STATISTICAL TOOLS AND THEIR IMPACT ON PROJECT MANAGEMENT HOW THEY RELATE

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Abstract: Although a project manager has many tasks, none are more important to success than the ability to lead and manage a project. A project manager typically has a strong business and economic background, but how are decisions made? An economic analysis is telling, but without the knowledge of data analytics and the different statistical analysis tools, decision-making might be difficult. With certain techniques, statistical analysis tools and methods will be explained with their relationship on how they correlate positively or negatively to a project managers' success. Key concepts include data collection, key descriptive statistics (i.e., the mean, standard deviation, range, correlation, and linear regression). They also include building confidence intervals, hypothesis testing, risk analysis, and understanding different statistical software that is available. With these skills, the chance of a project manager's success becomes more likely.

Keywords: Project Manager; Statistical Methods; Statistical Tools; Descriptive Statistics; Risk Analysis; Hypothesis Testing; Project Planning

1. INTRODUCTION

Background

The productivity and efficiency of a company help determine how successful the business will be. Though companies have many departments that help play key roles in maintaining daily operations, the profit generates is based on the success or failure of a project. These projects are managed by employees with the title of project manager. A project manager has many roles, but the main tasks include making business decisions, such as who will get the contract on completing the project, managing funds, directing internal personnel, and keeping the project on track with the desired completion date. Of course, these decisions cannot be made with just instincts. Some project managers would argue that there is nothing more important in decision-making than experience. Though that may be partially true, facts are now needed to support almost any decision. These facts may come from past experience, but the synonym for the word “facts” in business is now called "data". Data is what helps drive decision-making and helps to determine the further steps of a project, but there are a few questions revolving around data in any company, such as where the data comes from. Once that is answered, the following question is usually about what the data means or how it is read. After the dataset is read and understood, the most important questions are asked, such as which decisions can be made with the decision. Since this is the point where decisions are made, the project is now executed with possible adjustments along the way, depending on the progress and success of the project. At the end of the project, the results are then analyzed and compared to the initial thought from the data analysis.

There are two main types of projects that are led by project managers. Firstly, there is a one-time project, such as building a house or paving a road. While the second is creating a process to lead to better practices in the field, this will result in better outcomes for future projects. Rose et al. (2017); Parker, Parsons, & Isharyanto (2015); Lee et al. (2013) reported that when trying to change or create a process to help drive better business practices, the jumpstart method should be used. The jumpstart method is a six-step

Since data has become such an important piece of the project management puzzle, different methods of analyzing data can be studied. The origin of most data analytics lies around the key descriptive statistics, such as the mean, standard deviation, and correlation factors. With these statistics, the spread of the data can be determined, and linear regression analysis can be used to calculate the impact of one variable on another. However, what is a statistic, such as the mean or standard deviation, without the context of what the outcome truly is? This is the reason for hypothesis testing, which allows for the data to provide a true answer to whether or not a project or a segment of a project is considered to be valuable. Along with the methods above for analyzing data, the other case involves risk analysis. Multiple projects are compared to each other, or different segments of a project are compared to determine where the most risk takes place. This allows for a project manager to focus their resources on the problem area. As a project manager, there is a lot of responsibility, but with statistical analysis tools, methods, and techniques, the data used to back the decisions of a project becomes clearer.

Research Objective & Gap

Though literature establishes the importance of these variables, their concepts, and models in project management and performance, a research gap has formed from not studying why they enable such a smooth progression. Thus, this study addresses the research gap by evaluating the elements and applications of these variables, their concepts, and models to find overlaps and disparities. Then, this study will propose a framework with the best elements of the current model for a “universal” framework. This framework can apply to any aspect of projects, operations, and performances within any business. From the research, this study will answer important questions from experts on these variables by using evidence-based answers (i.e., how to maximize them for project management and performance goals).

Managerial Relevance

For an engineering manager, decision-making is a crucial part of their role. In the future, this role will only grow in importance for project management and engineering professions. In this study, the decision-making role will be discussed for the engineering management practitioner, as the future of these topics will apply to engineering management for effectively managing different operations, project management lifecycles, and project management environments. Also, the implications will be discussed in reference to organizational levels, such as the corporate level, the managerial level, and the project team level. An engineering management practitioner can utilize the conclusions of this study for improving the use of these variables, concepts, and models.

Originality

With this study, there will be more information on these variables, their concepts, and models, as well as their likenesses and differences. This study adapts various research perspectives and ideas to propose new solutions for current problems. First, this study uses a design-science-investigate strategy. Second, this study approves a valuable growth reveal for reasonable and hypothetical application. Finally, this study makes an assessment model of these variables, their concepts, and models with a focus on evaluation instruments as answers to the examination question. Development models are outlined, and the evaluation instrument is reviewed. Also, the method behind generating the outline is explained, along with an outline of the meetings. In conclusion, any primary discoveries and ideas for arranging the investigative limitations and future studies are provided. With real-world examples, this study reveals the importance of applying these theories in both theory and practice.

Organizational & Managerial Contribution & Relevance

In this study, the variables, their concepts, and models will be examined to propose a more unified and thorough framework to fill a research void. The results are applicable to multiple subjects from the business world, as it also contributes to each body of knowledge. There are recommendations for future research ideas and approaches, as well. Finally, a practitioner can better understand these variables and their relationship to yield more effective strategies, so the implications can become clear.

