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Project Manager Leadership Behaviors for Successful Digital Transformation Implementation: Contingency Theory Approach

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2024

Abstract

Project Manager Leadership Behaviors for Successful Digital Transformation

Implementation: Contingency Theory Approach

by

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MBA, University of Maryland, 2019

MS, University of Nevada, 2008

BS, University of Peradeniya, Sri Lanka, 1985

Doctoral Study Submitted in Partial Fulfillment

of the Requirements for the Degree of

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Abstract

Leaders of large industrial companies (LICs) are concerned about the leadership behaviors (LB) of digital transformation (DT) project managers (PMs), as over 75% of DT projects in LICs fail to be completed successfully**.** Grounded in contingency theory of leadership (CTL), the purpose of this quantitative correlational study was to examine the relationship between LB (task-oriented [TO] vs. relationship-oriented [RO]) of DT PMs and the successful completion of DT projects in three contingency situations: favorable, moderately favorable, and unfavorable. These situations were defined based on three independent variables: (a) PM's leader-member relationship, (b) PM's task structure, and (c) PM's position power. Data were collected from 214 PMs from U.S. LICs via online surveys and analyzed through binary logistic regression (BLR) and cluster analysis. BLR results indicated that PMs LB and situation interactively significantly predicted the DT project completion status in favorable (β = -.99, p = .025) and unfavorable (β = -90.73, p = .040) situations. Data well-separated into three clusters (mean Silhouette score = .54). Some PMs (47.20%) with RO LB completed DT projects successfully in favorable situations, and others did not. Key recommendations are PMs with TO LB to manage DT projects in LICs and improve situations through open communication among team members, excellent recognition and rewards and mentorship programs for DT employees, and clear articulation of the DT project's goals and objectives. The implications for positive social change include the potential for business leaders in LICs to increase employment opportunities and improve the quality of life for the populace in underserved communities through delivering advanced digital products and services.

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Dedication

I dedicate this dissertation to my beloved parents, who have meant and continue to mean so much to me and whose love for me knew no bounds. Although they are no longer of this world, their memories continue to regulate my life. I thank my dad so much for teaching me the value of hard work, which I will never forget. May you find peace and happiness in Paradise. I profoundly thank my mother, who left a void never to be filled in my life, whose constant love, support, and encouragement have sustained me throughout my life, and whose memory will live if I live.

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Section 1: Foundation of the Study

Digital transformation (DT) involves leveraging modern digital technologies such as social media connectivity, the Internet of Things (IoT), artificial intelligence (AI), cloud computing, machine learning, and intelligent manufacturing to transform organizations for improved business performance, increased sales, increased profits, and boosted customer satisfaction and retention (Doukidis et al., 2020; Kraus et al., 2021a; C.-H. Lee et al., 2021). Through the successful implementation of DT projects, organizations can achieve novel product and service offerings, advance the structure of their supply chains, and vastly improve processing power through reduced costs and improved product development, thereby reducing industry competition (Doukidis et al., 2020; Kretschmer & Khashabi, 2020; C.-H. Lee et al., 2021; Nasiri et al., 2020; Verhoef et al., 2021). In 2019, 40% of all technology investments by large industrial companies (LICs) globally were in DT and growing at a compound annual rate of 17.5% (Appio et al., 2021; Govindarajan & Immelt, 2019). According to Appio et al. (2021), the World Economic Forum predicted that AI or other digital technology would drive the processes and products of 90% of new enterprise applications by 2025, with only 21% of companies having completed their DT processes, an estimated 67% of the $100 trillion investment at stake from DT by 2025. Despite the significant investments, DT projects' massive failure is causing an extensive social and economic crisis, mainly affecting LICs. According to Brunner et al. (2023) and Müller et al. (2024), leadership behaviors (LB) of project managers (PMs) are an essential driver of employee performance, task planning, and productivity, leading to successful DT project implementation. With limited literature on the LB of DT PMs (Ahmad et al., 2022), this study investigated the relationship between the LB of PMs of DT projects and successful DT project implementation in LICs in the United States.

Background of the Problem

In the current digital age, the organizational survival of LICs depends mainly on their DT capabilities. According to Ghosh et al. (2022), LICs operate in the industrial environment where product differentiation is a competitive necessity, and digital technologies such as software, AI, cloud computing, IoT, big data, and intelligent manufacturing are major driving forces for growth and innovation. According to Cooney et al. (2021), 93% of chief executive officers (CEOs) of industrial companies globally see disruptive emerging technologies as driving competition in their industry and DT as a critical change program that is required to operate and survive. DT is a significant organizational change induced by digital technologies that have disrupted all industries during the past decade (Cooney et al., 2021; Ghosh et al., 2022).

According to a recent trend, LICs are spending massive amounts of money on transforming digitally for improved growth and innovation to enhance their business models through reduced repair and delivery time, reduced cost, and enhanced quality using digital tools. However, over 75% of the DT initiatives failed in LICs (Correani et al., 2020; Datta & Nwankpa, 2021; Reeves et al., 2018), demonstrating that most large companies from the industrial sector lack DT competency. Failed DT projects negatively impact profitability, competitive advantage, and companies' sustainability (C.-H. Lee et al., 2021). It is necessary to examine the reasons for the failure and identify the contributing factors for successful DT project implementation in LICs.

In many LICs, the PMs' LB positively and significantly influenced the success of DT project implementation (Ahmad et al., 2022; Brunner et al., 2023; Dubey et al., 2020; Müller et al., 2024; Shao, 2019). PMs must understand the complexity of DT projects and design their task structures effectively; they must also set clear project goals, maintain good relationships with team members, motivate, coach, and control the team effectively to accomplish project tasks and implement the DT projects successfully (Brunner et al., 2023; Müller et al., 2024). There is a considerable gap in the research on the impacts of LB of DT PMs on DT project implementation, resulting in over 75% failure of DT projects in LICs in the United States.

Problem and Purpose

The specific business problem that triggered this study is that some PMs in LICs do not know the relationship between PM's LB and DT project completion status. Therefore, the purpose of this quantitative correlational research study was to investigate the relationship between PM's LB and DT project completion status. The independent variables were (a) PM's LB, (b) PM's member relationship, (c) PM's project task structure, and (d) PM's position power. The dependent variable was DT project completion status. The target population consisted of PMs of LICs in the United States, focused on digitally transforming their businesses.

Population and Sampling

Population

The population for this doctoral research consisted of PMs who managed or were managing DT projects during this study from large companies (# of employees ≥ 500 as defined by the federal government) from the industrial sector in the United States and who focused on transforming their businesses digitally. I used the third-party Centiment Survey Panel (Centiment.co) to panel the population for this study. A large pool of PMs who met the eligibility criteria based on the screening criteria provided in Appendix A paneled through the Centiment.co company (hereafter Centiment) served as the population for this study. This population was appropriate for answering the research questions because this study's scope was to investigate the relationship between DT project completion status and the PMs' LB measured at the PM level in three contingency situations of the PM (PM's TS, PM's LMR, and PM's PP).

Unit of Analysis and Dependent Variable

The unit of analysis in a research study is the object of inquiry, which defines the structure of research data and is a central consideration in any methodology (W. Li et al., 2017). All persons conducting research studies must be clear about the unit of analysis used in their research study. The unit of analysis used in this research was the PM. The dependent variable of this study was whether the PM had completed a DT project or not completed it within the allocated budget, within the scheduled time frame, and per quality expectations by stakeholders but focused on transforming their businesses digitally. I have listed in Appendix C the screening questions used to collect data for the dependent variable of this study.

Independent Variables

The independent variables of this study were (a) PM's LB, (b) PM's LMR, (c) PM's TS, and (d) PM's PP. I collected primary data for the independent variables using the following four scales developed and used by Fiedler (1967): (a) the Least Preferred Coworker (LPC) Scale with 18 items, (b) the Leader–Member Relations (formerly referred to as Group Atmosphere) Scale with eight questions, (c) the Task Structure Rating Scale with 10 questions, and the (d) Leader's Position Power Rating Scale with five questions (Fiedler & Chemers, 1984) to collect data for PMs LB, PM's LMR, PM's TS, and PMs' PP, respectively. I administered the scales to the eligible participants through the Centiment survey administration tool and collected the data.

Sampling

This research study involved a quantitative method and correlation design to examine the relationship between the PM’s LB (primary independent variable) and DT project completion status (dependent variable) at three contingency variable levels (PM’s LMR, PM’s TS, and PM’s PP [independent variables]). The appropriate sampling method for this study, therefore, was probabilistic. I chose the stratified random sampling technique because there was variation in the targeted population, and the population size was not fully known. The population size came from the paneling statistics provided by Centiment, and the population size was only approximately known to me. The simple random sampling (SRS) method is appropriate when the population is homogeneous, and the research study involves all cases in the entire population (Bhardwaj, 2019).

The statistical testing technique used in this study was binary logistic regression (BLR) because the dependent variable was dichotomous. There is no common acceptance in determining sample size for BLR. A smaller than required sample size causes a loss of information and misjudgments, and a larger than required sample wastes resources. I conducted an a priori sample size analysis using the G*Power software (version 3.1.9.7) with *Z*-tests and logistic regression options. G*Power is an effective statistical software package that social scientists and business personnel use to conduct statistical power analyses and sample size requirement determinations (Kang, 2021). A priori sample size analysis conducted prior to the beginning of the study is ideal as a powerful analysis tool for its ability to enable controlling Type I errors (the probability of rejecting a true null hypothesis) and Type II errors (the probability of accepting a false null hypothesis; Lakens, 2022).

G*Power covers statistical power analyses for many different statistical tests in the families of *F*-test, *t* test, $\chi 2$-test, *Z*-test, and some exact tests (Kang, 2021). The probability $p1 = \Pr(Y = 1|X = 1) = H_0$, the probability of occurrence of the negative (–) effect is an input field in G*Power. The probability $p2 = \Pr(Y = 1| X = 1) = H_1$ is the probability of occurrence of the positive (+) effect is another input field in G*Power. Specifying the effect size is achievable in two ways: (a) directly by inputting the two probabilities (*p1* and *p2*) or (b) by calculating the odds ratio (*OR*) using the two probabilities and inputting the *OR* in the analysis (Kang, 2021).

In this study, I tested whether a statistically significant effect existed; therefore, I wanted to ensure that the sample size was large enough to prevent erroneous conclusions about the desired effect size. Assuming a medium effect size ($p1$ = .24), a standard significance alpha level of .05 (α = .05), and four predictor variables, the a priori power analysis indicated a minimum sample size required of 143 to achieve a statistical power of .80. A larger sample size lowers the likelihood of error in generalizing the findings to a target population (Lakens, 2022). Therefore, this study's sample size of 214 PMs was adequate and appropriate.

Nature of the Study

The chosen research method and the research design in this doctoral study to address its research questions were quantitative and correlation. The approach was to examine the relationship between PM’s LB (primary independent variable) and DT project completion status. In this study, I analyzed numerical data using inferential statistical tests to investigate the relationship between multiple independent variables and a dependent variable and inferred the results from a larger population, for which the quantitative research method was appropriate (Johnston et al., 2019).

Correlation research design enables prediction and explanation of the relationship between two or more variables without varying, manipulating, or controlling any of the variables. Unlike experimental research designs, correlational research designs analyze the extent to which the variables are related and the nature of the relationship among two or more variables without manipulating the variables (Seeram, 2019). I compared two categories of LB of PMs (task-oriented [TO] vs. relationship-oriented [RO]) who managed or were managing (during the study) DT projects on the two possible values of the dependent variable (yes/no) in three variable contingency situations (PM's LMR, PM's TS, and PMs' PP). The data collection for the dependent and independent variables occurred without control, interference, or manipulation. I tested hypotheses about the relationships between dependent and multiple independent variables without manipulating any variables, which made the correlation the best design (Seeram, 2019) for this study.

Research Questions

RQ1: What is the relationship between PM's leadership behaviors and DT project completion status?

RQ2: What homogenous clusters of PM's leadership behaviors emerge based on DT project completion status?

Hypotheses

Null Hypothesis $H_0 1_1$: There is no significant relationship between PM's leadership behaviors and DT project completion status.

Alternative Hypothesis $H_1 1_1$: There is a significant relationship between PM's leadership behaviors and DT project completion status.

Null Hypothesis $H_0 2_1$: There are no homogenous clusters of PM's leadership behaviors that emerge based on DT project completion status.

Alternative Hypothesis $H_1 2_1$: There are homogenous clusters of PM's leadership behaviors that emerge based on DT project completion status.

Theoretical Framework

The theory that grounded this study was the contingency theory of leadership (CTL) introduced by Fiedler (1958). The key constructs underlying the CTL are (a) good leader–member relations, (b) tasks with clear goals and procedures, and (c) the leader's position power to reward and punish per members' performance. According to Fiedler (1958, 1964, 1967), how the group receives the leader, the structure of tasks involved, and whether the leader can control the group depends on the leader's LB. The theory has evolved to address the adaptability of LB to manage external and internal business environments. In situations where the group members are inadequately skilled or rely on the structure of the task, such that tasks are complex or not well defined and structured, a leader must rely more on task-oriented LB (TOLB) to accomplish goals (Fiedler, 1967). On the contrary, when the members are skilled and independent, and the nature of the task is less complicated and well defined, human relations are vital, and the leader must rely on relationship-oriented LB (ROLB) to accomplish goals (Fiedler, 1967).

As applied to this doctoral study, the CTL was appropriate. CTL has directly moderated the relationship between the PMs' LB (TO vs. RO) and DT project completion status. Per several past studies (Henkel et al., 2019; Shao, 2019; Warner & Wager, 2019), the LB of leaders fell into a dichotomy of two metacategories: (a) TO and (b) RO; this dichotomy of LB of PMs influenced the DT projects' successful implementation.

Operational Definitions

Digital transformation: The process by which organizations adapt themselves to modern digital technologies such as the Internet of Things, social media connectivity, cloud computing, artificial intelligence, big data, and predictive analytics, among others (Albukhitan, 2020; Doukidis et al., 2020; Kretschmer & Khashabi, 2020).

Failed project: An abandoned, canceled, or unsuccessful project that the company did not complete or completed without adhering to its requirements (Correani et al., 2020).

Leadership behavior: The leader's ability to induce subordinates to work with enthusiasm and confidence is considered a central axis of the relationship between superiors and subordinates and one of the aspects of mutual influence between individuals and the group (Fiedler, 1967; Henkel et al., 2019).

Leader–member relationship: Fiedler (1967) defined the leader–member relationship as the interpersonal relationship the leader establishes with his team.

Leader's position power: The potential power that the organization provides for the leader's use to influence the leader's group members to get them to comply with and accept the leader's direction and leadership (Fiedler, 1967; Kovach, 2020).

Project completion: When the project manager has delivered the project within the agreed scope of the project, within the agreed cost, schedule, and quality, ensuring the fulfillment of all acceptance criteria, the satisfaction of stakeholders, and meeting all business objectives (L. H. Nguyen, 2021; Zid et al., 2020).

Project management: The planning, organization, monitoring, and control of all aspects of the project, with the motivation of all people, included to achieve project goals safely within the agreed schedule, budget, and performance criteria (Project Management Institute, 2023a; Venczel et al., 2021).

Project manager: The professional who plans, organizes, and executes projects within restraints such as allocated budgets and schedules, defines project goals, leads entire project teams, liaises with stakeholders, and ensures the successful closure of the project (Project Management Institute, 2023b).

Successful project: A project is successful if it meets cost objectives, completes within schedule, and meets expected quality (L. H. Nguyen, 2021).

Task-structure: The dimensions and characteristics that classify and describe the task or project that can be modified to enhance the dynamics of the task group or project team, including the amount of freedom and discretion that a team member has in performing assigned tasks, such as scheduling work, determining work methods, and the extent to which an employee requires materials, information, and expertise from colleagues to accomplish the task (Fiedler, 1967).

Assumptions, Limitations, and Delimitations

Assumptions

An assumption in research is an unwarrantable claim or supposition accepted as accurate without proof about any research component, such as the phenomenon studied, resources, cost, schedule, technology, or location (Nkwake, 2020). One of the central assumptions of this study was that PMs could successfully complete every DT project if they managed and controlled it correctly. Another critical assumption that drove this study was that the success of every DT project is directly linked to the correct application of contingency leadership behaviors (TO or RO) by project managers (PMs) to manage projects and control contingencies. Other assumptions included participants answered survey questions honestly and factually. A further assumption was that a DT project would be successful and considered completed if it were completed within an agreed-upon schedule and met the objectives of cost and quality criteria assigned during initiation. For this study, I assumed the research findings would improve business practices and people's lives in the United States.

Limitations

Limitations in research represent potential weaknesses, constraints, and unanticipated challenges associated with any research component that may limit the ability to generalize from the research’s findings, describe applications to practice, and the usability of the findings (Ross & Zaidi, 2019). I used existing standard survey instruments to collect primary data for the independent variables. This study had the following survey instrument limitations: (a) responses to the survey were subjected to the limitation of predefined response categories, thereby limiting the range of responses, and (b) respondents were limited to the text direction in the survey about how to complete it. The information relevant to this study that participants were unwilling to provide further limited the study. The assumption of linearity between the logit of the dependent and the independent variables (van Smeden et al., 2019) and the subsequent requirement of linear boundary constructs did limit the BLR procedure.

Delimitations

Delimitations in research reflect the choices the people conducting the research make regarding what they aim to achieve by conducting the research and what they will exclude studying (Akanle et al., 2020; Mengist et al., 2020). In this quantitative correlational study, I aimed to investigate the relationship between PM's LB and DT project completion status. The study's scope was limited to large (# employees ≥ 500) industrial companies. PMs from small and medium-sized companies (# employees < 500) were excluded from this study. The intended population included the PMs from U.S.-based LICs. PMs in LICs based in other countries were not considered and were out of scope. This study investigated the relationship between the LB of PMs and the completion status of DT projects managed in the past or managed during the data collection for this study; thus, DT projects not managed by PMs were outside the scope.

Significance of the Study

This study is significant in that the results may provide new insights regarding the identification and introduction of predictive models that can enable managers to make predictions about future outcomes using historical data that enhance the managers' capability and efficiency of making better decisions to complete DT projects and competitively deliver advanced digital products and services at large U.S.-based industrial companies. The results from the study may contribute to positive social change by promoting and facilitating the systematization of key digital processes within the practice of business. By adopting strategies related to DT, such as AI, big data analytics, machine learning, IoT, smart manufacturing, and more online customer services, LICs may lower costs and create tangible improvements regarding the availability of digital services within underserved communities, improving their living standards. They may enhance employment opportunities, increase spending, and boost the economy of the local communities and the U.S.

A Review of the Professional and Academic Literature

A doctoral study becomes credible when prior studies' findings are reviewed for conceptual, methodological, and thematic development, critically analyzed, and synthesized logically, and when gaps are identified (Paul & Criado, 2020). I conducted this quantitative correlational study to investigate the relationship between two categories of LB (TO vs. RO) of PMs who managed or were still managing (during data collection for this study) DT projects on DT project completion status in three contingency situations (PM’s PP, PM's LMR, PM's TS). The following two null hypotheses guided this study: (a) there is no significant relationship between PM's LB and DT project completion status, and (b) no homogenous clusters of PM's LB emerge based on DT project completion status. In this literature review, I discuss the theoretical framework for this study, the CTL introduced by Fiedler (1958), who stated that leaders acquire leadership style through their life experiences and that their leadership styles are impossible to change and must fit the situation.

Information contained in some leadership theories from literature provide contrasting evidence to Fiedler's (1958) CTL, including (a) situational leadership theory (SLT), introduced by Hersey and Blanchard (1970, as cited in Benmira & Agboola, 2021), who stated that leaders must compete with and adapt to the situation and transform their leadership styles to match the maturity (readiness) of their subordinates; (b) the behavioral theory of leadership (BTL) introduced by Blake and Moutan (1945, as cited in Benmira & Agboola, 2021), who believed that great leaders are not born and people can become leaders through proper training and observation and focused on the actions of leaders, and not their mental qualities or internal traits; and (c) the transformational leadership theory (TRFLT) founded by Burns (1978), who stated that leaders inspire followers using the strength of their vision, personality, and charismatic behavior, which alter the followers' preconceptions and perspectives and motivate them to work toward similar organizational objectives to improve organizational efficiency.

In contrast, several theories support CTL and help in examining its relevance and application, including (a) the trait theory of leadership (TTL), introduced by Allport (1936, as cited in Jayawickreme et al., 2019), who stated that successful leadership characteristics could be either inherited or acquired through training and practice and that successful leaders with the right combination of characteristics for a situation must be identified; (b) the great man theory (GMT) introduced by Carlyle (1840, as cited in Benmira & Agboola, 2021), who stated that leadership capacity is inherent that great leaders are born, not made; and (c) the transactional leadership theory (TRALT), developed by Burns (1978), who stated that leaders rely on authority such as reward and punishment for followers' efforts to motivate them to accomplish organizational goals. In other words, transactional leaders influence followers through contingent rewards and negative feedback or corrective coaching toward achieving established goals, completing required tasks, avoiding unnecessary risks, and maintaining the current organizational situation (Young et al., 2021).

In this academic literature review, I systematically review existing trends and literature, summarize and synthesize information from the literature on the independent and dependent variables, and discuss the primary independent variable of this study (LB of DT PMs) and the three contingency independent variables, PMs LMR, PM's TS, and PM's PP, through the theoretical framework lens of Fiedler's CTL (Fiedler, 1967; Henkel et al., 2019). I also discuss the literature related to the dependent variable of this study, the successful DT project completion status, critically analyzing the impacts of DT on businesses, factors affecting successful DT project implementation, successful DT project completion criteria, and significant reasons and impacts of DT project failures in organizations. I further discuss the measurement of this study's independent and dependent variables and describe how this study addressed a gap in the literature.

