs (E. Kim, 2000).

Purpose Statement

The purpose of this quantitative logistic regression study was to examine the relationship of SV, CV, and AC could predict the success of IT software programs in federal agencies completed between 2011 and 2014. The independent variables were SV, CV, and AC. The dependent variable was federal IT program success.

The population included U.S. Department of Defense, U.S. Department of Homeland Security, and the U.S. Department of Veterans Affairs contract data from IT software programs completed between 2011 and 2014. The geographic location of this study was in the United States. This study may contribute to social change by decreasing federal budget deficits that allowed more federal spending for health care, social security, and welfare, which affect both the social and the economic status citizens in the United States. My intent with this study was to increase the understanding of how program management tools such as EVM can help create successful federal IT programs (Naeni et al., 2014).

Role of the Researcher

My role in the data collection process of this quantitative correlational study was to collect, organize, and interpret the data (Daigneault, 2014; Kratochwill & Levin, 2014; D. Liu et al., 2014). Throughout the collection processs, I worked to ensure that I collected valid and reliable data. Given my work as an EVM specialist in the IT field, I was deeply familiar with, and was able to easily interpret the data that came from the U.S. Department of Defense, U.S. Department of Homeland Security, and U.S. Department of Veterans Affairs.

I adhered to the ethical research practices and the protocols articulated by the Belmont Report which ensure that studies undertaken provide measures for informed consent and protection, privacy, and anonymity of human participants. The Belmont Report summarizes ethical principles and guidelines for research involving human subjects (Brakewood & Poldrack, 2013; Dolan, 2015). Its three core principles are respect for persons, beneficence, and justice (Jones & McCullough, 2015; Mikesell, Bromley, & Khodyakov, 2013), and its three primary areas of application are informed consent, assessment of risks and benefits, and selection of subjects (Dolan, 2015; Jones & McCullough, 2015; Mikesell et al., 2013). Because this study required no participants, the guidelines of The *Belmont Report* did not apply.

Participants

The population I selected for this study was data from the federal IT Dashboard database administered by the federal government. This study included the U.S. Department of Defense, U.S. Department of Homeland Security, and U.S. Department of Veterans Affairs administrations. The population was appropriate for this study because all federal government departments have the same EVM requirements (DoD, 2006). There were no human participants. My quantitative research involved gathering and analyzing numerical data relating to the hypotheses (Daigneault, 2014; Venkatesh et al., 2013; Wisdom et al., 2012). My purposeful sampling method was suitable based on the expected availability of program data, described by Tongco (2007) as the nonprobability of convenience sampling.

My purposeful sampling emphasized quality assurance by choosing a sample based on set criteria (Tongco, 2007). The set criteria included all programs from the U.S. Department of Defense, U.S. Department of Homeland Security, and U.S. Department of Veterans Affairs completed between 2011 and 2014. Purposeful sampling is necessary for quantitative research studies like this because the criteria in purposeful sampling help to produce a desired representative sample (Byung-Cheol & Seong-Jin, 2015; Huang & Yang, 2010). In purposeful sampling, the samples have similar characteristics to the populations except for the number of programs (Huang & Yang, 2010). The program criteria for selection were that the program must have an AC of at least $20 million, belong to the U.S. Department of Defense, U.S. Department of Homeland Security, or U.S. Department of Veterans Affairs, and completed between 2011 and 2014.

Research Method and Design

The three methodology choices for social scientific research are qualitative, quantitative, and mixed methods (Leech & Onwuegbuzie, 2009). A researcher chooses a methodology for a study based upon its appropriateness for a specific research problem, purpose, and context (Wisdom et al., 2012). I determined that the quantitative methodology was suitable for this study based on its problem statement, purpose statement, and research question.

Method

Quantitative methodology was appropriate for this study because my research was on the relationship between independent and dependent variables. In addition, the quantitative method was well-suited to determine whether to accept or reject the hypotheses established for the test (Venkatesh et al., 2013). Hypothesis testing is a method for testing a claim or hypothesis about a variable in a population using data measured in a sample (Field, 2009; Smartt & Ferreira, 2014). Because the quantitative method is appropriate for studies on the relationship between independent and dependent variables (Venkatesh et al., 2013), the quantitative method was appropriate for this study because this study was on the relationship between EVM SV, CV, AC, and federal IT program success.

The qualitative methodology was not appropriate for this study because it involves researchers asking broad questions to collect descriptive information from participants using open-ended questionnaires and interviews (Marshall & Rossman, 2011). Using the collected information, qualitative researchers determine findings and conclusions based on patterns and traits exclusive to the participants (Daigneault, 2014). Thus, the qualitative research method did not align with my study because I was not looking for patterns and common themes specific to the participants.

The mixed methods methodology was also not appropriate for this study. The mixed methods methodology involves aspects from both the qualitative and the quantitative research methods (Marshall & Rossman, 2011). With the mixed methods methodology, researchers use both primary and secondary data (Leech & Onwuegbuzie, 2009). The mixed methods methodology involves research triangulation consisting of the collection and analysis of both qualitative and quantitative research methods (Marshall & Rossman, 2011). Mixed methods methodology was not appropriate for this study because my research problem involved determining the quantitative relationship between EVM SV, CV, AC, and federal IT program success for successful IT programs. The study thus did not require a qualitative aspect.

Nwagbogwu (2011), Shah (2014), and Townsend (2013) have performed quantitative studies similar to my own. Nwagbogwu evaluated the correlation between program management effectiveness and program success, Shah examined the perceived value of integration of EV management with a risk-management-based performance measurement baseline, and Townsend evaluated the schedule performance approach for level of effort tasks. In their quantitative methodologies, each researcher (a) developed hypotheses to test the theory, and (b) deployed computer-aided statistical analysis for data analysis (Nwagbogwu, 2011; Shah, 2014; Townsend, 2013). I chose the quantitative method because the Nwagbogwu, Shah, and Townsend studies were closely aligned with my own.

Research Design

Three quantitative design options are available for the quantitative methodology: correlative, experimental, and quasi-experimental (Leech & Onwuegbuzie, 2009). For this study, I used the quantitative correlational design because examining the relationship between EVM SV, CV, AC, and federal IT program success aligns with the correlational design. A correlational design was appropriate for this study on determining the extent of a relationship between four variables (EVM SV, CV, AC, and federal IT program success) using statistical data (Colin & Vanhoucke, 2014; Wisdom et al., 2012). Researchers using the correlational design seek and interpret relationships between and among a number of facts (Wisdom et al., 2012). The results from this relationship study should show if EVM SV, CV, and AC could predict federal IT program success.

The quasi-experimental design was not applicable because I was not creating a cause-and-effect relationship between variables. Instead of controlling the independent variable, quasi-experimental researchers measure the influence of the independent variables in relation to the dependent variable.