Contribution to the Field & Profession of Industrial Engineering

In the Industrial Engineering (IE) research field, this study is a significant contribution because of its capacity to expedite the work process for an engineer. For example, engineers can find guidance on the organization and maintenance of the system through using the latest technology. Also, this study can help to save time, money, materials, energy, work hours, machine time, and other resources that could slow down the work process.

As for the research field, this study offers helpful information for any reader, including industrialists, with clear and concise vocabulary. The theoretical framework within this study also provides relevant information to become a reference for future studies. Overall, this study can help to gain ground over the competition.

Paper Organization

Section two of this paper includes the literature review of works in these research fields. Subsequently, section three features the research methodology that was applied to the research study. In section four, there are the findings from the study and analysis. Lastly, section five features several aspects: an outline of the implications for the practitioner, ideas for future research, research limitations, and general conclusions.

LITERATURE REVIEW

As a project manager, there are many different topics that relate to the question of how statistical tools can help plan and execute a project. From basic concepts, all they want to understand is how to plan, conduct, and execute different types of statistical testing and analysis. Much research has been done with respect to this field of study.

Starting with the concepts of statistical analysis, articles were compiled that relate to key descriptive statistics, and other measures, such as correlation and linear regression. Many journals explain how the tools are used (Ferreira & Kuniyoshi, 2015; Labedz & Gray, 2013; Nagel, 2015; Zwikael, & Smyrk, 2012; Xue, Baron, & Esteban, 2016). In Ferreira & Kuniyoshi's (2015) study, the concepts of correlation are discussed with respect to how they can be used in decision-making. Although this study was found along with an introduction to key statistics (standard deviation and the mean), most of the research was related to more significant and complicated concepts, such as building confidence intervals and hypothesis testing. According to Labedz & Gray (2013), the standard deviation has a major role in determining deficiencies and uncertainties in the data. This is a key point to be made because it allows a project manager to understand how their project might differ from other projects. Unfortunately, here is where there is a gap in the literature. Most project managers would love to see how each topic would help in making decisions, but most research provides a case study where the tools are being used.

There was much discussion revolving around a few topics, as well. The main topics were correlation and linear regression, hypothesis testing, and risk analysis. Han, Lung, & Ajila (2016); Parast (2011); Shenhar & Levy (2007) ensured the models of defect prediction that revolve around linear regression. This is one of the many examples of how a case study is used to get a concept across. Defect prediction is a prime example of how a project manager might need to use statistics with the hopes of executing a successful project. However, with the gaps in literature revolving around key descriptive statistics and different graphical analyses, the linear correlation may be a difficult approach to use.

Although the topic of data collection was discussed frequently, the struggles and fears around data collection are typically not addressed. Bias in the data can lead to many issues when trying to plan a project. If data is skewed towards the high end, then the projected cost may not be enough. However, Moustafa et al. (2018) spoke about how bias in data can positively or negatively skew confidence intervals. Bias can cause an inaccurate point estimate or can even change the margin of error. Thus, the topic of data bias and uncertainty is definitely key.

Finally, risk analysis was discussed frequently, which ranges from linear regression to Pugh charts and even different versions of The Monte Carlo Simulation. Though there is definitely a gap in knowledge when discussing graphical analysis, Sadabad & Kama (2014) have coordinated a way to explain risk analysis with graphical techniques and methods. Many skills revolve around the basics, and it is essential that there is more research done about the beginning steps of analysis for a project manager. This paper is meant to fill these gaps, as the findings and discussions section is presented by topic (starting with data collection) and ranging to the complicated testing (hypothesis testing, confidence intervals, and risk analysis).

RESEARCH METHODOLOGY

Literature Review Research Approach

Two steps went into the literature review. First, there was the search for applicable information, including the inputs from keywords. Secondly, there was the review process, which involved the use of databases and searches strong, as well as a search through the tables of contents for two journals.

Part 1: Explorative and Unstructured Literature Review

This study aimed to reconsider some keywords, so certain publications were investigated. This yielded 31 journal articles and 7 books that were related. The keywords were then studied from the 38 publications to be applied as search terms in the structured review.

Part 2: Structured Literature Review

In the structured and systematic approach, it included review-conducting methods from other literature sources. The four phases of this section include (1) preparing and scoping, (2) review-planning, (3) searching, evaluating, and selecting literature, and (4) evaluating the final selected literature.

Phase (1) emphasized project-relevant research on marketing and strategic planning, so sufficient evidence was expected. Phase (2) involved finding a link between other concepts and keywords to find more information. Such concepts were the keywords, how they connect, and how they interact, while "success", "evaluation", and "impact" did not yield applicable results. Phase (3) concluded the compilation of results, which involved using ProQuest, Business Source Complete, EBSCO, ABI/Inform Global, and other databases. A total of 15 conference papers and 25 results related to the journals, so 40 results were found.

Additionally, once the search ended, the tables of contents were also scrutinized to find tier 1 and tier 2 journals that were both academic and practitioner-based to apply to the study. Any selected journals were intended to be premier specialty journals for the keywords, and this phase involved three streams: the explorative and unstructured search, the structured search with search strings, and scanning the tables of contents (see **Figure 1**).

