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Probabilistic Algorithms, Lean Methodology Techniques, and Cell Optimization Results

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This is to certify that the doctoral study by

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Walden University
2019

Abstract

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MS, Walden University, 2015

MBA, Ottawa University, 2013

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Doctoral Study Submitted in Partial Fulfillment

of the Requirements for the Degree of

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Abstract

There is a significant technology deficiency within the U.S. manufacturing industry compared to other countries. To adequately compete in the global market, lean manufacturing organizations in the United States need to look beyond their traditional methods of evaluating their processes to optimize their assembly cells for efficiency. Utilizing the task-technology fit theory this quantitative correlational study examined the relationships among software using probabilistic algorithms, lean methodology techniques, and manufacturer cell optimization results. Participants consisted of individuals performing the role of the systems analyst within a manufacturing organization using lean methodologies in the Southwestern United States. Data were collected from 118 responses from systems analysts through a survey instrument, which was an integration of two instruments with proven reliability. Multiple regression analysis revealed significant positive relationships among software using probabilistic algorithms, lean methodology, and cell optimization results. These findings may provide management with information regarding the skillsets required for systems analysts to implement software using probabilistic algorithms and lean manufacturing techniques to improve cell optimization results. The findings of this study may contribute to society through the potential to bring sustainable economic improvement to impoverished communities through the implementation of efficient manufacturing solutions with lower capital expenditures.

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Table of Contents

List of Tables

List of Figures

Section 1: Foundation of the Study

Background of the Problem

Systems analysts at lean manufacturing organizations routinely investigate new technologies to pursue quality and efficiency. However, when compared to other countries. there is a significant technology deficiency within the United States' manufacturing industry (Shih, 2014). Furthermore, impactful decisions regarding operation change planning are often made using unreliable data, which could increase costs to the organizations (Jamali et al., 2017). To adequately compete in the global market, lean manufacturing organizations in the United States need to look beyond traditional methods of evaluating their processes to optimize their assembly cells for efficiency.

Problem Statement

Despite multiple efforts through government interventions, inefficient manufacturing techniques continue to weaken the U.S. manufacturing sector and the strength of the United States in the global market (Shih, 2014).Hemphill (2014) noted that 75% of respondents to surveys believe that America should invest more in its manufacturing base. Lean based manufacturing companies in the United States are failing to apply advanced programming techniques to optimize growth and competitiveness. More specifically, some systems analysts within United States-based manufacturer companies lack understanding of the relationship between software-utilizing probabilistic algorithms, lean methodology techniques, and manufacturers cell optimization results. Although extensive research has been conducted on the benefits of lean manufacturing (see Abdulmalek & Rajgopal), no research has been conducted on the use programmatic simulations for lean environments. Furthermore, an understanding of how manufacturing firms make technological investment decisions has been correlated to the success of a U.S. technological revival (Nelson, 1991). Therefore, the focus of this study was on the relationships among software utilizing probabilistic algorithms, lean methodology techniques, and manufacturer cell optimization results to gain an understanding of how information technology decisions are made to optimize workflow changes.

Purpose Statement

The purpose of this quantitative correlational study was to examine the relationships among software utilizing probabilistic algorithms, lean methodology techniques, and manufacturer cell optimization results. The targeted population was systems analysts within manufacturing organizations who were practicing lean methodology techniques in the Southwestern region of the United States. This population was appropriate because systems analysts evaluate and select information technology tools to be utilized for specific tasks. The independent variables were the modeling software utilizing probabilistic algorithms and the lean methodology techniques. The dependent variable was the manufacturers' cell optimization results.

Nature of the Study

I chose the quantitative research method for this research study because it was appropriate for examining the relationships among variables (Karanja, Zaveri, & Ahme, 2013) through the use of statistical analysis, yielding numerical results (Curtis, Comiskey, & Dempsey, 2016). Qualitative methods, used to explain a phenomenon or explore the outcome of an incident (Myers, 1997), were not applicable for this research because explaining a phenomenon or exploring the outcome of an incident were not goals of this research. Because mixed-methods research utilizes multiple sources of data from both quantitative and qualitative sources (Leedy & Ormond, 2010), mixed-methods analysis was not applicable to this research.

Quasi-experimental and true experimental approaches were not selected for this research because I did not intent to manipulate the variables under investigation (Liao et al., 2014; Mutz & Pemantle, 2015). Quantitative correlation research design, as described by Leedy and Ormrod (2010), is not intended to change or influence the circumstances under investigation, but rather, to reveal statistical associations among variables. Therefore, I chose a quantitative correlational research design to explore relationships among software utilizing probabilistic algorithms, lean methodology techniques, and manufacturers cell optimization results without the intent to intervene.

Research Question and Hypotheses

What is the relationship between software utilizing probabilistic algorithms, lean methodology techniques, and the cell optimization results?

Null Hypothesis (H_0): There is no statistically significant relationship between software utilizing probabilistic algorithms, lean methodology techniques, and the cell optimization results.

Alternative Hypothesis (H_1): There is a statistically significant relationship between software utilizing probabilistic algorithms, lean methodology techniques, and the cell optimization results.

The independent variables were the modeling software utilizing probabilistic algorithms and the lean methodology techniques. The dependent variable was the cell optimization results.

Theoretical Framework

Task-technology fit theory for information systems was proposed by Goodhue and Thompson (1995), seeking to design a model to align individual performance of a task with technology. The theory was redesigned by Zigurs and Buckland (1998) to support group tasks rather than individual tasks. Task-technology fit theory is applicable to research problems in which researchers seek to understand the use of technology to support a specific task. More specifically, the framework of the task-technology fit theory can be used to analyze how a technology solution will impact individual or group performance. Additionally, the task-technology fit theory is appropriate for measuring an individual's or group's beliefs about how satisfactorily systems meet task needs, which can influence performance (Zigurs & Buckland, 1998). Applied to this study, the task portion of the theory was the practice of lean methodology techniques by systems analysts and the technology portion of the theory was software programs that used probabilistic algorithms.

Definition of Terms

Probabilistic algorithms: Algorithms that perform probabilistic inference through random variables (De Raedt & Kimmig, 2015).

Assumptions, Limitations, and Delimitations

Assumptions are realistic expectations that researchers can accept as true or possible (Silverman, 1993). I had three assumptions regarding this study. The primary assumption was that respondents would be truthful and thoughtful in their responses. The second assumption was that the information I retrieved from the U.S. Census Bureau about manufacturing organizations was accurate within an acceptable margin of error. Finally, I also assumed that survey respondents would be free of ulterior motives to shape the research through their responses to the research instruments.

Limitations are uncontrollable insufficiencies, contexts, or stimuli that might confine research studies (Silverman, 1993). Unknown, and thus unmeasured, factors or conditions can influence the hypothesized variable relationship (Kimberlin & Winterstein, 2008). I identified three limitations for this study based on their potential to influence the measured variable relationship: (a) the participants' career length in the manufacturing industry, (b) the participants' current employment status, and (c) the geographic location of the participants.

Delimitations

Delimitations refer to the boundaries of a research study (Thomas, Silverman, & Nelson, 2015). The primary delimitation of this study was the geographic location of the participants of the survey group. The geographic location of the survey population was the western region of the United States. Therefore, the results of this study might not be generalizable to systems analysts who work in another location in the United States or in another country.

Significance of the Study

Contribution to Information Technology Practice

Information technology provides multiple sources for tools that can be utilized to model possibilities when appropriate data sets are provided and explained. However, impactful decisions regarding operation change planning in manufacturing companies are often made using unreliable data, which could increase costs to the organizations (Jamali et al., 2017). The adoption of adaptive programming techniques such as probabilistic programming to analyze and model operational planning would help to increase the accuracy of data used for operation-related decisions (Jamali et al., 2017). To adequately compete in the global market, lean manufacturing organizations in the United States need to look beyond traditional methods of evaluating their processes to optimize their assembly cells for efficiency.

This study contributes to existing literature by providing knowledge about the relationships among programs with probabilistic algorithms, lean methodology techniques, and the results of cell optimization for information technology groups, as well as highlights the gaps in the skills and training of systems analysts in manufacturing organizations. These insights might inform management about the skill sets required for systems analysts to implement software utilizing probabilistic algorithms and lean manufacturing techniques to improve cell optimization results, as well as inspire further research in this area.

Implications for Social Change

The findings of this study may contribute to society through the potential to bring sustainable economic improvement to impoverished communities through implementation of efficient manufacturing solutions with lower capital expenditures. The ability for impoverished communities to implement these solutions could result in localized job creation. Furthermore, increased job creation could create a positive economic shift and increased discretionary spending. These benefits could increase the economic standing of the overall community.

A Review of the Professional and Academic Literature

The purpose of this quantitative correlational study was to examine the relationships among software utilizing probabilistic algorithms, lean methodology techniques, and cell optimization results with the intention to understand how information technology decisions are made to optimize workflow changes. Lean manufacturing techniques and their implications for multiple aspects of organizations have been explored by multiple researchers. In this section, I provide a synthesis of the literature related to probabilistic algorithms, lean methodology techniques, cell optimization, and task-technology fit theory. Within this synthesis, I offer an overview of (a) lean manufacturing techniques, (b) cell optimization functions, (c) how cell optimizations are performed, and (d) how cell optimizations are measured. Conducting a review of the professional and academic literature helped me to understand scholarly content regarding lean manufacturing implementations, including existing and new performance measurement techniques and strategies.

I primarily used Walden University's library search engines for my literature search, including EBSCOhost, ProQuest, dissertations, computer science specific databases, and Google Scholar. I narrowed my search to include only peer-reviewed articles and used the following keywords and phrases to search the literature for studies relevant to the manufacturing market: *cell optimization*, *genetic algorithms*, *learning systems*, *lean manufacturing*, *manufacturing*, *probabilistic programming*, *probabilistic algorithms*, and *stochastic*. The search returned an excess of 10,000 varied articles, dissertations, and books. Several hundred of the articles were from peer-reviewed journals. I verified the peer-review status of the articles by using Ulrich's Global Serials Directory, as well as by analyzing the journals' websites. I read 64 articles, of which 59 (93%) were peer reviewed. The number of articles within five years of my anticipated graduation date was 56 (87%). Some literature was intentionally omitted because it was not relevant to the topic.

Task-Technology Fit Theory

The task-technology fit theory was used as the theoretical framework for this study. Task-technology fit theory for information systems was initially proposed in 1995 by Goodhue and Thompson, seeking to develop a model that aligns individual performance of a task with technology. According to the theory, if the capabilities of Information Communication and Technology (ICT) match the responsibilities of the user, individual performance is improved (Wasikie, 2016). Facets of individual performance include efficiency, effectiveness, and quality (Lai, 2017).

Task-technology fit theory has been refined and expanded several times. Goodhue (1998) expanded the task-technology fit theory beyond individual performance to evaluate the overall information systems and services provided within an organization. Goodhue (1998) asserted that a multidimensional view is required to provide a true understanding of the technology fit within an organization. According to Goodhue's (1998) research, the task-technology fit model was a good tool for evaluating performance of an organization as it relates to the degree of fit between the technology and the user.

Whereas Goodhue's (1998) research focused on the individual users' perceptions of how their tasks needs were met with technology, Zigurs and Buckland (1998) expanded upon the theory to include group support systems, or groups of individuals within organizations. Zigurs and Buckland (1998) examined the relationship between a group's use of technology, the fit of the technology, and the degree of performance impact. The researchers asserted that an appropriate fit between task and technology would increase the group's overall performance. Upon completing their research, Zigurs and Buckland (1998) concluded that the task-technology fit model was an effective tool for evaluating performance as it relates to the degree of fit between technology and the group of users. Changchun, Haider, and Akram (2017) conducted research to investigate the relationship between groups of users and the adoption of new technology as it related to finances. More specifically, the research extended the task-technology fit theory to include the influence of users' attitudes toward the fit of technology to the task.

Theory Application

Task-technology fit theory is relevant to studies examining variables that influence technology utilization because it has been used to address practical problems concerning information technology and utilization across several disciplines. Furthermore, the task-technology fit theory is an expansive theory that is applicable to quantitative and qualitative studies for a wide range of research subjects. In this section, I discuss how researchers have applied task-technology fit theory in practical applications involving technology in countries around the globe.

Task-technology fit theory is suitable for a researcher to examine a diverse range of problems in information technology (Xiao, Meredith, & Gao, 2017; Zigurs & Buckland, 1998). Information technology is often utilized by organizations for solutions for business and organizational issues. Business leaders often attempt to utilize information technology to remediate the underlying cause of perceived deficits within organizational performance (Zigurs & Buckland, 1998). Researchers have demonstrated that organizations in multiple markets have increasingly utilized information technology for revenue expansion and cost reduction (Mithas & Rust, 2016; Shi, 2017). Organizations with logistics issues could apply the same technology for cost reduction. However, not all researchers have shared this belief regarding the impact of information technology. Kim, Park, Ahn, and Rho (2015) and Shih, Lai, & Cheng (2015) purported that the adoption or utilization of new technology does not guarantee improved performance. Rather, technology must properly support the individual’s or group’s tasks to expect performance improvement (Kim et al., 2015; Shih et al., 2015).

In their research on how to enhance the fit of technology to create perceived performance improvement of reverse logistics in U.S. companies, Huscroft, Hazen, Hall, and Hanna (2013) and Kembro, Näslund, and Olhager (2017) used the task-technology fit theory as the theoretical framework. The researchers determined that information technology could increase the performance of reverse logistics when the technology was a proper fit for the task. Furthermore, an understanding the fit of technology to the task can lead to an understanding of the performance impact (Huscroft et al., 2013; Kembro et al., 2017).

Task-technology fit theory has been employed by researchers to help explain the selection of a technology over other technologies to support tasks. Hsiao (2017) utilized the task-technology fit theory to help understand the reasons consumers choose one smartwatch over other options. Kim, Chung, Lee, and Preis (2013) used the task-technology theory to examine the relationships influencing the adoption of RFID. Additionally, Kim et al. (2013) further refined the task-technology fit theory by including the users' perceptions about the ease of use of the technology.

Xiao et al. (2017) used the task-fit technology theory as the theoretical foundation in their study to examine managers' choices regarding the use of tablets at work for decision making. From a business productivity and efficiency perspective, task-technology fit has been studied as a diagnostic tool for measuring the success of such information technology adoption (Goodhue & Thompson, 1995). In the context of task-technology fit theory, Goodhue and Thompson (1995) and Xiao et al. (2017) focused on the relationships among specific aspects of technology and managers' decisions to determine the fit.

Numerous researchers have sought to understand the reasons that technology integration projects fail due to lack of acceptance or poor fit within businesses. Based on the task-technology fit theory, the use of a technology may result in different outcomes, depending upon its configuration and the task for which it is used (Goodhue & Thompson, 1995). Despite considerable research into technology utilization, lack of acceptance and poor fit of technology are reported as frequent reasons for project failure (Brandon-Jones & Kauppi, 2018; Pelzer, Arciniegas, Geertman, & Lenferink, 2015). Lin (2014) created a list of characteristics that might encourage a researcher decide to utilize the task-technology fit theory over other task-oriented frameworks. These characteristics included: (a) mandatory technology use, (b) measurement of appropriateness of task characteristics, (c) and measurement of technology fit to the task and the individual or group. Lin (2014) and Shih et al. (2015) argued, however, that task-technology fit is not appropriate for measuring long-term performance for situations in which the technology used is not mandatory. In contradiction to Lin (2014), Tripathi (2017) asserted that while technology might be a fit for the task, its effectiveness depends upon acceptance of the technology. Because there is no validated measurement for the acceptance of technology by individuals or groups, the influence of users' attitudes toward technology was not explored in this study.