The experimental design was not applicable because the focus of the correlational study was on independent and dependent variables that are not suitable for an experimental laboratory setting. The experimental design was the true experimentation design because its basis was using the scientific method for establishing cause-and-effect relationships between groups of variables in a study (Callao, 2014; Roosta, Ghaedi, & Mohammadi, 2014; Yaripour, Shariatinia, Sahebdelfar, & Irandoukht, 2015). Because the experimental design includes the scientific method, an association often exists between the experimental design and laboratory studies (Barka et al., 2014; Dezhi & Shuang, 2014). Laboratory studies include clinical, scientific, and assessment studies, which are beyond the scope of the study (Mallick, 2013).

Cerreta (2012), Mafiana (2013), and Plumer (2010) all used correlational design. Cerreta's study was about exploring performance-based logistics predictors of EVM outcomes, Mafiana examined the relationships between internal control effectiveness and financial performance in the Nigerian banking industry, and Plumer examined the relationship between EVM metrics and customer satisfaction. All three researchers used the correlational design in their studies, and Cerreta and Plumer studied the relationship between variables with surveys using a Likert-type scale, while Mafiana used secondary data. The correlational design for the study was similar to that used in Cerreta, Mafiana, and Plumer's studies, as I examined the relationship between EVM SV, CV, AC, and federal IT program success.

Ethical Research

Walden University's Institutional Review Board (IRB) must approve the study before any data collection starts. The IRB ensured the study has met such criteria as the applicable law and institutional regulations and standards for professional conduct and practice (Check, Weinfurt, Dombeck, Kramer, & Flynn, 2013; Klitzman, 2013; Lee et al., 2013). Data collection did not take place until after receiving approval from the IRB. Walden University's IRB approval number was 06-02-15-0149856 dated June 2, 2015.

The quantitative logistic regression study does not involve collecting data from human participants. Therefore, my study did not require consent forms and confidentially agreements from participants who are over 18 years of age. In addition, I downloaded the data required for this study from the federal IT Dashboard website, which is a public website that Congress uses to create the budget (GAO, 2011c; Linders, 2012; Nam, 2014). I retained the data collected in hard copy and electronic formats and store the data for the required period of 5 years, which complies with Walden University guidelines. Data collection took place after received approval from the IRB. No work started until the IRB approved this study. For 5 years after the completion of this study, I will retain all study-related documentation in a safe that only I can open. After the 5-year period, I will destroy all documentation from this study.

Without recording the program names, I gathered and organized the data in the following columns: AC, CV, SV, and federal IT program success. These data remained on a compact disk and stored in a safe. The data will remain inaccessible and then destroyed once five years passed. The data collected in this study was confidential. The codes used for the programs were the numbers 1 to 155 (Check et al., 2013; Klitzman, 2013; Lee et al., 2013).

Instrumentation

I downloaded the data from the IT Dashboard database located at ITDashboard.gov. database into a Microsoft Excel spreadsheet. There was a lot of data for each program, and I prefer to use column input. In column input, the data for each variable always occur in a fixed range of columns, and delimiters are unnecessary. I used an identification number for each program, which was the same number recorded on the medium from which the data were originally collected. If during the screening of the data

I find numbers that are inaccurate, I can then go back to the original data to double check those numbers. I used SPSS Version 21 to analyze the data.

The independent variables (SV, CV, and AC) consisted of archival data from federal government. The federal IT Dashboard website is the official database where all contractors send their Exhibit 53 and Exhibit 300 data on a yearly basis. I used one group of data containing programs with a value of at least $20 million completed between 2011 and 2014.

The data set for this study consisted of archival data collected from ITDashboard.gov. The federal government published the IT federal website in 2009 (GAO, 2011b). On the website, agency administrators provide contract information for awarded contracts and pre-awarded, post-solicitation (IT Dashboard, 2014). Agencies are not required to provide future planned contracts, subcontract awards, and closed contracts (IT Dashboard, 2014). Future contract information is procurement sensitive (IT Dashboard, 2014). I broke down the data collected and classify them as either independent or dependent variables. The independent variables include SV, CV, and AC. The dependent variable was federal IT program success. Data for SV and CV came from the federal IT Dashboard website. The dependent variable was program success, which describes the degree in which the completed IT software program satisfied the customer's requirements. Completed IT software programs that satisfy customer's requirement have both CV and SV percentage between -5% and 10% (Plumer, 2010; DCMA, 2012). All data were numerical. SV, CV, AC, and federal IT program success are all ordinal values.

The available data satisfied the requirements of the quantitative correlation study. The concepts measured were the SV, CV, AC, and federal IT program success for IT software contracts administrated by the U.S. Department of Defense, U.S. Department of Homeland Security, and U.S. Department of Veterans Affairs administrators and completed between 2011 and 2014. All the raw data used in this study appeared in table format, located in Appendix A. As previously noted, this quantitative study involved measuring four variables.

The value of CV is *CV (dollars) = planned total costs – projected or actual total cost* (Mortaji et al., 2013). The value of SV is *SV in days = planned completion date – planned start date* (Kwak & Anbari, 2012). Finally, federal IT success was when both CV and SV percentages are between -5% and 10%; then the program was successful (DCMA, 2012; Fleming & Koppelman, 2005).

Program managers must continuously monitor the EV performance to determine cost and schedule exceptions to the baseline plan (Shah, 2014). For programs using EV, the program managers need to monitor the cost and schedule results against the authorized baseline for the duration of the program (Byung-Cheol & Seong-Jin, 2015; De Marco & Narbaev, 2013). Management focused on exceptions to the baseline plan with particular focus on negative values, which represents the program going over the set values (Hunter et al., 2014).

Plumer (2010) used the federal IT Dashboard for his study that included all 28 agencies nationwide. He used the performance metrics CV and SV in his study on customer satisfaction (Plumer, 2010). The reliability and validity properties of this instrument is the federal government administrators controlled the website and data involved (GAO, 2011b). The instrument has a certain degree of reliability when applied to certain populations under certain conditions, which are IT software programs valued at

$20 million or more for the U.S. Department of Defense, U.S. Department of Homeland Security, and U.S. Department of Veterans Affairs completed between 2011 and 2014 (DoD, 2006). The validity of an instrument succeeds in describing what the designer of the instrument designed it to measure, and this instrument measured SV, CV, AC, and federal IT program success (Linders, 2012; Nam, 2014; Whitmore, 2012). The validity test for the independent variable was checked against possible data ranges for each variable. I removed outlier data from the sample. Content validity measures the validity of the data collection tool, which in this instrument is the performance of federal IT programs using EVM SV, CV, and AC (Huijg, Gebhardt, Crone, Dusseldorp, & Presseau, 2014; Kehoe, 2012; Ployhart, 2012). There were no needed adjustments for the instrument. I used the instrument as is. Appendix A contained a list of raw data for my research study.

The independent variables (SV, AC, and AC) required for this study was from the federal IT Dashboard located at ITDashboard.gov for the IT software contracts that fit the criteria of this study and downloaded to an Excel spreadsheet. Organizational leaders may undertake programs to develop, enhance, modernize, or maintain an IT asset (Meng, 2012). Agency personnel should update program activity progression and operational performance when measuring the performance metrics at least every month (De Marco & Narbaev, 2013; IT Dashboard, 2014). To protect programs' privacy, I concealed the identity of the IT software programs. IT Dashboard data would be the original data reported from the U.S. federal agencies. This study did not require a pilot study because Plumer (2010) used the instrument successfully.