These three streams limited the results to 42 publications. The selection process ended in gathering between 24 and 18 results, as academic journal articles, literature reviews, conference papers and proceedings, and books were highlighted. Also, triangulation methods were used. With the first selection, it was expected to conclude if the publications were connected to the keywords and project research. The evaluation featured the use of a set of inclusion and exclusion criteria with a focus on the abstract, and some publications included the entire paper or just the introduction for the criteria.

Lastly, phase (4) entailed the arrangement of information into an inductive and deductive analysis. This was then documented with a software package, as the author's university was indicated, along with suggested categories.

Research genres were documented by the following: empirical research, theory development, research essays and literature reviews, or "other". Also, the deductive coding was provided with confirmation that the publications were linked to theoretical frameworks, such as with a research-based view and contingency theory. If a publication featured a model, this was also indicated.

A grounded theory approach was used in the inductive analysis for coding some publications with open and selective codes. Most publications were selected because of the annual average number of citations. Thus, older publications were balanced out. Some current publications were also included to significantly contribute to the keywords research. In phase (4), parts 1 and 2 of the literature review, as well as the final evaluation, occurred between April and August of 2018.

The key theme in these papers are that the variables and concepts are shared from descriptive and trait viewpoints. The statistical analysis and investigation of other variables allowed the research conclusions to become more significant. The following section features **Table 1**, which shows the 42 studies and the key themes.

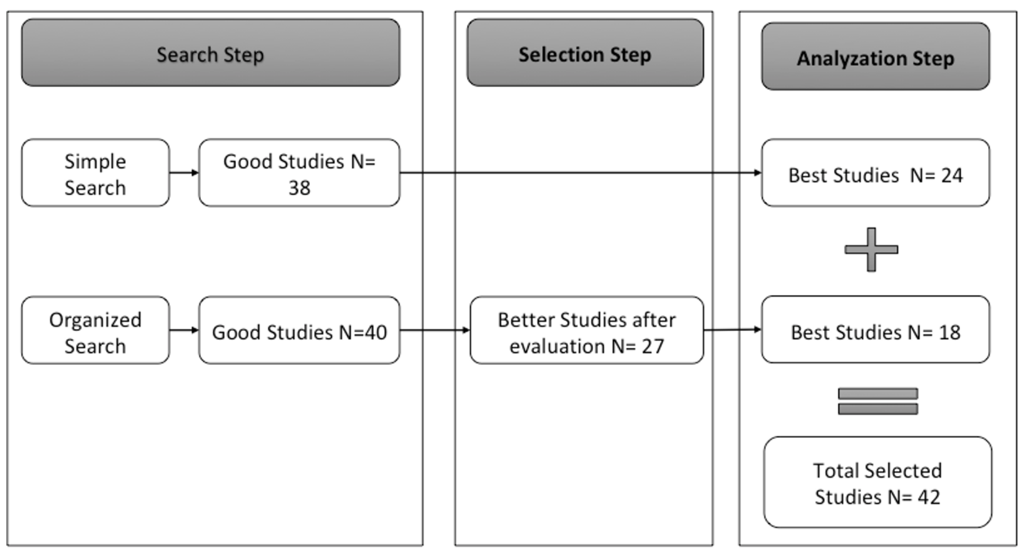

Figure 1: Research approach for literature review.

Thus, the literature assessed the keywords with many statistical methods from relational and causal viewpoints, which added weight to these conclusions. In **Table 2**, the statistical methods are summarized that were used for the 42 studies. **Table 3** summarizes the number of variables that were studied in the journals.

The next section features the findings for these research methods, which are based on the themes from later sections in this study.

FINDINGS & DISCUSSION

When starting a project, many parties need to align to be successful. With the lead of a project manager, this process becomes easier, as the key roles and tasks are all determined and directed from one key individual. As discussed above, every project's decisions are derived from analyzing data, but where does this data come from? In some cases, data can be used from historical projects, which allow for a real understanding of what has happened in the past, if it has been successful, or if the process needs to change. If historical data is not present, then the data collection process begins. There are many different methods in which data is collected, such as experiments, telephone surveys, written questionnaires, online surveys, and interviews. These methods are supported by Irujo (2017); Ahern, Leavy, & Byrne (2014); Andersen (2014); Burnes (2014), where the data collection process is described for a project. Their data collection methods included telephone interviews and open-ended surveys. Telephone interviews are used for the interviewer to control the conversation, whereas the open-ended surveys allow the interviewer to express their true comments about the question.