Other Frameworks

The task-technology fit theory is not the only theoretical framework available for evaluation of technology adoption. I considered multiple theoretical frameworks that could support the variables for this research study, including the theory of reasoned action, the technology acceptance model, and the diffusion of innovation theory, as all of these frameworks have been utilized by researchers in technology adoption studies.

The theory of reasoned action is a theory commonly used to examine technology adoption. According to Bölöni et al., (2018), the theory of reasoned action was initially developed in 1975 by Fishbein and Ajzen (1980) to offer an approach to examine and understand human behavior in order to address, change, and design functional interventions for human social behavior when necessary. According to Fishbein and Ajzen (1980), the theory of reasoned action could be applied to most all human behavior, including business involvement. The theory of reasoned action is an empirically valid and economical social psychology theory used to explain the various determinants involving the adoption of technology (Yousafzai, Foxall, & Pallister, 2010). Researchers have used the theory of reasoned action to explain consumer decision-making by examining the relationship between consumer attitudes and behavior toward electronic commerce adoption (Yousafzai et al., 2010). Although the potential for predicting behavior is one of the strengths of the theory of reasoned action, it is dependent on individuals making rational decisions and considering the results of their decisions (Furukawa, 2016). Attitude and social norms are fundamental concepts for the theory of reasoned action. Attitude and social norms for intention must be measured when applying the theory of reasoned action to research (Furukawa, 2016; Lee, Lin, Wu, Lin, & Huang, 2018). According to researchers Fishbein and Ajzen (1980), the measure of an individual's attitude and subjective normative beliefs towards an action can be used to predict behavioral intent. Because it was not my intention to understand the relationship between the reasoned action constructs (attitude and subjective norms) of systems analysts, I did not select the theory of reasoned action for the theoretical framework in this study.

The diffusion of innovation theory is the most preferred theory for investigating technology adoption due to the well-defined concepts and empirical evidence (Kim et al., 2015). Like task-technology fit theory, the diffusion of innovation theory has been utilized by researchers to help evaluate the implementation of technology to replace manual tasks. The diffusion of innovation theory was defined by Everett Rogers in 1962 as the process by which an innovation is communicated through certain channels over time among the members of a social system (Scott & McGuire, 2017). The theory has been expanded through further research. For example, research into the utilization of the diffusion of innovation theory was undertaken by Szymczyk and Kamiński (2014), who focused on the element of appropriateness of usage. According to the researchers, although the framework is supportive of innovations such as modeling, the narrow focus on user selection does not fully capture a broad reason of usage. The use of the diffusion of innovation theory as a framework would require that the study focus on the choice of a systems analyst regarding technology adoption (Szymczyk & Kamiński, 2014). Therefore, the diffusion of innovation theory was not appropriate for a framework for this study.

The technology acceptance model is similar to the task-technology fit theory regarding the use of technology by individuals and groups. The technology acceptance model was first introduced by researcher Fred Davis in 1986 as a theoretical model for evaluating technology (Brandon-Jones & Kauppi, 2018; Lai, 2017). The technology acceptance model was designed due to the need for a model to explain user behavior, which could further predict and explain the acceptance of technology. According to Davis, Bagozzi, and Warshaw (1989) and Brandon-Jones and Kauppi (2018), the model provides a basis for understanding the impact of external variables on a person's internal beliefs, attitudes, and intentions. These factors are what distinguishes the technology acceptance model from the task-technology fit theory.

Proponents of the technology acceptance model have suggested that the perceived ease of use and usefulness of a technology are the two most important factors in the evaluation of technology use (Wu & Chen, 2017). The technology acceptance model has undergone many refinements since its introduction to keep pace with new innovations while retaining its focus on the ease of usage and usefulness of a technology (Wu & Chen, 2017). On the other hand, proponents of the task-technology fit theory have argued that the technology acceptance model overlooks the fact that utilization of a technology does not always lead to higher performance, which negates the usefulness of the technology (Goodhue & Thompson, 1995). The focus of the task-technology fit theory is on the requirements of the task, task completion efficiency, and the usage of resources (Kim et al., 2015; Wu & Chen, 2017), which was appropriate for my study. The implementation of the technology acceptance model would require a focus on the degree of usefulness of the software and the system analyst rather than task-related variables. Therefore, I determined that the technology acceptance model was not appropriate for use in my study.

Theory Relation to Cell Optimization Results

Technology-based performance improvements are deemed successful when the technology supports the requirements of the task. Performance improvement in this context relates to the degree of perceived improvement in accomplishing the tasks by the individual or group. Goodhue and Thompson (1995) defined a *fit* as the meeting of the requirements of a task. Task-technology fit is the degree to which a technology may assist an individual or group in the performance of tasks.

The methods used to measure performance within manufacturing environments have remained standard. Global competition has caused some manufacturing organizations to investigate new methods of improvement and measuring performance. Performance management can lead to controlled overhead costs and reduced operational expenses, which could allow manufacturers to be more competitive (Karim, Tuan, & Kays, 2016; Omogbai & Salonitis, 2016). However, current methods of lean manufacturing performance measurement techniques have not advanced significantly from early lean assessment tools (Gündüz, 2015). Lean assessment tools, used to evaluate potential areas for improvement within an organization, do not provide an idea of how proposed changes will operate in reality (Gündüz, 2015; Omogbai & Salonitis, 2016). Gündüz (2015) asserted that advances must be made to determine the relationship between lean manufacturing change and the performance impact.

Researchers have explored nontraditional methods of measuring performance by incorporating techniques from other disciplines. For example, Ren et al. (2015) utilized principal parameters analysis combined with typical flow analysis to calculate performance of an assembly line after modification. The researchers determined that the measurement of changes to a manufacturing assembly area could benefit from an understanding of the details of the task. Likewise, understanding the fit between technology and task could enable a greater understanding of performance implications (Goodhue & Thompson, 1995; Tripathi & Jigeesh, 2015). Researchers have investigated the analysts' understanding of automated work results. For example, Treem, Dailey, Pierce, and Leonardi (2015) and Vieira da Cunha, Carugati, and Leclercq-Vandelannoitte (2015) examined the effectiveness of utilizing automated technology to augment a group's work when work instructions are provided. Researchers found that workers may not be able to describe automated work results as accurately as manual task results. This may be due to a lack of understanding of the task or the benefit the automated technology provides the worker (Treem et al., 2015; Vieira da Cunha et al., 2015). If technology is not helping knowledgeable workers at their personal level and is not aligned with the workers' skills, it can be perceived as an imposition (Treem et al., 2015).

Multiple mechanisms have been explored for measuring the improvement of manufacturing cells. Sarkar, Mukhopadhyay, and Ghosh (2015) conducted an experiment designed to increase the throughput of cells in a textile manufacturing facility through a reduction in idle time. They chose six-sigma as the process improvement framework instead of lean manufacturing techniques. According to Sarkar et al. (2015), previous cell optimization attempts using the prevalent best practices did not produce the desired improvements due to yield uncertainties. The researchers asserted that nonalgorithm methods of modeling are not appropriate in an environment that contains uncertainty or randomization of variables, and they determined that a more cost-effective approach would be simulating the changes through an understanding of the variables that need to be modified. Sarkar et al.'s research was focused on the application of an automated technology to replace a manual activity within a lean manufacturing environment. The application of the task-technology fit theory specifically evaluates the appropriateness of a technology solution for a distinct task.

Kim et al. (2013) and Kim et al. (2015) examined the challenges of technology improvements to improve performance in an organization. They used task-technology fit theory to examine the use of radio frequency identifiers in place of barcode technology and its impact on business performance. According to Kim et al. (2015), previous research focused on technology acceptance models ignored scenarios where technology usage was mandatory for the users. Likewise, Goodhue and Thompson (1995) and Zigurs Buckland (1998) asserted that technology acceptance models often overlook the fact that that greater utilization of technology does not necessarily lead to higher performance.

Theory Relation to Probabilistic Algorithms

The results of this study may assist manufacturers' understanding of the relationship between software that utilizes probabilistic algorithms to model and simulate changes and the impact on cell optimization. The ability to simulate changes for training or change analysis is not a new concept in the workplace. Wasikie (2016) conducted research using the task-technology fit theory to explore the implications of technology innovation to improve customer loyalty and its relationship to organizational performance. Goodhue and Thompson (1995) and Zigurs and Buckland (1998) used the task-technology fit theory to determine if the use of innovative technology in the banking industry would have an impact on overall bank performance. According to the researchers, the factors that determined task-technology fit included the following: (a) perceived value, (b) locatability, (c) user consent, (d) task compatibility, (e) ease of use, (f) offer of training, (g) production timeliness, (h) systems reliability, and (i) association with users. The systems reliability and ease of use factors were determined to have a direct influence on customer loyalty (Goodhue & Thompson, 1995; Zigurs & Buckland, 1998).

In their study on the use of simulation modeling to increase productivity after a building change for employees, Merschbrock, Lassen, Tollnes, and Munkvold (2016) used the task-technology fit theory for their framework and asked, “How can BIM and gaming be integrated to support professionals in their learning about the spatial layout of a new building?” The researchers sought to align the analysis of the results with task-technology fit constructs. Task-technology fit constructs are defined as (a) task requirements, (b) functionality of the information technology system, (c) individual abilities, and (d) user evaluation (Diatmika, Irianto, & Baridwan, 2016). The task-technology fit theory was employed in research by Park, Sawy, and Fiss (2017) as part of a theoretical foundation to examine the use of information technology in the context of business system tools within organizations to optimize business agility. More specifically, Park et al. (2017) sought to determine whether frameworks such as business-intelligence coupled with algorithms was sought after by organizations. The results of the study indicated that there were limited options readily available that fit organizational needs. Furthermore, existing solutions applied by smaller companies did not provide an adequate fit.

Theory Relation to Lean Methodology Techniques

The usage of lean methodology techniques within an organization provides a motivation to frequently measure to determine if progress has been made. Lean methodology techniques encourage frequent measurement to maintain efficiency within the organization. Karim, Tuan, & Kays (2016) and Sharma, Dixit, & Qadri (2016) conducted research which investigated the potential relationship between lean methodologies and manufacturing assembly performance. Identification of measurable variables that are impacted by manufacturing changes are essential to lean implementation projects. Sharma, Dixit, & Qadri determined that the indicators in the automotive sectors in India are: quality, employee satisfaction, waste, and supply chain performance. Alotaibi & Alotaibi (2016) have stated that the implementation of lean manufacturing techniques involves a process of continuous improvement. The process of sustaining continuous improvement involves the implementation team to measure after changes have occurred to determine if improvements have been made. The implementation of a standard simulator specifically designed for manufacturing environments would enable streamlined improvements (Chen & Wang, 2016). Chen & Chiu (2017) conducted experimental research to compare cloud-based manufacturing simulation to existing methodologies of manufacturing simulation. The research consisted of factory and job data collection, model construction, model validation and verification, running and replication, performance reporting, and optimization. Chen & Chiu utilized an extensive database to simulate the manufacturing operations including probability distributions.

The research product seeks an understanding of the relationship between software that utilizes probabilistic algorithms, lean methodology techniques, and cell optimization results changes. When the tasks to be done and the assistance the technology provides reach a certain degree of fit, the consumer's intention to adopt the technology increases (Goodhue & Thompson, 1995). Tasks have been previously broadly defined as the actions carried out in turning inputs to outputs in order to satisfy information needs. Current research has explored the impact of task characteristics. Researchers Kim, Park, Ahn, & Rho (2015) have stated that numerous empirical tests have shown that the task-technology fit model is a robust theoretical foundation for explaining the utilization and impact of information technology in work performance by evaluation of task characteristics and technology characteristics.

Lean Methodology

Manufacturing organizations have utilized multiple practices and methodologies in the pursuit of increased efficiency and perceived performance. Increased performance is still desired. I have focused my research on organizations using lean manufacturing techniques for several reasons. First, researchers such as Karim & Arif-Uz-Zaman (2013) and Dotoli et al., (2015) and Marin-Garcia & Bonavia (2014) have stated that lean manufacturing techniques are widely used and championed by several organizations. Additionally, lean manufacturing techniques compliment organizations that have a need for frequent technology changes. Karim & Arif-Uz-Zaman (2013) and Shah & Ward (2003) stated that organizations that have implemented lean manufacturing techniques experienced an increase in perceived performance and greater adaptability to change. Manufacturing organizations which utilize lean manufacturing techniques multiple practices and methodologies over other techniques may increase efficiency and perceived performance.

Researchers have defined lean manufacturing as a philosophy, a process, a systems approach for productivity improvement, a method and a business strategy. Figure 1 provides a graphical overview of the lean manufacturing techniques and the respective flow to get to the desired target of higher quality. It was further stated by Yadav, Nepal, Rahaman, & Lal (2017) that lean is an integrated socio-technical system with an objective to eliminate waste by through a reduction in supplier, customer, and internal variability. The pursuit of the objective to eliminate waste within the practice of lean for manufacturing organizations has appeared to result in the standardization of multiple techniques. Standardization has helped to refine the focus of researchers. The research conducted by Alotaibi & Alotaibi (2016) and Bhat et al., (2017) and Sharma, Dixit, & Qadri (2016) have allowed researchers to understand that manufacturing organizations have defined several groupings of lean methodology techniques by purpose. Researchers have further stated that the success of lean efforts to reduce waste has a reliance on (1) timely identification, (2) framing of the objectives of the change, (3) organizational buyin. There has been a penchant for treating lean implementation as a cost-cutting strategy to gain quick but short-term gains, or another tool added to a manager's toolkit, thereby corrupting the well thought out and e□ective management approach (Yadav, Nepal, Rahaman, & Lal, 2017). The lean manufacturing methodology is a complex system consisting of multiple practices and techniques which can assist an organization in reducing costs and waste.

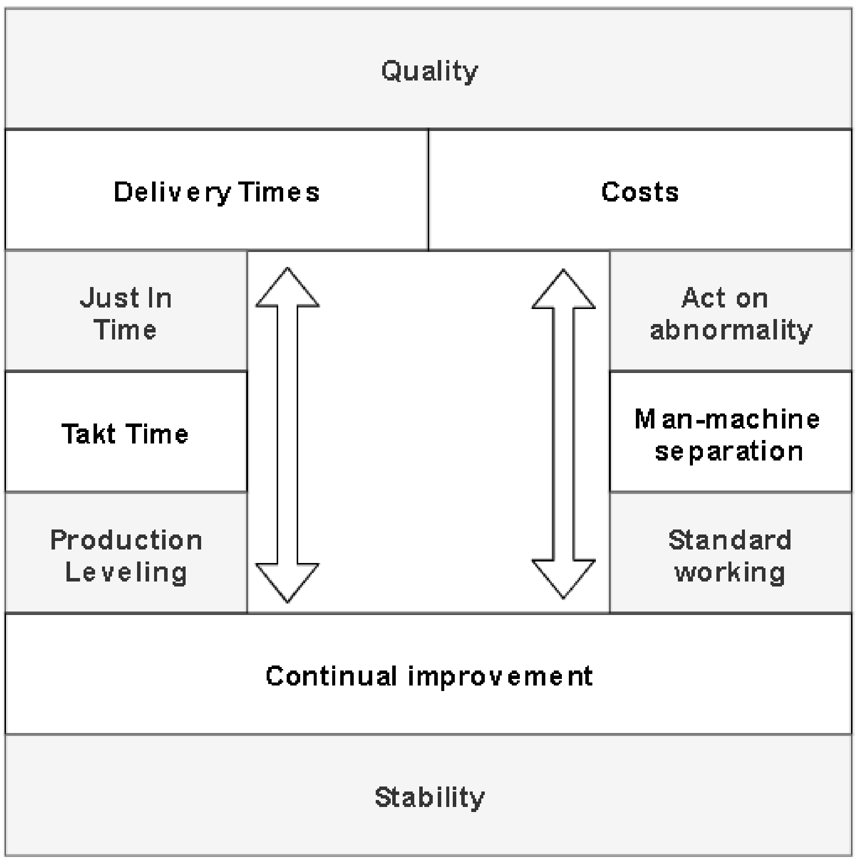

Figure 1. Diagram of lean methodologies and the respect flow.