Data Analysis Technique

I downloaded the data from the federal IT Dashboard database into a Microsoft Excel file. Then the Excel file was converted into an SPSS import file (Green & Salkind, 2011). SPSS is a statistical package produced by IBM (Green & Salkind, 2011) and designed to perform a wide range of statistical procedures (Starkings, 2012).

Mean and standard deviation are the basis of descriptive statistics and are valid for normally distributed or normal data (Green & Salkind, 2011). Researchers use these data in tests called parametric statistics (Field, 2009). If the data are ordered or non-normal, the mean and standard deviation of the raw data may not provide accurate information about the central tendency and variability (Starkings, 2012), and the preference would be to use median and a nonparametric test (Morgan, Leech, Gloeckner, & Barrett, 2011).

The two general methods used for exploratory data analysis are generating plots of the data and generating numbers from the data (Field, 2009). Both are important and can be useful methods of investigating the data (Field, 2009). Descriptive statistics (including the minimum, maximum, mean, and standard deviation), frequency distribution tables, boxplot, histograms, and scatterplot are a few techniques used in exploratory data analysis (Starkings, 2012).

Logistic regression is a statistical method used to test models for the ability to predict categorical outcomes of dependent variables (Cerreta, 2012; Narbaev & De Marco, 2014). For the dependent variable, I used federal IT program success, which was a categorical variable where the variable can be successful or unsuccessful. There is a family of logistic regression techniques available in SPSS that allowed me to explore the predictive ability of sets of blocks of variables and specify the entry of variables (D. Liu, Li, & Liang, 2014). I used a forced entry method, which is the default procedure available in SPSS (Morgan et al., 2011). In this approach, researchers test all predictor variables in one block to assess the predictive ability of the variables, which controls the effects of other predictors in the model (Field, 2009).

I did not used multiple regressions because the dependent variable was categorical, which is not allowed for multiple regression (Mills, Moreira, & Vilela, 2014). For multiple regressions, the dependent variable needs to be a continuous variable with scores normally distributed (Morgan et al., 2011; Narbaev & De Marco, 2014). Additionally, I did not used simple linear regression because this requires interval or ratio-scaled variables (Starkings, 2012). This research study included ordinal variables, which are categorical or continuous. If any of the data fields are missing, I removed the program from this research study. I checked the original data file for accuracy.

Logistic regression is a statistical technique that researchers can use for assessing the ability of predictor variables in explaining and predicting the category of the dependent variable (T. Wang et al., 2013). Thus, researchers can use logistic regression to develop a model with the predictor variables and assess the goodness of fit of the model (D. Liu et al., 2014). The goodness of fit of is an indicator of the relative importance and the interactions of the predictor variables in respect to the dependent variable (Namdari et al., 2014). Additionally, the goodness of fit summarizes the ability of the model in classifying cases based on the mode, which allows the user to calculate the sensitivity and specificity of the model and the predictive values (Quinn, Hosmer, & Blizzard, 2015).

I developed and analyze a logistic model based on the independent and dependent variables in SPSS Version 21. Prior to developing the model, I checked the data for outliers. Additionally, I removed categories within my data if there was not enough samples to build the model. Afterwards, I utilized SPSS to build the logistic model. SPSS coded the dependent variable as either 0 or 1 (Mazzocco & Hussain, 2012). Furthermore, SPSS coded the categorical predictor variables (T. Wang et al., 2013).

After developing the logistic model, I ran several tests to validate that the model best fits the data. I tested the goodness of fit with the Hosmer and Lemeshow test, which indicated the usefulness of the model respectively (Reed & Wu, 2013). I used a p-value of 0.05 where the values greater than the p-value are considered significant. Additionally, I used the Cox and Shell *R* square and Nagelkerke *R* square values since the values are an indication of the variance of how well the model explains the dependent value (Nooraee et al., 2014). I used the Wald test to test the contribution of the variables towards the output value with a p-value of 0.5, where values less than the p-value are considered significant (Quinn et al., 2015).

Once I have tested the model, I characterized the model. I used the *B*-value to determine the probability of a case falling into either of the dependent variable categories. Additionally, I found odd ratio or the chance in odds of being in one of the categories of the independent variable when the predictor value was increased by one. I found the odds ratio through the use of the 95% confidence interval to best guess the true value off the odds ratio. If the 95% confidence interval contains the value 1, I considered the result as statistically significant at the p-value of 0.05.

Validity

To confirm a study is reproducible and the results are generalizable to the population, quantitative researchers must focus on the study's reliability and validity (Wahyuni, 2012). Before considering a study valid for a larger population, the study must be reliable (Chinsongkram et al., 2014). For quantitative research, reliability is the instrument or tool's degree of consistency in collecting and analyzing data regardless of the user (Chinsongkram et al., 2014). Validity is the credibility of the data in regard to the study and the transferability of the results to a larger or different population (Wahyuni, 2012).

I took care to ensure data collected are accurate. Analysis of the data took place with every effort to eliminate researcher bias. I analyzed the data without favoring the statistical outcome for or against the use of EVM on IT software programs.

Internal and external validity are important for all researchers. Qualitative researchers focus on having strong internal validity in the research, while quantitative researchers focus on having a higher degree of external validity (Davis-Becker & Buckendahl, 2013). Internal validity emphasizes the explanation and verification of conclusions made about the causal relationship between variables (Chinsongkram et al., 2014). For qualitative research and experimental studies, high levels of internal validity are necessary because researchers may cause interference from their involvement with the study (Davis-Becker & Buckendahl, 2013). This study was a quantitative, non-experimental, correlational design study, and I have no intent to conclude a cause-and-effect relationship exists between EVM SV, CV, and federal IT program success.

External validity indicates the ability to apply the results from a sample to a larger population and the ability for other researchers to reproduce the results in a different setting (Wahyuni, 2012). Quantitative researchers have to document the data collection, coding, and analysis procedure meticulously to make the study reproducible (Kratochwill & Levin, 2014). U.S. federal agency administrators apply and regulate the EVM corporate business model in the same manner for every U.S. agency (DoD, 2006). Because the application method of EVM is the same within U.S. federal agencies, the similarities between agencies increase the probability the results can be generalizable to the total population, which increases the external validity of the study.

The validity of the study establishes the integrity of my findings and conclusion. The study may become invalid many ways, such as from measurement errors, unreliable instruments, flawed analysis, and researcher bias (Chinsongkram et al., 2014). Using SPSS did not compromised the data because SPSS is one of the most powerful statistical analysis software programs available (Raya et al., 2013). By following the described methods, precautions, and procedures, I was able to collect and analyze the data without influencing the data with personal interpretations.

External validity indicates how well a researcher can generalize theories and data to a larger population (Daigneault, 2014; Davis-Becker & Buckendahl, 2013; Saunders et al., 2013), which in this study referred to the extent to which the researcher can generalize the results to other federal agencies (Fernandez-Hermida, Calafat, Becoña, Tsertsvadze, & Foxcroft, 2012). EVM is a requirement for all contracts valued at $20 million and over (DoD, 2006). The application of EVM is the same throughout all federal agencies (DoD, 2006). Therefore, this research study results were valid for all federal agencies (Saunders et al., 2013).