Theme #1	Theme #2
A New Methodology for Temperature Testing (2018)	Al-Kadeem et al., (2017a)
Ahern, Leavy, & Byrne, (2014)	Badi & Pryke, (2016)
Arumugam, (2016)	Guidelines for Improving Logistic Performances (2016)
Cova & Salle (2005)	Irujo, (2017)
David, David, & David, (2017)	Lai & Ni, (2014)
Elzamly & Hussin, (2014)	Medina & Medina, (2015)
Eskerod & Blichfeldt, (2005)	Milner, (2016)
Galli & Kaviani, (2018)	Parast, (2011)
Galli et al., (2017)	Parker, Parsons, & Isharyanto, (2015)
Hartono, FN Wijaya, & Arini, (2014)	Sharon, Weck, & Dori, (2013)
Xue, Baron, & Esteban, (2016)	Shenhar & Levy, (2007)
Xue, Baron, & Esteban, (2017)	Yun, et al., (2016)
Andersen, (2014)	Gimenez-Espin, (2013)
Schwedes, Riedel, & Dziekan, (2017)	Kwak, & Dixon, (2008)
	Sutherland, (2004)
Theme #3	**Theme #4**
Arumugam & Babu, (2015)	Bamakan & Dehghanimohammadabadi, (2015)
Chaczko, Slehat, & Salmon, (2016)	Besner & Hobbs, (2012)
Detert, (2000)	Brown & Eisenhardt, (1995)
Easton & Rosenzweig, (2012)	Burnes, (2014)
Galli, (2018c)	Ferreira & Kuniyoshi, (2015)
Galli & Hernandez-Lopez, (2018)	Galli, (2018a)
Han, Lung, & Ajila, (2016)	Galli, (2018b)
Kock, (2016)	Kock, (n.d.)
Linden, (2018)	Li et al., (2017)
Svejvig & Andersen, (2015)	Magana, Seah, & Thomas, (2018)
Todorović et al., (2015)	Moustafa et al., (2018)
Labedz & Gray, (2013)	Xiong et al., (2017)
Lee et al., (2013)	Winter et al. (2006a)
Rose et al., (2017)	Loyd, (2016)
Usman Tariq, (2013)	Marcelino-Sádaba et al., (2014)
Varajao et al., (2014)	Nagel, (2015)
Von Thiele Schwarz, (2017)	Papke-Shields & Boyer-Wright, (2017)
Zhang et al., (2015)	Sadabad & Kama, (2014)
Zwikael & Smyrk, (2012)	Zhang et al., (2016)

TABLE 1. Identified Studies From Research Approach By Theme

Statistical Method	Number of Articles (Frequency)	Author(s)
Regression	17 (25.37% of total articles)	A New Methodology for Temperature Testing (2018) Bamakan & Dehghanimohammadabadi, (2015) Cova & Salle, (2005) David, David, & David, (2017) Detert, (2000) Easton & Rosenzweig, (2012) Elzamly & Hussin, (2014) Galli et al., (2017) Gimenez-Espin, (2013) Guidelines for Improving Logistic Performances (2016) Loyd, (2016) Sadabad & Kama, (2014) Sutherland (2004) Varajao et al., (2014) Xue, Baron, & Esteban, (2017) Zhang et al., (2015) Zwikael & Smyrk, (2012)
ANOVA	12 (17.91% of total articles)	Ahern, Leavy, & Byrne, (2014) Brown & Eisenhardt, (1995) Ferreira & Kuniyoshi, (2015) Galli, (2018b) Galli, (2018c) Han, Lung, & Ajila, (2016) Lai & Ni, (2014) Nagel, (2015) Papke-Shields & Boyer-Wright, (2017) Rose et al., (2017) Xiong et al., (2017) Yun, et al., (2016)
Q-Test	13 (19.40% of total articles)	Arumugam, (2016) Arumugam & Babu, (2015) Badi & Pryke, (2016) Kwak, & Dixon, (2008) Kock, (n.d.) Kock, (2016) Labedz & Gray, (2013) Linden, (2018) Moustafa et al., (2018) Parker, Parsons, & Isharyanto, (2015) Schwedes, Riedel, & Dziekan, (2017) Usman Tariq, (2013) Von Thiele Schwarz, (2017)
t-Test	12 (17.91% of total articles)	Andersen, (2014) Besner & Hobbs, (2012) Burnes, (2014) Chaczko, Slehat, & Salmon, (2016) Eskerod & Blichfeldt, (2005) Galli, (2018a) Winter et al., (2006a) Hartono, FN Wijaya, & Arini, (2014) Lee et al., (2013) Sharon, Weck, & Dori, (2013) Shenhar & Levy, (2007) Zhang et al., (2016)
Chi-Square Test	13 (19.40% of total articles)	Al-Kadeem et al., (2017a) Galli & Kaviani, (2018) Galli & Hernandez-Lopez, (2018) Irujo, (2017) Li et al., (2017) Marcelino-Sádaba et al., (2014) Magana, Seah, & Thomas, (2018) Medina & Medina, (2015) Milner, (2016) Parast, (2011) Svejvig & Andersen, (2015) Todorović et al., (2015) Xue, Baron, & Esteban, (2016)