The scope for the literature search was around DT at large industrial companies (LICs) in the private sector in the United States. I searched Walden University library databases through (a) ScienceDirect, (b) ProQuest Central, (c) Emerald Management, (d) EBSCOhost, (e) ERIC, (f) ABI/INFORM Complete, (g) Thoreau, (h) Sage Premier

Annual Reviews, and (i) Google Scholar. The key terms I used in the literature search for this review included (a) *digital transformation*, (b) *contingency theory*, (c) *leadership behaviors*, (d) *digital leadership competencies*, (e) *project management*, (f) *project completion criteria*, (g) *project success criteria*, (h) *project failure reasons*, (i) *large industrial companies*, and (j) *skilled employees.*

The literature review comprised 250 research articles, books, and web sources published between 1958 and 2024, of which 222 (88.80%, Table 1) fell within the last 5 years (2019 and after). Twenty-eight articles (11.20%) had publication years between 1958 and 2018 (Table 1) and addressed the theoretical framework and data analysis techniques. This review included 235 of the 250 sources (94.00%, Table 1) published in high-impact, active, and peer-reviewed scholarly journals. I used Ulrich's Web Global Serials Directory to confirm that the references cited were peer reviewed and active.

Table 1

A Summary of Literature Review Sources

Type of source	Current source (2019–2024)	Older source (before 2019)	Total	Percent
Peer-reviewed source	215.00	20.00	235.00	94.00
Other source	7.00	8.00	15.00	6.00
Total	222.00	28.00	250.00	100.00
Percent	88.80	11.20	100.00	

Contingency Theory of Leadership

Contingency theory (CT) is a class of behavioral theory that concerns the context of leadership whose proponents claim that there is no best way to organize a corporation, lead a company, or make decisions; the optimal course of action is contingent upon the internal and external situations (Fiedler, 1967; Shala et al., 2021). A group of researchers from Ohio State University (OSU researchers) first developed CT in 1950 (Anderson & Sun, 2017). According to the OSU researchers, effective leadership involves building good interpersonal relationships and initiating a structure ensuring task completion and goal attainment (Anderson & Sun, 2017). During the same time, another group of researchers from the University of Michigan's Survey Research Center (UMSRC researchers) investigated the relationship between group productivity and effective LB and found similar structural behaviors identified by the OSU researchers (Anderson & Sun, 2017). UMSRC researchers grouped the LB into two meta categories termed (a) ROLB and (b) TOLB.

Fred Fiedler, considered the pioneer of contingency theories in 1958, extended the research by UMSRC researchers and founded the contingency theory of leadership (CTL, the framework of this study), emphasizing LB as taking control over situations (Fiedler, 1967). Fiedler believed that leadership effectiveness significantly depended on leaders' ability to control the situation and postulated the two primary behaviors (TOLB and ROLB) of leaders in CTL. Fiedler (1967) developed the Least Preferred Coworker (LPC) scale to determine the effectiveness of LB. This scale suggests that the situation is highly favorable and fit when the job is clearly defined, the leader has the authority or position power, and a healthy relationship exists between leader and followers (Fiedler, 1967; Rehman et al., 2020). Fiedler (1967) suggested that the LB one adopts is fixed and challenging to change.

According to Fiedler (1967), in CTL, a leader's effectiveness depends on a combination of two forces: (a) the leader's managerial style displayed as the LB and (b) the favorableness of the situation. When the company aims to increase production and where the work is technically complex, a leader must focus on completing the tasks without necessarily considering employees' relationships or wishes. In contrast, if the company is working to increase teamwork through collaboration for project success, a leader must focus on RO management and getting the workers' consent. Thus, managers' LB must fit the context of the situation for the projects to be completed (Fiedler, 1967; Rehman et al., 2020). Once the LB is determined using the LPC questionnaire, a determination of the contingency situation that describes the leader's situational control is required, which, according to Fiedler (1964, 1967), includes the (a) leader's task structure, (b) the leader's position power, and (c) the relationship the leader maintains with their members.

Fiedler (1964), using the three contingency variables (leader's task structure, leader's position power, and leader's member relationship), divided the leader's situation into eight octants (I, II, III, IV, V, VI, VII, VIII) based on the favorability to the leader (Table E1 [Appendix E]). Fiedler (1964) conducted 12 studies that yielded 63 relationship combinations between leaders' LB and group performance in several industrial organizational situations and used the median Spearman's correlation for each octant from the results of the studies to derive the standard CTL model. I have presented Fiedler's (1964) results in Table E1 (Appendix E), representing the standard value of Fiedler's CTL model. According to Fiedler (1964), Spearman's rho correlations between the leaders' LPC and group performance measures were consistent across studies and the relations within eight octants were highly nonrandom in distribution. Ayman et al. (1995), Chemers and Skrzypek (1971, 1972), Fiedler and Chemers (1984), and Graen et al. (1970) confirmed Fiedler's (1964) results in their studies. I have displayed the results from Chemers and Skrzypek (1971, 1972) in Figure E3 (Appendix E).

Fiedler (1964), in CTL, further classified the eight octants into three categories of favorableness to the leader: (a) favorable situations (octant I, octant II, and octant III), (b) moderately favorable situations (octants IV, V, VI, and VII), and (c) unfavorable situations (octant VIII). Later, Fiedler (1967) and several other investigators, including Ayman et al. (1995) and Fiedler and Chemers (1984), classified octant VII as unfavorable to the leader based on their study's results. Chemers and Skrzypek (1971, 1972) classified octant III as a moderately favorable situation for the leader (Figure E3 in Appendix E). According to Ayman et al. (1995), Fiedler (1964, 1967), and Fiedler and Chemers (1984), TO leaders (with low LPC, < 73) perform best in favorable situations (octants I, II, and III) and unfavorable situations (octant VII and VIII); they perform the least in moderately favorable situations (octants IV, V, and VI), while RO leaders (with high LPC, ≥ 73) perform best in moderately favorable situations and least in favorable and unfavorable situations.

Constructs Underlying CTL

The vital constructs underlying the CTL are (a) good leader–member relations, (b) tasks with clear goals and procedures, and (c) the leader's position power for rewards and punishments per members' performance. How the group receives the leader, the success of tasks involved, and whether the leader can control the group depends on the leader's LB and the situation. Per CTL, in situations where the group member is not skilled or relies on the nature of the task such that tasks are not well defined, a leader must rely more on a TOLB to accomplish goals (Fiedler, 1967). On the contrary, when the members are skilled and independent, and the nature of the task is less complicated, human relations are vital, and the leader must rely on the ROLB to accomplish goals (Fiedler, 1967).

Fiedler (1967) defined *favorableness* as how the situation enables the leader to exert influence over his group and introduced the Least Preferred Coworker Scale to measure LB. The scale comprises 18 questions about how leaders handled their least preferred coworkers. Also, when the leader and the group members have the requisite physical resources, skills, and abilities, then the ability of the leader to motivate members and to direct and coordinate their efforts depends on three major contingency factors: (a) the leaders' position power, (b) the structure of the task, and (c) the interpersonal relationship between leader and members (Fiedler, 1967). The CTL has evolved to address the adaptability of LB to manage external and internal business environments for successful project implementation (Farhan et al., 2024; Henkel et al., 2019; Nicolás-Agustín et al., 2022; Shao, 2019; Warner & Wager, 2019).

Relevance of CTL to This Study

As applied to this doctoral study, CTL is appropriate because CTL has directly moderated the relationship between the PMs' LB (TOLB vs. ROLB) and DT project completion status. Henkel et al. (2019), in a quantitative descriptive research design study, used the Fred Fiedler leadership behavioral style self-assessment survey tool (FLBSSST) to measure 129 managers' LB (TOLB versus ROLB) related to successful project completion and showed that the distributed combination of the managers' TOLB and ROLB positively correlated to successful project completion. Popp and Hadwich (2018), in a quantitative correlational research study, used Fiedler's CTL on 315 industrial service participants and found a significant positive correlation between ROLB and employees' overall successful performance regardless of the three situations studied (employee–customer relationship, task structure, and personal power of the employees).

Warner and Wager (2019), in a qualitative multiple case study design using CTL, found cross-functional teams and leadership support as essential factors in building DT capabilities. Brown et al. (2021), in their meta-analytic investigation, reported that the TOLB and ROLB were critical regarding leader influence on virtual team collaboration. When task interdependence was high and team size was large, leaders' ROLB was necessary to enhance both the team and individual processes and outcomes; in contrast, when the task complexity was high, leaders' TOLB was essential to strengthen both the team and individual processes and projects (Brown et al., 2021). Research using CTL theory indicated that no single task structure equally applied to DT project success in all organizations. Still, organizational effectiveness depends on a fit or match between the technology, people, environmental volatility, the organization's size, the organizational structure's features, and its information system (Makhlouf & Allal-Chérif, 2019). Thus, the CTL upholds the approach to the study of DT, where LB is contingent on factors such as technology, culture, task complexity or organizational structure, and the external environmental influence that impacts the design and implementation of DT projects.

Leader's Position Power

French and Raven (1959) analyzed the complexities of leaders' position power (PP) and classified it into five categories: (a) referent, (b) expert, (c) legitimate, (d) reward, and (e) coercive. Referent and expert power are considered informal because they do not have a direct managerial span of control; they exist without any recognized formal official authority of the leader of a company (Kovach, 2020). The other three types of power (reward, coercive, and legitimate) are formal because these depend on the leader's formal position of authority in the organization (Kovach, 2020). According to French and Raven (1959), these three formal leaders' PP categories enable a person or group in the dominant position to influence another person or group in a submissive role. Fiedler (1967), in his CTL, stated that the leaders' PP is highly related to French and Raven's (1959) concepts of legitimate power and reward power.

According to Kovach (2020), leaders' PP allows the leader to influence and modify the behaviors and attitudes of individuals and groups and is the primary source of power for managers in achieving results or compliance from subordinates. Almazrouei et al. (2020) and Gregory and Osmonbekov (2019) found that employees who received rewards from their leaders developed a positive attitude toward their jobs and performed effectively. According to Fiedler's (1967) CTL, leaders' relationship with their group members depends to a significant extent on the power the leaders wield over their members under their position. Leaders with high PP get their group members to comply with and accept directions and leadership, making their job easier. In contrast, a leader with low PP must first convince his group members that they follow the leader, which hurts the leader–member relationship in the group. In CTL, Fiedler (1967) stated that the leader's reward power (power based on the leader granting valuable rewards to followers to carry out the leader's instructions) is a potent incentive to motivate followers to act. Adequate reward power creates a good relationship between leader and follower and influences how the followers perceive the leader. DT managers could enforce leaders' PP in the three formal French and Raven (1959) power categories (reward, coercive, and legitimate) for projects' successful implementation.

The published literature has little evidence addressing the relationship between the leaders' PP and successful project implementation. The least understood is through which processes some managers are acknowledged as good leaders by their subordinates while other managers are not, even when both have the same authority to reward and punish their staff, making it essential to study the LB of managers contingent on their PP. A leader's PP is the potential to influence, while leadership is the leader's LB that is conducive to exercising their influencing power. DT PMs' practice of the influence of power can enhance employee performance leading to successful DT project implementation in organizations because the leader's legitimate power of responsibility can help guide the powerless group members to overcome any fear of change and complexities of tasks.

Importance of Leaders' PP in DT Projects. DT necessitates significant changes in organizational structures, strategy, culture, and other properties to remain competitive, which calls for strong leadership to manage the large-scale transformative projects to align strategy with organizational culture and provide employees with the necessary training, knowledge, support, and guidance to embrace the change effectively (Gilli et al., 2023; Singh et al., 2020). The DT managers may need high PP to make the managers' job easier and interact with their members in terms of the roles and mutual expectancies. However, what leadership competencies are required to lead DT impactfully is unclear, although DT is at the top of several organizations' management agendas aiming to transform their organizations digitally (Firk et al., 2021; Gilli et al., 2023).

Leader–Member Relationship

Almazrouei et al. (2020) and Gregory and Osmonbekov (2019) showed that the leader-member relationship (LMR) determines the quality of work the followers perform in a workgroup. A high-quality LMR favors several benefits in projects, such as efficient resource allocation, challenging task assignments, and professional mentoring and guidance (Zhou et al., 2021). Good LMR attests to the positive relationship between leader and follower, leading to followers' high-performance behavior and job satisfaction and enhancing work performance, increasing operational efficiency and organizational productivity (L. H. Nguyen, 2021; Zhou et al., 2021). Follow-up followers reciprocate the leader's favorable treatment by engaging in discretionary behaviors to promote organizational productivity. A high-quality relationship goes beyond job-related contractual obligations and motivates followers to return with high productivity and in-role performance. Good leaders use their power to establish a good relationship with their subordinates, providing them with courage, rewards, and opportunities to motivate and develop themselves to improve their performance at work to the leaders' expectations (Fiedler, 1967; L. H. Nguyen, 2021). The above findings indicate that managers must constantly care for and improve their relationship with their followers and maintain an excellent relationship to enhance employees' job satisfaction and innovative capability for successful DT project implementation and organizational performance.

According to Fiedler (1967), the interpersonal relationship is something that the leader establishes with his team and depends on (a) leader's personality and (b) the nature of the organization. The leader's effective relations with group members and the acceptance and loyalty the leader can receive from his group members relate to the type of person and how the leader behaves in critical situations during group activities. Generally, the leader comes into the group with the required expert knowledge and the organization's approval, and the followers are supposed to follow the leader. It will require considerable artlessness on the leader's part to be rejected by his group (Fiedler, 1967). Some leaders who significantly overestimate their position power make over-confident and over-ambitious judgments, decisions, and biased evaluations and destroy the LMR. LMR is critical to enhancing positive outcomes for employees and the organization, considering that positive working environments increase employee effort and productivity (Fiedler, 1967; Kovach, 2020). According to Fiedler's (1967) CTL, a leader can change the subordinates' perceptions of the leader through his behaviors; thus, the most critical aspect of a good LMR is the leader (Fiedler, 1967).

Task-Structure

A task is an assignment the project group undertakes on behalf of the organization (San Cristóbal et al., 2018). The organization has a stake in seeing the task accomplished according to specifications, including time, cost, quality/scope, and customer satisfaction, and the PM is responsible for achieving the task (San Cristóbal et al., 2018). Fiedler (1967) in CTL classified the project task into two types: (a) structured or (b) unstructured, and stated that the task structure (TS) significantly determines the leader's influence on group members. When structured, tasks become clear and specific, and employees can efficiently complete them in a particular order at an exact time. There are never questions about a person's work assignment, and there is much less uncertainty and more oversight because the management clearly defines goals, policies, and procedures and expects all to follow them in a structured task system (Fiedler, 1967). Employees easily understand tasks when structured, monitor their progress, and get consistent feedback from management. Through consistent feedback, leaders influence their members by efficiently applying the organizational rules and policies, reinforcing their PP (Fiedler, 1967).

The unstructured tasks involve the day-to-day tasks that keep the organization running and are much more flexible, allowing everyone in the team to learn on the job, plan as they go, and complete tasks however they see fit without getting feedback from management. Per CTL, when the project group engages in a highly unstructured task system, the leader has a much more difficult job leading his group because the leader cannot use his PP (Fiedler, 1967). To operationally measure task structure in CTL, Fiedler

(1967) used the following four scales: (a) *decision verifiability* (the degree to which the solution to the tasks is satisfactory to the authority); (b) *goal clarity (*the degree to which the leader clearly states the requirements of the tasks for group members to understand); (c) *goal path multiplicity (*the degree to which multiple procedures or methods can solve the task); and (d) *solution specificity (*the degree to which there is more than one correct solution).

Importance of TS in DT Projects. Projects involving DT, software integration, and innovation continuously introduce changes and new product offerings (Guinan et al., 2019). In this case, the tasks may be too complex to outline in a step-by-step sequence making team members share knowledge, collaborate to figure out the best approach, overcome obstacles, determine their progress, and use their experience and best practices to help achieve the objectives. However, the PM's competency, competent team, clear project goals and objectives, adequate project planning, clear task structure, and usage of PMT methodologies, tools, and techniques led to highly successful PMT and enabled DT project success (Guinan et al., 2019; Singh et al., 2020). Project managers' knowledge of selecting the tools, methods, and procedures and how to use them to structure tasks are essential for DT project success. To structure or not to structure and how much to structure the DT tasks is an area that needs further research.

Supporting and Contrasting Theories

Because of the complexity and multidimensionality of the subject, leadership has become more critical than ever in today's fast-paced and increasingly globalized world. Leadership continues to generate captivating and confusing debate, and many different leadership theories exist in the literature. In this section, I discussed the following contrasting theories of CTL: (a) SLT introduced by Hersey and Blanchard (1970, as cited in Benmira & Agboola, 2021); (b) BTL introduced by Blake and Moutan (1945, as cited in Benmira & Agboola, 2021); and (c) TRFLT developed by Burns (1978). I also discussed in this section the following theories that support CTL: (a) GMT introduced by Carlyle (1840, as cited in Benmira & Agboola, 2021); (b) TTL founded by Allport (1936, as cited in Jayawickreme et al., 2019); and the (c) TRALT introduced by Burns (1978).

Supporting Theories

Great Man Theory (GMT). The Scottish-born Thomas Carlyle (1840, as cited in Benmira & Agboola, 2021) introduced the GMT. Like CTL, GMT claims that leadership traits of leaders are inherent and great leaders are born and not made. Both GMT and CTL focus on the innate characteristics of leaders and insist on identifying the personality traits and other effective leadership qualities in leaders. Fiedler, in CTL, states that leadership styles of leaders are inherent and cannot be changed; two factors determine a leader's success, (a) the leader's inherent leadership style and (b) the leader's situational control (Fiedler, 1967). According to GMT, the ablest man or the leader is truest-hearted and the most just and tells people to do the precise, wisest, and fittest, and the subordinates loyally surrender to the great man's command and may find their welfare in doing so. In CTL, Fiedler also suggests measuring a leader's leadership style using measurement scales he developed, identifying the situation of leadership control, and then determining if the leader's leadership style is suitable for the situation. In GMT, Carlyle identified an eclectic group of great men as prophets, poets, priests, writers, and kings whom he considered gifts from God and stated that the task for the rest of the world is to recognize the gifted and to follow them (Benmira & Agboola, 2021).

Trait Theory of Leadership (TTL). According to the founders of the TTL, people are born with inherited traits, and some of these traits or attributes make them great leaders (Hunt & Fedynich, 2019). Several studies analyzed leaders' mental, physical, and social characteristics to identify traits or the combination of attributes common among leaders; however, they have yet to yield any conclusive results due to a lack of psychometric evaluations (Hunt & Fedynich, 2019). However, the authors of TTL suggested four primary traits that can lead to successful leadership: (a) emotional stability, (b) admitting mistakes, (c) excellent interpersonal skills, and (d) intellectual ability. Like CTL, TTL claims that people inherit traits, and some inherited traits or attributes help them succeed as great leaders. In CTL, Fiedler (1967) used 18 traits or qualities of leaders to measure their leadership style or behavior in his LPC scale.

Transactional Leadership Theory (TRALT). According to Burns (1978), the founder of TRALT, a positive transaction that creates a mutually beneficial relationship between the leader and the follower makes the leadership. Like CTL, TRALT claims that the effectiveness of leadership depends on the leader's means to adequately reward (or punish) his followers for performing the leader-assigned tasks (Changar & Atan, 2021). The leader motivates followers through punishment and reward, and the anticipation of the reward keeps the followers obedient. Leaders share a highly valued relationship with their followers and depend on the followers' perception concerning the leader's fairness and equity of the relationship (Young et al., 2021). Like Fiedler's claim in CTL, authors of TRLT state that TRLT fits in organizations with a well-defined hierarchy that specifies the roles of leaders and followers, where people agree about the need within the organizational structure to complete tasks to accomplish goals which enhances leadership efficiency. In this hierarchy, everyone should know who the leader is and who is following, and the leader's effectiveness depends on the subordinates obeying the leader.

Contrasting Theories

Behavioral Leadership Theory (BLT). BLT was introduced by Blake and Moutan (1945, as cited in Benmira & Agboola, 2021). BLT focuses on the behaviors of the leaders and not considers their mental, physical, or any other inherent characteristics. Behavioral studies using the cause-and-effect relationship of specific human behaviors of leaders with psychometric measurements divided leaders into the following two categories: (a) those concerned with the tasks and (b) those involved with the people. The task concerned leaders focus on the organizational structure, the operating procedures, and management strategies. The people-oriented leaders mainly focus on satisfying the needs of the people and seeking to motivate staff through effective human relationships (Benmira & Agboola, 2021).

Situational Leadership Theory (SLT). The SLT introduced by Hersey and Blanchard (1970, as cited in Benmira & Agboola, 2021) indicates that leaders must adapt their leadership styles based on their team members' maturity and readiness levels to perform the specific tasks for projects under consideration. According to founders of SLT, employees or team members are different in (a) being knowledgeable, (b) willing, and (c) motivated to complete the assigned task or project work. Therefore, a manager must analyze the maturity (readiness) level of their employees or team members before applying a leadership style and then apply the appropriate leadership style for the situation. Founders of SLT define the employees' maturity or readiness as a combination of (a) competence (task-relevant knowledge and skills, and transferable skills) and (b) confidence/commitment (motivation, self-confidence, and attitude toward work and others).

According to the founders of SLT, there are four levels of maturity/readiness of employees or teams based on their competence and confidence/commitment: (a) low level of maturity/readiness (low competence and low confidence/commitment), (b) moderate level of maturity/readiness (low competence and high confidence/commitment), (c) moderately high level of maturity/readiness (high competence and low confidence/commitment), and (d) high level of maturity/readiness (high competence and high confidence/commitment) (Rodić & Marić, 2021). The authors of SLT outlined four leadership styles for managers based on the four levels of maturity/readiness of employees: (a) "Telling" leadership style, where managers must be very specific, provide clear directions to employees of what is needed to accomplish the tasks, answer all questions of all the aspects of the task assignment for the project; (b) "Selling" leadership style, where managers must seek input from their employees/teams to clarify the tasks for the project rather than just providing instructions on how to accomplish the tasks for the project; (c) "Participating" leadership style, where managers clarify the organization's goals and objectives with the teams and enhance employees'/team's willingness and sense of security related to the tasks, and (d)

"Delegating" leadership style, where managers empower their employees/teams to work independently, and only offer assistance when needed.