Transition and Summary

Section 2 contained the purpose for this study, which was to find the relationship between EVM SV, CV, AC, and program success. Increased global competition combined with rapid technological advancements make the successful performance on federal IT software programs a high priority (E. Kim, 2000). This study involved investigating whether an association exists between the implementation of EVM and the benefits to IT software programs in terms of improvement to program outcomes. The relationship between SV, CV, AC, and federal IT program success based on EVM contract performance reports underwent an examination in programs whose leaders use EVM.

If an association exists between high program success and EVM, the results of this study could encourage program managers to implement EVM on future programs. The conclusion of this research study may help IT software program managers could better manage IT software programs using EVM SV and CV. When IT software program managers do a better job, they may be able to save taxpayers money and help the economy.

Section 3: Application to Professional Practice and Implications for Change

Introduction

The purpose of this quantitative logistic regression study was to examine the relationship of SV, CV, and AC could predict the success of IT software programs that federal agencies completed between 2011 and 2014. Based on the findings of the statistical analysis, I rejected the null hypothesis. The results of the analysis were statistically significant and indicated the existence of a relationship between IT program success and SV, CV, and AC. Thus, I accepted the alternative hypothesis that SV, CV, and AC have a relationship with federal IT program success for IT software programs completed in the U.S. Department of Defense, U.S. Department of Homeland Security, and U.S. Department of Veterans Affairs between 2011 and 2014.

Presentation of the Findings

This study included logistic regression, which involved considering the number of cases in the data set and the number of predictor or independent variables. Logistic regression can fail to converge if researchers use a large number of predictors with a small data set (Morgan et al., 2011). Categorical predictors require more data to account for the increase in predictors (Elliott & Woodward, 2007). The independent variables in this study were SV, CV, and AC. The dependent variable was federal IT program success.

To test the predictability of the logistic model, my analysis included the Hosmer-Lemeshow test. The Hosmer-Lemeshow test indicates the goodness of fit by testing the capability of the model to predict the dependent variable (Fox, 1991). The basis of the Hosmer-Lemeshow statistic was the observed values, expected values, observation, predicted risk, and number of observations equated to a chi-square value (Quinn et al., 2015). I converted the chi-square value to a probability based on the degrees of freedom. The purpose of the test was to determine how well the independent variables predicted the dependent variable. The results of the Hosmer-Lemeshow test related to the hypothesis of this study because they reflected the predictability of the model.

I used the Wald test to test the relationship of the predictor variables in determining the dependent variable involved. The Wald test indicates the significance of each predictor variable in the predictability of a model, and the basis of the Wald statistic is the estimated values of the predicted variables (Chen & Wang, 2013). The purpose of the test is to determine whether the predictor variable affects the predictability of the model. The Wald test was useful for testing the hypotheses of this study because it indicated the impact of the independent variables on the model.

In addition to conducting the statistical tests, I employed descriptive statistics to understand the independent and dependent variables, and I analyzed the variables based on the mean, standard deviation, maximum, minimum, range, frequency, number of cases, and outliers. The mean is the average or the expected value of the variable (Green & Salkind, 2011). The standard deviation is the determination of the variance or the distribution of the variable (Field, 2009). The maximum is the largest value of the variable, while the minimum is the smallest value of the variable (Morgan et al., 2011). The range is the spread of the variable. The frequency is how often the value occurs (Field, 2009). The number of cases is the total number of data points for each variable (Green & Salkind, 2011). My study's data set contained no missing data points, so the valid percent was the same as the percent displayed in Table 2. The valid percent and the percent columns are the same because the data sets contained no missing data, as displayed in Table 3. The research question was as follows: What was the relationship of SV, CV, and AC could predict federal IT success? An explanation of the data used in the research question appears below.

Prior to conducting my main study, I ran a preliminary data analysis to identify and remove outliers or cases not well explained by the model, as identified by the box plots for each variable. From the initial set of data, only 132 of the cases remained because I removed the extreme outliers to keep a large sample size in order to run logistic regression. The resulting box plots for each variable after removing the extreme outliers appear in Figure 1. I produced box plots for SV, CV, and AC, respectively. The horizontal line in the middle of the box plot represents the mean, while the lower and upper regions of the box represent the first and third quartiles. The first quartile is the middle number between the minimum and the mean, and the third quartile is the middle number between the mean and the maximum. The whiskers represent the interquartile range or the dispersion of the data. The starred data points are the outliers that fall outside the interquartile range. Outliers are present with each variable. I kept the remaining outliers because the distribution for each variable appears skewed because the mean does not appear centered in the box plots. The sampled cases had a skewed distribution because the sample size may not have been large enough to describe the population fully.

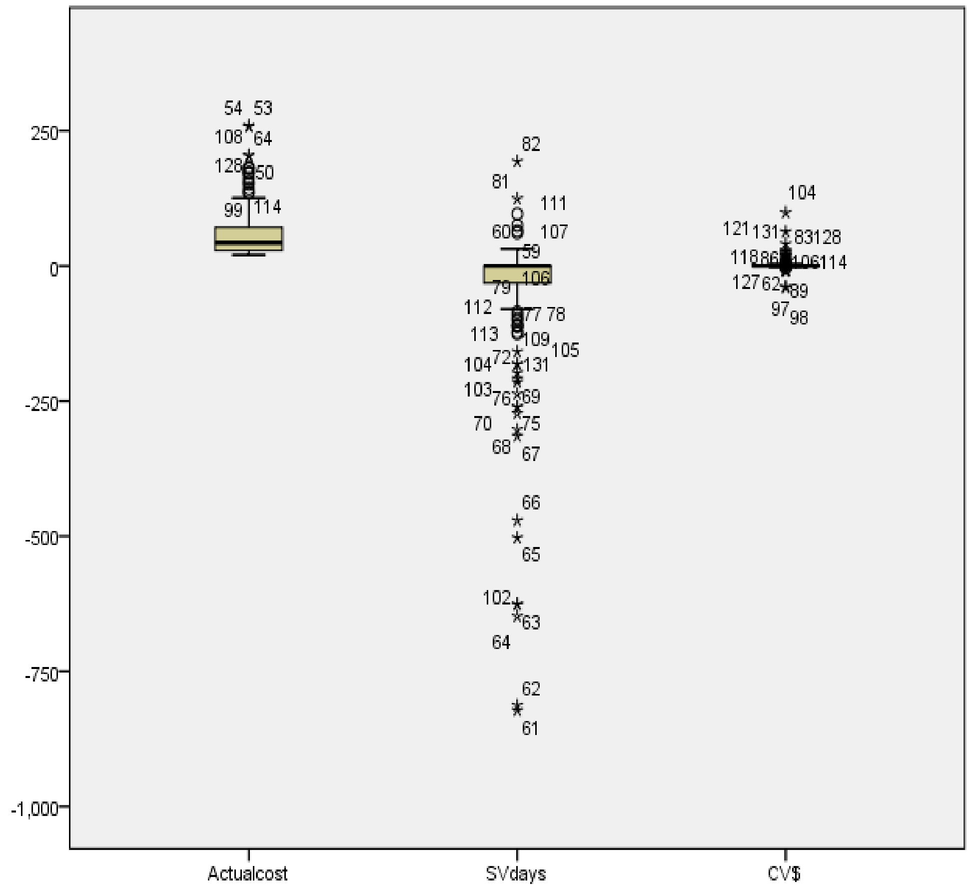

Figure 1. Boxplot of AC, SV in days (SV days), and CV dollars (CV$). Stars represent the outliers.