Organizations which seek to implement lean manufacturing are often pursuing a methodology to achieve a perceived increase in productivity with a reduction in costs. The target of lean manufacturing is to incorporate less human effort, less inventory, less time to develop products, and less space to become highly responsive to customer demand while producing top quality products in the most efficient and economic manner possible (Karim & Arif-Uz-Zaman, 2013). The implementation of a single technique is often not successful. Nawanir, Lim, & Othman (2016) and Zhu & Lin (2017) have published that companies using bundled lean techniques allow for a significant improvement in product design and assembly than companies that do not. The lean methodology has been promoted as a set of techniques to improve organizational performance. It was stated by Eaidgah, Maki, Kurczewski, & Abdekhodaee (2016) and Salonitis & Tsinopoulos (2016) that the objective of a lean implementation is organization performance improvement through a reduction of labor, space, capital, and delivery time. Benefits of lean implementations will often extend into organizational workflow improvements. The implementation of lean manufacturing could improve organizations through a decrease in human effort, inventory, time-to-delivery, and space when implemented using proven techniques and practices

Lean Methodology Techniques

Overproduction of products and excess inventory are examples of waste that are frequent targets for lean coordinators. Sharma, Dixit, & Qadri (2016) have stated that just in time is a system which strives towards production and inventory is maintained as demand-driven with minimal inventory. Just in Time as a practice is usually implemented to control inventory levels which can then encourage cell optimization.

Lean Six Sigma is a technique which can be utilized by analysts to maintain a lean manufacturing culture. Leaders of Lean Six Sigma (LSS) can influence the performance of multinational EMS companies as stated by Ali, Choong, & Jayaraman (2016). Officials of EMS companies who work for OEM companies provide outsourcing platforms to reduce operational costs. The leaders of EMS companies acquire the business from OEM company authorities by providing better services by reducing production costs by implementing LSS programs according to Ali, Choong, & Jayaraman (2016).

One technique used to create measurable process improvement within manufacturing environments is to implement a value stream mapping (VSM) practice. The practice of VSM provides organizations a framework for identifying waste. Multiple research teams including Dotoli, Epicoco, Falagario, Costantino, & Turchiano (2015) and Gündüz (2015) and Forno, Pereira, Forcellini, & Kipper (2014) have stated that organizations that have gone through VSM implementations have shown a measurable improvement in business performance. The implementation of VSM does not guarantee improvement. Belekoukias, Garza-Reyes & Kumar (2014) has stated that organizations should implement a practice to measure the change to detect performance changes. The box score is a common method to determine if the VSM practice is improving the process under investigation. Gündüz additionally states that the VSM team tracking business performance weekly within the box score to track the improvement. Forno, Pereira, Forcellini, & Kipper (2014) further stated that organizations that have implemented a VSM practice have a strategic advantage in market competitiveness through meeting customers' demands. The researchers determined that the advantage could be traced through better planning and control measures. The implementation of a VSM practice, with measurement tools, could create a measurable process improvement in a manufacturing organization with a direct impact on business performance.

Software Utilizing Probabilistic Algorithms

Advanced technologies and tools have been researched and implemented by manufacturing organizations in attempts to improve efficiency. Bodi, Dragomir, Banyai, & Dragomir (2015) have stated that process simulation software is a current topic under research for applicability within manufacturing organizations. Mathematical algorithms are often utilized by process simulation software for functionality. Probabilistic algorithms & programming are tools which analysts can use to perform decision management on incomplete or uncertain data. Many variants of probabilistic languages exist. De Raedt & Kimmig (2015) have stated that a common characteristic is the resolution of problems utilizing random values. Modification of manufacturing assembly cells for product changes involves several unknown variables.

Wilson, Arokiam, Belaidi, & Ladbrook (2016) conducted research to simulate manufacturing systems to determine optimal energy consumption. The researchers integrated to existing software packages to utilize algorithmic approaches to determine optimal usage. The researchers have noted that unknown values are not accommodated in an optimal fashion. The probabilistic algorithm *Monte Carlo* was proposed by Liu & Huang (2015) for modeling unknown values with random values for manufacturing environments. The ability to return a result within constrained probabilities in an efficient manner is a unique feature of a probabilistic programming (Li, Wendt, & Wozny, 2003; De Raedt & Kimmig, 2015). Manufacturing systems designed with probabilistic programming intentions have been advocated as a solution to decision making with uncertainties.

Manufacturing environments are frequently subject to time restrictions which require rapid response from management systems. Existing algorithmic solutions lack the depth and performance necessary for a sustained approach (Liu & Huang, 2015; Halko, Martinsson, & Tropp, 2011). New research into optimal algorithmic approaches shows improvements are possible. Halko, Martinsson, & Tropp (2011) conducted research that helped to determine that randomized algorithms are often faster and more robust than traditional deterministic algorithms. Improved algorithm performance can provide the opportunity for real-time simulations to alleviate time restriction concerns.

Process Improvement and Simulation

Organizations have long been researching and utilizing techniques designed to improve their business performance in order to remain cost competitive, profitable, and agile in the face of new competition and changing market conditions. Process improvement is one technique often utilized. Continuous process improvement workflows (see Figure 2) generally follow a sequence of (1) evaluation, (2) implementation, (3) control, (4) standardization.

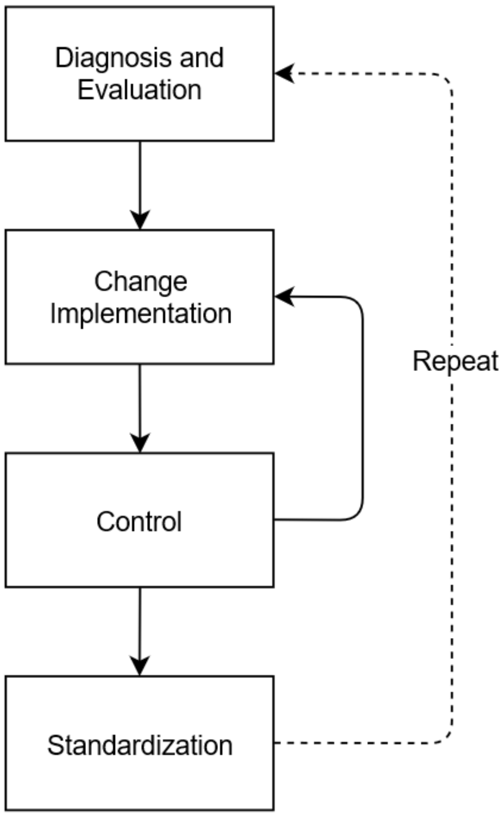

Figure 2. Example of a typical continuous process improvement workflow.

Cost-reduction is a constant concern for manufacturing organizations. While process improvement projects could incur unforeseen costs for the organization when the objective is not successful as stated by Nallusamy, Balakannan, Rekha, & Balasubramanian (2015). Simulation of process improvement as a cost-reduction technique has been utilized successfully by multiple industries including manufacturing. Bochmann, Bänziger, Kunz, & Wegener (2017) and Nallusamy, Balakannan, Rekha, & Balasubramanian (2015) have stated that the greatest cause of inefficiency within manufacturing is increased product individualization and shorter product life cycles to remain competitive in saturated commodity markets. To achieve greater cost reductions, simulation programs have investigated a wide variety of algorithmic approaches.

Noktehdan, Seyedhosseini & Saidi-Mehrabad (2016) stated that the most significant opportunity within manufacturing for algorithmic approaches is cellular manufacturing. Researchers have classified cellular manufacturing as a practice associated with multiple manual processes. The cell formation process is the most time-consuming and important step in cellular manufacturing as stated by Noktehdan, Seyedhosseini & Saidi-Mehrabad and Pinheiro, Martins, Protti, Ochi, Simonetti, & Subramanian (2016). Simulation techniques derived from other manufacturing simulation studies could be applied to reduce time expenditures within cell formation. Schoinochoritis, Chantzis, & Salonitis (2016) applied simulation to resolve an identified time-consuming process within an additive manufacturing organization. The research conclusion stated mixed results were determined. The researchers explained that while simulation had reduced overall time expended, the overall technology has not advanced at the pace expected. Figure 3 provides a graphical overview of how simulation could be added to a typical process improvement work flow.

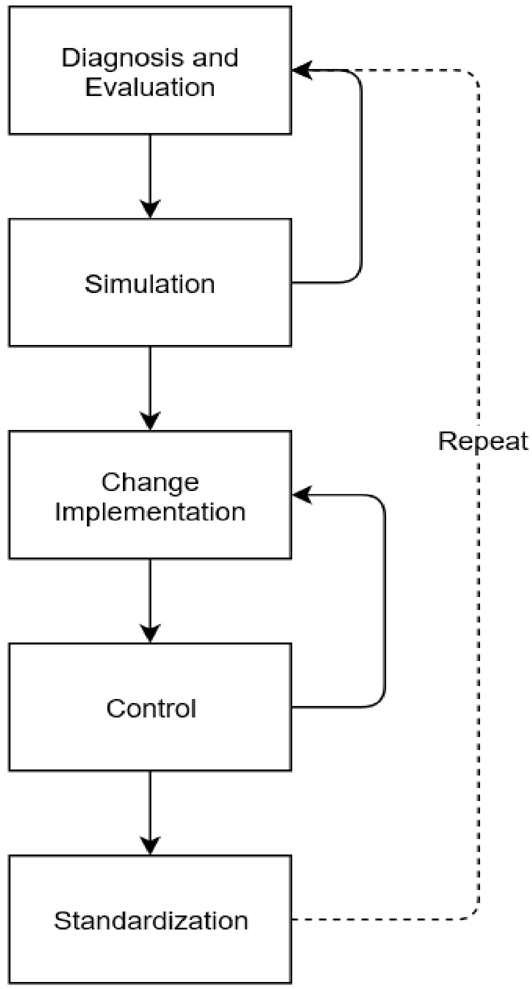

Figure 3. Example of a modified continuous process improvement work flow.

Related Studies

The purpose of this quantitative correlational research study is to examine the relationship between software utilizing probabilistic algorithms and lean methodology techniques has on a manufacturers cell optimization results. The independent variables are the modeling software utilizing probabilistic algorithms and the lean methodology techniques. The dependent variable is the cell optimization results. The targeted population will be systems analysts of manufacturing organizations who are practicing lean methodology techniques while operating within the Southwestern region of the United States. A review of the literature has shown that previous quantitative studies have provided informative research comparing lean manufacturing techniques and other variables on organizational performance. While these studies have provided foundational research, none have included probabilistic algorithms to examine the impact on cell optimization results.

Previous research has been conducted previously to evaluate lean manufacturing technique research with the task-technology fit theory. Researchers such as Tripathi & Jigeesh (2015) conducted studies involving a modified Task Technology Fit theory to evaluate the relationship between technology, groups, and performance. Zigurs & Buckland (1998) have stated that an appropriate fit between task and technology should improve performance.

Research has been conducted previously to investigate the usage of simulation software for lean manufacturing cell optimization. Research conducted by Fadzly, Saad, & Shayfull (2017) investigated the relationship between simulation software and the perceived results of cell optimization. The researchers sought to understand if the usage of purchased simulation software would have a positive impact upon lean manufacturing driven cell optimization. The researchers concluded after reviewing the research data that a positive relationship exists. The researchers concluded that the optimum design for the cellular layout is achieved through simulation software. Research conducted by Florescu, Barabaş, & Sârbu (2017) conducted similar research that echoed similar conclusions as Fadzly, Saad, & Shayfull. The researchers further stated that the variables must be known ahead of time to produce effective simulation results. Not all researchers agree. Researchers Devito, M., Gergle, D., & Birnholtz, J. (2017) have published conflicting results stating that awareness of algorithmic optimization could skew results. Knowledge of algorithmic enhanced technology systems could create bias depending upon user opinion.

Gap in Literature

The purpose of this quantitative correlational research study was to examine the relationship between software utilizing probabilistic algorithms and lean methodology techniques has on a manufacturers cell optimization results. A review of the literature identifies a gap in the literature in regards to the measuring of the success of cellular changes. Golhar & Stamm (1991) conducted research regarding an overview of lean methodology techniques. The research results led Golhar & Stamm to state that while there are studies on cellular changes, there is very little research existing that point to methods to measure the success of U-cell layout changes. Researchers have conducted similar research with the same conclusion. Aalaei & Davoudpour (2016) has stated that future research is needed to explore the development of the model with stochastic algorithms.

Additional gaps in the literature additionally extends to the relationship between software utilizing probabilistic algorithms and lean methodology techniques have on a manufacturers cell optimization results. Literature exists that has explored the relationship between cell optimization results and lean methodology but that relationship did not explain an association to software with probabilistic algorithms. Furthermore, literature existed regarding the relationship of software utilizing probabilistic type algorithms and lean methodology techniques yet literature did not explain the effect that relationship had upon cell optimization. The lack of empirical data pertaining to the association between software utilizing probabilistic algorithms and lean methodology techniques has on a manufacturers cell optimization has demonstrated a gap in the literature which should be explored.

Concluding Remarks

The purpose of this quantitative correlational research study was to examine the relationship between software utilizing probabilistic algorithms and lean methodology techniques has on a manufacturers cell optimization results. The conclusion yielded from the literature review provides ample evidence that there is lack of understanding of the relationship between probabilistic algorithms, lean methodology techniques, and cell optimization results. Software utilizing probabilistic algorithms does not appear to be widely utilized within the manufacturing sector. It was stated by Florescu, Barabaş, & Sârbu (2017) that the development of software to predict the impact of a manufacturing change may not currently return the economic investment desired. Therefore, there is justification to explore the relationship between the independent and dependent variables to find if a relationship exists or not between the variables.

Transition and Summary

This section provides an introduction to the topic of lean methodology techniques and software with probabilistic algorithms. The purpose of this quantitative correlational study is to examine the relationship between software utilizing probabilistic algorithms and lean methodology techniques has on a manufacturers cell optimization results. A sample of individuals performing the role of the systems analyst within a manufacturing organization utilizing lean methodologies in the Southwestern United States will be asked to respond to survey questions. The research problem, research question, and conceptual framework contribute to determining the existence of the relationship between the variables: modeling software utilizing probabilistic, lean methodology techniques, and cell optimization results.

The literature review provides a review of the different applications of lean manufacturing techniques, probabilistic algorithm implementation, and lean performance measurement techniques. My review of the academic and professional literature includes an analysis of sources of lean management cell optimization techniques for systems analysts. The review of the literature also includes theories that influence lean management techniques and their impact upon considerations for performance measurement techniques. The specifics of the overview of quantitative correlational described in Section 1 develop in Section 2. In Section 2, I provide my role, the research instrument, details of the potential participants, ethical considerations, expansion of the study's research method and design and data analysis, and reliability and validity.

Section 2: The Project

In Section 1, I discussed the background of the study, presented the problem and purpose statements, and described the nature of the study. I included in that section the research question, the hypothesis, and a discussion of the theoretical framework I used. I closed Section 1 with a review of the available and relevant academic literature. I discussed the research process I used to conduct my quantitative study of the relationship between probabilistic algorithms, lean methodology techniques, and the cell optimization results. In Section 2, I provide the purpose statement, discuss the role of the researcher, and describe the participants, research method, research design, population sampling, data collection techniques, instrumentation, data organization techniques, data analysis, and the reliability and validity of the study.