The theorists of SLT describe two behavioral categories appropriate for leaders: (a) TO behavior and (b) RO behavior (Henkel et al., 2019). During highly TO behaviors, managers should know all the details associated with all the tasks of the projects before acting or directing the team members to accomplish the tasks and apply a 'Telling" leadership style. Conversely, managers should develop trust and respect with the employees or their teams during RO behaviors to build action plans by applying the "Delegating" leadership style. The flexibility defined in STL that allows leaders to change and adapt their leadership style to meet the needs of employees makes it different from Fiedler's CTL, which states that a leader's LB is inherent and cannot be changed.

Transformational Leadership Theory (TRFLT). The TRFLT, one of the most studied and popular leadership theories, indicates that leaders inspire followers to alter preconceptions and perspectives and motivate them to work toward similar objectives because of the strength of their vision, personality, and charismatic behavior (Aboramadan & Kundi, 2020; Y. Lee et al., 2020; Yin et al., 2020). In transformational leadership, charisma, intellectual stimulation, and individualized consideration play significant roles as components of leadership, making the followers behave in a more mature and idealistic way, showing more significant concern for achieving goals, self-actualization, and the needs of their fellow workers, their organization, and society (Aboramadan & Kundi, 2020). Transformational leaders demonstrate a vision of a positive future, explain how this can be achieved, and lead by example through high-performance standards, confidence, and determination, influencing followers to think beyond their self-interest and work for the group with collective interest (Luu et al., 2019).

The Unit of Analysis and Measurement of Variables

Unit of Analysis

This unit of analysis defines the structure of the research data. It provides the correct contextual participant entities, which results in excellent and valid meanings that ensure the integrity of research outcomes (W. Li et al., 2017). I investigated the relationship between the LB of the PMs in charge of DT projects and DT project completion status in three contingency situations, namely (a) the PM's PP, (b) the PM's TS, and (c) the PM's LMR (Fiedler, 1967). Data for all the independent variables/constructs and the dependent variable I chose to study were available at the PM level. Therefore, the unit of analysis for this study was the PM, which was appropriate.

Selecting the proper unit of analysis is an integral component of any research study. Improper selection of the unit of analysis, such as choosing a unit at a micro-level rather than what is needed, will make the research more time-consuming and costly (W. Li et al., 2017). Suppose the chosen unit of analysis is at a much higher macro-level than required. In that case, meaningful connections and contextual meanings at smaller units may be missed in the investigation, leading to erroneous categorization and interpretation of the data (W. Li et al., 2017). Also, successful DT project completion requires effective resource governance, clear project goals, good LMR, and visibility into the DT journey for improved products, profitability, and customer experience (Pulkkinen et al., 2019).

The PMs who managed or are currently managing DT projects' successful implementation in LICs in the United States must possess knowledge of the above.

The selection of the PM responsible for managing the DT project for successful completion (dependent variable of this study) as the unit of analysis for this study aligns with the purpose of this doctoral research. The PM demonstrates LB (an independent variable in this study) and possesses the PP (independent variable) needed to influence and guide the employees (Gilli et al., 2023). Further, the PM cultivates good LMR (an independent variable in this study) to motivate group members and defines the project's task structure (an independent variable in this study) to enhance task completion (Appio et al., 2021). Therefore, the PM was an appropriate object for this doctoral study's unit of analysis.

Measurement of Variables

The dependent variable of this study was the DT project completion status achieved by the PM in the selected companies. The variable could take only two possible values (yes/no), thus binary and categorical. Besides, the primary independent variable was the LB of the PMs managing during the data collection for this study or managed DT projects in LICs in the United States. Per Fiedler's CTL model (Fiedler, 1967), PM's LB (the primary independent variable) can take only two values (TOLB or ROLB) and is categorical. Per Fiedler's CTL model (Fiedler, 1967), the three contingency independent variables can take only two possible values, which are categorical and dichotomous. PM's PP can be either weak or strong, the PM's LMR can be either good or bad, and the PM's TS can be structured or unstructured (Fiedler, 1967).

Primary Independent Variable: Leadership Behaviors of Managers

Over the past one hundred years, leadership research yielded convincing evidence that an organization's success depends mainly on its leaders' LB (Brunner et al., 2023; Halliwell et al., 2022; Kapucu, 2020; Klein, 2020; Müller et al., 2024; Porfírio et al., 2021; Yukl et al., 2019; Zeike et al., 2019). Three entities constitute the leadership: (a) the leader, (b) the tasks that require completion, and (c) the followers who strive to accomplish the tasks. According to several previous investigators, including Bartsch et al. (2021), Halliwell et al. (2022), Klein (2020), and Zeike et al. (2019), the LB of leaders falls into a dichotomy of the following two meta-categories: (a) TOLB and (b) ROLB. This dichotomy of two meta-categories of LB was the root of many leadership theories and taxonomies for more than 60 years (Bartsch et al., 2021; Halliwell et al., 2022; Klein, 2020; Zeike et al., 2019).

TOLB and ROLB categories are relevant to all work environments and project structures (Bartsch et al., 2021; Solberg et al., 2020; Yukl et al., 2019). According to Yukl et al. (2019), the TOLB category covers the following leadership competencies: (a) enhancing understanding of the current situation, (b) mitigating risks, (c) strengthening motivation, (d) encouraging innovation and collective learning, and (e) enhancing all change-oriented activities and is best applied when facilitating implementation in the planning and action phases of projects. The ROLB category covers effective leader-follower engagement in accomplishing objectives such as (a) increasing coordination to synchronize collective efforts, (b) promoting cooperation to encourage more outstanding individual contributions, and (c) motivating and activating resources to expand valuable contributions (Yukl et al., 2019). The two LB categories become important in contingent situations. For example, leaders encouraging numerous contributions without an established task structure cause risk. Also, leaders risk losing credibility and member support if they do not recognize individuals' most valuable contributions or discourage them from inappropriately contributing.

The Impact of LB on DT Project Implementation

The highly transformational situations in DT projects and the urgent requirement for sourcing employees with digital skills from multiple areas around the globe pose several challenges to companies. R. Ahmed et al. (2024), Brown et al. (2021), Cetindamar et al. (2024), and Ivanenko and Artamonov (2020) showed that managers' TOLB and ROLB are vital in overcoming these DT challenges. Managers with TOLB focused on attaining organizational objectives by clarifying each task's goals and monitoring work processes, while managers with ROLB focused on enhancing collaborative interaction among corporate members and establishing a supportive climate (Bartsch et al., 2021; Solberg et al., 2020). In their research, R. Ahmed et al. (2024) showed that supervisors' TOLB ($p < .001$) and ROLB ($p < .001$) had significant positive correlations with project success. In another study by Correani et al. (2020), DT managers who clearly defined project goals, job roles, processes, and procedures enhanced the organizational knowledge base through DT data generation and successfully implemented DT projects.

According to Dubey et al. (2020), aligning DT leaders' LB with digital technology adaption under different situations leads to enhanced operational performance. Research by Shao (2019) indicated a significant positive correlation between DT managers' LB and business strategy alignment and enterprise system assimilation mediated by organizational culture. Bartsch et al. (2021), using a quantitative correlational research design, investigating the relationship between leaders' TOLB and ROLB and the service employees' work performance found significant positive correlations between ROLB of leaders and individual employee's job autonomy ($\beta = .79$, $p < .01$) and team cohesiveness ($\beta = .33$, $p < .01$). Their study involved digital maturity in an unaccustomed virtual work environment (first-time exposure of employees to the virtual work environment) caused by the COVID-19 crisis (Bartsch et al., 2021).

In a quantitative correlational study using 129 experienced managers worldwide, Henkel et al. (2019) found a significant positive correlation between a distributed combination of the managers' TOLB and ROLB and successful project completion. In another quantitative correlational study conducted under multiple favorable and unfavorable project situations, Popp and Hadwich (2018) reported a significant positive correlation between managers' ROLB and employees' overall performance success regardless of the situation. The above evidence indicated that effective LB of PMs could lead to successful project implementation. The managers' TOLB and ROLB are the most effective project success factors based on project contexts.

Despite extensive studies indicating its importance, there is a massive gap in various dimensions of this significant subject. The effectiveness of LB (TOLB vs. ROLB) may contribute positively or negatively according to the context in which the leaders operate; leaders' organizational power relations may influence leaders' leadership values and challenge their approaches to leadership (Fiedler, 1967; Willis, 2019). A leader who is effective in one organizational setup may not remain as compelling in another, indicating that leadership studies related to DT project implementation must consider the context in which the leaders operate (Fiedler, 1967; Willis, 2019). Therefore, the relationship between leadership and successful DT project implementation necessitates more comprehensive investigations in organizations.

Dependent Variable: Successful DT Project Completion Status

Successful DT project completion is a topical issue of significant importance for all companies in all sectors worldwide as it changes customer relationships, internal processes, and value creation (Albukhitan, 2020). DT project completion is the process by which organizations adapt themselves to modern technology by leveraging digital technologies such as the IoT, AI, social media connectivity, cloud computing, big data analytics, and intelligent manufacturing technologies (I4.0) to transform organizations for improved performance (Albukhitan, 2020; Doukidis et al., 2020; Kretschmer & Khashabi, 2020; Warner & Wager, 2019). Successfully implementing and completing DT projects requires changes to the company's business model, products, and organizational structures to adapt to digital technologies, the most pervasive managerial challenge for companies currently and in the future.

According to Warner and Wager (2019), LICs must act now and invest in digitized process platforms that facilitate operational excellence by choosing solid digital technologies and strategies to enhance their value proposition, innovation, and responsiveness to new market opportunities to stay competitive. However, successful implementation of DT projects needs technology and people, as digital project tasks need skilled employees and executives with digital management competencies to achieve complex transformative task completion (Albukhitan, 2020; Kane, 2019; Ra et al., 2019). In recent years, scholarly attention in the DT literature has steadily increased, leading to a significant increase in articles addressing DT's different technological and organizational aspects and leaders' role in driving positive results from investments in digital initiatives. However, an underrepresentation of the leadership's role in DT project success results in incomplete DT project completion, negatively affecting business performance (Ahmad et al., 2022; Warner & Wager, 2019), and needs improvement in the literature. Considering this development, I provided a descriptive literature review reflecting on the current state of knowledge and a critical analysis of the field, assessing where, how, and who researched DT project implementation and leadership's role in its completion.

Impacts of Successful DT Implementation to Businesses

According to several previous researchers, including Albukhitan (2020), Doukidis et al. (2020), Govindarajan and Immelt (2019), Kretschmer and Khashabi (2020); Mustafa et al. (2020), Pacchini et al. (2019), Schumacher et al. (2019), and Singh et al. (2020) DT dramatically improve business processes, business strategies, customer experience, innovation, and operational execution across various levels, including individual, organizational, environmental, and societal. Cooney et al. (2021) reported that ninety-three percent (93%) of CEOs of global industrial companies out of the 3000 they surveyed globally saw disruptive emerging technologies as driving competition in their industry and DT as a critical change program and the solution to compete and survive.

Therefore, successful DT (implies DT projects) implementation is a crucial driver of competitive advantage that enables LICs to compete and survive; it is no longer optional but the only way they can survive (Govindarajan & Immelt, 2019).

The successful implementation of DT offered many opportunities to enhance customers, revenues, and performance (Ferreira et al., 2019; Hai et al., 2021). By embracing new digital opportunities into their strategies, innovative and agile businesses maintain their positions in competitive markets (Schumacher et al., 2019); by responding to new digital opportunities, they become resilient against risk (Björkdahl, 2020). Through the enhancement of resources and capabilities and the reconfiguration of processes and structures per modern technologies (Chirumalla, 2021), adjustments in leadership (Brunner et al., 2023; Klein, 2020; Ko et al., 2022; Porfírio et al., 2021), and the implementation of digital culture (Kretschmer & Khashabi, 2020) organizations enhanced their customer experience, productivity, competitive advantage, and sustainability. Successful implementation of DT projects enabled novel product and service offerings (Sony & Naik, 2019), transformed the structure of supply chains (Ishfaq et al., 2021), and vastly improved processing power through reduced costs, increased productivity, enhanced processing efficiency, and value-added through dedicated services, enabling faster time-to-market (Kraus et al., 2021a; Verhoef et al., 2021). The literature indicated that successful DT implementation enhanced customer relationships (Doukidis et al., 2020; Kretschmer & Khashabi, 2020), reshaped industry competition (Sony & Naik, 2019; Verhoef et al., 2021), and generated new value through interconnecting physical and digital assets with data and ecosystems (Schumacher et al., 2019; Verhoef et al., 2021).

Although success received much attention in DT literature, failure received much lesser attention (Mustafa et al., 2020). Plenty of cash flows into digital initiatives at industrial companies; despite the massive investment, the expected results often fail to materialize. In eighty-four percent (84%) of LICs, including GE, Ford, P&G, and many more, DT initiatives were a wasted opportunity that led to company failure (F. Li, 2020; Reeves et al., 2018). According to Datta and Nwankpa (2021), McCarthy et al. (2024), and Reeves et al. (2018), 70% of the U.S. enterprises' DT initiatives in 2018 failed to achieve their stated goals as forecasted, equating to over $900 billion out of the 1.3 trillion worth of spending that went to waste. Based on another McKinsey global survey of LICs, two-thirds of organizations generated only ten (10) to fifteen (15) percent of revenue through digital amidst a large amount of money invested in DT (1.3 trillion in the United States alone in 2018). According to Correani et al. (2020), recent estimates indicated 66% to 84% (an average of 75%) of DT projects' failures, a sizable proportion considering the monetary and other costs of putting these projects in place. The potential impact and scale are so significant that flawed and imperfect DT can significantly hurt companies' competition and survival. The uncertainties and challenges heighten the need to examine mechanisms through which DT can deliver the desired value.

Factors Influencing Successful DT Project Implementation

DT project implementation involves adopting complex digital technologies, acquiring digital talents, upgrading internal structures per selected digital technologies, enhancing digital platforms and innovation to improve customer experience, creating a digital culture, and achieving operational excellence by integrating processes and people with digital technologies. The literature contains limited representative examples of companies demonstrating successful DT project implementation (Ivančić et al., 2019). Also, the implementation of DT projects involves several dimensions: (a) technology, (b) organization and business processes, (c) people, and (d) environment (Müller et al., 2024) and many success factors, including strategies, leadership, culture, employee training and motivation, and customer and stakeholder relations (Schumacher et al., 2019; Verhoef et al., 2021).

A significant trend discovered from the literature review was a shift of attention from technological factors to managerial and organizational issues in the years, a theory supported by several past researchers including Brunner et al. (2023), Facchini et al. (2022), Ko et al. (2022), Metwally et al. (2019), Müller et al. (2024), Mustafa et al. (2020), Schumacher et al. (2019), and Singh et al. (2020). Incompatible leadership behaviors with the organizational culture and capabilities potentially pose significant challenges, causing cultural incongruence, transformation obstacles, and managerial challenges leading to the failures of DT projects (Brunner et al., 2023; Müller et al., 2024). Also, no standard methods and best management practices are currently available for organizations to successfully implement DT projects (Cichosz et al., 2020; Fischer et al., 2020).

Success Dimensions of DT Project Implementation

When considering projects, there are two main success concepts: (a) project success and (b) project management (PMT) success. According to the Project Management Institute (2023a), PMT is the "application of specific knowledge, skills, tools, and techniques to deliver value to people." According to Mishra (2020) and Venczel et al. (2021), PMT is "planning, organization, monitoring, and control of all aspects of the project," with the motivation of all people to achieve project goals safely within the agreed schedule, budget, and performance criteria. Thus, PMT aims to complete projects as intended, most efficiently, by minimizing cost and time and achieving external goals related to customer needs.

Although there are several similarities and differences between the two success dimensions, one significant difference is that project success is the overall project goals achievement, while PMT success is successful project implementation within the traditional measurements of time, cost, and quality; the two success criteria are mutually related, and therefore it is hard to differentiate between them strongly. Factors such as scope, time, budget, resources, risk, and performance specifications designed to meet a specific customer need limit the project's success (San Cristóbal et al., 2018). PMT and project manager's leadership competencies played an essential role in achieving project success and positively influenced it (Alvarenga et al., 2020; Oh et al., 2021). Therefore, PMT practices and project success are significantly positively related, and PMT success is an essential element of project success because the latter is hardly achievable without it.

Despite the considerable efforts to meet success goals, many projects continue to run late, exceed their budgets, or fail to meet customer satisfaction (Correani et al., 2020; Ivančić et al., 2019; Mustafa et al., 2020; Reeves et al., 2018). No standard methods and best management practices are available for organizations to successfully implement DT projects (Cichosz et al., 2020; Fischer et al., 2020). Lack of employee engagement and ineffective strategy planning (Ko et al., 2022), weak or nonexistent cross-functional collaboration, poor organizational design (Singh et al., 2020; Verhoef et al., 2021), lack of knowledge among PMs regarding modern technology and how to structure project tasks, lack of strategic guidance from top management towards realization (Brunner et al., 2023; Müller et al., 2024; Pacchini et al., 2019; Schumacher et al., 2019), and poor quality management practices (Brunner et al., 2023; Müller et al., 2024) are causes of the failure of DT projects. There is a huge need for scholars to investigate how organizations could manage a DT project to succeed.

Successful DT Project Completion Criteria and Models

According to the PMT Institute (San Cristóbal et al., 2018), a *project* involves a group of activities that begin and end at specific points in time based on a pre-defined schedule and within a consistent budget that specified team members execute to meet a set of objectives to achieve a desired goal. A DT project provides the necessary structure through which an organization implements its DT initiative with DT success as the goal and embodies the processes necessary to reach that goal. PMs combine the project's different parts, the team, technology, processes, governance structures, and other elements via complex interactions to deliver a common objective. Hence, DT projects are complex systems with a high risk of facing uncertainties that may benefit from effective management practices (Fischer et al., 2020). Although there is no consensus definition of project success, there is an agreement in the literature that good PM actions, such as good PMT, lead to project success.

The iron triangle model (ITM) was the first applied to measure PMT and project success (Goldsmith & Boeuf, 2019). According to the concept of ITM, a project is successful if it meets the objectives of ITM (within budget, on schedule, and per agreed-upon quality [per stakeholder satisfaction]). ITM has been the standard measure of project success for decades in the business community; businesses commonly measure the successful completion of projects through the ITM components (Goldsmith & Boeuf, 2019; Zid et al., 2020). According to Goldsmith and Boeuf (2019) and L. H. Nguyen (2021), ITM's three components contribute significantly, are strongly linked to successful project implementation, and are reliable. An increase in scope without a corresponding increase in time and cost can result in poor quality of work, or a decrease in time without a decrease in scope can lead to poor quality if cost remains constant (Zid et al., 2020). Organizations could define project success using the ITM success criteria (cost, time, and quality) to meet the stakeholders' satisfaction and expectations; the inability to complete projects on time, within budget, or per quality expectations poses challenges in executing projects (Ika & Pinto, 2022; Zid et al., 2020). Despite the massive investments, many projects face many challenges, such as expenditures exceeding the budget, which can cause project failures, delays in completing the project on time, cost overruns, and low-quality products that build defects, leading to disappointment and lost customers (Ika & Pinto, 2022; X. Wang et al., 2023; Zid et al., 2020).

Recent research by L. H. Nguyen (2021) indicated that the ITM measure of success implies that a project that is a day late or above budget by a dollar might be unsuccessful even if it meets quality expectations; hence, it is not a valid measure of project success. According to Goldsmith and Boeuf (2019) and Yan et al. (2019), project success depends not only on time, cost, and quality but also on integration, human resources, technology, communication, risk, and procurement management. According to Al Dabbas and Alkshali (2021), businesses must include customer satisfaction in project success assessments using the ITM objectives. Thus, the ITM measure needs broadening to include these factors for stakeholders' satisfaction, benefits to the organization that owns the project, and long-term impacts on the project environment. Currently, only conflicting evidence exists regarding the success criteria of projects.

Integration and Capability Building

DT is an ongoing process and depends on the capabilities in multiple dimensions of the companies to balance internal and external collaboration, redesign manageable governance structures, and improve and promote the workforce's productivity (Rehman et al., 2020; Warner & Wager, 2019; Zhou et al., 2021). Managing the multi-product customer experiences and changes to business processes requires integration across business units and managing customer data, global operations, work silos, organizational politics, and path-breaking exogenous and endogenous mechanisms (Rehman et al., 2020; Warner & Wager, 2019; Zhou et al., 2021). The capability-building process depends mainly on trust, collaboration, knowledge sharing, and good interpersonal relationships among all the people involved (Klein, 2020; Porfírio et al., 2021; Warner & Wager, 2019). Superior leadership with digitalization experience and knowledge of managing conflicting demands are significant to successful DT project implementation.

In the literature, the following two capabilities currently exist as core to DT project success: (a) digital capability (DC) and (b) leadership capability (LC); Companies can transform digital technology into a business advantage with these two capabilities (Klein, 2020; Porfírio et al., 2021). DC enables companies to use innovative digital technologies to improve elements of their business (Porfírio et al., 2021). LC enables companies to envision and drive organizational change, fostering strategic technology initiatives systematically and profitably in the digital era (Klein, 2020; Porfírio et al., 2021). According to Bonnet and Westerman (2021), Ivančić et al. (2019), and Mager and Katzenbach (2021), successful change management and talent development are essential requirements of DT in LICs and supported by strategic DT initiatives from the top leaders necessitating mutually respectful relationship among all stakeholders.

Collaboration among all stakeholders, creating cultural change, enabling agile work environments, and choosing appropriate DT technology led to DT projects' success in LICs (Gurbaxani & Dunkle, 2019; Ko et al., 2022). Suitable alignment of a company's DT strategy to the leaders' task focus (Singh et al., 2020), adequate planning during the DT implementation (Correani et al., 2020; Fischer et al., 2020; Gurbaxani & Dunkle, 2019; Reeves et al., 2018), project managers adopting quality leadership behaviors (Klein, 2020; Müller et al., 2024; Porfírio et al., 2021), and employees' firsthand insights into where processes needed improvement (Bonnet & Westerman, 2021; Sousa-Zomer et al., 2020) had strong potential to support organizations' successful DT implementation.