I also ran descriptive analysis on the remaining 132 cases. The descriptive statistics of the dependent variable are in Table 2. The dependent variable was a categorical variable. Thus, I coded the outcome of the federal IT programs as either 0 for failure or 1 for success. In the data set, 72 programs were failures and 60 programs were successes. Therefore, 54.5% of the data set contained failed programs and 45.5% of the data set contained successful programs. The cumulative percent is the running summation of the percentages for the categories.

Table 2

Performance

Valid	Frequency	%	Valid %	Cumulative %
Failure (0)	72	54.5	54.5	54.5
Success (1)	60	45.5	45.5	100.0

The descriptive analysis for agencies contained within the data set appears in Table 3. The agency code was the codes that database managers assigned to the agencies. The agency codes were 7, 24, and 29 for the U.S. Department of Defense, U.S. Department of Homeland Security, and U.S. Department of Veterans Affairs, respectively. The data set consisted of 34 programs from the U.S. Department of Defense, 53 programs from the U.S. Department of Homeland Security, and 45 programs from the U.S. Department of Veterans Affairs. Thus, 25.8% of the programs were U.S. Department of Defense programs, 40.2% of the programs were U.S. Department of Homeland Security programs, and 34.1% of the programs were U.S. Department of Veterans Affairs programs. The cumulative percentages are the running summation of the percentages.

Table 3

Agency

Agency code	Frequency	%	Valid %	Cumulative %
7	34	25.8	25.8	25.8
24	53	40.2	40.2	65.9
29	45	34.1	34.1	100.0

The descriptive statistics for the independent variables are in Table 4. The independent variables were SV in days, CV in dollars and AC. The column *N* represents the number of data points for each variable. For each variable, *N* equaled the total number of cases because the data set contained no missing data. The range for AC, SV, CV was $239, 1,015 days, and $139.02, respectively. The maximum and minimum for the AC were $20 and $259. The mean was $62.60, and the standard deviation was $50.992. The maximum and minimum for the SV were -822 days and 193 days. The mean was -60.25, days and the standard deviation was 161.496 days. The maximum and minimum for the CV was -$40.73 and $98.29. The mean was $2.5692 and the standard deviation was $13.14521. SV and CV have negative values because program managers may complete the programs before the expected completion date and with less than the assigned budget, respectively.

Table 4

Descriptive Statistics

Variables	*N*	Range	Minimum	Maximum	Mean	*SD*
AC	132	$239	$20	$259	$62.60	$50.992
SV in days	132	1015	-822	193	-60.25	161.496
CV in dollars	132	139.02	-40.73	98.29	2.5692	13.14521

Descriptive statistics were important for logistic regression. The number of cases in the subgroups of the sample was important because the analyses were sensitive to differences in sample sizes between subgroups (Starkings, 2012). If group sizes vary, a researcher may be unable to use some of the analysis techniques (Morgan et al., 2011).

Logistic regression involved evaluating the statistical assumptions made for using logistics regression. My assumptions were that the sample size adequately represented the population, and that the sample could represent the relationship between the independent and the dependent variables (Field, 2009). Researchers with a small sample and many predictors may have issues analyzing data because the logistic regression solution may fail to converge (Morgan et al., 2011). The issue arises when categorical predictors contain a limited number of cases in each category (Elliott & Woodward, 2007). To avoid analyzing data on a limited number of cases, I ran the descriptive statistics on each predictor and considered deleting categories based on the number of cases. I did not adjust the categories because the difference in the number of program failures and successes was not significant.

This study included no assumptions concerning the distribution of scores for the predictor variables. However, logistic regression is sensitive to multicollinearity or high correlations among predictor variables (Field, 2009). High intercorrelations among independent variables can result in false positives in hypothesis testing. Thus, I checked the independent variables for high intercorrelations before assuming that no correlations existed between the independent variables. To check for collinearity, I used the multiple regression procedures to request collinearity diagnostics. From the collinearity diagnostics, I focused on the coefficient table and the columns labeled under collinearity statistics and ignored the other outputs. The coefficient table from the collinearity diagnostics appears in Table 5. In the table, the tolerance values less than 0.1 indicate that the variables have high correlations with other variables in the model (Field, 2009). The variance inflation factor (VIF) is a quantification of the degree of multicollinearity between the predictor variables, and values greater than 10 indicate multicollinearity (Fox, 1991). Tolerance value for AC, SV, and CV are 0.987, 0.993, and 0.990, respectively. No tolerance values were below 0.1. Therefore, no high correlations between the independent variables existed. The VIF values were 1.013, 1.007, and 1.010 for AC, SV, and CV, respectively. The VIF values were less than 10. Thus, I did not violate the multicollinearity assumption.

Table 5

Coefficients

	Unstandardized coefficients		Standardized coefficient		Collinearity statistics	
Model	B	Std. error	Beta	Sig.	Tolerance	VIF
(Constant)	.524	.066		.000		
CV in dollars	-.006	.003	-.147	.077	.990	1.010
AC	.000	.001	.013	.874	.987	1.013
SV	.001	.000	.338	.000	.993	1.007

Note. VIF = variance inflation factor. Dependent variable: Performance.

Outliers can influence the results of logistic regression (Field, 2009). The presence of outliers can lead to misclassification of cases and a reduction in the goodness of fit of the model (Fox, 1991). In logistic regression, a model may predict a case to be one category when the case belonged to the other category (Elliott & Woodward, 2007). Inspecting the data prior to running logistic regression can identify outlying cases (Elliott & Woodward, 2007). Additionally, issues with the goodness of fit of the model are resolvable by inspecting the data for outliers (Elliott & Woodward, 2007). I removed 14 outliers from the data set because the values fell out of the range defined by the box plots for the variables. Five samples had large values for AC, five samples had large values for SV, and four samples had large values for CV.

The research question was as follows: What is the relationship of SV, CV, and AC could predict federal IT success? This study involved testing the null hypothesis that SV, CV, and AC have no relationship with federal IT program success for IT software programs completed in the U.S. Department of Defense, U.S. Department of Homeland

Security, and U.S. Department of Veterans Affairs between 2011 and 2014. To address the research question and the hypothesis, I used logistic regression to build a model to predict federal IT program success. Researchers use logistic regression to assess the ability of predictor variables to predict or explain the categorical dependent variable (Elliott & Woodward, 2007), and researchers can determine the adequacy of a model by assessing the goodness of fit (Elliott & Woodward, 2007). Goodness of fit is an indication of the relative importance of each predictor variable or the interaction between the predictor variables and the categorical dependent variable (Fox, 1991). The goodness of fit analysis is a summary of the accuracy, sensitivity, and specificity of the model in classifying cases and relations between the predictive values and the dependent variables (Fox, 1991).