TABLE 2. Systematic Analysis Results by Statistical Analysis Method

No. Factors Studied	Number of Articles (Frequency)	Author(s)
1	14 (20.90% of total articles)	Andersen, (2014) Bamakan & Dehghanimohammadabadi, (2015) Besner & Hobbs, (2012) David, David, & David, (2017) Galli, (2018b) Han, Lung, & Ajila, (2016) Lee et al., (2013) Medina & Medina, (2015) Nagel, (2015) Papke-Shields & Boyer-Wright, (2017) Sadabad & Kama, (2014) Sutherland, (2004) Von Thiele Schwarz, (2017) Yun, et al. (2016)
2	13 (19.40% of total articles)	A New Methodology for Temperature Testing (2018) Al-Kadeem et al. (2017a) Arumugam & Babu, (2015) Brown & Eisenhardt, (1995) Galli & Hernandez-Lopez, (2018) Guidelines for Improving Logistic Performances (2016) Irujo, (2017) Kock, (2016) Lai & Ni, (2014) Rose et al., (2017) Shenhar & Levy, (2007) Varajao et al., (2014) Xue, Baron, & Esteban, (2016)
3	14 (20.90% of total articles)	Arumugam, (2016) Badi & Pryke, (2016) Elzamly & Hussin, (2014) Eskerod & Blichfeldt, (2005) Galli et al., (2017) Gimenez-Espin, (2013) Li et al., (2017) Linden, (2018) Loyd, (2016) Marcelino-Sádaba et al., (2014) Svejvig & Andersen, (2015) Usman Tariq, (2013) Winter et al., (2006a) Zhang et al., (2016)
4	11 (16.42% of total articles)	Ahern, Leavy, & Byrne, (2014) Detert, (2000) Easton & Rosenzweig, (2012) Galli, (2018a) Kwak, & Dixon, (2008) Kock, (n.d.) Labedz & Gray, (2013) Moustafa et al., (2018) Parast, (2011) Todorović et al., (2015) Zwikael & Smyrk, (2012)
5	6 (8.96% of total articles)	Burnes, (2014) Chaczko, Slehat, & Salmon, (2016) Cova & Salle, (2005) Galli, (2018c) Sharon, Weck & Dori, (2013) Xue, Baron, & Esteban, (2017)
6	9 (13.43% of total articles)	Ferreira & Kuniyoshi, (2015) Galli & Kaviani, (2018) Hartono, FN Wijaya, & Arini, (2014) Magana, Seah, & Thomas, (2018) Milner, (2016) Parker, Parsons, & Isharyanto, (2015) Schwedes, Riedel, & Dziekan, (2017) Xiong et al., (2017) Zhang et al., (2015)

TABLE 3. Systematic Analysis Results by Number of Variables Studied

A big concern when collecting data through interviews and surveys is the fear of having biased data. This can be discussed based on what the survey is about and who is being interviewed. Some obvious examples of bias can be found in politics. For example, if a survey question is “Do you like the president?” then the sample of people being surveyed should not be the president’s cabinet. Another example of bias in the data would be apparent if a class was surveyed about the attendance rate. Obviously, the survey would lean towards the idea that attending class is important, as it was administered in class (Linden, 2018; Milner, 2016; Marcelino-Sádaba et al., 2014; Todorović et al., 2015; Schwedes, Riedel, & Dziekan, 2017). As a project manager, it may be compelling to make the data show that the project will be successful, but if the data is interpreted wrong, then a project that was supposed to be successful may fail. Thus, there can be a negative impact on both the business and the project manager's career.

The second question that was asked in the introduction was now that the data is collected, how is it read and analyzed? This begins with graphical analysis through tables and charts, which allow for quick visualization of how the data has acted in the past and how it can be expected to act in the future. With data analytics, there are three key parts: understanding how the data has acted in the past, how to manage a project in the present, and predicting how the data will appear in the future. Through tables and charts, the first portion is derived with the hopes that the second and third parts will be discussed. One of the simplest charts to create is a frequency chart, or a relative frequency chart. This allows for an executive or a project lead to have a quick glance at what values have been accrued in the past. Without context, it can help predict what will happen in the future. Again, a political question is a good example of how frequency charts can be helpful but misleading. If the question was about gun control, but the survey was conducted in a hunting store, there would be an overwhelmingly large number of opponents (Varajao et al., 2014; Xue, Baron, & Esteban, 2017; Svejvig & Andersen, 2015; Sharon, Weck, & Dori, 2013). Essentially, a project manager is in control of deciding who should be surveyed to prevent bias in the data. Other forms of graphical analysis include bar and pie charts. Bar charts and column charts can be used by a manager to determine which category has a higher quantity. Although the pie chart is similar to the bar/column chart, the difference is that the pie chart shows percentages, rather than true quantity.

Furthermore, executives hear different values thrown around all day, so in a presentation, pie charts give quick overviews of what parts or segments may have the higher cost or time needed to complete them (Kock, 2016; Medina & Medina, 2015; Hartono, FN Wijaya, & M. Arini, 2014). The term that is often thrown around in the basics of data analytics is key descriptive statistics, which are calculated from either the sample or population of the data to help construe new information that will help drive a decision. The list of key descriptive statistics includes mean, median, mode, range, interquartile range, standard deviation, and correlation coefficient. These statistics all help draw conclusions, but some are used more frequently than others. The mean and standard deviation appear in just about every conversation, normally to get a baseline understanding about the history of a project (Magana, Seah, & Thomas, 2018; Zhang et al., 2016; Yun et al., 2016; Sutherland, 2004). However, the correlation coefficient is the metric that describes how closely two or more variables are related, and project managers would love to see that information. If it is proven that rainy days lead to more money spent, then they might decide to only work on sunny days. Correlation is used in graphical analysis with scatter plots where it is clear to see if there is a relationship in the data, which is the root of the term linear regression. On a scatter plot, a linear regression can be determined from the average line that paces through it, but in cases where statistical software is not used, the regression needs to be calculated in conjunction with the correlation coefficient (Ferreira & Kuniyoshi, 2015; Galli, 2018a; Galli, 2018b; Galli, 2018c). The historical trends of data can be seen using linear regression and can then be modeled if one or more of the variables are known. Essentially, linear regression is the graphical form of algebra, where the missing piece to the equation can be found if the remaining unknowns are assumed or calculated.