How This Research Addressed a Literature Gap

In the literature, research investigating the role of LB in the context of planned organizational change existed. However, no studies exist related to the role of effective LB in a rapid and volatile organizational change like DT. This study offered practical contributions to the meager literature on LB, which could support businesses in managing the challenging digital task fulfillment and employee relationship for successful DT project implementation and completion. Because of the scant literature on DT and LB, this study aimed to reveal information on enabling and managing LB for successful DT project implementation and completion.

Transition

In section 1, I introduced this doctoral study with a brief background related to its business problem. I included a few critical elements of the study, such as a problem statement, a statement of the study’s purpose, the nature of the study, research questions addressed, hypotheses tested, theoretical framework used, operational definitions, assumptions, limitations, and the study’s delimitations, the significance of the study, and a review of the professional and academic literature. In section 2, I described this study’s quantitative research method and design approach, including the participants, population and sampling, instrumentation, data collection techniques, data analysis, and study validity. In section 2, I also included my role as a researcher in this study and ethical research conduct. In section 3, I presented this research’s findings, including the application to professional practice, implications for social change, recommendations for action, suggestions for further research, reflection, and the study's conclusion.

Section 2: The Project

In Section 2, I discuss the project procedures related to studying the relationship between project managers' (PMs') leadership behaviors (LB) and successful digital transformation (DT) project completion in large industrial companies (LICs) that employed over 500 people in the United States. Section 2 also includes a purpose statement and addresses my role as a researcher in conducting this research, the study participants, the sampling strategy, and the data collection process, including the chosen population for this study and the total sample size, participant recruitment procedure, and instruments used to collect data. Section 2 further includes the research method and design chosen to support the study’s relevancy, an overview of the data analysis process, the study's validity, and ethical conduct during the entire study.

Purpose Statement

The specific business problem was that some PMs in LICs do not know the relationship between a PM's LB and DT project completion status. Therefore, the purpose of this quantitative correlational study was to investigate the relationship between PM's LB and DT project completion status. The independent variables were (a) PM's LB, (b) PM’s LMR, (c) PM's TS, and (d) PM's PP. The dependent variable was DT project completion status. The target population consisted of PMs of LICs located in the United States, with a focus on digitally transforming their businesses.

Role of the Researcher

In quantitative (QUAN) research studies, the primary roles of the person conducting the study include generating practical research questions related to the study’s business problem, collecting and organizing data, conducting hypothesis tests, and combining and documenting the findings (Mohajan, 2020). I identified and reviewed exhaustively the most relevant scholarly literature published by previous researchers related to this study's area within the past 5 years, carefully selected and reported the test variables, designed relevant research questions to explain the research problem, and selected appropriate research design(s) to fit the research questions addressed. I identified and used psychometrically robust and contextually sensitive measurement instruments and appropriate data collection tools, appropriately selected participants, generated sufficient data, and performed accurate analysis. I further chose and applied appropriate statistical methods to process the data, whether the prediction was confirmed or not, verified the results, drew conclusions, presented the findings from the hypotheses testing, and shared the findings with participants, the public, and other relevant authorities.

Completing the Collaborative Institutional Training Initiative (CITI Program) certification prepared me to follow ethical research principles. I followed the Belmont Report's protocols (Office of Human Research Protections [OHRP], 2022) and protected participants' rights, including confidentiality, privacy, respect for persons, beneficence, and justice, which captured the ethical values inherent in quality research. I ensured participants' privacy by conducting an anonymous survey and not collecting participants' names or business organizations. In QUAN studies, data collection happens independently of the person collecting the data, thereby minimizing the chances of bias and undue influence on the participants. I ensured respondents' confidentiality strictly through a robust informed consent process. I ensured participants' confidentiality through (a) explaining to the participants that their participation in the study was strictly voluntary without compensation or incentive and (b) ensuring that research participants understood that they could withdraw from participation at any time without penalty or loss of any benefits that they might be entitled to if they intended to.

Per the Belmont Report's basic ethical principle of beneficence (OHRP, 2022), I chose the appropriate research design and situation to maximize benefits and reduce risks to participants as much as possible and ensured that this research's findings would improve their lives and circumstances (Head, 2020). Per the principle of justice of the Belmont Report protocol (OHRP, 2022), I ensured justice during research by (a) considering that the potential societal benefit from the research justifies the cost to subjects and (b) not using the data collected for purposes outside the scope of this research study. The Belmont Report further insists on informing the participants of the study's purpose and their eligibility to access the results and a copy of the research findings. The informed ICF included information about this study's purpose and participants' rights and access to the study's findings (Appendix B). No termination of any participants from the study occurred.

In quantitative studies, one of the main goals is to generalize the findings from a sample to a population (Shieh, 2020). When the sample size in the hypothesis test is large, minor effects become detectable through hypothesis testing, sampling error becomes less of a problem, and accurate inference is guaranteed, which is a closer approximation of the population (Bhardwaj, 2019; Fricker et al., 2019). However, any research study that involves data collection and analysis requires resources, including subjects, time, and money, that need consideration when selecting a sample size (Bhardwaj, 2019; Lakens, 2022; Park et al., 2020). I conducted an a priori power analysis and identified the required minimum sample size that satisfied the following: (a) balanced the research's statistical validity and resource constraints, (b) avoided an underpowered study with a low probability of detecting a significant effect with a smaller than required sample size (Lakens, 2022), (c) was large enough to have sufficient power to detect meaningful effects (Bhardwaj, 2019; Lakens, 2022), (d) met the requirements of the chosen analysis methods and tools, (d) minimized waste, and (e) was small enough to avoid exposing participants to unnecessary risks (Kang, 2021).

Participants

This doctoral study's participants consisted of PMs who managed or were managing (during data collection of this study) DT projects sampled from large companies (# of employees ≥ 500 as defined by the federal government) from the industrial sector (LIC) in the United States, with a focus on digitally transforming their businesses. The participants were from the LICs because LICs possess tremendous potential and the necessity for DT (Ghosh et al., 2022; Reeves et al., 2018). The eligibility criteria that I considered for the participants of this study included (a) participants were PMs who managed or were managing one or more projects that involved DT and were initiated within the past 5 years from the beginning of data collection for this study; (b) the sample of participants came from the target population; (c) the participants were between 18 and 80 years of age, male or female, of any race and nationality, located in the United States, and had worked or were working (during data collection for this study) for a U.S.-based large (companies having ≥ 500 employees) industrial company (LIC); and (d) the participants did or did not complete the DT project they managed or were managing. In addition, participants were willing to participate in the study and had access to the internet or electronic mail to complete the survey.

This study included participant PMs with one of the following project completion statuses: (a) completed at least one DT project successfully (on time, within budget, and per quality standards), or (b) did not complete any of the DT projects that they initiated successfully (did not complete the DT projects or completed not on time, not within budget or not per agreed-on quality standards or a combination of the three). A project completed successfully in this study meant the project was completed within schedule (within 3 years or as defined by the company), within the allocated budget, and per the quality criteria intended. A project not completed successfully meant one of the following: (a) the project was either completed but not within the schedule or not within the allocated budget, or not per agreed quality criteria and any combination of these; (b) the project was never completed and in progress after the scheduled completion date; or (c) the project was abandoned due to causes such as inadequate resources, a flaw in the design, or the like.

I conducted an anonymous survey using Walden's IRB's *Anonymous Survey Consent Form for DBA Survey* (*ASCFDS*). As the first step, Centiment obtained a panel of participants from the LICs who met the participant eligibility criteria (Appendix A) and screening questions on project completion status (Appendix C) I provided. Through Centiment's online survey tool, the eligible, willing, and available participants accessed the *ASCFDS* form (Appendix B). I transferred the survey of about 50 closed-ended questions and the *ASCFDS* form to Centiment for administration through Centiment's free online survey tool to eligible and willing participants. All eligible participants who read and agreed to *ASCFDS*'s terms and clicked a continuing link through Centiment's online survey tool and completed the survey indicated their consent to participate. The survey remained anonymous, and no personal information was collected. I monitored the website periodically for any assistance needed by any participants. I exercised caution concerning the legitimacy of the internet source used to collect data and cross-checked the accuracy of the data collected with other legitimate sources and documents. Centiment is highly reliable, profiles its respondents extensively, and collects high-quality data (https://www.linkedin.com).

Effective and continuous communication stimulates active participation and safety of participants (Y. Wang et al., 2019). The anonymous online survey conducted in this study facilitated easy access, speed of data collection, and lower cost. I ensured that Centiment notified the participants via statements the week before posting the survey questionnaire, provided reminders periodically after posting the survey, and gave adequate time to prepare and answer the questions through Centiment's online survey tool. I provided the participants with a brief overview of the study in *ASCFDS* without discussing the survey questions or directly discussing the study's aim, participant selection criteria, and how I planned to use the results. Through the *ASCFDS*, I emphasized that the information gathered would help formulate better strategies and models to improve DT initiatives and enhance the company's profitability and success. None of the participants needed special aids, such as translation tools or training, to answer the questions.

Research Method and Design

Research Method

Quantitative (QUAN), qualitative (QUAL), or mixed-method research methods are possible choices for doctoral studies (Blair et al., 2019). QUAN was the chosen research method for answering the research questions for this doctoral study. QUAN methods yield better results and allow for informed decisions in doctoral research studies aimed at collecting numerical data that involve technology (Hosseini et al., 2019), are appropriate when testing hypotheses for verifying existing theories (Yue & Xu, 2019), and are essential in studying project success in dynamic and complex environments with disruption risks (Hosseini et al., 2019). In this research, I used a single theory and correlational research design to find answers to research questions by testing hypotheses using objective and impartial statistical methods.

I used a theoretical framework to obtain a reliable estimate of a generalized relationship between the outcome and multiple predictor variables, used structured research instruments such as survey questionnaires to collect numerical data for the selected variables, developed and tested hypotheses guided by the framework, and concluded and inferred the results to a larger population. Therefore, the QUAN method was appropriate for this study. This study constituted a large sample size (N = 214) to represent the population and aimed at inferring the results to a larger population. QUAN methods use large samples with results generalized to an entire population, subpopulation, and other legitimate studies (Lo et al., 2020; Mohajan, 2020; Nzekwe-Excel, 2022) and were, therefore, appropriate for this study. QUAN methods also adopt an objective perspective and help minimize researcher bias (Bloomfield & Fisher, 2019).

In doctoral studies, QUAL methods do not allow the measurement of facts or objects or report numerical data (Köhler et al., 2022; Nzekwe-Excel, 2022) and use data collected from a few participants' experiences and behaviors through interviews, conversations, observations, and or field notes aligned with subjectivist epistemology, which reduces the possibility of generalizability to a larger population (Ames et al., 2019; Köhler et al., 2022; Nzekwe-Excel, 2022), making QUAL methods inappropriate for this study, as this study used numerical data and aimed to generalize the findings to a larger population or subpopulation. An MM approach that combines QUAL and QUAN methods into a single study is appropriate only when neither a QUAN nor QUAL approach alone addresses the research topic or when a study requires one method to inform or clarify another (Fàbregues et al., 2021; Halcomb, 2019; Şahin & Öztürk, 2022). The QUAN method was appropriate and adequate, but a QUAL or an MM approach was not proper or necessary for this doctoral study. Also, according to the theory of incompatibility of paradigms, the assumptions for QUAN and QUAL methods are different, and ad hoc mixing of the QUAN and QUAL methods can severely threaten research validity (Denzin, 2012; Şahin & Öztürk, 2022; Yousefi Nooraie et al., 2020).

Research Design

A *research design* is a plan that helps the person conducting the research answer specific research questions by determining the hypothesis, conducting the study, and analyzing and interpreting the data (Bloomfield & Fisher, 2019). I chose a correlation research design for this research to systematically investigate the nature of the relationship between multiple dichotomous independent (predictor) variables and a dichotomous dependent variable without manipulating the variables but occurring naturally. For the dependent and independent variables, data collection occurred without interference or manipulation by the person collecting the data (in this case, me), for which the nonexperimental design, such as correlational research design, was appropriate (Seeram, 2019). Further, I used statistical analysis, including calculating correlation coefficients, conducting regression analysis, and conducting other statistical tests to determine the strength and direction of the relationship between the dependent and predictor variables and to determine whether the data supported a theory for which correlational research design was the best (Seeram, 2019).

Descriptive research designs enable the description of the status of a variable or phenomenon, such as the frequency of something that exists, particularly a new phenomenon, or about which very little information is available (Bloomfield & Fisher, 2019). Although the findings from descriptive research studies may help develop hypotheses, they do not help establish relationships or study the correlation between variables; therefore, they were inadequate and inappropriate for this study. Experimental and quasi-experimental research designs help establish cause-effect relationships among multiple variables and test interventions' effectiveness. Therefore, they require the manipulation of one or more independent variables while controlling other variables to study the cause–effect relationship (Bloomfield & Fisher, 2019). Experimental or quasi-experimental designs did not apply to this study because this study predicted the relationship between multiple binary independent variables and a binary dependent variable without manipulating the variables.

Population and Sampling

Population

The population for this doctoral research consisted of project managers (PMs) who managed or were managing during data collection for this study DT projects from large companies (# of employees ≥ 500 as defined by the federal government) from the industrial sector in the United States who focused on digitally transforming their businesses. This population aligned with the research question and the hypotheses for this study because this study investigated the relationship between PM's LB and DT project completion status. The population consisted of PMs paneled through the Centiment Survey Panel (Centiment). Centiment paneled a large pool of PMs who met the eligibility criteria based on the screening criteria provided in Appendix A and Appendix C, who were the population for this study.

Sampling

Sampling involves selecting a subset from the target population. I did not have adequate resources or time to use the entire population of all PM participants managed or managing DT projects from all the LICs in the United States in this study; therefore, I selected a sample from the large target population using an appropriate sampling method to answer the RQs of this study. Sampling has two primary methods: (a) probability or random sampling and (b) nonprobability or nonrandom sampling. Selecting an appropriate sampling method (probability or nonprobability) in a research study ensures the study's quality and validity (Matthes & Ball, 2019).

Probability Sampling

Probability sampling, which is selected based on probability theories from mathematical statistics, is the primary sampling method appropriate in quantitative studies (Berndt, 2020; Bhardwaj, 2019). Probability or random sampling has the greatest freedom from bias and is an efficient way to reduce bias (Berndt, 2020; Bhardwaj, 2019); it ensures that every item in the target population possesses an equal chance of being selected, making the sample more representative and findings effectively generalized to a larger population (Lamm & Lamm, 2019; Rahman et al., 2022), therefore was best suited to this QUAN study.

Nonprobability Sampling

The nonprobability sampling method uses nonrandomized methods such as the judgment of the person conducting the research, convenience, and ease of access to the population (ex., selecting friends and classmates) in place of randomization (Andrade, 2021; Rahman, 2023). The purposive nonprobability sampling selects participants based on characteristics defined for a purpose relevant to the study, and the convenience nonprobability sampling method involves selecting the study participants based on their availability (Andrade, 2021; Rahman, 2023). Although nonprobability sampling costs less and consumes less time, they do not adequately represent the population (Andrade, 2021; Rahman, 2023), and results using data from this sampling technique lack generality and generalizability to a larger population (Lamm & Lamm, 2019), therefore was inappropriate for this QUAN doctoral study.

Sampling Subcategory

Probability sampling has two subcategories: (a) stratified random sampling (STRS) and (b) simple random sampling (SRS). The chosen sampling subcategory for this doctoral study was the STRS. I could not use the SRS because SRS is appropriate when the population is homogeneous and a complete sampling frame, which is all the units in the entire population, is known (Bhardwaj, 2019; Fowler & Lapp, 2019). This study's population size consisted of paneling statistics provided by Centiment, and the population size was only approximately known to me. Centiment divided the target population into subgroups called strata and drew samples from each stratum. The strata were more homogeneous than the total population, with each element within a stratum identified, the situation was well-informed, and the samples were more reliable and contained detailed participant information. This sampling approach of participants enabled effective generalization of the research findings to the larger population.

Sample Size Selection

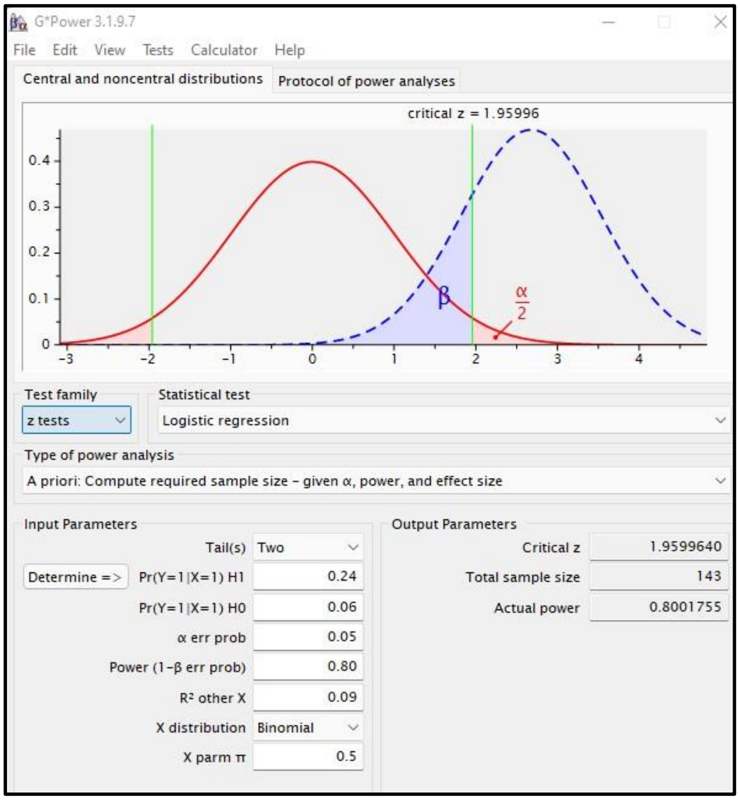
I performed an a priori power analysis using G*Power 3.1.9.7, a standard method to identify the minimum required sample size for BLR (Darling, 2021; Kang, 2021). I have displayed the G*Power sample size interphase with the settings used and calculation in Figure 1. The G*Power estimates statistical power using the Wald test and calculates effect size directly from user inputs (Figure 1) of the two probabilities, *p1* = (Pr(Y = 1|X = 1) H_0)) and the *p2* = (Pr(Y = 1|X = 1) H_1) or by calculating the odds ratio (*OR*) and inputting the *OR* (Darling, 2021). The *p2* is the probability of occurrence of the positive factor; the group coded 1 in the binary outcome variable; the *p1* is the probability of occurrence of the negative factor; the group coded 0 in the binary outcome variable.

I chose the 'Z tests' as the test family and 'logistic regression' as the statistical test in the power analysis because the dependent variable was binary (had only two responses [yes = 1; no = 0]). I chose a power value of .80 in the analysis because power values between .80 and .90 are acceptable in research studies (Giner-Sorolla et al., 2024; Kang, 2021). I assumed a moderate correlation of the three contingency predictor variables

(PMs' PP, PM's LMR, and PM's TS) with the primary predictor variable (PM's LB) and used an R^2 value of .09 in the power analysis (Figure 1).

Figure 1

*Sample Size Determination Using G*Power Analysis*



I further based the power analysis on a two-tailed distribution because symmetrical distributions like the *Z* distributions (ex., binomial distribution) have two tails (A. Ali et al., 2019; Costello et al., 2022) and chose binomial for the X distribution a standard when the primary predictor variable is dichotomous (Darling, 2021; Riley et al., 2019). I assumed a value of .24 for the *p2* (Figure 1) because, on average, there is a 76% failure rate of DT projects' completion by the PMs in U.S.-based LICs (Correani et al., 2020; Datta & Nwankpa, 2021; Reeves et al., 2018). I assumed an alpha value for error probability (α) as .05 for the power analysis to have a less than 5% chance that the data tested occurring under the null hypothesis; the α value measures the degree of data compatibility with the null hypothesis (Di Leo & Sardanelli, 2020). With the above settings and information, the a priori power analysis with G*Power 3.1.9.7 yielded a minimum sample size of 143. The actual sample size of this study was 214, which was larger than the minimum sample size determined through power analysis. A larger sample size lowers the likelihood of error in generalizing the findings to the target population and a larger sample size than 100 increases the accuracy of the estimates in BLR analysis (Lakens, 2022; Riley et al., 2019). Therefore, the sample size of 214 was adequate and appropriate for this study.

Ethical Research

Ethical conduct in research promotes achieving the research goals, such as knowledge of the truth, minimizes error by prohibiting fabricating, falsifying, or misrepresenting research data, and promotes the values essential to collaboratively conduct research, ensure trust, accountability, mutual respect, and fairness (Cumyn et al., 2019; Head, 2020), and attracts funding and employment opportunities (Hutchings & Michailova, 2022). I followed the appropriate ethical public, federal, university, and other institutional guidelines for proper research conduct, including authorship guidelines, copyright policies, patenting, data sharing, confidentiality rules, protection of participant rights, and intellectual property rights during this research. I also ensured appropriate research conduct to not jeopardize the Walden school staff's and employees' safety in business.

Informed Consent Process

Walden University's Institutional Review Board (IRB) approved this study's research protocol. It provided an informed consent form (ICF), the *ASCFDS*, for use with the participants during data collection (displayed in Appendix B). Walden University's ethics IRB approval number for this study was 10-13-23-1017545. The *ASCFDS* form included the ethics approval number, information on the study's purpose, implications to business, the participants' roles and rights in the study, the requirement for participants to give their voluntary consent to participate, the participant's right to withdraw from the study at any time without hindrance and encumbrances, and the confidentiality of participants' data and information collected. I provided participants with a link to the *ASCFDS* during survey administration. I ensured they read it and *agreed to its terms* before involving them in all data collection processes; participants who agreed to the *ASCFDS*'s terms clicked a continuing link voluntarily and completed the survey. Before administering the survey to participants, I purchased a license from the publisher (Appendix F) to use and reproduce the survey instruments.