Purpose Statement

The purpose of this quantitative correlational study was to examine the relationships among software utilizing probabilistic algorithms, lean methodology techniques, and manufacturer cell optimization results. I have sought to gain an understanding of the tool selection process utilized by systems analysts to model change within manufacturing organizations that use lean techniques. The targeted population consisted of systems analysts within manufacturing organizations who were practicing lean methodology techniques in the Southwestern region of the United States. This population was appropriate because systems analysts evaluate and select information technology tools to be utilized for specific tasks. The independent variables were the modeling software utilizing probabilistic algorithms and the lean methodology techniques. The dependent variable was the cell optimization results. The implication for social change is the potential to bring sustainable economic improvement to impoverished communities through the implementation of efficient manufacturing solutions with lower capital expenditures.

Role of the Researcher

The role of the quantitative researcher is to gather, organize, analyze, and report research results in a manner that is consistent, repeatable, and ethical (Guo, 2015; McCusker & Gunaydin, 2015). I adhered to published ethical standards for quantitative research, which includes guidelines for handling participants and data. More specifically, I followed the ethical guidelines and principles published by the Belmont Report (U.S. Department of Health and Human Services, 2016). According to the Belmont Report, there are three basic ethical principles: (a) respect for persons, (b) respect for beneficence, and (c) respect for justice. I also adhered to the standards of the Walden University Institutional Review Board (IRB).

I was the only individual responsible for ensuring the reliability and validity of the quantitative research data and instrument (Hagan, 2014). To ensure reliability of the data, I was the only person to gather and analyze the data, using approved tools and techniques. . I ensured that the data were valid by utilizing an empirically validated data collection instrument.

Participants

The participants for this doctoral study consisted of individuals performing the role of the systems analyst within a manufacturing organization utilizing lean methodologies in the Southwestern United States. Researchers should set criteria for the participants that will best fit that individual study because utilizing a common standard could lead to invalid results (Coghill & Yarnitsky, 2015; Stuart & Rhodes, 2017). The participants for this study were selected using the following criteria: (a) have now or within one year performed the role of a systems analyst, (b) have more than one year of experience within that role, (c) are located in the Southwestern area of the United States, and (d) have a working knowledge of lean methodology techniques. Systems analysts have a vital role within supply-chain and logistics within manufacturing organizations (Bonney & Jaber, 2014). These criteria restrictions allowed for a statistical measurement of the target population by using a defined sample (Coghill & Yarnitsky, 2015).

I recruited survey participants from online resources, including mailing lists and social media websites that had an aggregation of individuals by career and industry. According to Setia (2016), study participants must be representative of the overall population. All survey participants were solicited through an introductory e-mail in which I introduced myself and described the study. The introductory e-mail was my first point of contact, initiating the formation of the researcher and participant relationship. Because prospective research participants be fully informed about the procedures and risks involved in the research and provide their consent to participate (Guo, 2015; Jajoo & Kakkad, 2016), the e-mail invitation included a link to an online website that included a consent form, a detailed background information disclosure statement, a description of the voluntary nature of the study, the risks of being in the study, privacy statements, contact information of the researcher, contact information for Walden University personnel, and statements that all participants were guaranteed anonymity. The participants were directed to digitally sign the online consent form to confirm their agreement to participate in the study.

Research Method and Design

I chose the quantitative correlation research design for this study to examine the relationships among software utilizing probabilistic algorithms, lean methodology techniques, and the cell optimization results. Correlational research design is not intended to change or influence the circumstances under research, but instead examines the relationship based on statistical associations that could yield evidence (Leedy & Ormrod, 2010). The objective of this quantitative correlational study was to examine the relationships among software utilizing probabilistic algorithms, lean methodology techniques, and manufacturer cell optimization results. The independent variables were the modeling software utilizing probabilistic algorithms and the lean methodology techniques. The dependent variable was the cell optimization results.

Method

I chose the quantitative research method for this study because it was appropriate for examining the relationships among variables (Karanja et al., 2013) using statistical analysis, yielding numerical results (Curtis et al., 2016; Johnson & Onwuegbuzie, 2004; McCusker & Gunaydin, 2015). Quantitative research involves the use of measurements to examine relationships among variables, as well as cause and effect (Watson, 2015). The measurement used in this study enable me to gather statistical data to identify the cause and effect relationships among the following variables: (a) probabilistic algorithms, (b) lean methodology techniques, and (c) the cell optimization results.

Qualitative methods, used to explain a phenomenon or explore the outcome of an incident (Myers, 1997), were not applicable for this research because explaining a phenomenon or exploring the outcome of an incident were not goals of this research. Additionally, qualitative research allows for an inductive approach—or the search of patterns from observation to produce meanings—in the pursuit to advance and build theory (Barczak, 2015; Leedy & Ormrod, 2010; Salkind 2018).. The inductive approach was not suitable for this study because manufactures are not utilizing software that uses probabilistic algorithms. The qualitative approach was not suitable for this study because the relationships among the variables being studies must first be understood before developing a theory. Furthermore, the results of qualitative research typically reflect the experiences of the participants and is characterized as situational, interpretive, and experience-based (Matete, 2017; Sieber, 1973). Because this research project was an analytical study of the relationships among variables and not a study of individual interpretation or observation of a phenomenon, I deemed the qualitative approach inappropriate for use in this study. mixed-method

The mixed-method approach includes a combination of both qualitative and quantitative methods in a single study (Ghosh, 2016; Halcomb & Hickman, 2015; Leedy & Ormond, 2010; Molina-Azorin, Bergh, Corley, & Ketchen, 2017). Quantitative and qualitative approaches combined can be used to develop a better understanding of a phenomenon, to explore the outcome of an incident, or to expand or a develop theory

(Myers, 1997; Sieber, 1973). Furthermore, according to Sieber (1973), mixed-methods researchers should ensure that the data gathering of the qualitative and quantitative data is scheduled to ensure that the study is evaluating relatable data. The scheduling of manufacturing cells is an expensive undertaking for manufacturers without statistical data to provide a predictable degree of success. Because mixed-methods research utilizes of data from both quantitative and qualitative sources, mixed-methods analysis was not applicable to this research.

Research Design

The quantitative method of data collection includes the use of tools that are closed-ended, such as surveys, questionnaires, and correlational analysis (Timmins, 2015). I selected a correlation design and used a survey instrument in this study in order to reach systems analysts across a large geographical area. The output produced by quantitative data collection tools are analyzed through techniques such as counting, comparing, and statistical analysis due to the primarily numerical nature of the data as stated by Hagan (2014). Correlational studies are suitable for determining the existence of relationships among variables and for making predictions about the variables (Becker et al., 2015; Curtis et al., 2016). The correlational research design was suitable for my study because the purpose of the study was to determine the relationships among software utilizing probabilistic algorithms, lean methodology techniques, and manufacturer cell optimization result.

Quasi-experimental and true experimental approaches include a randomization component in which there is an element of manipulation by the researcher (Gerber, Arceneaux, Boudreau, Dowling, & Hillygus, 2015; Heyvaert, Wendt, Van den Noortgate, & Onghena, 2015; Krass, 2016; Liao et al., 2014; Mutz & Pemantle, 2015; Wells, Kolek, Williams, & Saunders, 2015). The nature of this study was an examination of the current relationship among the variables of which manipulation was not possible. Therefore, I did not select quasi-experimental or true experimental approaches for this research because I did not intend to manipulate the variables under investigation. The nature of the hypotheses, the theoretical framework, and the use of surveys in the supporting literature made survey use most appropriate to this study.

Population and Sampling

The population was systems analysts within manufacturing organizations who were practicing lean methodology techniques within the Southwestern region of the United States. Through an Internet page, invited participants completed a set of screenings questions to vet the participant against the demographic requirements for the target population. According to Durand (2013) and Muskat, Blackman, and Muskat (2012), the researcher must choose a population that can provide a sufficient sample size for producing accurate data to determine if there is a relationship between the independent and dependent variables. This population was appropriate for this study because systems analysts evaluate and select information technology tools to be utilized for specific tasks.

I utilized a non-probabilistic convenience sample, which is a common method for non-probability research (Setia, 2016). The convenience sampling method is appropriate when participants are to be selected by availability and convenience (Martínez-Mesa, González-Chica, Duquia, Bonamigo, & Bastos, 2016). A disadvantage to convenience sampling is that the sample is not representative of the population (Etikan, Musa, & Alkassim, 2016). In order to ensure that I received a response rate sufficient for the sample size and requirements of the study, I used a process to remind participants to complete and return the survey. Although multiple factors have an impact upon response rate, the length of a survey has the highest independent influence on response rate (Song, Son, & Oh, 2015; Van Mol, 2016). A low response rate could create nonresponse bias, affecting the validity of survey results independently of the sample size, and even invalidate a study (Song et al., 2015; Van Mol, 2016).

Researchers utilize multiple peer-approved methods to calculate a sample size for quantitative research. G*Power is a free to utilize user-friendly program used by researchers to calculate sample size for research (Kang, Yeon, & Han, 2015; Schoemann, Boulton, & Short, 2017; see Figure 4). The calculation of effect size must be determined first. A common technique used by researchers to estimate effect size is to review the findings of existing research (Anderson, Kelley, & Maxwell, 2017). Using the task-fit technology theory as their framework, Doleck, Bazelais, and Lemay (2017) and Tam and Oliveira (2016) and determined that a medium effect size would be acceptable for their research. According to Cohen (2009), research studies should be designed in such a way to that they have an 80% probability of detecting an effect. Utilizing a two-tail test with a statistical power of 80% yielded a sample size of 82 (see Figure 5).

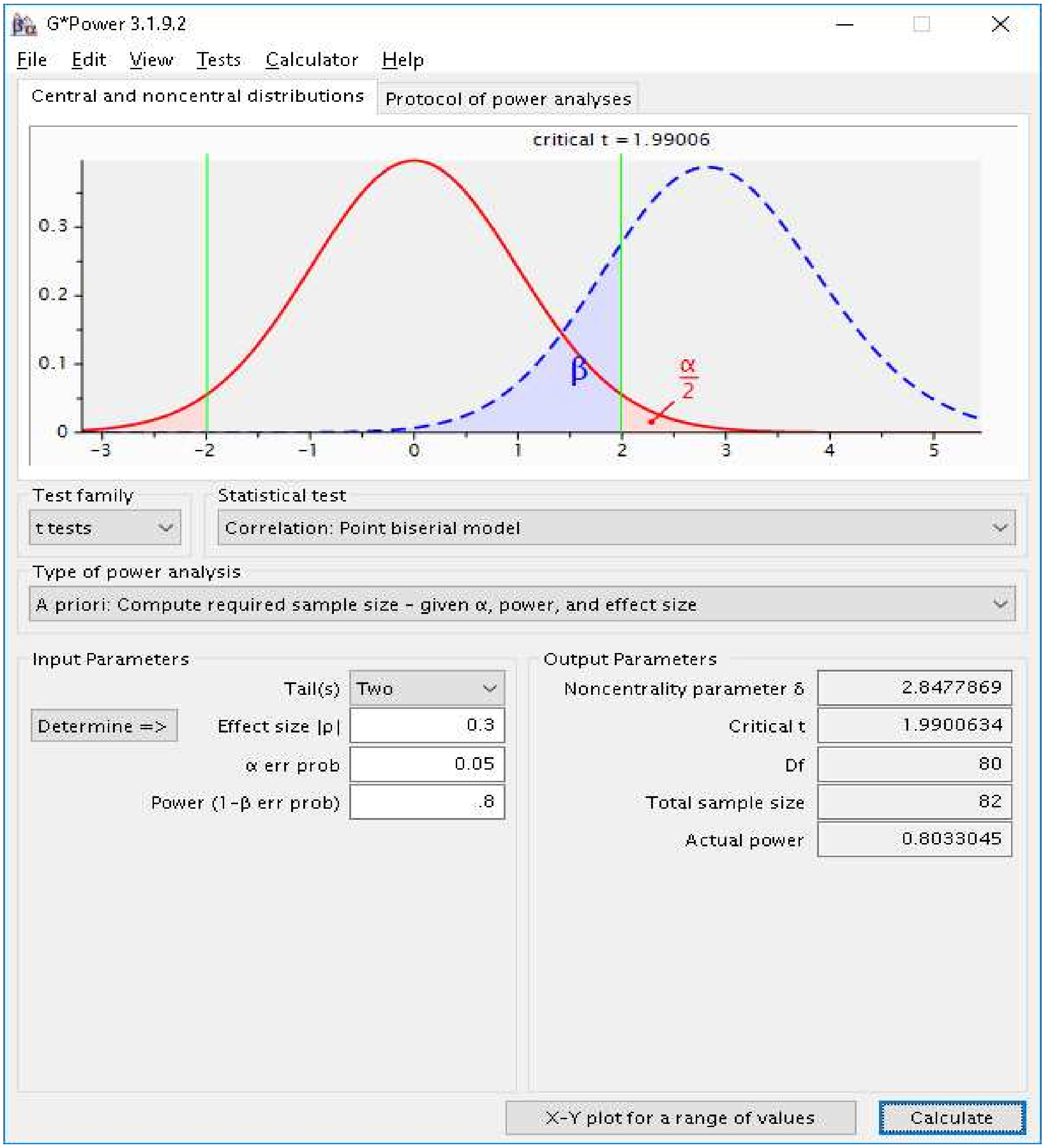

Figure 4. Graphic display of power analysis to compute sample size.

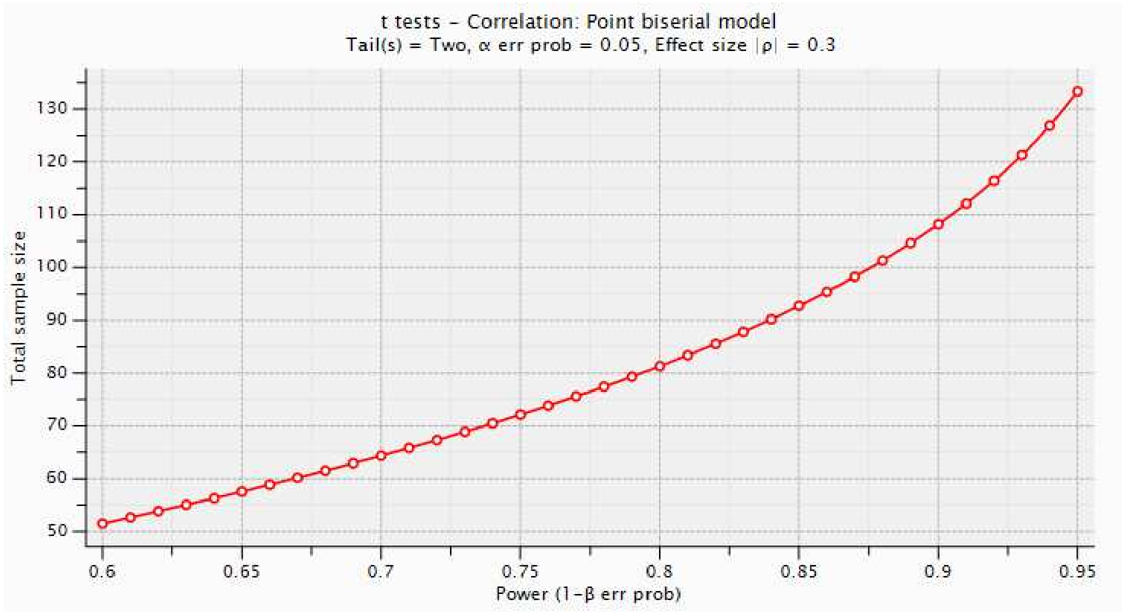

Figure 5. Graphic display of power X-Y plot to show sample size.