Logistic regression on the independent and dependent variables appears in several tables. The analysis of the data set based on number of samples appears in Table 6. The selected cases contained no missing cases, so the number of cases for selected cases included in the analysis was the total number of samples for this study. The values of the other categories were zero because this study did not include any excluded or missing cases. Thus, I used 100% of the cases in the data set.

Table 6

Case Processing Summary

Unweighted cases [a]	*N*	%
Selected cases		
Included in analysis	132	100.0
Missing cases	0	0.0
Total	132	100.0
Unselected cases	0	0.0
Total	132	100.0

[a] If weight is in effect, see classification table for the total number of cases.

Before conducting logistic regression, the process involved coding the dependent variable because program success was a categorical variable. The coding for the dependent variable appears in Table 7. I coded program failure as 0 and program success as 1.

Table 7

Dependent Variable Encoding

Original value	Internal value
Failure	0
Success	1

In SPSS, I used the Enter method for logistic regression analysis to test all the independent variables at the same time. I tested all the independent variables at the same time because a limited number of variables were under examination. The iteration history of the model in Table 8 includes the likelihood and the coefficient constants when SPSS omits predictor variables based on the method used for logistic regression. For the model, SPSS iterated the model twice without subtracting independent variables from the model. Step 0 is the initial model containing every independent variable. The likelihood of the baseline model was 181.898 for both iteration numbers 1 and 2. The coefficient constant remained as -0.182 for each iteration. Thus, I removed none of the independent variables from the model based on the Enter method.

Table 8

Iteration History [a, b, c]

Step	Iteration	-2 log likelihood	Coefficients constant
0	1	181.898	-.182
	2	181.898	-.182

[a] Constant is included in the model. [b] Initial -2 log likelihood: 181.898. [c] Estimation terminated at Iteration 2 because parameter estimates changed by less than 0.001.

The Hosmer-Lemeshow test is a way to examine the goodness of fit of a model by measuring the lack of fit. Within IBM SPSS, the Hosmer-Lemeshow test is the most reliable test for goodness of fit available. The Hosmer-Lemeshow test was suitable for testing the null hypothesis by stating the current model is capable of predicting the observations. When a test value is less than 0.05, researchers should reject the null hypothesis in favor for the alternative hypothesis. The alternative hypothesis was the current model poorly predicted the observations. The result of the Hosmer-Lemeshow test appears in Table 9. The step was one because SPSS used one step to develop the model. The chi-square value for the Hosmer-Lemeshow test was 29.727, with a significance level of .000 based on 8 degrees of freedom. Thus, the Hosmer-Lemeshow test results indicated that the model did not fit the data well.

Table 9

Hosmer-Lemeshow Test

Step	Chi-square	*df*	Sig.
1	29.727	8	.000

The model summary contains values for the *R*-square statistics used, indicated the variation of the dependent variable described by the model (see Table 10). The step was one because SPSS used a single step to build the model. The Cox and Snell *R*-square and the Nagelkerke *R*-square values are pseudo *R*-square statistics that indicate the variation in the dependent variable explained by the model where the values range from a minimum value of 0 to a maximum of approximately 1. From the analysis, the Cox and Snell *R*-square and Nagelkerke *R*-square values were .198 and .264, respectively. Thus, the set of variables explained between 19.8% and 26.4% of the variability.

Table 10

Model Summary

Step	-2 log likelihood	Cox and Snell *R* square	Nagelkerke *R* square
1	152.840[a]	.198	.264

[a] Estimation terminated at Iteration 5 because parameter estimates changed by less than .001.

Table 11 is a classification table that includes an indication of how well the model predicts the correct outcome for each case. The rows indicate observed failed and successful programs. The columns are the predicted failed and successful programs. The last column is the percentage of correctly predicted performances based on the initial model containing no predictor variables. The model correctly classified 72.7% of the cases and failed to classify 26.3% of the cases. The model predicted program failure and program success correctly 56.9% and 91.7% of the time. The model falsely predicted program failure and success 44.1% and 8.3% of the time.

Table 11

Classification Table [a]

Observed	Predicted		
	Performance		
	0	1	% Correct
Performance			
0	41	31	56.9
1	5	55	91.7
Overall percentage			72.7

[a] The cut value is .500

Table 12 is a classification table for when the model contains the independent variables. With the addition of the AC, SV, and CV, the model increased in ability to predict failed programs and reduced the ability in predicting successful programs. Of the 132 programs, the model correctly predicted the failed programs 100% of the time. However, the model incorrectly predicted project failure for successful programs and correctly predicted program success 0% of the time.

Table 12

Classification Table [a, b] *Block 0*

Observed	Predicted		
	Performance		
	Failure	Success	% Correct
Performance			
Failure	72	0	100.0
Success	60	0	0.0
Overall percentage			54.5

[a] Constant is included in the model. [b] The cut value is .500.

In the variables in the equation table (see Table 13), the values of the coefficients are in Column *B* and the exponential form of the coefficients, or the odds ratio, is in Column Exp(*B*). The values of the coefficients determine the impact of the variables in classifying program success and failure. The SV days had a coefficient of 0.013 and an odd ratio of 1.013. Therefore, SV was 1.013 times more likely to affect project performance. The Wald test is a test to determine if a tested coefficient within a model is equal to zero. If the Wald test result is not statistically significant, the coefficient does not affect the predictability of the model. At an alpha level of .05, only SV days was significant with a *p* value of .002. Thus, the AC and CV in dollars were not major factors in influencing program success. Based on the results of the Wald test, the coefficients for AC, CV dollars (CV$), and constant did not affect the ability of the model to predict success and failure. However, the Wald significant value for CV$ may become significant if the sample size for this study is larger because the insufficient sample size in representing the total population may cause the large variability present in the descriptive statistics.

Table 13

Variables in the Equation

							95% CI for Exp(*B*)	
	B	S.E.	Wald	*df*	Sig.	Exp(*B*)	Lower	Upper
Step 1[a]								
AC	.001	.004	.113	1	.737	1.001	.994	1.009
SV in days	.013	.004	9.570	1	.002	1.013	1.005	1.021
CV$	-.034	.022	2.382	1	.123	.967	.927	1.009
Constant	.153	.306	.249	1	.618	1.165		

[a] Variable(s) entered on Step 1: AC, SV days, CV$.

Based on the results of the analysis, I rejected the null hypothesis that none of the independent variables related to program success. The coefficient for SV days was significant for the Wald test. Thus, a relationship between IT program success and the SV, CV, and AC exists for programs completed in the U.S. Department of Defense, U.S.

Department of Homeland Security, and U.S. Department of Veterans Affairs between 2011 and 2014.