They were tying data collection and graphical analysis back to the main points of how statistical analysis tools can help in planning a project. Data is the source of information regarding the analysis of a project, so it is essential that the data collection techniques are not going to make the data set unbiased. Biased data can be avoided by choosing sample sets of many demographics that have apparent controversial opinions about the questions. Along with choosing the correct samples, allowing for open-ended questions takes away the opportunity of forcing the interviewees to select the desired choice. The other way to collect unbiased data is by conducting experiments that would be similar to the project. By conducting the experiment, actual results can be made that should be representative of the actual project. Unfortunately, experiments are costly and not very time-efficient. Although frequency charts can show what the data spread looks like, biased data cannot always be seen. Bar and pie charts help to show the key descriptive statistics that allow for the project manager to make key decisions about the project. Finally, the statistic regarding correlation helps provide a linear regression to the model, as it is important for the project manager to see how different variables react to the outcomes of each other.

Along with the basics of statistical analysis above, such as data collection, key descriptive statistics, and correlation analysis, another category of statistical tools that can help manage a project falls around the subject of probability. Probability analysis can help managers determine which events have a high chance of occurring or visa-versa. This is a great example of how the above methods can be used in making decisions. One might ask about which data is used when calculating the probability of certain outcomes. The answer can be historical data or by using one of the data collection methods from above. Although the probability is key in making decisions, it can also be used with other tools to help drive more significant conclusions. This can be seen in methods referred to as probability distributions, as they give a clearer image on the mean and the standard deviation. The knowledge of how to create probability distributions is imperative when trying to see how the data is spread. Depending on the spread of the data, the project manager can determine the tools that can further analyze the data to make essential business decisions.

Additionally, distributions work well with probability because it requires many samples of the same data set is taken, which can help find the mean and the standard deviation of the data. In more technical terms, this mean would be considered the expected value of the data set and can be calculated by taking the sum of the product of all samples and their unique probabilities of occurring. This is very beneficial to a project manager in understanding the true value of the data. For example, without sampling distributions, a manager might look at one of the samples and think that it was a true representation of the data. In reality, it was an outlier that could cause the wrong conclusions to be reached. There are many different outcomes of a sampling distribution, including the binomial distribution, possion’s distribution, but most commonly, the normal distribution. A binomial distributions' shape and size can differ based on two parameters: the sample size that is being analyzed and the probability of an event occurring. The ideal sampling distribution of working with is the normal distribution because of its unique properties that facilitate data analysis. The more samples that are taken and the closer that the probability of an event occurring is to 50 percent, then it is more likely that a binomial distribution will look like the normal distribution. Another method in trying to create distributions is via simulations and random sampling (Labedz & Gray, 2013; Winter et al., 2006a; Al-Kadeem, et al., 2017a; Badi & Pryke, 2016; Cova & Salle, 2005) If the data is in a pool and is randomly selected, then an unbiased distribution can be created.

As mentioned above, the normal distribution is ideal because of its unique characteristics. The normal distribution is defined as a curve where the mean lays directly in the middle of the data. Also, 50 percent of the data is above the mean, and 50 percent of the data is below the mean. Consequentially, the normal distribution allows for the amount of data in different regions to be estimated using some basic principles. Within plus or minus 1 standard deviation lays 68 percent of the data, while 2 standard deviations are 95 percent of the data and 3 standard deviations is 99.7 percent of the data. The lean six sigma principle is frequently used in project management, and it states that all of the data would be included within plus or minus 6 standard deviations of the mean. With these rules of thumb, someone analyzing the data can know what to expect from the project. Depending on the situation, data may not ever be originally represented as a normal distribution, but with other theorems, this shape can form. One of the most commonly used theorems in statistics is known as The Central Limit Theorem (Li, et al., 2017; Arumugam, 2016; Besner & Hobbs, 2012; Detert, 2000). This theorem states that the distribution of the sample means should be very close to a normal distribution. A key point in using The Central Limit Theorem is by using an appropriate amount of samples, so the more samples that are used lead to a smoother curve. A sample size of 1 plot the population, which would leave a rectangular or triangular distribution. If this number increases, then the distribution will appear to be more normal.

Although the probability is a big stepping stone in helping drive decisions, it is more of the concept of probability and distributions that lead to the conversation of what methods to use when drawing conclusions. The basis of all of these tests revolves around confidence intervals, which are used when there is uncertainty in the data. Confidence levels fall anywhere from 99 percent to 80 percent with the hope in creating a range of acceptable values. This is commonly done by the project managers with the hopes of taking out any concerns of miscalculations. The political example can be used when talking about confidence intervals. When news channels are releasing data on who may be winning a poll, there is always a value of uncertainty involved. The anchor might say something along the lines of candidate A leads by 7 percent, plus or minus 3 percent. This follows the formula for confidence intervals: Confidence Interval=Point estimate ±(critical value)(standard error)

The critical value is determined based on the confidence rate that is given, while the standard error is influenced by the sample size, since the standard deviation is not a statistic that can be changed. If a project manager wants something with more accuracy, then the number of samples and/or rate of confidence will be increased. The closer that the confidence rate is to 1, then the lower the range will be. In the case above, the Z-value is used to determine the critical value. It is one of the least accurate critical values because it is pre-determined and independent of any other features of the data besides for the confidence rate. Another example of a critical value is calculated using the t-value, which is not to be confused with the t-test. Although they are related, this is not used for decision-making, but it is yet another tool to help set-up a range for a desired level of confidence. Also, the t-value is not pre-determined, but it is calculated from the sample mean, population mean, sample standard deviation, and sample size. In a study, the sample size is a key factor in determining confidence intervals, along with choosing the correct confidence level (Arumugam & Babu, 2015; Easton & Rosenzweig, 2012; Eskerod & Blichfeldt, 2005). The desired sample size can be calculated by knowing the critical value, which is derived from knowing the confidence level, the population standard deviation, and the desired margin of error. If all of these are known, then the sample size can be calculated.