Ethical Research

It is the responsibility of researchers to maintain the highest levels of credibility, ethical responsibility, and trustworthiness when carrying out research activities. The Belmont Report (U.S. Department of Health and Human Services, 2016) offers several principles to preserve the confidentiality of participants. In addition to these principles, I complied with the IRB requirements, as established by Walden University for this research study. According to Nebeker et al. (2016), the IRB is responsible for evaluating the benefits of the research and assess possible harm to research participants. Harris (2016) suggested that researchers not begin data collection until after completing training about protecting human research participants through the National Institute of Health. To comply with these requirements and to meet the standards established by the Walden University IRB, I completed the training course offered by the National Institutes of Health Office of Extramural Research and received a certificate of completion.

I provided full disclosure to participants regarding the intent of the research project in order to not place the participants in a situation in which physical or psychological harm might occur. Research participants were invited through an introductory e-mail asking for voluntary participation. The basic principle of voluntary participation is that participants not be coerced into participating in the research project by providing enough information about the purpose of the project for the invited participants to provide informed consent (Jajoo & Kakkad, 2016). Additionally, prospective research participants must be fully informed about the potential risks involved in participating in the research (Guo, 2015; Jajoo & Kakkad, 2016; Roberts & Allen, 2015). To facilitate these requirements, I delivered a formal invitation via e-mail to all prospective participants that included a background information disclosure statement, the voluntary nature of the study, the risks of being in the study, privacy statements, contact information for the researcher, contact information for Walden University personnel, and statements that all participants would be guaranteed anonymity. The prospective participants were permitted to invite other participants by forwarding the e-mail containing the anonymous survey link to other systems analysts within their network. All participants submitted an online digitally signed consent form. The consent form included a background information disclosure statement, research study procedures, the voluntary nature of the study, the risks of being in the study, the benefits of the study, payment information, privacy statements, contact information of the researcher, as well as contact information for Walden University personnel. Additionally, the survey instructions that I provided included statements covering (a) ethics, (b) confidentiality,

(c) the background of the study, (d) the procedure for completing the survey, and (e) a statement about the voluntary nature of the survey. The survey instructions did not include any personal or organizational names.

According to Harris (2016) and Roberts and Allen (2015), it is a best practice to allow participants to withdraw consent at any point without reason. Therefore, I understood that some participants might choose to withdraw from the study. I provided all participants with instructions on how to withdraw from the study at any time through electronic means, including e-mail. I did not offer an incentive to prospective participants to participate the study because offering incentives to participate in a research study is not a best practice (Harris, 2016; Roberts & Allen, 2015). The consent forms and other research materials will be kept in a locked safe for 5 years at a secure storage facility in the city of Phoenix, Arizona to ensure the integrity and confidentiality of the participants. After the 5-year period, I will destroy the research material in a secure manner.

Data Collection

Instruments

I collected data for this study using an online survey tool that met the reliability and validity criteria in previous studies (Gunn, 2018; Todorova, 2013), thus eliminating the need for a pilot study. The data collection instrument is based upon two other survey instruments, slightly modified. The practice of adapting a data collection instrument with minor modification is a common and accepted practice among researchers (Song et al., 2015; Sousa, Matson, & Lopez, 2016). I obtained permission to use the survey instruments (see Appendix D).

Todorova's (2013) survey instrument was adapted for use in this study. The instrument was initially developed with the intention to measure three key factors (a) level of lean implementation adoption, (b) satisfaction with lean implementation, and (c) perceived operational performance. The reliability and validity of this instrument was determined by Todorova (2013) through the use of two methods: (a) confirmatory factor analysis using the SmartPLS software and (b) Q-sort pilot testing.. The judges for the pilot process were selected and graded based upon their experience and history with lean implementation. The pilot testing yielded a Cohen's Kappa score of less than 0.81 and 0.81.

Todorova's (2013) survey instrument consisted of Likert-type scale questions with ordinal values (see Appendix E). I employed a Likert scale ranging from 1 to 7, where 1 means strongly disagree, 2 means moderately disagree, 3 means somewhat disagree, 4 means neutral (neither disagree nor agree), 5 means somewhat agree, 6 mean moderately agree, and 7 means strongly agree. Using Likert-type scale questions is an appropriate method for research (Curtis et al., 2016; Song et al., 2015; Timmins, 2015). The content reliability has been established by performing a literature review that validated the measurement factors used and by using instruments and survey questions validated in previous research that provided direct relevance to the theory being tested (Cook, Zendejas, Hamstra, Hatala, & Brydges, 2014; Finn & Wang, 2014; Jorg Henseler, & Ringle, & Sarstedt, 2014).

Data collection instruments must align with the research study variables to establish the credibility and validity of the study. Todorova's (2013) survey instrument aligns with the independent and dependent variables in my study because it places an emphasis on (a) lean methodology, (b) company performance, and (c) supporting systems. Applying the questions for measuring company performance had no impact by measuring cell optimization performance. Manufacturing organizations measure overall organizational performance by manufacturing performance. The utilization of programs with probabilistic algorithms is to support lean methodologies. Systems and processes that support lean implementation evolve as needs are discovered. For research on the impact of lean, a software program is equivalent to a chalkboard in function. Applying the questions for lean supporting systems to programs that utilize probabilistic algorithms did not influence the viability of the data collection instrument. I reassessed the validity of the data collection instrument through using Cronbach's alpha. As it related to this study, the survey instrument was used to measure the lean methodology technique usage and the cell optimization measurement usage.

Gunn's (2018) survey instrument was also used in this study. The instrument consists of a 7-point Likert-type scale, which is an appropriate method for conducting research (Curtis et al., 2016; Song et al., 2015; Timmins, 2015). The survey instrument is based upon several other instruments that had been proven to be reliable and valid (Gunn, 2018). To further ensure validity and reliability, Gunn (2018) conducted an examination of the average variance extracted, outer loadings, and composite reliability. The pilot study yielded an AVE value range of 0.651 and 0.858, deeming the survey instrument valid and reliable. I reassessed the validity of the data collection instrument using

Cronbach's alpha. I used the survey instrument to measure systems analyst selection and usage of software utilizing probabilistic algorithms.

Data Collection Technique

I utilized an internet-based survey instrument to collect data for the quantitative research study. Precedent exists for using internet-based survey instruments. According to Timmins (2015), utilizing an internet-based survey instrument can be effective in increasing the available participant pool. Following IRB approval, I distributed my survey to research study participants through a convenience sample. The raw data collected from the survey is included in the research paper. Figure 6 provides a graphical overview of the process flow for data collection and analysis for this research study.

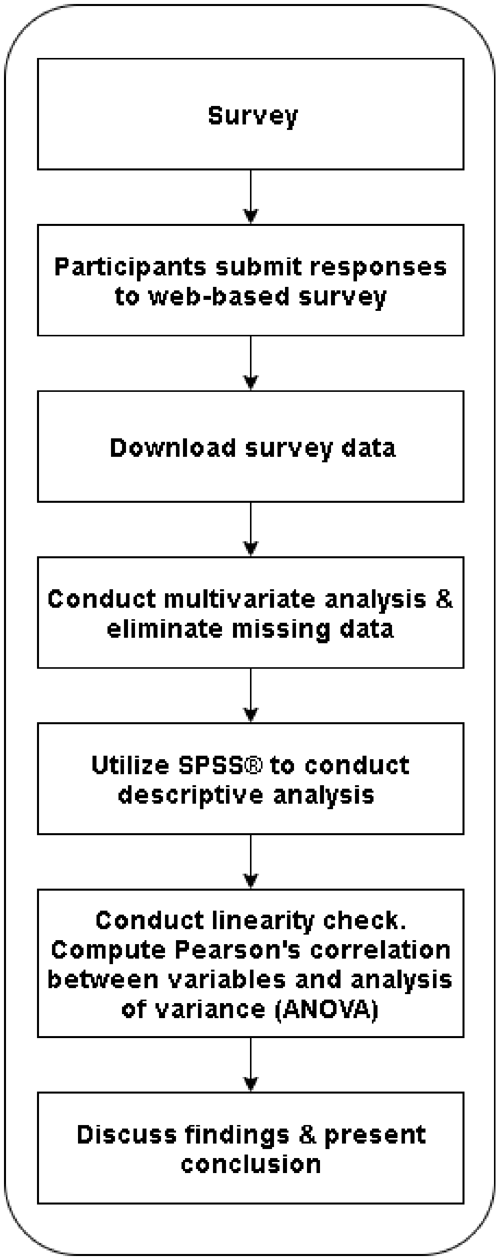

Figure 6. Graphical display of process flow for data collection and analysis.

The questions from the modified surveys were presented as an online survey through a website operated by SurveyMonkey. The SurveyMonkey platform hosted the survey, responses, and securely stored the data until I closed the account. I created the account for SurveyMonkey and configured it with my Walden e-mail account. To avoid the possibility of invitations being caught within spam filters, e-mails had been sent using the SurveyMonkey platform but appeared to come from my Walden e-mail address. Contacting potential respondents from multiple methods yields the highest response rate (Aßmann et al., 2017; Dillman, Smyth, & Christian, 2014). Therefore, I contacted prospective respondents through multiple e-mails and social media messages.

I formatted the survey using a page-skip logic structure. The utilization of page-skip logic afforded the prospective participants the opportunity to deny participation, as well as for me to disqualify any participants who did not meet the established criteria for survey participation (see Appendix E). Aßmann et al. (2017) asserted that skip-patterns within surveys allow users to navigate quickly and can potentially decrease frustration. To participate in the survey the participant must have been employed by a manufacturing organization within the Southwestern United States, been 18 years or older, employed at the time of the survey, and not self-employed. Participants who provided a disqualifying answer to any of the three questions were not allowed to complete the survey.

One primary advantage with the utilization of SurveyMonkey was access to a large existing pool of potentially qualified candidates. Researchers Varela et al., (2017) have stated that SurveyMonkey allowed access to a significant number of candidates in a shorter time for their research study. The platform allows the researcher to provide an incentive to qualified candidates to complete the survey. Existing research has tested the effective utilization of the SurveyMonkey platform. Research conducted by Bentley, Daskalova & White (2017) compared the effectiveness of SurveyMonkey with traditional university or commercial panel platforms. The research study results demonstrated that the platform can provide sampling results on-par with traditional university or commercial panel platforms. Similar research by Aßmann et al., (2017) and Dillman, Smyth, & Christian (2014) has proven that internet surveys in general are an effective means to collect research data. To collect data for the survey, I established a new account. I collected survey results until I obtained enough results to meet the required minimal sample size.

I collected the data using web-based surveys which were converted to Microsoft Excel spreadsheets. The Excel spreadsheets were then imported into SPSS to interpret the results. All of the survey results had been entered into secured computer files. I utilized encrypted software programs to encode the computer files to obfuscate the data. I am the only individual who has access to the software decryption keys. The GNU Privacy Guard (GPG) encryption software is the software utilized for the data encryption and decryption. As stated by Binnie (2016) the GPG software suite is a capable platform to secure files and ensure privacy of data. Paper copies of the research data collected during the research project will be stored in a bank safety deposit box and destroyed after five years.

Data Analysis Technique

The research question for this research study was:

What is the relationship between software utilizing probabilistic algorithms, lean methodology techniques, and the cell optimization results?

The null and alternative hypotheses were:

- Null Hypothesis (H_0): There is no statistically significant relationship between software utilizing probabilistic algorithms, lean methodology techniques, and the cell optimization results.
- Alternative Hypothesis (H_1): There is a statistically significant relationship between software utilizing probabilistic algorithms, lean methodology techniques, and the cell optimization results.

The data for the research study required preparation before data analysis could begin. Rowley (2014) has stated that data should be prepared through the following steps: (a) reviewed for incomplete records, (b) enter data into analysis software consistently, (c) review loaded data for mistakes. I employed multiple linear regression analysis to analyze the relationship between the independent variables, (a) software utilizing probabilistic algorithms, (b) lean methodology techniques and the dependent variable of manufacturer's cell optimization results. It has been stated by Grégoire (2014) that multiple linear regression is an appropriate option where there is an interest in a relationship between a single dependent variable and multiple independent variables. Researchers Kim, Chung, Lee, & Preis (2013) have used confirmatory factor analysis (CFA) to analyze the data collection from task-technology fit theory research. While CFA is a multi-variant analysis, the objective of my research is understanding the relationship between variables. The purpose of CFA is a data reduction analysis to align data to a model as stated by Kim, Chung, Lee, & Preis (2013) and Rowley (2014).

The data collected from the survey website was first loaded and stored with Microsoft Excel. I screened the data by checking for missing values as well as errors in the raw data transfer from the internet. I then utilized the Statistical Package for the Social Sciences (SPSS) to extrapolate meaning from the data. Multiple researchers utilized SPSS (Brezavšček, Šparl, & Žnidaršič, 2014) to analyze the data in their quantitative studies. I then examined the collected data to confirm the underlying assumptions: multicollinearity, normality, linearity, homoscedasticity, and independence of residuals. Multiple methods were utilized to test and examine the assumptions. The use of scatter plots is generally accepted methods for testing multiple regression assumptions. Violations of multiple linear regression assumptions will be addressed in a below subsection.

Multicollinearity

The assumption of multicollinearity refers to multiple predictors being highly correlated to one another in the regression analysis as stated by Dormann et al., (2012) and Voyer & Voyer (2015). I plan to utilize SPSS to identify multicollinearity through regression diagnostics. Olivoto, et al. (2017) have stated that a correlation matrix could be utilized to examine multicollinearity and to examine the possibility of a strong suit of correlation. I will utilize the correlation matrix to look for presence of large correlation coefficients. The existence of these with the predictor variables which would indicate multicollinearity.

Normality

The usage of normal probability plots was introduced by Filliben (1975) and are generally accepted means of normality testing. Ho and Yu (2015) published research advocating the usage of exploratory data analysis to test for normal distribution. I plan to conduct exploratory data analysis based on the inspection of kurtosis and skewness values to determine if the variables are normally distributed. Research was published by Kim (2013) which states that a kurtosis and skew value of a normal distribution is zero. I plan to utilize the descriptive statistics test, which is available in the IBM SPSS® software package to examine both values.

Linearity

The assumption of linearity is that there is a linear relationship between the research variables as stated by Dumitrescu, Stanciu, Tichindelean, and Vinerean (2012). I plan to test for linearity utilizing scatterplots for testing the linearity between the variables. Arendacká (2012) and Zhang (2016) have stated that visually examining a scatterplot for linearity between continuous variables and the outcome is an acceptable practice. I will examine the scatterplots to ensure linearity. If the scatterplots show a nonlinear association then the assumption has been violated.

Homoscedasticity

The homoscedasticity assumption or constant variance of the error terms is that the random errors have the equal constant variance across independent variables (Arendacká, 2012; Vindras, Desmurget, & Baraduc, 2012). Multiple method to test for homoscedasticity exist. Commonly used tests include Anova, Alexander-Govern, Durbin-Watson, Brown-Forsythe, and Levene as stated by Grégoire (2014) and Vindras, Desmurget, and Baraduc (2012). I plan to utilize a Durbin-Watson test, which is available in the IBM SPSS® software package to assess the homoscedasticity assumption. Scatter plot and residuals plot will be utilized to examine homoscedasticity visually.

Independence of Residuals

Independence of residuals refers to the assumption that residuals are responding independently with indicates independence as stated by Nikolaou (2016) and Voyer & Voyer (2015). Standard scores and test results will not be accurate when violations of the assumption occur (Voyer & Voyer, 2015). The residuals should be random and pattern less. It was published by Meuleman, Loosveldt, & Emonds (2014) and Nikolaou (2016) that boxplots and residuals plots are acceptable tools to examine independence of residuals. I plan to utilize the boxplot graphing technique to examine the independence assumption. I will visually examine the boxplot to look for clustering which will indicate a violation.