In summary, the results of this study answered the research question, which was as follows: What was the relationship of SV, CV, and AC could predict federal IT success? The results supported the concept that program managers can use SV, CV, and AC to predict federal IT success. Program managers use EVM to integrate the scope of work of a project with cost, schedule, and performance elements to improve project planning and control (Hunter et al., 2014). Fleming and Koppelman (2005) found that the values used in EVM might falsely indicate that the project is failing. I observed the same trend in this study because the model containing coefficients for the independent variables falsely identified successful programs as failed programs. The model may falsely identify successful programs as failures because program success may depend on additional variables not yet considered. A negative SV may not necessarily constitute a serious scheduling issue for a program (Fleming & Koppelman, 2005). The SV reflects the difference in scheduled days from the approved baseline, and such deviations may or may not be critical to the success of a project (J. Kim et al., 2012). SV data in the data set were largely negative because the mean was -60.25 days, with a standard deviation of 161.496 days. Despite the negative SV, the programs were successful.

With further analyses of the results, I agreed that SV affects program success. I did not observe the same trend that others observed with CV and AC affecting program success. Fleming & Koppelman (2005) and Gershon (2013) noted that CV can provide insight into the efficiency of resource usage based on deviations from planned cost performance while assisting in estimating the final cost of the program. I found that CV and AC did not affect the model for predicting the outcome of the program because the Wald tests for the variables were not significant. However, the Wald test significance value for CV was lower than the value for AC, and CV would be significant if the alpha level used was 0.15.

The basis of this study was to understand the theoretical framework of EV project management. Program managers rely on the EV metrics AC, CV, SV, and schedule performance index to track performance of projects. Depending on the values of the EV metrics, the program managers estimated the likelihood of program success. Thus, I studied three of the major EV metrics to understand the relationship between the metrics and federal IT program success. By building a logistic regression model, I quantified the relationship between the EV metrics and program success and found that the model was not significant through the Hosmer-Lemeshow test. Additionally, I found that the model failed to predict project success because the model would falsely classify successful programs as failed programs based on the three metrics. The result of this study contradicted the theoretical framework because the developers of the EV metrics designed the metrics for predicting program outcomes. However, program managers use multiple EV metrics to track program progression. Thus, I cannot disregard AC, SV, and CV as EV metrics for predicting program outcomes. In addition, I found a strong correlation between the outcome of the program and SV because the results of the Wald test were significant for SV and insignificant for AC and CV. Thus, I concluded that program managers can use SV for predicting the program outcome, which contradicts the results of the Hosmer-Lemeshow test.

To conduct my study, I limited this study to programs that had expenditures of at least $20 million per year from three different agencies with a set period of between 2011 and 2014. With the limitations, I concluded that the results of this study might not represent the population of this study because I had large ranges in the data with numerous outliers that might not have been outliers if I used more data points. The findings are applicable to the IT programs produced by U.S. Department of Defense, U.S. Department of Homeland Security, and U.S. Department of Veterans Affairs only for programs completed between 2011 and 2014, as this study was on data from the three departments. The findings will apply to all the departments because the EV project management tools are the same for all departments.

The findings supported Fleming and Koppelman's (2005) statement that EV project management theory integrates cost and schedule aspects. Hunter et al. (2014) and Gershon (2013) confirmed the findings that the use of EVM for integrating the scope of a program could provide successful IT programs. Acebes et al. (2014) enforced the findings that EV is an irreplaceable tool for any type of program management.

Applications to Professional Practice

EV project management can help improve performance on any program (Acebes et al., 2013). Therefore, a relationship must exist between IT program success and EV metrics such as SV and CV. By understanding the relationship between EV metrics and IT program success, program managers could implement EV to avoid program failures. In assessing project cost and schedule status, project managers and customers receive and report accurate data through using EVM on larger IT software projects (Hunter, 2014; Salari, Bagherpour, & Reihani, 2015). Users of EVM systems get early warnings on projects that are off scheduled or spend over the set budget (Narbaev & De Marco, 2014). However, the project team must have employed the project management tool to control cost and schedule to benefit from the use of EVM.

Implications for Social Change

This study may contribute to social change by decreasing federal budget deficits. With the decrease in federal budget deficits, the federal government could devote federal spending on tangible improvements for health care, social security, and welfare, which would affect both social and the economic status in the United States (Allen, 2013; Kumhof & Laxton, 2013). This study findings supported the idea that program managers should balance cost, schedule, and performance to achieve project success (Hazir, 2015). Thus, this study reinforced the understanding of how program management tools could help produce successful IT software projects with the proper application of EVM (Batselier & Vanhoucke, 2015c). Additionally, the U.S. government would not have to furlough federal employees to cut costs.

Recommendations for Action

I propose recommendations for action that logically follow from the limitations of this study that indicated discrepancies exist between the findings of this study and other published work. I limited the study to three EV metrics and three different agencies based on the available data. From the limited data set, I found that the studied EV metrics could not accurately predict program outcome despite previously published studies. Thus, I recommend focusing on other combinations of EV metrics to predict program success.

Although the results of this study conflict with other published work, I believe that program managers can learn from this study. I exemplified the complexity of predicting program success through modeling program outcomes based on three EV metrics. I suggested that the developed model could not accurately predict program outcomes because several factors affect program success. Thus, program managers should not focus on a set of EV metrics for predicting program success. Instead, program managers should consider multiple combinations of EV metrics to predict program success.

In addition to program managers, I suggest that senior management and customers of program managers who use EVM should pay attention to the results of this study. Both customers and senior management need to understand the implementation of EVM. By understanding EVM, customers and senior management can understand the reasoning behind the program manage actions (Bernroider et al., 2014; Islam et al., 2014). Customers can alter deadlines or funding based on understanding the predicted outcomes, and senior management can provide additional support to the program manager based on the projected outcomes (De Souza, 2015; Mortaji et al., 2015).

To distribute the results of this study, I suggest distributing this study to program managers at Project management and EVM conferences and EVM training seminars. The program managers could distribute the results of this study to senior management after the EVM conferences and EVM training seminars. Additionally, the program managers could offer copies of this study to the customers to spread the results of this study further. The program managers should distribute the results of this study to the senior management and the customers. By increasing senior management’s and customers’ understanding EVM, senior management and customers are more likely to accept the program managers’ actions.

Recommendations for Further Research

Researchers should address the following limitations of this study:

The limit of studying programs with expenditures of at least $20 million per year should be increased to study programs with expenditures greater than $100 million. In response to this limitation, researchers should study the relationship of EV metrics further with a focus on using the threshold of AC equal to or greater than $100 million. By changing the threshold, researchers could narrow the gap of the current study. In the current study, I focused on the AC range equal to or greater than $20 million.

For future studies, the number of agencies should increase from the three studied agencies, which were the U.S. Department of Defense, U.S. Department of Homeland Security, and U.S. Department of Veterans Affairs, to include all 28 agencies to improve the sample size. In response to the second limitation, I limited this study to three agencies out of the 28 agencies included in the database. To improve on the applicability of this study, future researchers should focus on more than three agencies, which would increase the sample size. The major limiting factor of this study was the sample size. Due to the small sample size, I was incapable of accounting for the variability of the data. By increasing the sample size, a researcher could account for a larger degree of variability and the data would better represent the population.