Depending on the situation, the necessary sample size may not be met because of time or cost conflicts. For example, in the car industry, samples need to be created by crashing cars, so a large sample size is not ideal. If the desired confidence rate of 99 percent is preferred, then the range will be quite large. As a project manager, it is important to weigh accuracy with cost to allow for optimal project performance. With the combination of probability, critical values, and confidence intervals, one of the largest decision-making tools for project managers can be derived, which is known as hypothesis testing. A hypothesis test is used when there are two different outcomes of an event and one of the results is more desired than the other. Zhang et al., (2015); Galli & Hernandez-Lopez (2018); Gimenez-Espin (2013) studied the concept of drawing conclusions using hypothesis testing. This can be done by stating both of the potential outcomes and then using a test statistic with the help of determining a confidence rate to prove which of the outcomes is more likely to occur. Also, this is useful when a project manager wants to know if the project or a new program will be beneficial to the productivity of a company or can help a business to be more successful. Knowing the different types of hypothesis tests and knowing when to use them also helps a project manager become more successful.

Additionally, there are one-tailed and two-tailed hypothesis tests. The one-tailed test is used when the null or alternate hypothesis has a greater than (>) or less than (<) symbol. The reason why this infers a one-tailed test is because it eliminates one side of the data. The other case is a two-tailed test, which is used when the null and alternate hypotheses are used to test equality (=). The two-tailed test is used because probability on both sides of the normal distribution is in question. Along with the different types of tailed tests, a hypothesis test can be completed by using either the critical value (either z or t) or the p-value, which is based on the probability of an event occurring.

A specific type of hypothesis test is the t-test, where the t-value from above is now used to determine if the null hypothesis should be accepted or rejected. As a project manager, decisions on which test to use can help identify the possible outcome of an event occurring. An event does not have to be a whole project, but it could be a segment of a project. T-tests can be used in cases where there are two populations and the goal is to compare the two populations (Lai & Ni, 2014; Galli and Kaviani, 2018; Galli et al., 2017). If a project manager wanted to compare the quality of a product from two different vendors, then a t-test would be an appropriate form of a hypothesis test if the data were normally distributed. As discussed above, The Central Limit Theorem can always be used to offset that issue to approximate the normal distribution. Overall, the concepts of probability, the understanding of sampling distributions, the basics of confidence intervals, and the confidence levels can all help a project manager's success. This would allow for hypothesis testing to occur in ways, such as using the critical value with the goal of determining the likelihood of an event occurring. All of these concepts not only allow for the project manager to define if a project will be successful, but it can also help highlight the riskiest parts of a project through simulation and a different style of analysis, which is known as risk analysis.

As mentioned above, the techniques, methods, tools, and skills of statistical analysis can really help drive a project manager to be successful. Unfortunately, many of the most successful projects do not come without a lot of risk, but a majority of the unsuccessful projects also have a lot of risk involved. The question becomes: how much risk should be taken and where are the points of this project that can be riskier? One method is using the same correlation method that was used when talking about the key descriptive statistics along with linear regression. The fundamentals of this concept revolve around knowing which two variables interact with each other and how much one affects the other (Chaczko, Slehat, & Salmon, 2016; Hoon Kwak, & Dixon, 2008; Loyd, 2016; Usman Tariq, 2013). A basic example of this comes from the cost of products versus the quality of the parts being used. First, it needs to be determined which factor is more important. It is hard to choose both in this scenario because the correlation of cost to quality is very strong, so one would have to be compromised (Elzamly & Hussin, 2014; Xiong et al., 2017; David, David, & David, 2017; Brown & Eisenhardt, 1995). Using this technique, it becomes much more apparent on where the risk on a project should be taken. Another method includes a Pugh Chart, as all of the possibilities are laid out and then ranked with different categories on a scales system. This is used mostly in engineering design, where the categories may be cost, quality, efficiency, etc.

One of the most well-known risk analysis techniques is referred to as a Monte Carlo Simulation. The Monte Carlo Simulation uses methods like a Pugh Chart with the correlation risk assessment to solve for the risk behind an event happening. The Monte Carlo Simulation is fit for its name, as it is most commonly used in casinos for slot machines and determining spreads on sports gambling, but can also be used by a project manager (Bamakan & Dehghanimohammadabadi, 2015; Von Thiele Schwarz, 2017; Papke-Shields & Boyer-Wright, 2017). As a project manager, it may be required to submit a plan of where the riskiest segments of a project are, such as in the prototyping phase, the contractual negotiations, the actual execution of the plan, or any combination of these. The simulation technique allows for the deterministic percentages to indicate the likelihood of an event occurring. Though this sounds like basic probability, it takes outside factors into account and is quite a lengthy process. First, it labels the segments of the project or different tasks and then ranks them on importance. With the process above put in conjunction with listing where the challenges that may appear, the final risk assessment can be provided to help drive a project manager to develop a successful project. Also, the manager can have more time to work if it is known which segments of a project need the most attention. If a segment is very low risk, then the same supervision may not be required, as opposed to a high risk task.