Participants' Withdrawal Process

The *ASCFDS* contained the necessary information on participants' right to withdraw from the study at any time without penalty or loss of any benefits they may be entitled to. I provided the following options for the participants who intended to withdraw from the study: (a) stop participating in the data collection without any notice or (b) send an email or text message informing me of their withdrawal. I also provided the necessary instructions in the *ASCFDS* (Appendix B) on whom to contact if they decided to discontinue participation or had any questions or concerns during or after completing the study. I also informed the participants within the survey that during the participant's voluntary withdrawal from the data collection process at any time before completion, the data already collected before withdrawal may be retained and used by the study investigators consistent with the study's purpose.

Ethical Protection of Participants

The data collection process was entirely voluntary, and others did not learn about or influence the volunteers' participation in the study. I further protected participants' rights and privacy by (a) taking good care of the data collected, (b) not using the data collected for purposes outside the scope of the research study, (c) ensuring participants' information was kept very private during data gathering, data storage, and data analysis (Hutchings & Michailova, 2022), and (d) making sure the participants and their organizations were unidentifiable directly or unintentionally through conducting anonymous surveys. I carefully designed the data collection process (including participant screening questions) to avoid recruiting vulnerable adults (elderly [>80 years]) and never even unknowingly recruited minors (<18 years old); as per the Belmont Report, adult recruitment procedures must deliberately avoid recruiting minors.

I ensured that only the study's primary researcher (me) and the Walden faculty/staff (ex. committee chair, second committee member) viewed the raw data. I have stored all the collected data as follows: (a) paper documents, including any notes and permissions letters sent via mail to me in locked file cabinets at my home; (b) all electronic surveys and other electronic documents on a password-protected personal computer backed up on a personal external password-protected hard drive, and a password-protected cloud drive, and (c) the collected data remained stored for five years and disposed of securely after 5-years. This study did not require organizational masking and exceptions to organization-masking regulations and did not incentivize participants because the data collection was anonymous.

Data Collection Instruments

In this study, I used existing survey questionnaires as the primary data collection instrument to collect primary data for the independent variables. The survey instruments used to collect data for this study were published and available in the book by Fiedler (1967) and the book chapter by Ayman et al. (1998). I legally purchased copyright permission (license #: 1412887-1, Appendix F) to reprint, use, and reproduce the scales in this study from the publisher, Emerald Group Publishing Limited. I have included the license's number (license #: 1412887) granted to me by the publisher in all scales reproduced in Appendix D. I used or reproduced these survey scales in this study with the copyright holder's permission, thereby eliminating infringing on the copyright. Raw data will be available upon request from the researcher. I have listed below the details of each questionnaire.

Least Preferred Coworker Scale

I used the LPC survey questionnaire (Table D4) developed by Fred Edward Fiedler (Fiedler, 1967) to collect data on participating PMs' LB (primary independent variable). Several previous researchers, including Henkel et al. (2019), Kundu and Mondal (2019), Shala et al. (2021), and Yammarino et al. (2020), have confirmed the validity of the applicability of the LPC questionnaire to measure LB of PMs. On the LPC scale, the leader rates the one person he or she has worked with in the past or is currently working with whom he or she can work the least well. The LPC scale consists of 18 bipolar (positive/negative) adjective items (ex. pleasant-unpleasant, friendly-unfriendly) with ratings from 1 to 8. The LPC score for a PM is the sum of the individual item scores on the 18 bipolar adjective items with a high LPC score (≥ 73), indicating ROLB and TOLB otherwise. Raters can complete the LPC scale in 5 minutes.

According to Fiedler (1967), the LPC score is an indication of the relative strength of two discrete leadership orientations: (a) the leader is TO and (b) the leader is RO. Leaders who score low on the LPC scale (< 73) are more TO than RO, find gratification and self-esteem through task achievement, and feel confident and comfortable when a task is highly structured. In contrast, the leaders who score high on the LPC scale (≥ 73) are more strongly RO than TO, value how others regard them, and find satisfaction, self-esteem, and confidence in maintaining good interpersonal relations

(Fiedler, 1967; Fiedler & Chemers, 1984). Ayman et al. (1995) reported the LPC scale to have high internal consistency (IC) reliability (Cronbach's Alpha = .88) and comparatively high test-retest reliability (.67). LPC scale yields uniformly high split-half reliability coefficients of about .90 (Fiedler, 1967, p. 44). Based on the above results of psychometric properties, LPC can be considered a stable instrument. Further, the LPC scale is reliable, effective in describing the LB of leaders, and identifies the hierarchy (the psychological distance) the leader maintains between the leader and his subordinates (Bartsch et al., 2021; Fiedler, 1967; Henkel et al., 2019; Kundu & Mondal, 2019; Yammarino et al., 2020).

Leader's Contingency Situation

Fiedler (1964) considered three contingency variables that determine the situational favorability for the leader: (a) the leader's leader-member relationship (LMR), (b) the leader's position power (PP), and (c) the leader's task structure (TS), that together with leader's LB determine whether TO or RO leadership is the best for the leader's project environment (Table 2; Fiedler, 1964). I used the three contingency variables from Fiedler's (1967) CTL as independent variables to describe the PMs' situation in this study. Fiedler (1967), in CTL, based on the three contingency variables, grouped the leader's situation into eight octants (Table E1) of favorableness (favorable to unfavorable). According to Fiedler (1967), in real-life business and individual organizations, in favorable and unfavorable situations, low LPC leadership (TO leadership) is appropriate, and in moderately favorable situations, high LPC leadership (RO leadership) is appropriate (Table 2, Table E1).

Table 2

Contingency Model of Leadership Effectiveness

Leader-member relations	Task structure	Leader's position power	Favorability to leader	Most effective leader
Good	Structured	Strong	Favorable	TO
Good	Structured	Weak	Favorable	TO
Good	Unstructured	Strong	Favorable	TO
Good	Unstructured	Weak	Moderately favorable	RO
Poor	Structured	Strong	Moderately favorable	RO
Poor	Structured	Weak	Moderately favorable	RO
Poor	Unstructured	Strong	Moderately favorable	RO
Poor	Unstructured	Weak	Unfavorable	TO

Note. TO = task-oriented, RO = relationship-oriented. Adapted from "Contingency Model of Leadership Effectiveness: Antecedent and Evidential Results," by G. Graen, K. Alvares, J. B. Orris, and J. A. Martella, 1970, *Psychological Bulletin*, *74*(4), 285–296 (https://doi.org/10.1037/h0029775).

Leader Member Relations (LMR) Scale

Fiedler used a self-report instrument, which the leader completed, called the LMR scale, with eight LMR questions, to collect data for the LMR variable. Each item in the LMR scale scored on a 1 to 5 Likert scale ('*strongly agree*,' '*agree*,' *neither agree nor disagree*,*' disagree*,' or '*strongly disagree*'). The LMR scale is a powerful indicator of the leader's LMR (Fiedler, 1967). The LMR variable indicates how well the leader gets along with individual group members, which reflects the level of cohesiveness in the work team and the degree of support the leader gets from his team members (Ayman et al., 1995;

Fiedler, 1964, 1967). Ayman et al. (1995) reported high IC reliability (Cronbach's Alpha = .80) and high construct validity for the LMR scale. The highest score possible on the scale is 40. A combined score of 20 or above indicates a good to moderately good leader's LMR, and a score below 20 indicates a poor leader's LMR (Fiedler, 1967; Fiedler & Chemers, 1984). In this study, I used the leader's rating of the LMR scale used by Fiedler (1967) with eight questions to collect primary data for PM's LMR, a binary independent variable (good PM's LMR vs. poor PM's LMR).

Task Structure (TS) Rating Scale

TS, defined as the clarity of tasks designed by the leader and perceived by the project team members, is another contingency situational variable that Fiedler (1967) used. According to Scheiter et al. (2020), employee performance is affected by PM's TS, which moderates the employees' effort and task performance. Fiedler (1967) and Fiedler and Chemers (1984) used a 'TS Rating Scale,' which includes ten questions and can measure TS in the following four dimensions: (a) *goal clarity*, the extent to which members clearly understand the task's requirements (Fiedler, 1967; Fiedler & Chemers, 1984; Shaw, 1963); (b) *goal-path multiplicity*, the extent to which a variety of different procedures or paths exists for the team members to perform the task, (c) *decision verifiability*, the extent to which the leader uses logic, mathematics, or feedback to demonstrate the correct solution to team members (Fiedler, 1967; Laughlin & Ellis, 1986), and (d) *solution specificity*, the extent to which there is more than one correct solution.

In the TS rating scale, the leader rates each of the ten questions on a three-point scale scored as '*usually true* = 2', '*sometimes true* = 1', and '*seldom true* = 0'. Scores on all ten questions summed give the leader's TS score. The maximum possible score on the TS scale is 20, and a combined score of 14 or above indicates the tasks are structured and unstructured otherwise (Fiedler, 1967; Fiedler & Chemers, 1984). Ayman and Chemers (1991) reported high IC reliability (Cronbach's Alpha = .81), and Fiedler (1967) reported high interrater reliability (between .80 and .88) for the TS Rating Scale. In this study, I used this 'TS Rating Scale' to collect primary data for the PM's TS, a binary independent variable.

Position Power (PP) Scale

The third and final contingency situational variable Fiedler (1967) considered in the CTL model was the leader's position power (PP), defined as the legitimate power inherent in the leadership position, such as rights, duties, and obligations. PP measures whether the leader has the authority to hire or fire, give rewards and punishments, and approve raises in rank and compensation to followers, which is the right of the leader to exercise power to persuade the followers to support the leader's efforts and establish good relationships with subordinates while maintaining authority. Fiedler (1967) originally developed the 'PP Scale,' with 13 questions. Fiedler and Chemers (1984) modified the 13-question 'PP Scale' into five questions answered on a three-point scale. According to Fiedler and Chemers (1984), the sum of the scores to the five questions is a highly reliable scale for measuring a leader's PP. Fiedler (1967) reported a high interpreter reliability of .95 for the PP Scale. The highest score possible on the PP scale is ten, and a value of seven or above denotes a strong leader's PP (Fiedler, 1967; Fiedler & Chemers, 1984). In this study, I used the modified five-question PP Scale by Fiedler and Chemers (1984) to collect primary data for the PM's PP, a binary independent variable.

Instrument Administration

I used the free online survey tool that Centiment provided to administer surveys online. All the respondents accessed the online survey tool, which was the primary and sole method of survey administration in this study. With online survey administration, the return rate was higher than by post or email because it was easier and faster for the respondents to complete the survey online. Online survey administration compels the respondents to answer the questions, enhancing the return rate and clarifying if the survey contains ambiguous questions (Einola & Alvesson, 2021).

Strategies Used to Assess Instrument Validity and Reliability

Survey instruments used to collect data in research studies must be valid and reliable (Elangovan & Sundaravel, 2021; Story & Tait, 2019). *Validity* is how well the survey instrument measures the intended attribute (Almanasreh et al., 2019; Knekta et al., 2019). *Reliability* is the values obtained of the same attribute from the same instrument in multiple experiments under the same conditions are the same (Elangovan & Sundaravel, 2021). I performed a reliability and validity analyses of the four survey instruments I used to collect primary data for the study’s independent variables. I have presented and discussed the results of the reliability and validity analyses in section 3 of this document.

Content Validity and Criterion Validity

A content validity analysis of items in the questionnaire ensures that the questionnaire includes all essential items and eliminates undesirable items to a particular construct (Almanasreh et al., 2019). A criterion validity analysis evaluates if the measure agrees with a gold standard and to what extent. I performed item-to-total (ITT) score correlation analyses and quantitative correlation analyses on the data collected from the four survey scales to evaluate their content and criterion validity.

Construct Validity

Construct validity evaluates how well the constructs in a study translate into functioning and operating measures. The construct validity has two components: (a) convergent and (b) discriminant (divergent) validity. Discriminant validity allows the evaluation of whether the individual indicators of the construct are significant (account for acceptable variance in the observed variables). Convergent validity allows the estimation of when two measures of constructs are related and when they should be related. I evaluated the construct validity (discriminant and convergent validity) of the four survey instruments by conducting factor analysis (FA) with the principal component analysis (PCA) extraction method and the varimax rotation and verified the significance of the factor loadings (if $> .40$) using the 'factor ' procedure in SPSS. The FA results satisfy the construct validity criteria if the loading is at least .40 (Knekta et al., 2019). I used the Kaiser-Meyer-Olkin (KMO) and Bartlett's sphericity tests to assess the data's factorability, as Shrestha (2021) suggested.

Reliability

The reliability of existing survey questionnaires relates to consistency across the parts of the measuring instrument (internal consistency [IC]) (Knekta et al., 2019; Schrepp, 2020). The most used IC reliability measure to assess instruments is Cronbach's Alpha coefficient, and a minimum value of .70 for Cronbach's Alpha is agreeable (Schrepp, 2020). I evaluated the IC reliability of the four survey questionnaires I used to collect primary data for the independent variables through Cronbach's Alpha coefficient, ensuring a minimum Cronbach's Alpha value of .70.

Data Collection Technique

Online Survey

The survey is the best and the most common method to collect quantitative data, among several primary data collection methods often used by psychologists and sociologists to analyze leadership behaviors (Knekta et al., 2019; Story & Tait, 2019). With the wide availability of computer systems and internet connectivity, online surveys such as computer-administered surveys, electronic mail surveys, and web surveys allow a global reach and much easier, faster, and more flexible administration (M. -J. Wu et al., 2022). To address the research questions of this study, I collected quantitative numerical data for the dependent and independent variables using questionnaires administered through an online survey. I prepared the survey questionnaires using the free online tool Centiment provided, included the link to the ICF I obtained from IRB, and then passed it on to Centiment for online administration. Centiment successfully administered the survey questionnaires to the eligible participants online. Eligible participants who read and agreed to the terms of the ICF could click on a continuing link provided along with the ICF, access the survey, and complete it.

In this study, online survey services enabled faster data collection, convenience, ease of data entry and analysis, large samples easier to manage, and prevented the inefficiency and expense of transforming the paper data into an electronic form for processing and analysis, allowed question format diversity and ease of providing instructions and reminders through alerts to enhance response rates resulting in sufficient data. Survey research errors such as an unrepresentative sample, a low response rate (<30%), and nonresponder bias could reduce the validity and reliability of the data collected through online surveys (M. -J. Wu et al., 2022). I avoided or minimized these errors by (a) providing adequate information and clarity to participants on survey questions, (b) evaluating the validity and reliability of survey questionnaires and data collected through appropriate statistical tests, and (c) using adequate sample size identified through an a priori power analysis which improved the response rate and minimized nonresponder bias.

Data Analysis

The research questions addressed in this study were: (1) what is the relationship between PM’s leadership behaviors and DT project completion status (RQ1)? and (2) what homogenous clusters of PM’s leadership behaviors emerge based on DT project completion status (RQ2)? The RQ1 involved a dependent variable, one primary independent variable (PM's LB), and three contingency independent variables: (a) PM's PP, (b) PM's LMR, and (c) PM's TS. I used the BLR statistical method to test the hypotheses and answer RQ1. I used a two-step cluster analysis with pre-clustering performed with the hierarchical cluster (HC) analysis followed by the k-means method to answer RQ2.

Logistic Regression

Logistic regression (LR), which describes the relationship between a predictor variable Xi (or a series of predictor variables) and the conditional probability that an outcome variable Yi equals one (success event), is appropriate when the research involves a categorical dependent variable given one or more independent variables (Dao et al., 2022; Sommet & Morselli, 2017; Zou et al., 2019). The equation of the predictor variable in the LR model, $\beta_0 + \beta_i * Xi$, is the same as in the linear regression; however, in the LR model, the exponent of the equation of the predictor variable, $exp(\beta_0 + \beta_1 * Xi)$ is applied to obtain an odds ratio (OR). The OR is the factor by which the probability of an event occurring rather than not occurring $((P(Yi = 1))/(1 – P(Yi = 1)))$ changes (increases or decreases depending on the sign of β_i) when the predictor variable Xi increases by one unit (Šinkovec et al., 2019; Sommet & Morselli, 2017). The sign of β_i can be positive or negative. When OR is not significantly different from 1, the odds of an event occurring remain the same as Xi changes. This case indicates that the null hypothesis (H_0) is true and must be accepted; a value of OR significantly different from 1 and greater than 1 indicates a significant positive effect (Šinkovec et al., 2019; Sommet & Morselli, 2017).

The higher the predictor variable effect value, the higher the odds of an event occurring. Suppose OR is < 1 and significantly different from 1, the lower the odds of the event occurring (a negative effect); in these two situations, the H_0 must be rejected (Šinkovec et al., 2019; Sommet & Morselli, 2017).

Binary Logistic Regression

There are three types of LR: (a) binary LR (BLR), (b) multinomial LR (MLR), and (c) ordinal LR (OLR). In BLR, the dependent variable can take only two possible categories (ex., yes/no, male/female, true/false); in MLR, the response of the dependent variable has three or more categories without any ordering within the categories (ex., four different presidential candidates); in OLR, the dependent variable has three or more categories with an ordering among the categories (ex., rating variables, bad/good/excellent) (Dao et al., 2022; Harris, 2021). The BLR allows modeling the relationship between a dichotomous dependent variable and multiple independent variables, either continuous or categorical (Dao et al., 2022; Harris, 2021). The dependent variable of this study, the DT project completion status achieved by the PMs in their companies, could take only two possible values (yes/no), thus categorical and binary. Therefore, BLR was the appropriate analysis method for this research. Linear regression methods such as multiple linear regression and analysis of variance (ANOVA) require that the dependent variable be continuous; hence, it is not appropriate to model this study's data with a dichotomous dependent variable.

Cluster Analysis

Cluster analysis (CA), a technique to cluster similar observations based on the observed values of several variables, can create groups of observations in data, like customers, products, employees, projects, and the like, based on similar properties (Karim et al., 2021). When the outcome variable is dichotomous, variation and heterogeneity in outcomes leading to clusters occur (Austin & Leckie, 2020). Clustering methods include HC, centroid-based (e.g., k-means and k-median clustering), distribution-based, density-based, and self-organizing maps (Karim et al., 2021). HC and centroid-based (k-means and k-median) methods are the simplest yet most effective ways of creating clusters, frequently in research studies, and are the commonly used approaches for clustering dichotomous data (Adolfsson et al., 2019; M. Ahmed et al., 2020; Torrente & Romo, 2021). The HC method in SPSS allows the calculation of distances and linking clusters by the calculated distances to accurately identify the number of clusters; therefore, it helps identify how many clusters the data has (Galak, 2020a). K-means partitioning, the most prominent clustering approach in scientific research has proved effective for partitioning dichotomous data (Galak, 2020a). The k-means cluster analysis method allows effective data partitioning by the number of clusters identified from the HC method (Galak, 2020b; Torrente & Romo, 2021).

In CA, after performing a cluster analysis using the k-means or HC method, a Silhouette analysis used to obtain a mean Silhouette score helps assess whether the number of clusters chosen was correct, whether the clusters formed were valid, and if the clustering solution was suitable. The Silhouette analysis in SPSS uses the cluster number assigned for each observation by HC or k-means clustering. It calculates a Silhouette score for each observation, which varies between -1 and 1, with higher values > .50, indicating that the observation fits its cluster well and adequately differs from members in other clusters (Pedersen et al., 2023). The total mean Silhouette score of all observations provides valuable insights into cluster cohesion and separation of the data, allowing to validate data groupings; mean Silhouette score > .50 confirms the correct number of clusters chosen and the data points were grouped meaningfully (Shutaywi & Kachouie, 2021).

I initially clustered the data using the hierarchical clustering (HC) technique, Ward’s cluster separation method, and the squared-Euclidean distance measure with all variables included in SPSS software. The HC method in SPSS allows the calculation of distances and linking clusters by the calculated distances for accurately identifying the number of clusters; therefore, it helps identify how many clusters the data has (Galak, 2020a). Ward’s method, a popular clustering partitioning method for binary and continuous data, allows calculating the distance of all clusters to the grand average of the clusters, creating evenly sized clusters based on the distances and predicting the significance of differences between the clusters using the F statistic value (Galak, 2020a; Govender & Sivakumar, 2020). The squared Euclidean distance measure is a popular dissimilarity distance measure for binary data, computed as the number of discordant cases with a minimum value of 0 and no upper limit, and quickly processed using statistical software like SPSS (Albuquerque et al., 2022).

Next, I used the k-means clustering method and partitioned the data into the number of clusters already identified by the HC method. This two-step approach to cluster analysis allowed me to identify significant clusters on dependent and independent variable groups with binary variables (Galak, 2020b; Karim et al., 2021). I then performed a Silhouette analysis using the cluster number for cases obtained from the k-means method using the absolute difference dissimilarity measure. I used the Silhouette score obtained from Silhouette analysis for each observation and calculated the mean overall Silhouette score.

Bootstrapping

Bootstrapping is a statistical procedure to model uncertainty and variability during statistical estimation (Austin & Leckie, 2020). According to the American Statistical Association (ASA), conclusions from research studies and anything scientific or practical importance must not solely rely on the statistical significance of associations. Using the bootstrap method in research studies enables the estimation of the sampling variability of measures of variance and heterogeneity, which allows for precise assessment of statistics in the analysis (Austin & Leckie, 2020). I used bootstrapping to estimate the sampling variability in the BLR models, keeping with ASA's recommendations. As stated by Austin and Leckie (2020), the bootstrapping increased the sample size and permitted the construction of confidence intervals around BLR and cluster-specific predicted random effects, which provided a richer interpretation of the data than a simple reliance on statistical significance testing, allowing valid conclusions from the statistical analysis.

Data Cleanup Strategies

Study results can be unreliable or misleading when data collection and analysis include incorrect or poor-quality data and cleaning the data before any statistical analysis can improve data quality and results. Data quality is usually considered in the following four dimensions: (a) accuracy, (b) completeness, (c) consistency, and (d) timeliness (Xu et al., 2020). Data is accurate when the collected data is appropriate for the phenomenon studied, and data is complete when it covers the entire study objectives. Consistency is when the data is in the correct format and structure. In this study, I cleaned the data for outliers, missing values, and inaccuracy (when data did not meet the statistical assumptions) using SPSS. Outliers in data indicate incorrect data. Missing values in the data collected break the continuity of data. Missing data is a severe issue in quantitative research with questionnaires because most statistical analyses assume no missing data and need complete observations in the calculations (Xu et al., 2020). Inaccurate data makes it challenging to apply valid statistical analysis methods and make intelligent conclusions or extract valuable information (Xu et al., 2020).