Program managers' skill level affects program outcomes. Future researchers should consider program managers' skill level in relation to program outcomes. The IT Dashboard divides the data based on agencies and the skill level of program managers. Thus, future researchers can use the data from the IT Dashboard to study the effect of program managers' skill level on program outcomes.

Reflections

At the start of this study, I noticed a correlation between IT program success and SV, CV, and AC. The expectations of the results based on previous studies did not influence the findings because I used archival data from IT Dashboard. I applied logistic regression analysis because the categories variables were the dependent variable. According to this study results, the SV had a relationship with IT program success, but CV and AC did not have a relationship with IT program success.

During this study, I observed the statistical consequence of small sample sizes. To decrease the impact of outliers within the data, I reduced the sample size from 146 to 132. However, removing the outliers did not improve this study because the model could not accurately predict program outcomes. The results of this study conflicted with previous research in which researchers showed the existence of a relationship between the EV metrics and program success (Fleming & Koppelman, 2005). I suggest the cause of the discrepancy was the small sample size in relation to the population. The sample had large variations for each variable, with numerous outliers identified with the boxplots. By increasing the sample size, the outliers may decrease because the identified outliers may not be outliers in the population. Additionally, I would account for more variability by increasing the sample size. The larger sample would improve the developed model because I developed the model based on the sample.

My thinking changed throughout the course of this study. Originally, I thought a clear relationship existed between AC, SV, CV, and program outcome. However, the relationship between the three EV metrics and program outcome was complicated because the developed model could not predict program outcome based on the three metrics. In future studies, I would consider the impact of sample size as well as the use of multiple metrics in determining the relationship between the EV metrics and program success.

Conclusions

The results of this study were not in agreement with previous studies in which researcher showed a relationship existed between EV metrics and customer satisfaction (Plumer, 2010). From the results of this study, I concluded that the selected EV metrics could not predict program outcome. However, I concur that a relationship does exist between program outcome and SV based on the significance of SV in the model. Additionally, I studied three of the numerous EV metrics that program managers use in predicting program success, and I may have excluded key EV metrics that are important for predicting program success. Based on the results of this study, program managers should focus on multiple EV metrics, instead of a set number of metrics, as the relationship between program success and the EV metrics is complex.

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Appendix A: Raw Data

Agency Code	Actual cost	SV	CV	Success
29	61	-9.27	-6.59	1
29	30	-6.29	-6.69	1
29	40	-3.58	-2.35	1
7	77	-4.18	0	1
24	25	-5.68	0.77	1
7	23	-1.97	0.26	1
24	40	-8.55	8.91	1
29	30	-1.34	-2.01	1
24	39	-0.89	-0.51	1
24	66	-0.38	0	1
24	21	0	0	1
24	21	0	0.04	1
24	21	0	-9.13	1
24	22	0	3.81	1
7	22	0	0	1
24	23	0	-5.29	1
24	23	0	8.79	1
7	25	0	0	1
24	25	0	0	1
7	28	0	-0.04	1
7	29	0	7.68	1
7	30	0	0	1
24	30	0	-2.36	1
7	30	0	0	1
24	34	0	4.25	1
24	35	0	0	1
7	37	0	0	1
24	40	0	0	1
24	40	0	0	1
24	42	0	8.46	1
7	42	0	0	1
24	43	0	0	1
24	43	0	0	1
24	46	0	0	1
24	47	0	1.99	1
24	49	0	5.19	1
24	50	0	0	1
24	50	0	5.58	1
24	54	0	0	1
29	55	0	0	1

29	56	0	0	1
24	58	0	0	1
24	61	0	0	1
24	67	0	0	1
29	68	0	8.34	1
24	98	0	0	1
29	32	1.94	-1.58	1
24	28	2.37	7.77	1
24	89	5.01	0	1
24	43	9.02	0	1
24	100	0.91	-3.37	1
24	100	0.91	-3.37	1
7	109	0	0	1
7	136	0	0	1
24	162	0	0	1
7	180	0	0	1
24	181	9.28	0	1
24	182	-2.27	0	1
24	258	0	0.39	1
7	259	0	0	1
7	503	0	7.17	1
24	67	-26.07	5.24	0
29	60	-11.74	0	0
24	72	-27.79	0	0
29	25	-11.88	6.63	0
29	44	-11.72	0	0
7	51	14.01	0	0
24	46	12.44	0	0
7	87	11.33	0	0
29	102	-23.99	0	0
24	173	-19.76	1.08	0
7	40	-102.11	-0.37	0
24	66	-93.77	-6.79	0
7	63	-151.37	0	0
7	26	-94.39	-6.17	0
7	25	-78.1	-9.73	0
29	69	-41.78	-8.27	0
24	29	-43.16	-0.45	0
7	35	-74.79	0	0
24	34	-32.91	9.88	0
7	59	-51.1	0	0
29	21	-46.09	-0.94	0
7	85	88.36	0	0

24	110	-657.14	0	0
7	135	-51.1	7.37	0
7	155	-36.18	0	0
7	203	-258.69	0	0
29	27	-9.38	-10.15	0
29	25	0	-19.38	0
29	26	0	-25.53	0
29	39	0	20.34	0
7	46	0	14.85	0
29	50	0	25.65	0
24	73	0	15.18	0
7	75	0	13.08	0
29	82	0	13	0
29	39	0.39	-25.92	0
29	35	0.49	-13.86	0
29	73	0.68	25.89	0
29	25	1.51	18.53	0
29	24	2.83	24.62	0
7	123	0	16.62	0
7	126	-8.39	-16	0
24	143	-5.66	22.34	0
29	151	1.51	10.49	0
24	172	0	-19.44	0
29	41	-17.86	12.6	0
7	1595.233	20	14.69	0
24	48	-190.4	15.21	0
24	53	-190.4	16.63	0
24	50	-63.93	29.83	0
24	21	-149.18	24.86	0
7	70	88.36	25.39	0
7	570	-65.57	-16.98	0
7	21	-0.93	100	0
29	21	0	-231.55	0
29	23	0	91.63	0
29	23	0	44.97	0
29	23	0	-46.19	0
29	25	0	61.61	0
24	26	0	73.32	0
29	27	0	-133.61	0
29	33	0	-81.74	0
29	34	0	48.87	0
29	41	0	-31.94	0
7	41	0	66.25	0

29	44	0	93.95	0
29	47	0	-1402.42	0
24	60	0	35.77	0
29	71	0	-83.83	0
7	70	1.1	100	0
29	39	2.44	-75.49	0
29	100	0	-52.26	0
7	104	0	31.26	0
24	21	-12.16	-36.45	0
29	49	-10.3	60.5	0
7	27	27.27	51.77	0
29	204	-26.61	35.7	0
24	50	-229.71	54.34	0
24	51	-242.49	43.9	0
7	25	-36.2	72.39	0
7	98	-50	100	0
29	38	-33.62	-32.34	0
29	45	36.31	-192.84	0
29	122	-44.97	97.3	0
7	416	913.33	-3389.02	0