Missing Data

I needed to examine the data collected for missing data before data analysis could begin. The practice of discarding data that is incomplete before analysis is one approach utilized. Cohen (2009) has stated that discarding data with at least one variable value missing is acceptable until the statistical power is diminished. It was my intention to review the data collected for incomplete variable values and discard incomplete data.

Outliers and Violation

Multiple methods exist to address outliers and violations of the assumptions regarding the data. According to Meuleman, Loosveldt, & Emonds (2014) and Montoya & Hayes (2016), software packages like SPSS version 24 have routines such as bootstrapping to address the assumptions. Kaufmann & Wittmann (2016) conducted research that demonstrated bootstrapping techniques are equivalent or better to human judges. Based upon the wide usage of bootstrapping, it was my plan to utilize bootstrapping as a means to address outliers and violations. I did not have to utilize bootstrapping.

Reliability and Validity

Reliability

The establishment of reliability of a data collection instrument is crucial to the integrity of a research study. Reliability refers to the consistency, stability, and repeatability of results (Twycross & Shields, 2004). Multiples measures to assess reliability exist. According to Twycross & Shields (2004) the three primary types of reliability include: Stability, Homogeneity, and Equivalence. The data analysis process will involve an interpretation of the data which should provide an understanding of the data. Cronbach's alpha test is a generally accepted method of measuring the reliability of the instrument as stated by Leedy & Ormrod (2010) and Zhang & Yuan (2016). The instrument and resulting data were previously calculated by Todorova (2013) utilizing the Cronbach's alpha test. For the purpose of this study, the Cronbach alpha will be calculated to assess and report the reliability.

Validity

Within the research ecosystem, the term validity has multiple meanings with no universally accepted definition as stated by Twycross & Shields (2004). Flower, McKenna, & Upreti (2016) has stated that validity is determined by the consistency between two ratings of the same measurement. For the purposes of this research, validity is defined as the accuracy of the data and tool. Ensuring the validity of the data collection instrument and data is an integral responsibility of the researcher. Hamby & Taylor (2016) stated that the assessment of validity is the most important step in research. This research study validity would be subject to two types, internal and external. It has been stated by Maggino & Facioni (2017) and Torre & Picho (2016) that internal validity refers to the verification of the validity of the results of the study from the targeted population, external validity concerns the populations outside the scope of the study. It was stated by Leedy & Ormrod (2010) and Twycross & Shields (2004) that validity specifically can be defined as the extent to which the data collection instrument measures what it is supposed to measure. The instrument that I will be utilizing was first validated by Todorova (2013) utilizing the SmartPLS software and Q-sort pilot testing.

Validity concerns must be addressed during analysis of the data itself. Statistical conclusion validity refers to the correct treatment of data in order to study variations in the observed data during data analysis as stated by Maggino & Facioni (2017). Statistical conclusion validity can be improved by incorporating randomization within the design as stated by Heyvaert, Wendt, Van den Noortgate, & Onghena (2015). Subject inattentiveness is one specific statistical conclusion validity threat to my research study. Cheung, Burns, Sinclair, & Sliter (2017) have explained that subject inattentiveness is a threat to online based surveys are often not proctored. Maggino & Facioni (2017) has stated multiple methods including multi-variant outlier analysis exist to address statistical conclusion validity. Cheung, Burns, Sinclair, & Sliter (2017) stated that multiple methods should be utilized to detect validity concerns. I plan to address the identified threats to statistical conclusion validity by conducting multi-variate outlier analyses as well as direct, archival, and statistical screening techniques.

For this research study I utilized a convenience sampling strategy. Convenience sampling could affect the dependent variable and produce contradictory results. It was stated by Aßmann et al., (2017) & Hamby & Taylor (2016) that sampling rations and responses are a contributing validity factor with quantitative research studies. The specific threat to this research study would be under or over-sampling of the population. To address external validity threats, I plan to limit my sample size to 82. The target of 82 is equivalent to the calculation performed within G*Power.

Transition and Summary

I used a quantitative, correlational design with multiple linear regression analysis to examine the extent and nature of the relationship between software utilizing probabilistic algorithms and lean methodology techniques has on a manufacturers cell optimization results. This research study will consist of a survey facilitated by SurveyMonkey®. The survey will consist of questions relating to the participants' demographic characteristics and lean manufacturing knowledge. Information gleaned from the study will be indicative of the role that an individual's (a) knowledge of lean, (b) usage of probabilistic algorithms, (c) tenure has in affecting cell optimization by identifying the magnitude of the relationship among the independent and criterion variables. In Section 3, I will present the study findings and identify areas for future research based on the study results.

Section 3: Application to Professional Practice and Implications for Change

In Section 2, I discussed the purpose statement and the role of the researcher, and described the participants, research method, research design, population sampling, data collection techniques, instrumentation, data organization techniques, data analysis, and the reliability and validity of the study. In Section 3, I present an overview of the research study and a summary of study findings. I also discuss how the findings relate to information technology practice, including the impact of the findings on systems analysts' decisions to utilize software with probabilistic algorithms. I describe the implications of my research for social change, offer recommendations for action and further study, share some reflections, and provide a conclusion.

Overview of Study

The purpose of this quantitative correlational study was to examine the relationships among software utilizing probabilistic algorithms, lean methodology techniques, and a manufacturer cell optimization results.

Presentation of the Findings

The data collected consisted of 118 responses. I utilized a non-probabilistic convenience sample for my study. The participants were invited through the social media platform LinkedIn. I visually scanned the data to discard incomplete responses and further assessed the data for missing responses and outliers. There were negligible missing responses, which were managed using the default SPSS likewise deletion method. Outliers were detected using the bootstrapping as set forth by Kaufmann and

Wittmann (2016). Bootstrapping techniques standardized *z* scores were calculated and then assessed for responses with values less than -3.29 or greater than +3.29.

Reliability Analysis

I found it necessary to create composite scores to be used in the data analysis. I assessed the value of each composite score using Cronbach's alpha. Alpha coefficients were interpreted according to George and Mallery's (2016) guidelines, in which coefficients of .70 and above are considered acceptable, coefficients of .80 and above are good, and coefficients of .90 and above are excellent. Software utilizing probabilistic algorithms was created from the mean of 28 survey questions and had excellent reliability (α = .905). Lean methodology techniques were created from the mean of 47 survey questions and had excellent reliability (α = .913). Manufacturer's cell optimization results were created from the mean of 14 survey questions and had good reliability (α = .84; see Table 1).

Table 1

Reliability Statistics

Variables	Cronbach's alpha	N of items
AL	.905	28
LE	.913	47
CO	.84	14

Note. LE = Lean Methodology, AL = Algorithms, CO = Cell Optimization

Assumptions

I used several tests of assumptions to assist me in validating the findings of this research study. These tests included multicollinearity, normality, linearity, homoscedasticity, outliers, and independence of residuals. I examine each of these tests and present the findings in the following sections.

Multicollinearity. To check for multicollinearity of the data, I employed the usage of a correlation matrix with SPSS to detect the possibility of multicollinearity (see Table 2). A Variance Inflation Factor (VIF) above 10 indicates multicollinearity (Dormann et al., 2013). Based on the Coefficients output, collinearity statistics, an obtained VIF value of 1.017, indicates that multicollinearity is not a concern.

Table 2

Multicollinearity Test Results as Correlation Matrix Display

	Model	UB	Coefficients Std. Error	SB	*t*	Sig.	CT	Statistics VIF
1	(Constant)	8.756	3.240		2.702	.008		
	AL	-.001	.019	-.006	-.070	.000	1.000	1.000
2	(Constant)	-.315	1.971		-.160	.874		
	LE	.102	.010	.761	10.649	.000	.983	1.017
	AL	.026	.011	.166	2.319	.023	.983	1.017

Note. LE = lean methodology, AL = algorithms, UB = Unstandardized B, SB = Standardized Coefficients Beta, CT= Collinearity Tolerance;
Dependent Variable: CellOpt

Normality. I used SPSS to detect normality by checking for skewness and kurtosis (see Table 3). Kurtosis and skew value of a normal distribution is zero (Kim, 2013). I utilized the descriptive statistics test to examine both values. Based on an obtained Shapiro-Wilk significance value of less than .05, normality was not a concern.

Table 3

Tests of Normality

	Kolmogorov-Smirnov			Shapiro-Wilk		
Variable	Statistic	Df	Sig.	Statistic	Df	Sig.
Algorithms	.125	88	.002	.891	88	.000
Lean	.138	88	.000	.963	88	.013

Note. *Lilliefors Significance Correction*

Linearity. I created a scatterplot with SPSS to check for the possibility of linearity (see Figure 7). Visually examining a scatterplot for linearity between continuous variables and the outcome is an acceptable practice (Arendacká, 2012; Zhang, 2016). A visual inspection of the generated scatterplot in Figure 7 demonstrates a distributed set of results that are not skewed in any one direction. Therefore, this distribution of data indicated that linearity was not a concern.

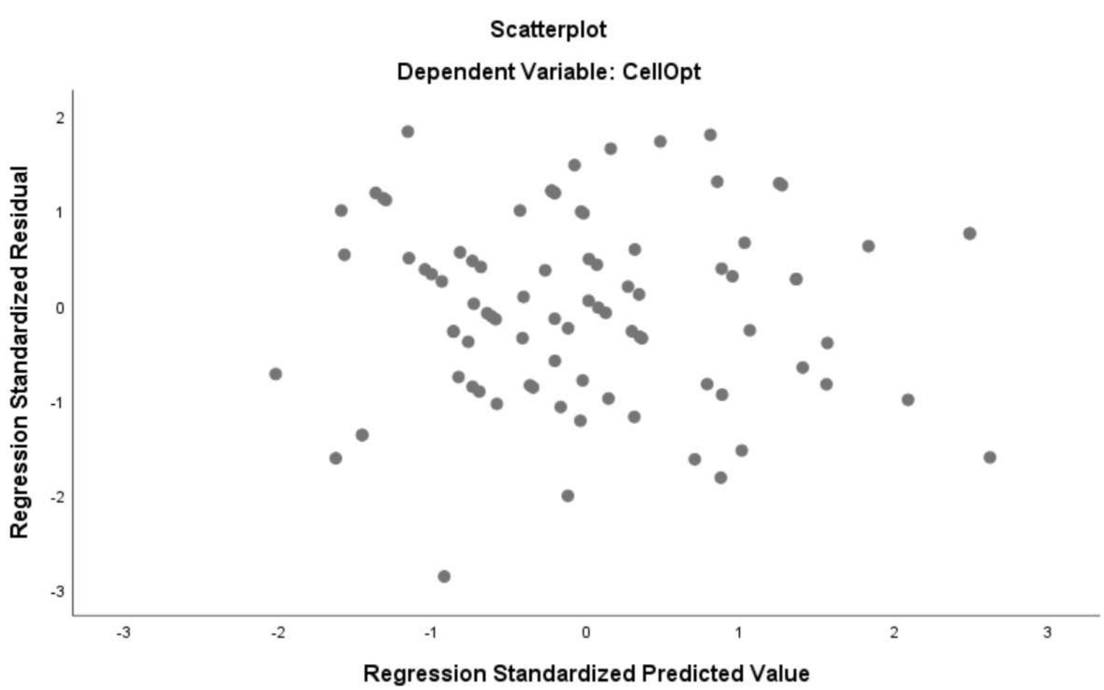

Figure 7. Scatterplot diagram generated from SPSS.

Homoscedasticity. I used a Durbin-Watson test with SPSS to detect the possibility of homoscedasticity (see Table 4). A statistical value between 1.5 and 2.5 indicates data that is not autocorrelated (Grégoire, 2014). Based on the Durbin-Watson test, an obtained statistic value of 1.578, homoscedasticity was not a concern.

Table 4

Homoscedasticity Test Results as Durbin-Watson – Model Summary

Model	R	R^2	Adjusted R^2	Std. Error of the Estimate	Durbin-Watson
1	.598	.357	.342	3.79800	1.578

Note. Predictors: (Constant), Lean, Algorithms
Dependent variable = cell optimization

Independence of residuals. I created a boxplot with SPSS to detect the possibility of linearity (see Figure 8). Boxplots and residuals plots are acceptable tools to examine independence of residuals (Meuleman, Loosveldt, & Emonds, 2014; Nikolaou, 2016). A visual inspection of the generated boxplot in Figure 8 demonstrates an even linear curve of results that are not skewed in any one direction. This distribution of data indicated that independence of residuals was not a concern.

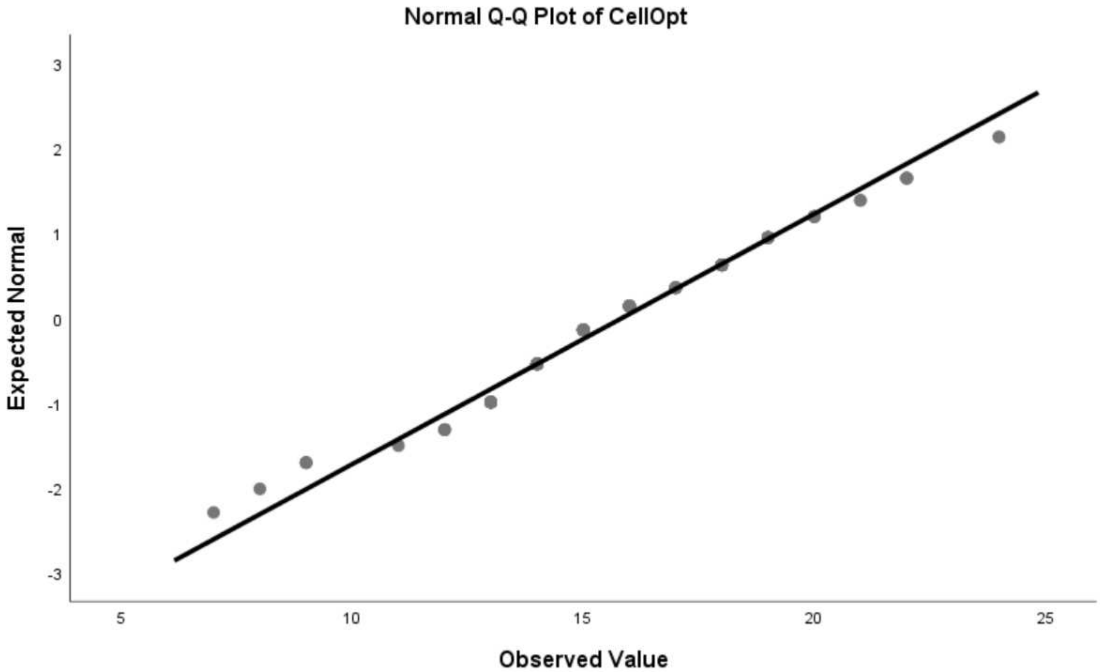

Figure 8. Boxplot generated by SPSS to check for independence of residuals.

Descriptive Statistics

The total number of surveys completed by the participants was 118 and 28 of the surveys were removed due to missing or incorrect data. Each of the remaining surveys was fully completed and no errors were identified during the data analysis. Table 5 contains the descriptive statistics for all the survey questions. Table 6 contains the results from an ANOVA test for all the survey questions.

Table 5

Means and Standard Deviations for Quantitative Study Variables

	N	Minimum	Maximum	*M*	*SD*
Predicted Value	88	16.4055	29.6409	22.2614	2.79754
Residual	88	-7.24579	11.68535	.00000	3.75409
Std. Predicted Value	88	-2.093	2.638	.000	1.000
Std. Residual	88	-1.908	3.077	.000	.988

Note. Dependent variable = cell optimization

Table 6

ANOVA Test-Statistical Significance for Quantitative Study Variables

Model		*SS*	*df*	*MS*	*F*	Sig.
1	Regression	680.881	2	340.441	23.601	.000
	Residual	1226.107	85	14.425		
	Total	1906.989	87			

Note. Dependent variable = cell optimization
Predictors: (Constant), Lean, Algorithms

The sample consisted of systems analysts within manufacturing organizations who were practicing lean methodology techniques within the Southwestern region of the United States. Primarily, the largest proportion were males (85.7%) in the age range of 35 – 44 (27.5%). There was a small percentage of individuals who chose to not disclose some demographic information (see Table 8).