Handling Missing Values

Handling missing data in regression models includes listwise and pairwise deletion techniques. The listwise deletion technique, also known as the complete-case analysis (CCA), removes all data for the case or observation with one or more missing values, a commonly used technique when conducting empirical studies (Osman et al., 2018; Stavseth et al., 2019). However, the listwise and pairwise deletion techniques require an essential assumption that data are missing completely at random (MCAR); in other words, CCA relies on the assumption that the probability of data missing in the dependent variable is unrelated to the independent and dependent variables (Osman et al., 2018).

CCA may result in reduced power, significant bias, and too wide confidence intervals because of reduced sample size; however, CCA is still the most used approach to handling missing data (Osman et al., 2018). Most statistical analyses and software packages, including SPSS, assume that all variables in the model are measured and, by default procedure, usually delete cases with missing data on the variables of interest, which is CCA (Osman et al., 2018). When using a data set with missing observations, the major disadvantage is that the software package will remove a large proportion of the sample, leading to a severe loss of statistical observations and power (Osman et al., 2018).

According to Fiedler (1967), the CTL framework requires nonmissing data for all variables to adequately describe the PM's LB based on the projects' situations the PMs manage to make valid conclusions. I obtained 214 complete survey responses without missing data via Centiment. PM's LB was contingent on the three situational independent variables: (a) PM's PP, (b) PM's LMR, and (c) PM's TS. Therefore, I carefully designed the data collection process to prevent and minimize missing data by (a) providing adequate information and clarity to participants on survey questions and (b) using an adequate sample size to increase the response rate and minimize nonresponder bias, which resulted in 214 complete responses.

Assumptions of Statistical Analysis

The inferences drawn from statistical test results are valid only when the data meets assumptions associated with the statistical tests (Knief & Forstmeier, 2021; Nyitrai & Virág, 2019; Turner & Deng, 2020). Violations of statistical assumptions can lead to the inaccurate probability of the test statistic, distorting Type I and Type II error rates (Knief & Forstmeier, 2021; Turner & Deng, 2020). In this study, I tested the data for the assumptions associated with BLR statistical analysis and the associated factor analysis. I identified and used appropriate statistical techniques to check for assumptions and identified and applied ways to find remedies when data did not meet the necessary assumptions. I used SPSS software to test and apply resolutions for the violation of assumptions.

Assumptions of BLR

An excellent fit of the BLR model to the sample data occurs when the difference between the model-predicted and observed values is statistically insignificant (Nyitrai & Virág, 2019). The various goodness-of-fit diagnostic statistical measures available to estimate a BLR model's adequacy must meet a few assumptions (Boateng & Abaye, 2019). BLR analysis must meet the following assumptions: (a) the dependent variable in

BLR must be dichotomous; (b) independence of observations, which means the observations must be independent and not from repeated measurements or matched data; (c) linearity in the logit for continuous independent variables, (d) absence of or little multicollinearity among the independent variables, which means little or no correlation among the independent variables, and (d) lack of powerful outliers, influential observations, or high leverage points (Nyitrai & Virág, 2019). Additionally, the number of events or observations per independent variable must be adequate to avoid model overfitting. I tested for the above assumptions of BLR using standard tests in SPSS. I have explained in sections below the above assumptions and the processes I used to test data for the assumptions. I have discussed the test results of the BLR assumptions analyses in section 3.

Outliers, Influential Observations, and High Leverage Points. Outliers, influential observations, and high leverage points in data may result from human errors, instrument errors, sampling errors, incorrect or corrupted data, or usage of missing values coded as actual data (Costa e Silva et al., 2020; H. Wang et al., 2019). Outliers are unusual observations with exceptionally large outcome values that generate large residuals (Costa e Silva et al., 2020). High leverage points are observations with extreme predictor values for one or more predictors and influential observations are unusual observations that unduly influence one or more areas of the regression analysis, including the predicted responses, the estimated coefficients, and the hypothesis test results (Costa e Silva et al., 2020). Outliers, high leverage points, and influential observations can lead to inaccurate parameter estimates and incorrect fit of the BLR model (Costa e Silva et al., 2020).

Outlier Detection and Mitigation. The sigmoid function tapers with outliers in the BLR models. Presence of extreme outliers affect the covariate pattern, resulting in misleading interpretations, and lowering the performance of the BLR model; therefore, detecting outliers in BLR modeling and taking appropriate mitigation measures to obtain a good fit is necessary. Residual measures are the generally used techniques to identify outliers in BLR models. Several residuals calculated from a fitted BLR model, including Pearson residuals and studentized or normalized Pearson residuals, and deviance residuals allow outlier detection (Hickey et al., 2019; Nyitrai & Virág, 2019; Sarkar et al., 2011).

Plotting BLR model residuals against the predicted probabilities that displays a linear trend, are accurate and reliable ways of detecting outliers (Sarkar et al., 2011). Generally, absolute values of standardized or deviance residuals for good observations in BLR are within ±2. Standardized, normalized, or deviance residuals outside the range of ± 2 or ≥ 3 in extreme cases are potential outliers and require closer attention, and may require exclusion from the analysis (Costa e Silva et al., 2020; Hickey et al., 2019; Sarkar et al., 2011). Deleting outlying cases with the most significant residuals almost always improves the fit of the BLR model (Hickey et al., 2019).

Influential Observations Detection and Mitigation. Diagnostic plots, such as influence plots (plotting the derived diagnostic statistics against the estimated logistic probability and observed cases), can reveal the presence of influential observations (Hickey et al., 2019). For a BLR model, Cook's distance (Cook's *D*) can measure the influence of each observation on the regression parameter estimates. Cook's *D* of the fitted model greater than or equal to .50 indicates the observation is influential (Costa e Silva et al., 2020).

High Leverage Points Detection and Mitigation. High leverage points are observations with extreme predictor values. In any BLR model, the leverage values vary between 0 and 1 inclusive. An observation is a high leverage point if its leverage value is larger than 2 times the mean leverage value (MLV) or, in extreme cases, larger than 3 times the MLV (Costa e Silva et al., 2020). Plotting the BLR model predicted leverage values against the estimated logistic probabilities or observed cases can reveal the presence of high leverage points.

Multicollinearity. Multicollinearity in the BLR model indicates the existence of highly correlated independent variables. These variables can reduce the accuracy of the BLR model fit when included together in a single model as separate independent predictors, especially when they share 49% or more variance (Harris, 2021; Ozgur & Franklin, 2021; Zeng & Zeng, 2021). Predictors with multicollinearity cause unstable estimates and inflate variances of the parameter estimates, leading to incorrect predictions of the relationships between independent and dependent variables. Multicollinearity affects confidence intervals and hypothesis tests and causes type II errors (Ozgur & Franklin, 2021).

Multicollinearity Detection. The Spearman's rho correlation matrix obtained with the pairwise correlation coefficients for the binary independent variables from the SPSS output can allow the identification of the presence of multicollinearity in binary independent variables. Alternately, Phi and Cramer's *V* coefficients measure the strength of an association between two categorical variables; Phi and Cramer's *V* accurately predict the correlation between categorical independent variables (Akoglu, 2018). Phi and Cramer's *V* coefficients measure the strength of association between two nominal variables, are nonparametric tests that utilize a contingency table (also known as a *cross-tabulation*, *crosstab*, or *two-way table*) in which data classification is according to two categorical variables (Akoglu, 2018). Each categorical variable must have two or more categories. The categories for one variable appear in the rows, and the categories for the other variable appear in columns. Each cell reflects the total count of cases for a specific pair of categories. Statistical software like SPSS allows the calculation of Cramer's *V* and Phi. Cramer's *V* values vary between 0 and 1 without any negative values, and a value close to 0 means no association, and a value bigger than .25 of Cramer's *V* may indicate a very strong association (Akoglu, 2018). Phi values vary between -1 and 1, and a value close to 0 means no association, and a value bigger than .25 or smaller than -.25 of Phi may indicate a very strong association (Akoglu, 2018).

Examining the correlation matrix may help detect multicollinearity, but it is insufficient; it is possible to have data in which no pair of variables has a high correlation, but several variables may be highly interdependent (Harris, 2021). The tolerance and variance inflation factor (VIF) allows a better multicollinearity diagnosis. The tolerance of any specific independent variable is 1 - R^2, where R^2 is the coefficient of determination for the regression of the independent variable involved in all remaining independent variables. In linear regression models, tolerance values <.10 and <.20 in extreme cases often indicate multicollinearity, but in nonlinear models such as BLR, variables with tolerance values <.40 may be problematic (Harris, 2021). The VIF is the reciprocal of tolerance, estimated as 1/ (1 - R^2) (Harris, 2021). The VIF indicates how much the multicollinearity inflates the variance of the coefficient estimate; in linear regression models, VIF values exceeding ten (10) indicate multicollinearity, but in nonlinear models such as BLR, variables with VIF values above 2.50 may be problematic (Harris, 2021).

Multicollinearity Mitigation. The Spearman's rho correlation matrix, Cramer's *V*, and Phi coefficient scores obtained for the independent variables indicated the existence of multicollinearity in this study's data. I have discussed the results in section 3. Because multicollinearity existed, I performed dimension reduction through exploratory FA with the PCA method and varimax rotation. I used the factors to fit the BLR model with bootstrapping to solve for multicollinearity. The uncorrelated factors created through FA with PCA minimized information loss and improved the BLR model's predictability. I also obtained the factors' correlation matrix to confirm the multicollinearity resolution in the data. I resampled the data through bootstrapping, performed the hypotheses testing and statistical analysis, and estimated confidence intervals on bootstrapped samples to eliminate the influence of multicollinearity and violations of other possible assumptions, and improved inferences about the study population.

Independent Observations. The BLR model requires observations that are independent of each other and that they do not come from repeated measurements or matched data. In this study, the 214 participants who completed the survey to obtain primary data for the study's variables were unrelated, and the observations were independent and not from repeated measurements. I used bias-corrected estimates of the parameters for the BLR model to account for any unknown dependence of observations that arose from the surveys with potential stratified and clustered designs.

Large Sample Size. BLR requires a relatively large sample size. The recommended minimum value ranges from 10 to 20 events per covariate (Nyitrai & Virág, 2019). I determined this study's minimum sample size requirement through an a priori power analysis using G*Power 3.1.9.7 to achieve a power level of .80, a recommended standard (Giner-Sorolla et al., 2024; Kang, 2021; Riley et al., 2019). An experiment with a power level of .80 has an 80% chance of predicting the effect present at the population level. The sample size used in this study (214) was larger than the minimum required sample size of 143 obtained from the power analysis for BLR analysis and was large and adequate.

Assumptions of Factor Analysis

When performing FA, unlike the maximum likelihood extraction method, the PCA extraction method does not assume the sample is from a multivariate normal distribution but focuses on maximizing the variance of the components. However, FA with PCA assumes the following: (a) multiple variables on a numeric scale, preferably continuous; (b) sampling adequacy; PCA extraction method depends on large enough sample sizes to produce reliable results. I used the Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy in SPSS in this study, a generally used procedure to evaluate data for this assumption (Schreiber, 2021; Shrestha, 2021); (c) suitability of data for reduction, PCA requires significant or adequate correlations between the variables for reduction into a smaller number of components. I used Bartlett's test of sphericity in SPSS, a generally used procedure to evaluate this assumption (Schreiber, 2021; Shrestha, 2021); and (d) no significant outliers; I used residual measures including Pearson residuals and studentized or normalized Pearson residuals, and deviance residuals to identify outliers in the data, a recommended procedure (Nyitrai & Virág, 2019).

I encoded the survey scores of the independent variables as numeric binary variables (0s and 1s) and standardized them into scale variables through z-score normalization before performing the FA with PCA. In the normalization step, I computed the mean values of the variables subtracted from the original variable and divided by the standard deviation for each variable so that all variables used the same scale and contributed equally to the analysis. This procedure is recommended when performing FA with PCA extraction with binary variables (Greenacre et al., 2022; IBM, 2023; R. M. Wu et al., 2023). I have displayed the descriptive statistics of the z-normalized independent variables in Table E2 (Appendix E).

PCA is a linear technique better suited for variables with linear relationships (Schreiber, 2021). PLC coefficient is a statistical measure that indicates the degree to which variables change their values about each other. PLC is commonly the most used linear correlation coefficient, expressing the level to which two variables are linearly related (Šverko et al., 2022). I validated the linearity among the z-normalized independent variables through correlation analysis; significant bivariate Pearson linear correlations (PLC) of independent variables indicated linearity as stated by Šverko et al. (2022).

Assumptions of Cluster Analysis

There are no assumptions associated with cluster analysis (CA). However, CA requires significant care when choosing the group of variables or the construct of interest that can group similar observations into clusters. Besides, CA requires selecting an appropriate clustering method, testing its robustness before application, and performing sensitivity analyses using various cluster solutions and different sets of clustering variables with the chosen methods to determine their appropriateness (Karim et al., 2021). Also, confirming the validity of CA results by theory and cluster descriptions is helpful (Karim et al., 2021).

Study Validity

Statistical Conclusion Validity

Threats to internal validity do not apply to the nonexperimental correlation research design, which was the research design of this study.

However, threats to the validity of the statistical conclusion related to statistical power are of concern. Statistical power equal to 1- β of a hypothesis test is the probability of correctly predicting a sample effect in the population (Kang, 2021). The statistical power is inversely related to a Type II error. A test with high statistical power has a more significant probability of correctly rejecting a false null hypothesis (Kang, 2021).

In statistical analysis, the statistical power of the test (1- β) depends on three factors: (a) the significance alpha level, (b) the study sample size, and (c) the effect size (Darling, 2021; Kang, 2021). The more significant the significance alpha level, the larger the sample size, and the greater the effect size, the greater the power of the test (Darling, 2021; Kang, 2021). I warranted a balance between the statistical validity of the research and the practical resource constraints by selecting the right sample size to make valid conclusions. I performed an a priori power analysis with G*Power 3.1.9.7 software, input appropriate values for the significance alpha level (.05, a standard) and the effect size (Figure 1), and calculated the required sample size with a power of .80 (an accepted standard); the power analysis resulted in a minimum sample size of 143. By selecting a larger than the minimum required sample size of 214, I ensured a larger actual power (.92) in this study, which enabled the assurance of accurate inference. I minimized bias though ensuring the reliability of the data collected from the survey questionnaires through Cronbach's Alpha coefficient, ensuring a minimum

Cronbach's Alpha value of .70 for all independent variables; reliable data are relatively independent of the skills, moods, and honesty of the person collecting it hence are less biased, leading to accurate inference (Duckett, 2021; Moon, 2019).

External Validity (Generalizability)

Large random samples in the hypotheses test increase the statistical power and more closely approximate the population (Darling, 2021; Kang, 2021). I selected a larger than required sample size (214), ensuring the study's generalizability. I used bootstrapping to increase the sample size further, which provided a richer interpretation of the data, allowing valid conclusions from the statistical analysis and leading to a superior generalizability of the findings. I also ensured the validity and reliability of the instruments used to collect the study's data. I also assessed and mitigated the study's data for all violations of statistical assumptions through appropriate statistical tests and methods using SPSS software. Given the validity and reliability of the instruments and accurate statistical analysis, the inferential results based on the data were valid and reliable, leading to better generalizability.

Objective Validity

Objective validity evaluates using no subjective judgment by the person collecting the data when recording or interpreting data. Objectivity is of concern if the survey questionnaires measure attitudes, emotional characteristics, and the like. I collected primary data using survey questionnaires for PM's LB, PM's LMR, PM's PP, and PM's TS, which did not measure the attitudes or emotional characteristics but measured PMs'

LB. I ensured the objective validity by collecting adequate samples, applying reliable data collection procedures, using appropriate statistical analysis methods, and testing and mitigating data for statistical assumptions. I also performed a validity analysis in SPSS for the data collected using the instruments by obtaining item-to-total score correlations, the correlation between each item's score and the total score from all items on the survey scale, which is a reliable assessment method for the validity of survey scales (Rossell et al., 2019).

Transition and Summary

In section 2 of this research document, I described the research method and design, the population, sampling, participants, data collection instruments, data collection techniques, and data analysis methods used for the study's reliability and validity analysis of the instruments and inferential data analysis. In section 2, I also discussed my role as a researcher and ethical research conduct. In section 3, I presented the results of the reliability and validity analysis of the instruments used to collect primary data for the independent variables, the research findings from the inferential data analysis, and an evaluation of the statistical assumptions used in the analysis with appropriate tables, figures, and illustrations. In section 3, I also presented a detailed description of the applicability of the findings to professional practices, the tangible social change implications, recommendations for action, reflection, and suggestions for further research. Finally, I presented the study's conclusion.

Section 3: Application to Professional Practice and Implications for Change

Introduction

This quantitative correlational study uncovered the intricate relationship between PMs' LB and DT project completion status in three project situations of the PM. I examined four independent variables: (a) PM's LB, (b) PM's LMR, (c) PM's TS, and (d) PM's PP. The dependent variable I focused on was DT project completion status. The good psychometric properties of the instruments used in this study led to valid and reliable data collection and inferential results. Factor analysis with adequate of KMO test measure (> .50), highly significant Bartlett's sphericity test measure (χ^2 [6, N = 214] = 39.14, p < .001), significant factor loadings (> .40) for all the independent variables, significant communalities (> .50) of all variables in the factors, highly nonsignificant Pearson correlation coefficient (.000, p = 1.00) between the factors, anti-image correlation coefficients ≥ .57 for all variables in the factors allowed the extraction of two valuable factors from the independent variables. BLR analysis with the extracted factors indicated a significant (p < .05) relationship between PM's LB and DT project completion status in favorable and unfavorable situations, leading to accepting the alternate hypothesis for Research Question 1 with 95% confidence. In favorable and unfavorable contingency situations, the PMs with ROLB could not complete their DT projects successfully, creating a need for PMs with TOLB. Cluster analysis with significant contribution of all variables (p < .05) indicated the existence of three distinct clusters in the data, leading to accepting the alternate hypothesis for Research Question 2 with 95%

confidence. The results supported and confirmed the application of CTL for DT projects in LICs in the United States.

Presentation of the Findings

In this section, I present descriptive statistics of data, results of missing value analysis, analysis of violations of statistical assumptions, the reliability and validity analysis of the survey scales used to collect primary data for the independent variables, and the results of the inferential statistical tests of BLR and cluster analyses. I have discussed how the analyses I performed addressed the hypotheses of this study and answered the research questions and the theoretical perspectives of the findings. Appropriate APA tables and figures accompany the analysis results. The research questions addressed in this study were as follows:

RQ1. What is the relationship between PM's leadership behaviors and DT project completion status?

RQ2. What homogenous clusters of PM's leadership behaviors emerge based on DT project completion status?

I performed a BLR analysis procedure to address RQ1 and cluster analysis to address RQ2 in SPSS software (version 28).

BLR is the correct statistical analysis method when predicting a binary outcome (dependent) variable from one or more independent (predicting) variables (Boateng & Abaye, 2019; Dao et al., 2022; Harris, 2021). A preliminary Kolmogorov-Smirnov normality test of data indicated that the independent variables belonged to nonnormal distributions (Table E3 [Appendix E]), which further confirmed the appropriateness of BLR analysis of the data. I also performed an exploratory FA using the PCA method and varimax rotation to correct for significant associations among independent variables and ensure the independence of observations. I used the factors to fit the BLR model and enhanced its accuracy. The answer to RQ2 included a cluster analysis (CA, also known as clustering) to investigate the underlying structure of the data, described as the grouping of objects that shared similar characteristics. I performed a two-step cluster analysis in SPSS: (a) initially identified the number of clusters by the HC method, and (b) applied the k-means clustering method and partitioned the data into three clusters already identified by the HC method.

I used bootstrapping (≥ 1,000 samples) to increase the sample size, calculating bootstrapped 95% confidence intervals (CI) for all estimates, including descriptive statistics, correlations, model coefficients, and estimates necessary to solve potential assumption violations and to improve the BLR model fit. Bootstrapping allows resampling the data and analyzing the resampled data, improving BLR model fit and making more accurate inferences about a study's population (Noma et al., 2021; Ogundunmade & Adepoju, 2019). Through bootstrapping, I increased the sample size, made valid conclusions from the statistical analysis, and enhanced the generalizability of the findings.

Descriptive Statistics

In this subsection, I present descriptive statistics for the study's categorical dependent (project completion status) and categorical independent (PM's LB, PM's PP, PM's TS, and PM's LMR) variables for the study's data. I collected 214 complete responses from participants through anonymous surveys. A missing value analysis of the data in SPSS indicated no missing values in any of the variables for any observations (Table 3).

Table 3

Missing Value Analysis Results

Variable	*N*	Missing	
		Count	Percent
Project completion status	214	0	0
PM's LB	214	0	0
PM's LMR	214	0	0
PM's PP	214	0	0
PM's TS	214	0	0

Note: PM = project manager, LB = leadership behavior, LMR = leader member relations, PP = position power, TS = task structure.

I have presented the frequencies and percentages of the study's dependent and independent variables with a bootstrapped (1,000 samples) 95% confidence interval (CI) for the percentages in Table 4. Results indicated that 56.1% of the 214 participants (hereafter PMs) completed the DT projects successfully, and 43.9% did not (Table 4). Most of the PMs (91.1%) displayed high LPC (≥ 73), indicating ROLB, while 8.9% displayed low LPC (< 73), indicating TOLB (Table 4). Ninety percent of PMs who completed their DT projects and 93% who did not complete their DT projects successfully displayed ROLB. Ten percent of PMs who completed and 7% who did not complete their DT projects successfully displayed TOLB.