With technology advancing, there are many kinds of computer software that create an easier experience for a project manager. This software starts with the basic programming languages, such as python, MATLAB, R, SQL, and many others. They all have statistical packages that can calculate the key descriptive statistics and even perform hypothesis testing. As time has evolved, people lost interest in learning these programs, so user interfaces were created, such as excel, Alteryx, Tableau, and Google. With this software, all analysis becomes easier, such as through creating graphs, tables, charts, and ranging to hypothesis testing and sampling distributions. Thus, the work of 10 analysts can be replaced by a highly skilled project manager.

Organizational Implications

As seen within this research of the acquired skill and management strategies, it is clear that these variables, their concepts, and models are vital to business projects and project management, as they can generate teamwork skills to help achieve goals. Furthermore, there must be strategic planning behind any leadership approach, which includes a top-down and bottom-up approach for project management, operations management, and process improvement. Thus, leadership and management need proper training for project management, performance, and overall growth. This study shows that insufficient leadership is at the root of project management and operational performance, so the bottom line should not only be emphasized. The most fundamental finding is that these variables, their concepts, and models need more emphasis over financial elements. A financial focus will only lead to short-term results, so leadership needs to emphasize the management of many business elements (i.e., operations, project management, financials, performance, strategy, and human resources). In the end, leadership will have realized that many aspects of a business affect its present and future success.

Managerial & Team Implications

Firstly, the results examine the variables, concepts, and models in a new fashion to fill a research void. Furthermore, this study examines how the variables, concepts, and models are affected by each other and outside factors. Secondly, this study is a useful outline for projects and performances of organizations that can yield more effective management and training materials. Businesses and teams will better realize their shortcomings and performance gaps, which can lead to more successful projects and objectives. Thirdly, this study reveals the advantages of more comprehensive training programs within projects and businesses. Most of all, project teams, project leadership, and organizational leadership will find better training constructs for examining a team, project, or business's performance to measure it against standard and industry accepted models. Overall, performance and effectiveness will improve.

Implications & Applications to Fields of Project Management & Engineering Management

Engineers and technical professions also could use more attention. An engineer's function was to utilize math and technology to problem-solve, but the role of the contemporary engineer is now to use these skills to generate economically viable solutions. As a result, these variables, their concepts, and models are necessary to engineering decisions, as business management and maturity models will help the engineer to gain technical knowledge for their investors' best interests.

Engineering and management concepts both rely on scientific constructs, which has created different management schools of thinking. Furthermore, the basis of engineering is the cause and effect relationship, which is a scientific term that makes management and engineering correlate. Since research takes a business approach to explain the models, then this study takes an engineering perspective. Also, pure engineering filed techniques, including budgeting, equipment, and purchasing material, are addressed, so engineers and project managers will gain methods for decision-making in engineering problems.

Assessing scholarly information on these variables, their concepts, and models is the root of this research, and the objective of this study is to find their best practices for future reference. These variables, their concepts, models, and principles are highlighted within this study, as the research is based on literature to aid in managing projects to improve current management standards. In the IE/EM profession and research field, project management and operational performance are essential. With lean thinking, all problems cannot be solved. Thus, these variables, their concepts, and models are best for creating a new environment in the IE/EM profession. However, it must be made clear that the structural orientation of a scope can make those within the IE/EM generate the scopes of interest needed at every level.

Lastly, stakeholders (i.e., system engineers, project managers, other industrial engineering and engineering management experts) will gain knowledge on initiating maturity into project management. Also, stakeholders can find encouragement to best utilize the system engineering and project management roles, which will help business projects to become more successful.

CONCLUSIONS

Future Research

In future research, the variables, concepts, models, and relationships can be explored in reference to other industries and managerial settings to find their strengths, weaknesses, and other impacts. Also, future research can assess these factors and their relationship within organizational, strategic, cultural, and other perspectives to see how the relationship is viewed within these different arenas. It can be better understood how deeply the variables, concepts, models, and their relationship influence culture, strategy, human resources, and operations.

Limitations

There are several limitations within this study. First, this study features a small sample size. Also, only certain factors were studied from this limited sample, which can lead to bias for the findings and conclusions. A larger sample size would alleviate the limitation. Second, this study only assessed the key factors and their relationship from a project environment perspective, which makes the conclusions and analysis exclusive to project environments. Thus, the findings may not apply to other arenas, including supply chain management, operations management, or strategic management, as the conclusions and analysis have become too specific.

General Conclusions

Essentially, the success of a project manager is defined by the success of the project that they are leading. If their reputation is known for completing projects on time and being successful, then it is directly correlated with the success of that manager. On the other hand, if a project manager is constantly having trouble and cannot complete tasks efficiently or successfully, then their time in that position may not last too long. Personality plays a big role when managing anything, but what is constant for any manager is the fact that there are tools and software out there. The basic skills, such as building charts, can help understand the data and can give executives a better view of the current situation. With the direction of graphs, an experiment can be defined to help prove results about the future of a project, which is done with the basics of probability, confidence interval design, and hypothesis testing. The knowledge of these methods with the understanding of the statistical computer software can allow a project manager to define his or her own success. He or she can develop a plan that will help create the concepts of a project, identify the key points, break the project up into tasks, identify the risks, and generate a well realized analysis for a project's success.

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