Table 7

Frequencies and Percentages of Demographic Characteristics

Variable		N	%
Age range	45-54 years old	15	16.5
	35-44 years old	25	27.5
	25-34 years old	21	23.1
	18-24 years old	7	7.7
	Prefer not to answer	22	24.2
Gender	Female	7	7.7
	Male	78	85.7
	Prefer not to answer	5	5.5
Marital status	Single/ never married	1	1.1
	Married or domestic partnership	8	8.8
	Widowed	1	1.1
	Divorced	3	3.3
	Prefer not to answer	77	84.6
Ethnicity	Asian/Pacific Islander	1	1.1
	White/Caucasian	82	90.1
	Hispanic	5	5.5
	Prefer not to answer	2	2.2
Uses a computer at home	Yes	88	96.7
	No	1	1.1
	No Answer	2	2.2
Education	Bachelor’s degree	6	7.0
	Prefer not to answer	64	70.0
	Master’s degree	6	7.0
	Some College	15	16.0

Multiple Regression Results

The quantitative correlation research design was selected for this research study to examine the relationships among software utilizing probabilistic algorithms, lean methodology techniques, and the cell optimization results. I utilized a correlation design with a survey instrument for this research study. A standard multiple linear regression, $\alpha = .05$ (two-tailed), was used to examine the relationships among software utilizing probabilistic algorithms, lean methodology techniques, and a manufacturer cell optimization results. The independent variables were the modeling software utilizing probabilistic algorithms and the lean methodology techniques. The dependent variable was the cell optimization results. The null hypothesis and alternative hypothesis were:

Null Hypothesis (H_0): There is no statistically significant relationship between software utilizing probabilistic algorithms, lean methodology techniques, and the cell optimization results.

Alternative Hypothesis (H_1): There is a statistically significant relationship between software utilizing probabilistic algorithms, lean methodology techniques, and the cell optimization results.

The results of the overall regression model were significant with both variables showing the ability to predict the cell optimization variable. Although both variables demonstrated this ability, lean methodology techniques were shown to be four times more likely than probabilistic algorithms to predict cell optimization results. A multiple linear regression was utilized to predict cell optimization results based on probabilistic algorithms and lean methodology techniques. The multiple linear regression model was: Cell Optimization = -.001 * AL + .120 * LE + -8.756. The results of the overall regression model were significant, (F (2, 85) = 23.601, $p < .000$), with an R^2 of .357. Table 8 shows the results of the multiple linear regression analysis. The model showed an adjusted R^2 of our model is .342 with the $R^2 = .357$. The F value is significant (see Table 9). Therefore, the null hypotheses can be rejected.

Table 8

Results of the Regression Analysis – Model Summary

Model	*R*	*R*²	Adjusted *R*²	Std. Error of the Estimate	Durbin-Watson
1	.598	.357	.342	3.79800	1.578

Note. Predictors: (Constant), Lean, Algorithms
Dependent variable = Cell Optimization

Table 9

ANOVA Test - Statistical Significance for Quantitative Study Variables

Model		*SS*	*df*	*MS*	*F*	Sig.
1	Regression	680.881	2	340.441	23.601	.000
	Residual	1226.107	85	14.425		
	Total	1906.989	87			

Note. Dependent variable = Cell Optimization
Predictors: (Constant), Lean, Algorithms

Theoretical conversation on findings. After analyzing the data that I collected from the survey I was able to show that a relationship did exist between the combined values of software utilizing probabilistic algorithms and lean methodology techniques has on a manufacturers cell optimization results. Goodhue and Thompson (1995) have defined a *fit* as the meeting of the requirements of a task. Task-technology fit is the degree to which a technology may assist an individual or group in the performance of tasks. The positive relationship between the variables aligns to the Task-technology fit allowing for the fitness of the technology to the task. The findings of the data collected from the research align with research data published by Fadzly, Saad, & Shayfull (2017). Fadzly, Saad, & Shayfull published that cellular optimization results are more successful when utilizing simulation software.

An examination of published literature has showed that studies performed to examine performance management of manufacturing organizations the results have showed a positive relationship between lean methodology techniques and perceived performance results. Karim, Tuan, & Kays (2016) and Omogbai and Salonitis (2016) conducted research that included lean methodology techniques and organizational performance. Organizational effectiveness and efficiency were found to be increased when implementing lean methodology techniques as stated by Karim, Tuan, & Kays. Omogbai and Salonitis found that performance measured increased by when lean methodologies were implemented over conventional manufacturing methods. Similarly, in my study, the data analysis found a positive relationship software utilizing probabilistic algorithms and lean methodology techniques has on a manufacturers cell optimization results.

Research was conducted by Gündüz (2015) and that exposed the belief that current methods of lean manufacturing performance measurement techniques have not advanced significantly from early lean assessment tools. This assessment by Gündüz aligns with my research results that state that lean methodology techniques is four times more likely to predict cell optimization results than probabilistic algorithms. Specifically, Gündüz evaluated the relationship of value stream mapping and organizational performance through the usage of a box score. Gündüz found that the usage of value stream mapping and a box score could have long-term performance benefits. This study supports the literature that lean methodology techniques can have a positive relationship with performance-oriented variables.

The impact of lean manufacturing techniques within organizations has been studied from multiple facets. Researchers such as Zhu and Lin (2017) have studied the impact of introducing lean manufacturing techniques combined with research and development and the overall impact on company value. Zhu and Lin stated that the data analysis demonstrated a positive increase in overall value. This is also similar to the type of significant positive relationship found in my study between the variables of probabilistic algorithms and lean methodology and cell optimization results. Research was conducted by Dotoli et al., (2015) to understand the impact of lean manufacturing techniques on warehouse performance. The research utilized a case-study to examine the usage of lean manufacturing techniques, a warehouse management system, and overall warehouse performance. The analysis of the case-study demonstrated an improvement in multiple key areas. My research found a similar positive relationship between similar variables while focusing on optimization. Dotoli et al., have called for further research with automated controls that utilizes historical data. This type of software could utilize probabilistic algorithms.

The usage of software utilizing software utilizing probabilistic algorithms and lean methodology has been evaluated by multiple researchers. Chen and Chiu (2017) and Chen and Wang (2016) conducted experimental research to simulate manufacturing environments that would enable streamlined improvement for manufacturing task estimation. The research conducted by Chen and Wang consisted of simulation tasks that would optimize the estimation accuracy of tasks. Chen and Wang found that the usage of simulation tasks surpassed six existing methods for manufacturing task estimation. Chen and Chiu compared cloud-based manufacturing simulation to existing methodologies of manufacturing simulation. The research utilized an extensive database containing probability distributions to simulate the manufacturing operations. Chen and Chiu found that their model had greater performance optimization compared to existing methods. This study supports the literature that simulation-oriented variables can have a positive relationship with manufacturers cell optimization results.

Applications to Professional Practice

This quantitative correlational study aimed at examining the relationship between software utilizing probabilistic algorithms and lean methodology techniques has on a manufacturers cell optimization results. The outcomes of this study provided options and suggestions to current and future research studies by illustrating the gaps in current skills, training, and direction for systems analysts in manufacturing organizations. This insight may allow systems analysts to provide their management with the necessary conclusions regarding skillsets required to implement software utilizing probabilistic algorithms and lean manufacturing techniques to improve cell optimization results.

Social and professional interactions may also influence the adoption of software utilizing probabilistic algorithms as well as lean methodology techniques to influence cell optimization. Certain lean techniques such as Six Sigma can provide professional social interactions such as user groups and conferences for systems analysts. Additionally, the system analyst's social network might include friends, colleagues at other manufacturing organization which practice lean methodology techniques. These interactions might allow for discussions on software utilizing probabilistic algorithms as well as lean methodology techniques to influence cell optimization.

Regarding cell optimization, the implications of this study are clear. Noktehdan, Seyedhosseini, and Saidi-Mehrabad (2016) stated that the most significant opportunity within manufacturing for algorithmic approaches is cellular manufacturing. The data collection from this research study has provided insight into positive relationships among software utilizing probabilistic algorithms and lean methodology techniques and a manufacturers cell optimization results. Systems analysts working in manufacturing organizations that practice cellular optimization could look towards the inclusion of software utilizing probabilistic algorithms to enhance cell optimization.

Implications for Social Change

This quantitative correlational study aimed at examining the relationship between software utilizing probabilistic algorithms and lean methodology techniques has on a manufacturers cell optimization results. The findings of this study may contribute to society through the potential to bring sustainable economic improvement to impoverished communities through implementation of efficient manufacturing solutions with lower capital expenditures. The ability for impoverished communities to implement these solutions could result in localized job creation. Furthermore, increased job creation could create a positive economic shift and increased discretionary spending. These benefits could increase the economic standing of the overall community.

Recommendations for Action

The purpose of this quantitative correlational study was to examine the relationship between software utilizing probabilistic algorithms and lean methodology techniques has on a manufacturers cell optimization results. The results of this research study are a request for systems analysts to investigate software that utilizes probabilistic algorithms coupled with the usage of lean methodology techniques when seeking to improve cell optimization. This study provides a review of the relationship between software utilizing probabilistic algorithms and lean methodology techniques has on a manufacturers cell optimization results. Systems analysts that already utilize lean manufacturing techniques may start by getting familiar with software that utilizes probabilistic algorithms.

Organizations that do not already utilize lean manufacturing techniques should first become familiar with the lean methodology techniques. Suggested lean methodology techniques to implement are noted in the Review of the literature within Section 1 including: Just in Time, Lean Six Sigma, and value stream mapping.

Recommendations for Further Study

This research study is subject to some limitations. First, I located companies that were identified through the U.S. Census Bureau as manufacturing organizations within the Southwestern region of the United States. Utilizing those company names, I recruited participants through social media channels, namely LinkedIn® to solicit analysts either working or had previously worked at those companies. The primary assumption of this research study was that respondents will be truthful and thoughtful in their responses.

Although the demographic of the population of this study rests in the information technology business sector, recruiting through a social media tool, may have had an influence on the survey responses. Nevertheless, the sample population of this study was compliant with Walden IRB requirements as related to the data collection. Furthermore, I did not collect any personal identification of any participants, guaranteeing anonymity, which could have led to biased survey responses. Furthermore, I relied on the geographic location of the respondents and the organizations, and the classification of these organizations as manufacturing companies for which the participants worked for as provided in LinkedIn®. Despite this limitation, I found statistically significant positive results for the variables measured in this research study.

Through the analysis of the data collected I discovered in this study that the combination of software utilizing probabilistic algorithms and lean methodology techniques had a statistically significant positive impact on cell optimization results. However, others researchers could undertake future studies an investigation on the relationship between the different types of probabilistic algorithms and the individual lean methodology techniques and behavior in other geographical areas. It was stated by Shih, Lai, & Cheng (2015) that the adoption of new technology does not guarantee an increase in productivity. Further research could explore if demographic conditions could play a factor in cell optimization results. Finally, future researchers can validate the explanatory power of the findings of this study by using other categories of participants, different sample sizes, different geographic areas, and different research designs.

Reflections

Although challenging, I had a life changing learning experience from the research process at Walden University. At many points through the process, I was overwhelmed by the demands, I had to draw strength from my personal beliefs to sustain my perseverance. I experienced several personal setbacks through the course of my journey which significantly increased the length of my doctoral journey.

Furthermore, I started this project without a sound understanding of the Task-technology fit theory and how the authors derived the various factors as predictors of system utilization. Through the different phases of the research project and by reading many author’s articles and multiple peer reviewed articles, I gained a thorough understanding of the theory’s factors and its association with understanding task and technology fitness. Accordingly, I developed a deep awareness of how significant the theory is to research seeking an understanding of the relationship between task and technology.

I began this research study to examine the relationship between software utilizing probabilistic algorithms and lean methodology techniques has on a manufacturers cell optimization results with no preconceived biases. The results indicated that software utilizing probabilistic algorithms and lean methodology techniques does have an impact on cell optimization efforts. The findings of this study provide some indications to systems analysts on the implications of software utilizing probabilistic algorithms and lean methodology techniques on their cell optimization efforts and can inspire future researchers. Academic association is the only experience I have with programs with probabilistic algorithms. The education through this association may lead to bias with opinions on how programs should utilize probabilistic algorithms. I had no relationship with any of the participants of the research study. Evidence should always be examined to closely by researchers regardless if it supports or negates a claim by the researcher. Vydiswaran, Zhai, Roth, and Pirolli (2015) stated that by adhering to these principles, bias originating from the researchers beleifs can be reduced. To support this principle, I have reviewed literature that supports as well as contradicts my beliefs regarding probabilistic algorithms.

Summary and Study Conclusions

I conducted a quantitative research method using a non-experimental survey instrument that consisted of Likert-type scale questions with ordinal values. The survey design was employed to examine the relationship between software utilizing probabilistic algorithms and lean methodology techniques has on a manufacturers cell optimization results. The survey instrument employed was based upon two other survey instruments that have been proven as reliable (Todorova, 2013; Gunn, 2018). I conducted the data collection using an online survey built with Survey Monkey. I sent out several hundred invitations over the course of several weeks, and I received 118 responses among which, incomplete responses were discarded. The data collected was exported from Survey Monkey and imported into SPSS software. I performed in SPSS the descriptive statistics, reliability and validity analysis, and a standard multiple regression analysis to test the hypothesis derived from the question. The data analysis results led to my findings of a positive relationship between software utilizing probabilistic algorithms and lean methodology techniques on the cell optimization results.

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Appendix A: Researcher's NIH Certificate

Certificate of Completion

The National Institutes of Health (NIH) Office of Extramural Research certifies that **michael mccurrey** successfully completed the NIH Web-based training course "Protecting Human Research Participants".

Date of completion: 09/11/2015

Certification Number: 1849998

Appendix B: Confidentiality Agreement

Name of Signer:

Throughout the course of the collection of data for this research: "A quantitative correlational study of probabilistic algorithms, lean methodology techniques, and cell optimization results", I will have access to information, which is confidential and should not be disclosed. I acknowledge that the information must remain confidential and that improper disclosure of confidential information could be damaging to the participants of the research study.

By signing this Confidentiality Agreement, I acknowledge and agree that:

1. I will not disclose or discuss any confidential information with others, including friends or family.
2. I will not in any way divulge, copy, release, sell, loan, alter or destroy any confidential information except as properly authorized.
3. I will not discuss confidential information where others can overhear the conversation. I understand that it is not acceptable to discuss confidential information even if the participant's name is not used.
4. I will not make any unauthorized transmissions, inquiries, modification or purging of confidential information.
5. I agree that my obligations under this agreement will continue after termination of the research that I will perform.
6. I understand that a violation of this agreement will have legal implications.

Signing this document, I acknowledge that I have read the agreement, and I agree to comply with all terms and conditions stated above.