Table 4

Frequencies and Percentages of Variables

Variable	Type	Category	Frequency	Percent	Bootstrapped 95% CI of percent[a]	
					LL	UL
Project completion status	Dependent	Yes	120	56.1	49.5	62.6
		No	94	43.9	37.4	50.5
		Total	214	100.0		
PM's LB	Major independent	RO	195	91.1	86.9	94.9
		TO	19	8.9	5.1	13.1
		Total	214	100.0		
PM's LMR	Independent	Good	51	23.8	18.2	29.9
		Poor	163	76.2	70.1	81.8
		Total	214	100.0		
PM's PP	Independent	Strong	66	30.8	24.8	37.4
		Weak	148	69.2	62.6	75.2
		Total	214	100.0		
PM's TS	Independent	Structured	140	65.4	58.9	71.5
		Unstructured	74	34.6	28.5	41.1
		Total	214	100.0		

Note: PM = project manager, LB = leadership behavior, LMR = leader–member relations, PP = position power, TS= task structure, LPC = least preferred coworker, TO = task-oriented (LPC score < 73), RO = relationship-oriented (LPC score ≥ 73), CI = confidence interval, LL = lower level, UL = upper level. Sample size (*N*) =214.

[a] Bootstrap results are based on 1,000 bootstrap samples.

Correlation Between PM’s Leadership Behavior and Digital Transformation Project Completion Status

I divided this study's data into eight octants, grouping them into the three categories of situational favorableness for the leader: (a) favorable (octants I, II, and III), (b) moderately favorable (octants IV, V, and VI), and (c) unfavorable (octants VII and

VIII), as indicated in the CTL model (Fiedler, 1967; Fiedler & Chemers, 1984). I obtained descriptive statistics of PM's LB and the dependent variable (DT project completion status) by the three situational favorableness categories. I also obtained nonparametric Spearman's rho correlations between PM's LB and the dependent variable in each octant. I have presented the results in the next two subsections.

Descriptive Statistics by Situational Favorability

Of the 214 PMs, 77.10% experienced favorable situational control, 12.62% experienced moderately favorable situational control, and 10.28% expressed unfavorable situational control. Most PMs under favorable situations displayed ROLB (94.50%), while 77.80% under moderately favorable situations and 81.80% under unfavorable situations displayed ROLB. PMs with TOLB were 5.50% under favorable situations, 22.20% under moderately favorable situations, and 18.20% under unfavorable situations. Also, 57.60% of PMs under the favorable situation, 50.00% under the moderately favorable situation, and 51.90% under the unfavorable situation completed their DT projects successfully.

Correlations of PM's LB and DT Project Completion Status by Octants

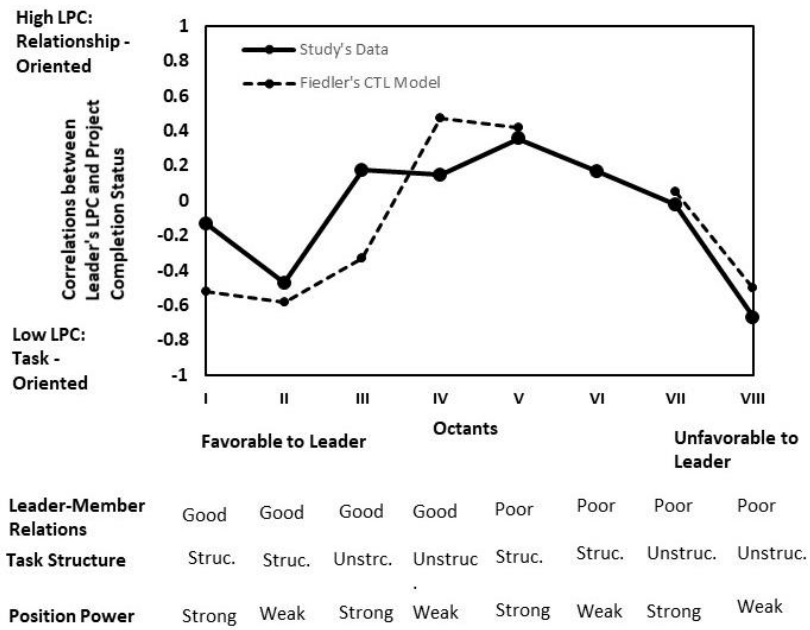
I have displayed the Spearman's rho correlations between the dependent variable and PM's LB in Figure 2, with Fiedler's standard CTL curve superimposed for comparison. Results indicated that the relationship between PM's LB and DT project completion status was nonrandom in this study, as shown by Fiedler (1964) in the CTL model and other investigators, including Ayman et al. (1995), Chemers and Skrzypek

(1971, 1972), and Fiedler and Chemers (1984) in their studies. Negative correlation existed between the successful DT project completion status and the PM's LB under favorable situation: (a) octant I (rho = -.13, [-.24, .03]) and (b) octant II (rho = -.47, [-1.00, -.26]) and under unfavorable situation: (a) octant VII (rho = -.02, [-.47, .41]) and (b) octant VIII (rho = -.67, [-1.00, -.25]). The successful DT project completion status increased with PM's LB from favorable situation (octant I, octant II, and octant III) towards moderately favorable situation (octant IV, octant V, and octant VI), remained positive and high in moderately favorable situation, and became negative and decreased as the situational favorability decreased towards unfavorable (octant VII and octant VIII) situation (Figure 2).

The negative correlation coefficients in the favorable and unfavorable situations indicated that the PMs of ROLB (with high LPC) performed the least, and the PMs of TOLB (with low LPC) performed the best in these two situations. In moderately favorable situation, the PMs of ROLB showed better performance (more successful completion of the DT projects they managed) as indicated by the positive correlations between DT project completion status and PM's LB in this situation: (a) octant III (rho = .18, [.14, .37]), (b) octant IV (rho = .15, [-.48, .90]), (c) octant V (rho = .35, [.18, .65]), and octant VI (rho = .17, [.49, -.67]).

Figure 2

Spearman rho Correlations Between PM's LB and DT Project Completion Status



Note: Struc. = structured, Unstruc. = unstructured, PM = project manager, LB = leadership behaviors. The correlation coefficients on the Y-axis are Spearman's rho coefficients. Source of Fiedler's CTL model: "Contingency Model of Leadership Effectiveness: Antecedent and Evidential Results," by G. Graen, K. Alvares, J. B. Orris, and J. A. Martella, 1970, *Psychological Bulletin*, *74*(4), 285–296 (https://doi.org/10.1037/h0029775).

The sign and correlation coefficient numbers remained in the hypothesized direction of Fiedler's (1964) CTL model in all eight octants. However, some of the correlations were low and nonsignificant at the .05 level because of the transition from positive to negative values and vice versa of correlations, a criterion of statistical instability. Overall, the study's results supported the central hypothesis of Fiedler's (1964, 1967) CTL model and its application to DT projects in LICs in the United States. The results were compatible with the CTL theory's assumption that the leader's contribution to his group's performance depends upon the leader's LB and the nature of the situation (favorableness for the leader).

Test of Statistical Assumptions

The BLR model assumes (a) a binary dependent variable; (b) a large sample; (c) no multicollinearity in data; (d) no outliers, influential observations, or high leverage points existing in the data; and (e) the observations being mutually exclusive and exhaustive. I evaluated the data for the above statistical assumptions of the BLR model. I used the standard tests in SPSS to ascertain violations.

Binary Dependent Variable

In this study, the dependent variable (project completion status) took only one of two values (yes or no). I coded the values as yes = 1 and no = 0; thus, the dependent variable was binary. Frequency analysis of the survey data (Table 4) indicated that the response of all 214 participants to the dependent variable questions fell into one of these two categories. The survey results indicated no redundant, incorrect, or invalid participant responses, and I used all 214 observations in the analysis. The data met the assumption of binary dependent variable for BLR analysis.

Large Sample

Small to moderate sample sizes overestimate the effect they measure because, with small sample sizes, the Hosmer-Lemeshow goodness of fit test has low power and cannot detect minor deviations from the BLR model (Boateng & Abaye, 2019). I performed an a priori power analysis with G*Power 3.1.9.7, which yielded a minimum required sample size of 143 with an actual power of .80 and a critical *Z* value of 1.96 for BLR analysis (Figure 1). The actual study sample size ($N = 214$) was larger than 143, large, and adequate for BLR analysis with four independent variables. There were no missing data in the sample (Table 3), which could reduce the sample size when removing the participant cases with missing data. I used all the 214 cases in the BLR analysis. Besides, I used bootstrapping to increase the sample size (≥ 1,000) in all tests to obtain more accurate estimates with the 95% CI. The data met the assumption of the large sample.

Multicollinearity

I computed the nonparametric Spearman's rho pairwise correlation coefficients for the study's independent variables in SPSS to evaluate the existence of multicollinearity. Unlike the Pearson correlation, the Spearman correlation does not assume that the variables are normally distributed and computes bivariate correlations expressed as the strength of association between two variables in a single value between -1 and +1, hence could be effectively used to estimate the correlation between categorical variables; however, for categorical variables, Spearman's rho values as small as ±.25, may indicate a strong correlation (Mesfioui et al., 2022). I also used the chi-square correlation test for categorical variables (Phi and Cramer's *V* tests) in SPSS to determine pairwise correlations of the study's categorical independent variables. Phi and Cramer's *V* are nonparametric tests that measure the strength of association between two categorical variables, (Akoglu, 2018). A value greater than .25 or less than -.25 of Phi or greater than .25 of Cramer's *V* indicates a very strong correlation between the categorical variables (Akoglu, 2018). Using a linear regression procedure, I estimated the tolerance and VIF multicollinearity statistics for the study's independent variables in SPSS. The variance inflation factor (VIF) and tolerance scores obtained in SPSS for a variable quantifies how well the other variables explain that variable in the model. For BLR, the VIF score value of two or larger (≥ 2.0) contain multicollinearity and can be problematic (Harris, 2021).

The nonparametric Spearman's rho (rho) correlation matrix for the study's independent variables indicated a significant positive correlation between (a) PM's LMR and PM's LB (rho = .18, p = .008), (b) PM's LMR and PM's PP (rho = .19, p = .005), (c) PM's LMR and PM's TS (rho = .22, p = .001), (d) PM's LB and PM's PP (rho = .25, p < .001), and (e) PM's PP and PM's TS (rho = .15, p = .025) (Table 5), indicating the possible existence of multicollinearity in the data. No evidence of high correlations existed between PM's LB and PM's TS (rho = .03, p = .653). The Phi and Cramer's *V* correlation coefficients for the pairwise binary independent variables also indicated similar significant positive correlations between (a) PM's LMR and PM's LB, (b) PM's LMR and PM's PP, (c) PM's LMR and PM's TS, (d) PM's LB and PM's PP, and PM's PP and PM's TS (Table 6).

Table 5

Spearman's rho Coefficients, Significance, and CI of Independent Variables

Variable Pair		*N*	Spearman's rho	Significance	Bootstrapped 95% CI for Spearman's rho[a]	
					LL	UL
1.	PM's LMR vs. PM's LB	214	.18**	.008	.01	.35
2.	PM's LMR vs. PM's PP	214	.19**	.005	.02	.36
3.	PM's LMR vs. PM's TS	214	.22**	.001	.08	.36
4.	PM's LB vs. PM's PP	214	.25**	<.001	.04	.45
5.	PM's LB vs. PM's TS	214	.03	.655	-.11	.18
6.	PM's PP vs. PM's TS	214	.15*	.025	.01	.30

Note. CI = Confidence interval, LL = Lower level, UL = Upper level, PM = Project manager, LB = Leadership behaviors, LMR = Leader member relations, PP = Position power, TS = Task structure.

[a] Bootstrap result are based on 1000 bootstrap samples.

** Correlation is significant at the .01 level (two-tailed).

* Correlation is significant at .05 level (two-tailed).

Table 6

Phi and Cramer's V Coefficients and Significance of Independent Variables

Variable Pair		*N*	Phi	Cramer's *V*	Approximate significance	Exact significance
1.	PM's LMR vs. PM's LB	214	.18**	.18**	.008	.014
2.	PM's LMR vs. PM's PP	214	.19**	.19**	.005	.008
3.	PM's LMR vs. PM's TS	214	.22**	.22**	.001	.002
4.	PM's LB vs. PM's PP	214	.25**	.25**	<.001	.002
5.	PM's LB vs. PM's TS	214	.03	.03	.653	.798
6.	PM's PP vs. PM's TS	214	.15*	.15*	.025	.038

Note. PM = Project manager, LB = Leadership behaviors, LMR = Leader member relations, PP = Position power, TS = Task structure.

** Correlation is significant at the .01 level (two-tailed).

* Correlation is significant at .05 level (two-tailed).

None of the independent variables indicated VIF > 2.50 or tolerance < .40 (Table 7). All the variables indicated VIF values below 1.20 and high tolerance values above or equal to .90 (Table 7), indicating no severe multicollinearity of variables in the study data. However, the VIF and tolerance value computation assumed a linear regression model and may not apply for the nonlinear BLR model. Based on the results from the nonparametric bivariate correlations, this study's data indicated the possible existence of severe multicollinearity. Five of the six bivariate independent variable pairs indicated significant correlations with $p < .05$ (Table 5 and Table 6).

Table 7

Collinearity Statistics of Independent Variables

			Collinearity statistics	
	Variable	*N*	Tolerance	VIF
1.	PM's LMR	214	.91	1.11
2.	PM's LB	214	.92	1.09
3.	PM's PP	214	.90	1.11
4.	PM's TS	214	.94	1.07

Note. VIF = Variance inflation factor, PM = Project manager, LMR = Leader member relations, LB = Leadership behaviors, PP = Position power, TS = Task structure.

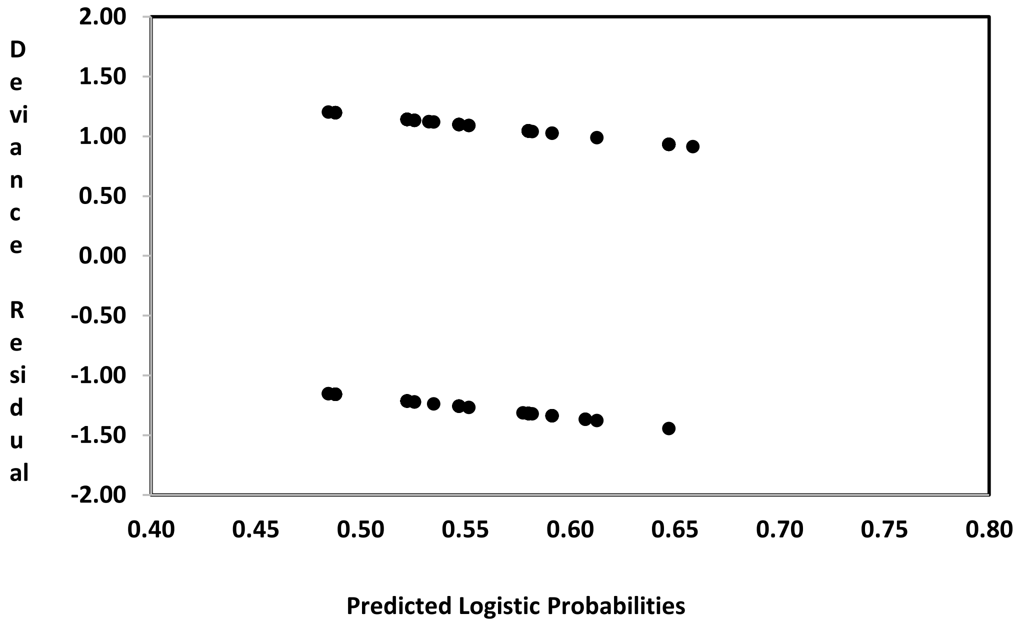
Outliers, Influential Observations, and High Leverage Points

I obtained and analyzed the residuals and diagnostic statistics from an initial BLR model fitted for the binary dependent and the four binary independent variables (PM's LB, PM's PP, PM's LMR, and PM's TS). The Hosmer–Lemeshow goodness of fit test results ($\chi2$ [4, N = 214] = 1.98, $p = .74$) indicated an adequate fit of the initial BLR model. I plotted the model-generated residuals, Cook's *D* values, and leverage points against the observation indices and the model-predicted probabilities to evaluate data for the existence of outliers, influential observations, and high leverage points.

Outliers. I have presented the plots of deviance (Figure 3) and standardized (Figure E1 in Appendix E) residuals from the initial BLR model against the model-predicted (predicted) probabilities. Model residuals plotted against the predicted probabilities indicated two almost linear trends, with slope -1 indicating decreasing residuals, as expected. The deviance residual values ranged from -1.50 to 1.25, and none of the observations in the plot indicated deviance residual values > 2 or < -2 to be an outlier. Both residual plots indicated no residuals with values > +2 or < -2. The plot of deviance residuals from the initial BLR model against the observed case indices (Figure 4) indicated no observations with deviance residual values outside of ±2. Thus, there were no outliers in the observed data, as all the residual values remained within ±2. The frequency histograms plotted (with trend lines added) of the deviance (Figure 5) and standardized (Figure E2 in Appendix E) residuals from the initial BLR model displayed asymmetric distribution and did not indicate a long tail in one direction or a bar outside the ±2 values, indicating no outliers present in the data.

Figure 3

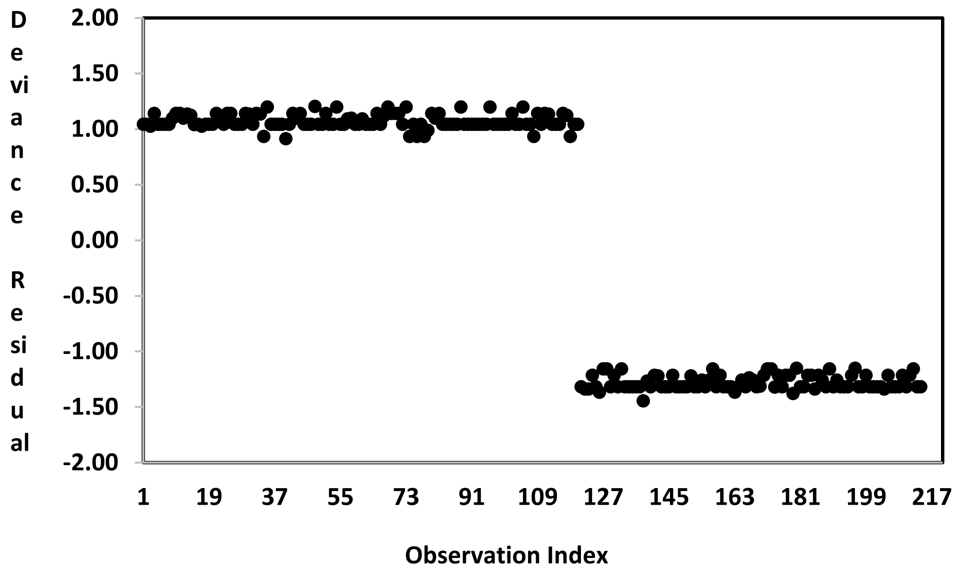
Deviance Residuals Against Predicted Probabilities From Initial BLR Model



Note. Dependent variable is project completion status. Independent variables are PM's LMR, PM's PP, PM's TS, and PM's LB. $N = 214$.

Figure 4

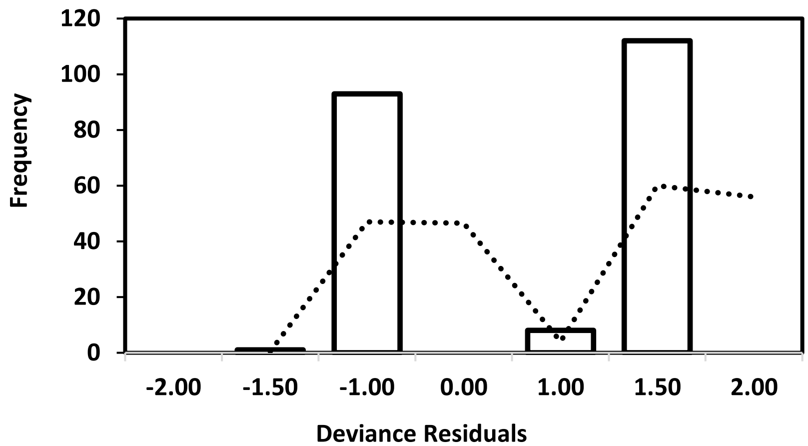
Deviance Residuals From Initial BLR Model Against Observation Indices



Note. Dependent variable is project completion status. Independent variables are PM's LMR, PM's PP, PM's TS, and PM's LB. $N = 214$.

Figure 5

Frequency Histogram of Deviance Residuals From Initial BLR Model

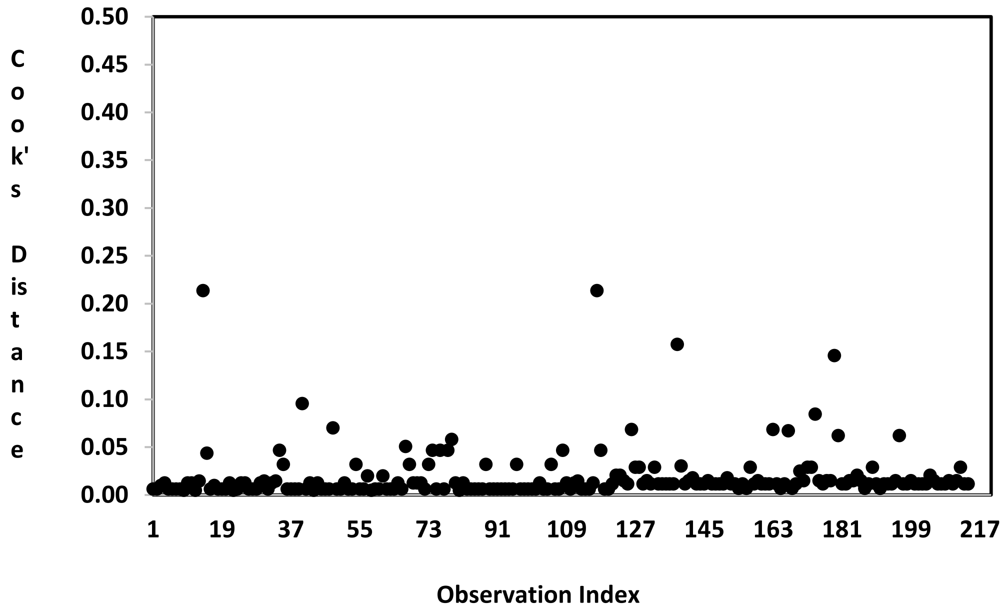


Note. Dependent variable is project completion status. Independent variables are PM's LMR, PM's PP, PM's TS, and PM's LB. *N*=214.