Appendix C: Sample Size via G*Power Analysis

[1] -- Thursday, December 08, 2016 -- 17:27:30
t tests - Correlation: Point biserial model
Analysis: A priori: Compute required sample size
Input: Tail(s) = One
Effect size |ρ| = 0.3
α err prob = 0.05
Power (1-β err prob) = 0.95
Output: Noncentrality parameter δ = 3.3133098
Critical t = 1.6589535
Df = 109
Total sample size = 111
Actual power = 0.9503016

Appendix D: Permission to Use Data Collection Instrument

Michael,
You have my permission to use the dissertation survey instrument in your research study. I am looking forward to your completed research.
Best wishes!
Daniela

On Thu, Dec 1, 2016 at 1:58 PM, michael mccurrey wrote:
Dear Daniela Todorova:
I am a doctoral student from Walden University writing my doctoral study titled "A quantitative correlational study of probabilistic algorithms, lean methodology techniques, and cell optimization results" under the direction of my doctoral committee chaired by Dr. Steven Case, who can be reached at phone/e-mail. The Walden University IRB Committee Chair can be contacted by:
e-mail
I would like your permission to use the dissertation survey/questionnaire instrument in my research study. I would like to use and print your survey under the following conditions:

- I will use the surveys only for my research study and will not sell or use it with any compensated or curriculum development activities.
- I will include the copyright statement on all copies of the instrument.
- I will send a copy of my completed research study to your attention upon completion of the study.

If these are acceptable terms and conditions, please indicate so by replying to me through e-mail
Sincerely,
Michael McCurrey
Date: 12/1/2016
Name: Michael McCurrey
Student at Walden University

From: Matthew Gunn
To: Michael Mccurrey
Subject: Re:
Date: Wed, 23 May 2018 17:37:38 +0000
Michael,
Yes, feel free to use the survey and alter it in any way you need for it to fit your study. I look forward to seeing your results. Good luck!
Regards,
Dr. Gunn

From: Michael Mccurrey
Sent: Wednesday, May 23, 2018 11:08 AM
To: Matthew Gunn
Cc: Michael Mccurrey
Subject:
Dear Dr. Gunn:
I am a doctoral student from Walden University writing my doctoral study under the direction of my committee chaired by Dr. Steven Case.

I would like your permission to use the "The role of task difficulty in technology acceptance" survey/questionnaire instrument in my research study. I would like to use and print your survey under the following conditions:
I will use the surveys only for my research study and will not sell or use it with any compensated or curriculum development activities.
I will include the copyright statement on all copies of the instrument.
I will send a copy of my completed research study to your attention upon completion of the study.
If these are acceptable terms and conditions, please indicate so by replying to me through e-mail.
Sincerely,
Michael McCurrey
Walden University

Appendix E: Lean Manufacturing & Probabilistic Survey

Item No.	Part 1. Demographic Questions	
1	What is your age range?	a. 75 years or older b. 65-74 years old c. 55-64 years old d. 45-54 years old e. 35-44 years old f. 25-34 years old g. 18-24 years old h. Prefer not to answer
2	What gender do you identify with?	a. Female b. Male c. Prefer not to answer
3	Ethnicity	a. Asian/Pacific Islander b. Black/African American c. Native American d. White/Caucasian e. Hispanic f. Other g. Prefer not to answer
4	Education	a. High school diploma/GED b. Some college c. Trade/technical/vocational training d. Associate's degree e. Bachelor's degree f. Master's degree g. Doctoral degree h. Professional degree i. Prefer not to answer (M.D.,J.D., D.M.D.,etc.)
5	Marital Status	a. Single/ never married b. Married or domestic partnership c. Widowed d. Divorced e. Separated f. Prefer not to answer

<table>
<tr><td>Item No.</td><td colspan="3">Part 2. Manufacturing Questions
Please write or select one answer</td></tr>
<tr><td>6</td><td>Total number of employees at the plant location</td><td colspan="2">____________________</td></tr>
<tr><td></td><td>Categorize your product mix</td><td colspan="2">a. High Volume/High Variety b. High Volume/Low Variety
c. Medium Volume/Medium Variety d. Low Volume/High Variety
e. Low Volume/Low Variety</td></tr>
<tr><td></td><td>Definitions</td><td colspan="2"><u>Job Shop</u>: high flexibility, many different products, and low volumes, e.g. a machine tool shop, a machining center, a paint shop.
<u>Batch shop</u>: moderate flexibility, several products and moderate volumes. Usually a set up time is required to change from one product to another. e.g. an injection molding.
<u>Assembly line</u>: low flexibility, a few products, and high volumes. e.g. an automobile plant.
<u>Continuous flow</u>: very low flexibility, one product and very high volume. Usually the product is measured by weight or volume. e.g. a petroleum refinery or a sugar refinery.

(please make sure that the total is 100%)</td></tr>
<tr><td></td><td>What portion of your plant operations is:</td><td colspan="2">Job Shop ________
Batch Shop ________
Assembly Line ________
Continuous Flow ________</td></tr>
<tr><td></td><td colspan="2">To what extent has your company implemented lean in your manufacturing processes?</td><td>o Not implemented
o Not implemented but planning to start
o Implemented in some manufacturing processes</td></tr>
</table>

		○ Implemented in many manufacturing processes ○ Fully implemented lean
	For how many years has your company used lean?	____ ________
	Is your company located in the USA	○ Yes ○ No
	In which country is located your company?	____ Please type in
	What is the ISIC code that most closely represents your organization?	____ Please type in
	What is the SIC code that most closely represents your organization?	____ Please type in
Item No.	Part 3. Manufacturing Processes	

	Our products are	○ Highly Customized ○ Somewhat Customized ○ Balanced Between Customized and Standardized ○ Somewhat Standardized ○ Highly Standardized
	Our product volume is	○ Very Low ○ Somewhat Low ○ Neither High, nor Low ○ Somewhat High ○ Very High
	Our manufacturing processes are	○ Highly Divergent ○ Somewhat Divergent ○ Balanced of Divergent and Standardized ○ Somewhat Standardized ○ Highly Standardized

External Just in Time	Strongly Agree	Agree	Neutral	Disagree	Strongly Disagree
We use JIT with our suppliers	O	O	O	O	O
We do not produce a product, unless the customer has order it	O	O	O	O	O
We link all processes to customer demand through Kanban	O	O	O	O	O

		Strongly Agree	Agree	Neutral	Disagree	Strongly Disagree
	Internal Just in Time	Strongly Agree	Agree	Neutral	Disagree	Strongly Disagree
	Production at each station is "pulled" by demand from the next station	O	O	O	O	O
	We use Kanban signals for production control	O	O	O	O	O
	We produce exactly as many pieces as needed	O	O	O	O	O
	Continuous Flow	Strongly Agree	Agree	Neutral	Disagree	Strongly Disagree
	Products are classified into groups with similar processing requirements	O	O	O	O	O
	Equipment is grouped to produce a continuous flow of families of products	O	O	O	O	O
	Families of products determine our factory layout	O	O	O	O	O
	Heijunka	Strongly Agree	Agree	Neutral	Disagree	Strongly Disagree
	Our production volume is distributed evenly over time	O	O	O	O	O
	We do not have peaks and valleys in our production schedule	O	O	O	O	O
	Our production mix is distributed evenly over time	O	O	O	O	O
	Quick Setup	Strongly Agree	Agree	Neutral	Disagree	Strongly Disagree
	Our employees achieve setups that save time	O	O	O	O	O
	We are working to lower setup times in our plant	O	O	O	O	O
	We have low setup times of equipment in our plant	O	O	O	O	O
	Jidoka	Strongly Agree	Agree	Neutral	Disagree	Strongly Disagree
	We detect process deviations with automated technology	O	O	O	O	O
	We detect quality deviations with automated technology	O	O	O	O	O
	Most inspections are done by automated technology	O	O	O	O	O

	Poke-Yoke	Strongly Agree	Agree	Neutral	Disagree	Strongly Disagree
	We have poke-yoke devices designed for our work place conditions	O	O	O	O	O
	We use simple, inexpensive error proofing devices	O	O	O	O	O
	Our poke-yoke devices are used 100% of the time	O	O	O	O	O
	Andon	Strongly Agree	Agree	Neutral	Disagree	Strongly Disagree
	Everyone working on the production floor is able to stop the production line if a defect is detected	O	O	O	O	O
	We have a device to stop the production line if a defect is detected	O	O	O	O	O
	Our employees stop the production line if a defect is detected	O	O	O	O	O
	Standardized Work	Strongly Agree	Agree	Neutral	Disagree	Strongly Disagree
	Our work processes are standardized	O	O	O	O	O
	We use our standards as a basis for improvement	O	O	O	O	O
	We change our work process standards as needed for improvement	O	O	O	O	O
	5 S Systems	Strongly Agree	Agree	Neutral	Disagree	Strongly Disagree
	We organize our work place with labeled positions for each tool	O	O	O	O	O
	We have cleaning responsibilities assigned to the team members	O	O	O	O	O
	We keep our workplace organized	O	O	O	O	O

Item No.	Part 3. General Questions Please circle one answer	
6.	I use a computer at home	a. Yes b. No c. Prefer not to answer
7.	My organization has an IT policy	a. Yes b. No c. Prefer not to answer
8.	I can choose which analysis tool I use.	a. Yes b. No c. Prefer not to answer
9.	I regularly use a computer at work	a. Yes b. No c. Prefer not to answer
	Circle the number that matches the degree to which you agree with each statement. 1=Strongly Disagree, 7=Strongly Agree	
10.	I would prefer to use other software packages than those provided by the company to complete my work assignments/tasks	1 2 3 4 5 6 7
11	My company provides me with the training I need to use the provided software	1 2 3 4 5 6 7
12	Learning to use the software – (analysis tools) was easy for me	1 2 3 4 5 6 7
13	It would be easy for me to become skillful at a new analysis tool.	1 2 3 4 5 6 7
14	I find new company analysis tools easy to use.	1 2 3 4 5 6 7
15	I generally find IT easy to understand.	1 2 3 4 5 6 7
16	As my IT based- tasks become difficult I am more willing to use company provided software	1 2 3 4 5 6 7

17	I find company provided software useful for completing my tasks.	1 2 3 4 5 6 7
18	Using company provided software provides me with information that leads to better decisions	1 2 3 4 5 6 7
19	Using company provided software enhances my effectiveness in my work.	1 2 3 4 5 6 7
20	Company provided software increases my work productivity	1 2 3 4 5 6 7
21	Company provided software enhances my work performance.	1 2 3 4 5 6 7
22	There is an understandable sequence of steps than can be followed in doing my work.	1 2 3 4 5 6 7
23	I often encounter problems that I cannot immediately solve.	1 2 3 4 5 6 7
24	I consider the tasks I must complete to be difficult.	1 2 3 4 5 6 7
25	I frequently deal with work tasks that I consider difficult.	1 2 3 4 5 6 7
26	I can rely on others for assistance with completing a task.	1 2 3 4 5 6 7
27	I could complete my job using a particular software package if I had never used a package like it before	1 2 3 4 5 6 7
28	I could complete my job using a particular software package if I could call someone for help if I needed assistance	1 2 3 4 5 6 7
29	I could complete my job using a particular software package if someone showed me how to do it first	1 2 3 4 5 6 7

3 0	I could complete my job using a particular software package if I had used similar packages before this one to do the same job.	1 2 3 4 5 6 7
3 1		1 2 3 4 5 6 7

General

1. How many employees are in your organization?
2. Categorize your product mix (select one)
    - o High Volume / High Variety
    - o High Volume / Low Variety
    - o Medium Volume / Medium Variety
    - o Low Volume / High Variety
    - o Low Volume / Low Variety
3. What percentage portion of your plant operation is: (total should equal 100)

_ _ Job Shop

_ _ Batch Shop

_ _ Assembly Line

_ _ Continuous Flow

4. To what extent has your company implemented lean in your manufacturing processes?
    - o Not implemented
    - o Not implemented but planning
    - o Implemented in some manufacturing processes

- Implemented in many manufacturing processes
- Fully implemented

5. For how many years has your company used lean?
6. Is your company primarily located in the USA?
   - Yes
   - No

Manufacturing process

7. What most closely defines your products:
   - Highly Customized
   - Somewhat Customized
   - Balanced between customized and standard
   - Somewhat standardized
   - Highly standardized
8. What most closely defines your products volume:
   - Very Low
   - Somewhat Low
   - Neither High, nor low
   - Somewhat High
   - Very High
9. Our manufacturing processes are:
   - Highly Divergent
   - Somewhat Divergent

- Balance of Divergent and standard
- Somewhat standard
- Very Standardized

12. External Just in Time (JIT)
    - We use JIT with our suppliers.
    - We do not produce a product, unless a customer orders it.
    - We link all processes to customer demand through Kanban.
13. Internal Just in Time
    - Production at each station is “pulled” by demand from the next station
    - We use Kanban signals for production control
    - We produce exactly as many pieces as needed
14. Continuous Flow
    - Products are classified into groups with similar processing requirements
    - Equipment is grouped to produce a continuous flow of families of products
    - Families of products determine our factory layout
15. Heijunka
    - Our production volume is distributed evenly over time
    - We do not have peaks and valleys in our production schedule
    - Our production mix is distributed evenly over time
16. Quick Setup
    - Our employees achieve setups that save time
    - We are working to lower setup times in our plant

- We have low setup times of equipment in our plant

17. Jidoka

- We detect process deviations with automated technology
- We detect quality deviations with automated technology
- Most inspections are done by automated technology

18. Poke-Yoke

- We have poke-yoke devices designed for our work conditions
- We use simple, inexpensive error-proofing devices
- Our poke-yoke devices are used 100% of the time

19. Standardized Work

- Our work processes are standardized
- We use our standards as a basis for improvement
- We change our work processes standards as needed for improvement

20. 5 S systems

- We organize our work place with labeled positions for each tool
- We have cleaning responsibilities assigned to the team members
- We keep our workplace organized

21. Total productive/Preventive Maintenance

- We dedicate a portion of every day to planned equipment maintenance related activities
- We maintain all our equipment regularly
- We maintain excellent records of all equipment maintenance related activities

22. Kaizen (Continuous Improvement

    - Our employees participate in rapid improvement events
    - Our employee’s suggestions are generally implemented
    - Our employees work to eliminate waste in an ongoing fashion

Simulation

23. Our companies experience with workflow simulation software is

    - Our company has no history
    - Our company has used it in the past, but not currently
    - Our company actively uses software

24. My experience with workflow simulation software is

    - I have no work history with workflow simulation software
    - I have worked with workflow simulation software in the past
    - I am actively using workflow simulation software

25. Operation performance since implementing simulation software (select all that apply)

    - We reduced overall production costs
    - We improved quality
    - We improved delivery on time

26. Cell optimization results since implementing simulation software

    - Our expectation was not met
    - Our expectation was mostly met
    - Our expectation was met

27. Satisfaction with the simulation software (select all that apply)

    - The use of software has met our expectations
    - Our company has achieved cell optimization goals with the software
    - We are pleased with our simulation software

Assembly Cell Modification

28. Our company has a defined process to make changes in the assembly cell?

    - Yes
    - No

29. What methods have been used to make changes to assembly cell workflow (select all that apply)

    - Manual adjustment
    - Manual sketching (Whiteboard / Visio / Chalk)
    - Predictive analytics
    - Modeling software
    - Other

30. Can employees make modifications to the assembly cell workflow automatously?

    - Yes
    - No

31. Analysts are aware of simulation software for assembly cell workflow changes?

    - Yes
    - No

Lean Processes

32. Value Stream Mapping

- We use value stream mapping to eliminate muda
- We use VSM to improve our business process
- We use VSM to improve our production flow

33. Muda

- Our workers identify non-value-added activities
- We are working to minimize non-value-added activities
- Everybody participates in eliminating non-value-added activities

34. Operation performance since implementing lean

- We reduced overall production costs
- We improved quality
- We improved delivery on time

35. Firm performance since implementing lean

- Our sales have increased
- Our market share has increased
- Our return on investments has increased

36. Satisfaction with the lean program

- The use of lean has met our expectations
- Our company has achieved lean program goals
- We are pleased with our lean program

37. Your lean knowledge (check all that apply)

- Lean experienced
- Lean training

- Lean certificate
- Six-Sigma/Lean certificate Green Belt
- Six-Sigma/Lean certificate Black Belt
- Six-Sigma/Lean certificate Master Black Belt
- Other