Influential Observations. Figure 6 displays the Cook's distance (Cook's *D*) from the initial BLR model for the study data against the observed case indices. Cook's *D* measures the influence of each observation on the BLR model parameter estimates; an influential observation is that it has Cook's *D* value > .50 (Costa e Silva et al., 2020). In the BLR model of study data, Cook's *D* values ranged from .005 to .214, and none of the observed cases indicated Cook's *D* > .50 to be influential. Thus, no influential observations existed in the study data.

Figure 6

Cook's Distances From Initial BLR Model Against Observation Indices

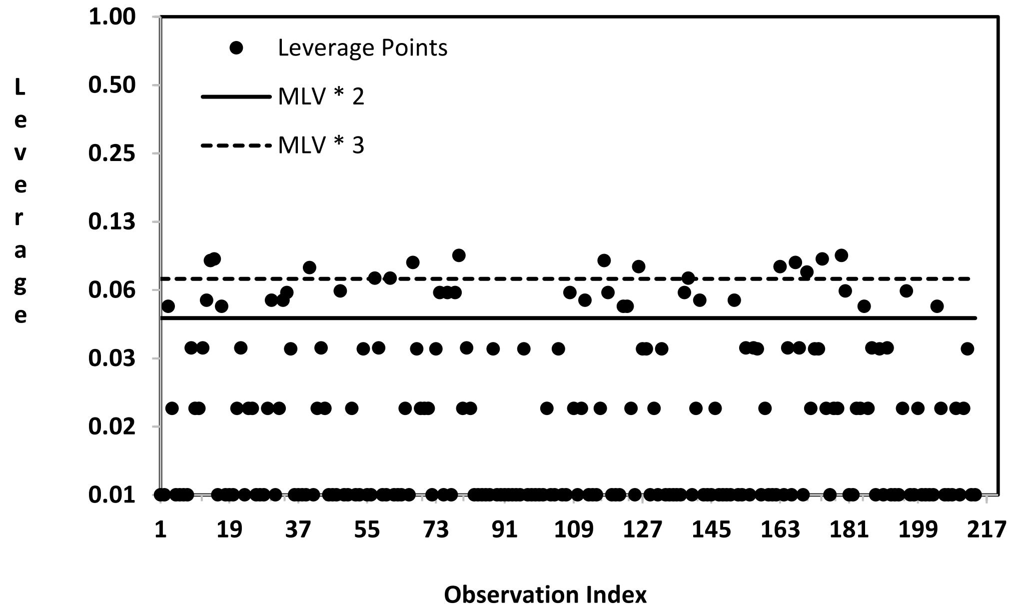


Note. Dependent variable is project completion status. Independent variables are PM's LMR, PM's PP, PM's TS, and PM's LB. *N*=214.

High Leverage Points. Figure 7 displays the leverage values from the initial BLR model for the study data against the observed case indices. In the BLR model of study data, the leverage values ranged between .006 and .196, with a mean leverage value (MLV) of .019; 2 times the MLV was .037 and 3 times the MLV was .056. Twenty-one (21) observations had leverage values larger than 2 times the MLV or > .037, and 17 observations had leverage values larger than 3 times the MLV or > .056 indicating existence of several high-leverage points in the data (Figure 7).

Figure 7

Leverage Values From Initial BLR Model Against Observation Indices



Note. MLV = Mean leverage value. MLV = .019, MLV * 2 = .037, MLV * 3 = .056.

Independence of Observations

The data for each observation was independent or came from separate participants. The data did not come from repeated measurements for any participants entered twice. Further, the deviance residuals plot against the observation indices (Figure 4) indicated random patterns around the two dependent categories (0 and 1), indicating that the observations were independent. Thus, the data met the assumption of independent observations.

Reliability and Validity Analyses of Survey Instruments

I performed reliability and validity analyses on the four survey scales (LPC rating scale [18 items], TS rating scale [10 items], LMR rating scale [8 items], and PP rating scale [5 items]) that I used to collect primary data for the study's independent variables. I assessed the reliability of the scales in terms of split-half reliability and IC reliability, which are acceptable tests for the reliability assessment of survey scales (Kishore et al., 2021; Rossell et al., 2019). I used the 'Alpha' and 'Split-Half ' options under reliability analysis in SPSS separately to assess the survey scales for these two reliabilities. I obtained the Cronbach's Alpha values for the four scales in SPSS to assess their IC reliability. Analysis of the split-half reliability in SPSS allows to divide the questionnaire's items into two halves and calculate correlations between the two halves with high correlations (> .50) between the two halves, indicating high split-half reliability of the scales (Kishore et al., 2021; Rossell et al., 2019). I also obtained the Spearman-Brown (SB) coefficient and the Guttman Split-Half coefficient of the four scales to further assess their split-half reliability. I assessed instrument validity by obtaining item-to-total score correlations. According to Rossell et al. (2019), the correlation between each item's score on the survey scale and the total score from all items is a reliable assessment method for the validity of survey scales.

Reliability Analysis Results

The Cronbach's Alpha values ≥ .70 for the LPC rating scale (.97) and TS rating scale (.70) indicated adequate IC reliability of these survey scales. The < .70 Cronbach's

Alpha value of the LMR rating scale (.67) indicated questionable IC reliability of this scale. The Cronbach's Alpha value of the PP rating scale (.40) indicated inadequate IC reliability of this scale. Ayman and Chemers (1991) reported good IC reliability for the LPC scale (Cronbach's Alpha = .90) and the LMR scale (Cronbach's Alpha = .80). In a recent study, Arjanto et al. (2022) reported high IC reliability with a Cronbach's Alpha value = .75 for the LPC scale. Previous IC reliability data for the PP rating scale is available from only one study by Ayman and Chemers (1991), where it had a low Cronbach's Alpha of .31. According to Ayman and Chemers (1991), this low IC reliability value of PP rating scale is the result of the multidimensional nature of the scale, which measures several bases of power reported by the leader. This five-item scale measures the leader's discretionary power to reward and punish, job-relevant expertise, and official status. According to Fiedler and Chemers (1984), like the TS, PP is defined at the individual level for the leader and contributes to the overall level of control in the leader's situation; several field studies indicated that the leader's self-report was reliable.

The low IC reliability scores < .70 found in this study for the PP rating scale and the LMR scale made understanding and applying the data per CTL model difficult. The reliability statistics of the LMR scale indicated two items (Question 1 and Question 5, Table D1) on the LMR scale having low IC scores; deleting these items would improve the overall reliability of the data collected. Similarly, the reliability statistics of the PP rating scale indicated one item (Question 5, Table D3) on the PP rating scale having a low IC score; deleting this item would improve the overall reliability of the data collected. These items were irrelevant and scored on different scales than the others, creating nonreliable data. I removed these questionable items and reevaluated the reliability of the LMR and the PP questionnaires. I have displayed in Table 8 the Cronbach's Alpha values for all scales after removing the nonreliable items from the LMR and PP rating scales. The Cronbach's Alpha values obtained for the LMR scale (.85) and the PP rating scale (.48) in this study were larger (Table 8) than the values reported by Ayman and Chemers (1991) for the LMR scale (.80) and the PP rating scale (.31).

According to Fiedler and Chemers (1984), the cutoff scores for the high and low levels of control need adjustment for the prescribed categories by the maximum number of points possible on each scale. Previous researchers in their studies, in some cases, have used extreme scores (cutoffs based on a standard deviation on each side of the mean or the top and bottom 10% or thirds of the distribution [e.g., Ayman & Chemers, 1991]). Past researchers used median or mean split in other studies to categorize high and low scores (e.g., Chemers et al., 1985). Fiedler (1967) and Fiedler and Chemers (1984) used the 75th percentile score of the distribution as the cutoff point for the high and low levels of the scales; I used the 75^{th} percentile score of the new total as the cutoff point for the LMR and the PP scales.

The high (> .70) split-half SB reliability coefficients for the LMR rating scale (.84), LPC rating scale (.95), and TS rating scale (.74) indicated high split-half reliability of these scales (Table 8). Correlation coefficients between the split halves were also high

(> .50) for these scales, further indicating adequate split-half reliability (Table 8). The low correlation (.18) coefficient and low SB coefficient (.30) of the PP rating scale indicated that the reliability of this scale needed to be revised.

Table 8

Reliability Statistics of Survey Instruments

	Reliability statistics			
	IC reliability statistics	Split-half reliability statistics		
Instrument	Cronbach's Alpha	Correlation between halves	Spearman Brown coefficient	Guttman split-half coefficient
LMR rating scale	.84	.74	.85	.85
TS rating scale	.70	.53	.70	.70
PP rating scale	.48	.18	.30	.28
LPC rating scale	.97	.90	.95	.95

Note: IC = Internal consistency, LMR =Leader member relations, TS = Task structure, PP = Position power, LPC = Least-preferred coworker.

Validity Analysis Results

Highly significant ($p < .001$) item-to-total score correlations for all items in all four scales confirmed the high validity of the four scales (Table 9). All item-to-total score correlations were positive, further verifying the four scales' validity. Negative correlations between item and total scores indicate errors in the scale, thus invalidity of scales (Rossell et al., 2019), which was not the case in this study. The high factor loadings above .40 for all variables in the factors (Table 10) indicated that the data satisfied the construct validity, including the convergent validity and the discriminant validity (Knekta et al., 2019). Fiedler (1967) reported strong construct validity for the four scales.

Table 9

Correlation Between Item and Total Scores of Survey Scales

Instrument	Item #	Pearson correlation coefficient	Significance (2-tailed)	Bootstrap[a] 95 % CI	
				LL	UL
LMR rating scale	1	.64**	<.001	.59	.72
	2	.59**	<.001	.48	.68
	3	.62**	<.001	.52	.71
	4	.53**	<.001	.42	.62
	5	.57**	<.001	.49	.66
	6	.57**	<.001	.47	.67
	7	.68**	<.001	.59	.76
	8	.54**	<.001	.43	.64
PP rating scale	1	.69**	<.001	.61	.76
	2	.68**	<.001	.59	.76
	3	.37**	<.001	.26	.47
	4	.41**	<.001	.31	.51
	5	.36**	<.001	.25	.45
TS rating scale	1	.56**	<.001	.46	.66
	2	.51**	<.001	.40	.60
	3	.56**	<.001	.45	.65
	4	.45**	<.001	.34	.56
	5	.50**	<.001	.38	.60
	6	.52**	<.001	.42	.61
	7	.57**	<.001	.46	.66
	8	.53**	<.001	.42	.62
	9	.49**	<.001	.38	.59
	10	.42**	<.001	.31	.53
LPC rating scale	1	.75**	<.001	.63	.84
	2	.81**	<.001	.72	.87
	3	.82**	<.001	.75	.87
	4	.73**	<.001	.68	.80
	5	.71**	<.001	.62	.79
	6	.78**	<.001	.70	.85
	7	.79**	<.001	.70	.87
	8	.75**	<.001	.67	.82
	9	.80**	<.001	.59	.80
	10	.75**	<.001	.77	.90
	11	.72**	<.001	.59	.80
	12	.82**	<.001	.73	.88
	13	.83**	<.001	.76	.88
	14	.85**	<.001	.77	.90
	15	.83**	<.001	.77	.88
	16	.85**	<.001	.81	.89
	17	.88**	<.001	.83	.91
	18	.83**	<.001	.75	.89

Note. Details of the items by item # in each scale are presented in Appendix D in Tables D1, D2, D3 and D4. CI= Confidence interval, LL = Lower level, UL = Upper level.

[a] Bootstrap result are based on 1000 bootstrap samples.

** Correlation is significant at .01 level (2-tailed).

The reliability and validity analysis results confirmed that the instruments used in this study had good psychometric properties, and the data collected based on these instruments were of adequate quality. Given the validity and reliability of the instruments, the inferential results based on the collected data were valid and reliable. Based on the results from this study, further validations through test-retest reliability and inter-rater reliability analysis with additional data would benefit future research.

Inferential Results

Factor Analysis Results

Although BLR provides a parsimonious combination of the best predictor variables, the significant association of any two independent variables adversely impacts the results of a BLR model by reducing the association of the independent variables with the outcome variables (Akoglu, 2018). The existence of multicollinearity in the data results in incorrect or underpredicted overall levels of significance from the BLR model and leads to individual predictors not predicting the outcome correctly or the degree of relationship between a predictor and the outcome incorrectly established (Akoglu, 2018). Combining the correlated predictor variables or removing one of the variables could significantly improve the accuracy of the BLR model (Akoglu, 2018).

Significant nonparametric correlations existed in this study's data between the following binary independent variable pairs: (a) PM's LMR and PM's TS (p = .001), (b) PM's LB and PM's PP (p < .001), (c) PM's PP and PM's TS (p = .025), (d) PM's LMR and PM's LB (p = .008), and (e) PM's LMR and PM's PP (p = .005) (Table 5 and Table

6). Besides, the study data contained several high-leverage points (Figure 6), causing significant problems, including erroneous goodness-of-fit statistics, wrong *OR,* and wrong Wald statistics (Costa e Silva et al., 2020). Significant ($p < .05$) linear Pearson bivariate correlations existed among the *Z*-normalized independent variables (Table E4 [Appendix E]), indicating linear relationships among variables. I performed an exploratory FA using the PCA extraction method and varimax rotation to extract significant factors of the study's *Z*-normalized independent variables using the 'factor' procedure in SPSS. The goal in performing FA was to organize the four independent variables obtained from the survey questionnaire scores into a valid set of uncorrelated composite factors representing the original predictor variables.

In FA, the PCA extraction method is a valuable analysis tool to identify the factors underlying the predictor variables of a data set to measure the outcome (Shrestha, 2021). PCA method transforms the data into orthogonal uncorrelated variables known as principal components, preserves the total variance in the original data, and rejects the combination of variables that do not explain much of the variance in the data; PCA minimizes or eliminates common issues such as multicollinearity and overfitting (Shrestha, 2021). The orthogonal varimax rotation procedure forces factors to be independent (Nájera et al., 2023). It maximizes the variances of factor loadings across variables of each factor, enhancing the interpretability of the result (Muhamad et al., 2024). BLR with extracted principal components can result in a more accurate model with a superior fit than the one fitted with the original correlated independent variables (Costa e Silva et al., 2020; Muhamad et al., 2024; Shrestha, 2021).

I used the Kaiser-Meyer-Olkin (KMO) test to measure sampling adequacy, Bartlett's sphericity test to assess the factorability of the data and calculated the determinant score of the correlation matrix to examine the multicollinearity among the variables during FA. The KMO test measures the suitability of data for factor analysis and measures the sample adequacy for each variable in the model; A KMO value > .60 is acceptable for a sample size < 100, and a KMO value between .50 and .60 is acceptable for sample sizes between 100 and 200 (Galak, 2020c; Shrestha, 2021). Because of the larger than 200 ($N = 214$) sample size of the study's data, a KMO value >.50 was acceptable. Bartlett's sphericity test tests the null hypothesis, Ho: When accepted, the variables have an original correlation matrix (an identity matrix), indicating that the variables are unsuitable for factor detection (Galak, 2020c; Muhamad et al., 2024). The KMO test and the Bartlett sphericity test together measure the construct validity of the factors through calculating sample adequacy (Shrestha, 2021).

KMO test measure (.59) for sampling adequacy and the significance of Bartlett's sphericity test (χ^2 [6, N = 214] = 39.14, $p < .001$) results indicated that the correlation matrix of the data was appropriate for FA (Shrestha, 2021). The factors indicated convergent validity. The diagonal Anti-Image correlation coefficients larger than .50, which must be larger than .50 (Shrestha, 2021) for all the independent variables (a) PM's

LB (.57), (b) PM's LMR (.61), (c) PM's PP (.60), and (d) PM's TS (.57) further indicated adequacy of FA for the data (Table 10).

Table 10

Anti-Image Correlation Matrix of Independent Variables

Variable	PM's LMR	PM's PP	PM's TS	PM's LB
PM's LMR	.61[a]	-.13	-.20	-.15
PM's PP	-.13	.60[a]	-.12	-.22
PM's TS	-.20	-.12	.57[a]	.04
PM's LB	-.15	-.22	.04	.57[a]

Note. PM = Project manager, LMR = Leader member relations, PP = Position power, TS = Task structure, LB= Leadership behaviors.

[a] Measures of sampling adequacy (MSA).

The Kaiser's eigenvalue of a factor represents the amount of the total variance explained by that factor. In FA, the factors having eigenvalue ≥ one explains more common variance and hence are retained, which is an acceptable rule in FA (Shrestha, 2021). Further, the scree plot (plot of eigenvalue against the component number) obtained in FA helps to identify the optimum number of factors; the factor before the plot starts to flatten out should be extracted (Shrestha, 2021). I examined Kaiser's eigenvalue criterion and Scree plot from the FA to determine the number of factors to retain and apply and the varimax orthogonal factor rotation method to optimize the number of variables with high loadings (> .40) on each factor. The FA with PCA method and varimax rotation resulted in four components, with two having acceptable eigenvalues (Table 11). I retained the two factors with rotated eigenvalues equal to 1.29 (Factor 1) and 1.23 (Factor 2). FA's scree plot (Figure 8) started to flatten after component 3, indicating that the amount of unique variance began to dominate the common variance starting at component 3. The eigenvalues and the scree plot confirmed the retention of Factor 1 and Factor 2 for further analysis.

Table 11

Total Variance Explained by Extracted Factors

Factor	Rotation sums of squares loadings			Rotated component matrix			
	Total	Percent of variance	Cumulative percent of variance	PM’s LB	PM’s PP	PM’s TS	PM’s LMR
1	1.29	32.22	32.22	85	.67		
2	1.23	30.66	62.88			.88	.62

Note. Extraction method is principal component analysis. PM = Project manager, LMR = Leader member relations, PP = Position power, TS = Task structure, LB= Leadership behaviors.

Factor 1 explained 32.21% of the rotated total variance, and Factor 2 explained 30.66% with a cumulative variance of 62.88% (Table 11). Principal components with a percentage of more than 10% variance and a cumulative variance of at least 60% are considered acceptable (Muhamad et al., 2024). Factor 1 indicated high positive loading values for PM's LB (.85) and PM's PP (.67) and adequately represented these two independent variables (Table 12). Factor 2 indicated high positive loading values for PM's TS (.88) and PM's LMR (.62) and represented them adequately (Table 12). The correlation matrix's determinant score (.83), closer to 1, indicated the absence of multicollinearity (Shrestha, 2021) in the extracted factors.

Figure 8

Scree Plot of Extracted Components

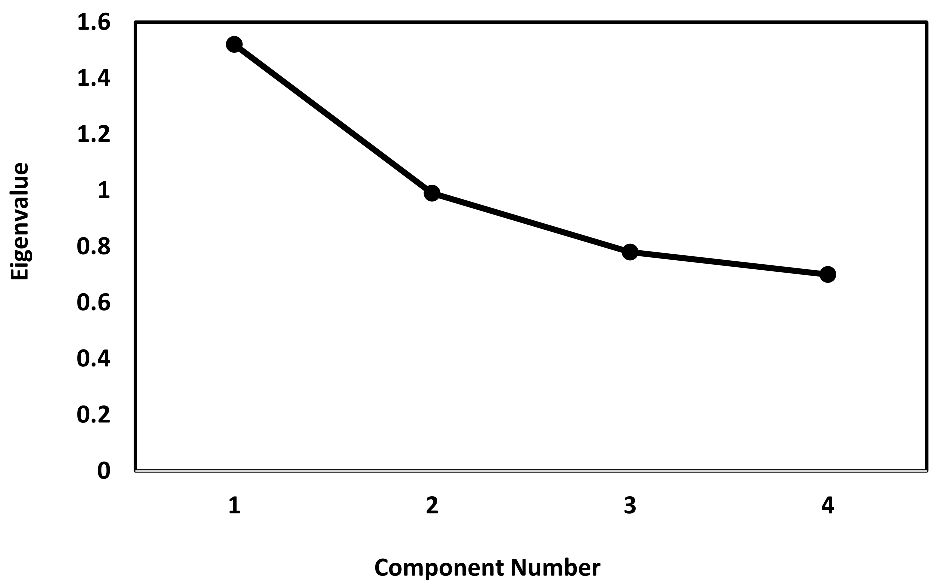


Table 12

Factor Loadings and Communalities of Independent Variables

Variable	Factor loading		Extraction communality
	Factor 1	Factor 2	
1. PM's LB	.85		.72
2. PM's PP	.67		.52
3. PM's LMR		.62	.51
4. PM's TS		.88	.77

Note. Extraction method: Principal component analysis. Rotation method: Varimax with kaiser normalization. PM = Project manager, LB = Leadership behaviors, LMR = Leader member relations, PP = Position power, TS = Task structure.

The communality of a variable in FA, which varies between 0 and 1, reveals the proportion of variation in that variable explained by the extracted factors. The communality of a variable will be equal to one when that variable does not have any unique variance (its explained variance is 100% a result of other variables). Communalities of variables > .50 in extracted factors indicate that the factors explain most of the variation in those variables and are preferred (Shrestha, 2021). When a factor has loadings greater than .60, the factor is stable regardless of sample size, and when the communalities are ≥.50, the sample size needed is around 200 and below .50, 500, or more (Schreiber, 2021). All the independent variables of the study used in the FA had communalities >.50 (PM's LB [.72], PM's TS [.77], PM's PP [.52], and PM's LMR [.51]); thus, extracted factors explained 72% of variation in PM's LB, 77% of variation in PM's TS, 52% of variation in PM's PP, and 51% of variation in PM's LMR (Table 12). The significant factor loadings (> .60) of all the independent variables in the two factors, significant communalities (> .50) of all the variables in the factors, and the highly nonsignificant Pearson correlation coefficient (.000, p = 1.00) between the two factors indicated the factor model was superior. The results indicated that the FA allowed the detection of relevant combinations of variables and the extraction of valuable factors from the data set. Applying FA for component extraction allowed me to focus on a few essential factors valuable in BLR model fitting.

BLR Analysis Results

To answer RQ1, I investigated the relationship between the four independent variables (PM's LB, PM's LMR, PM's TS, and PM's PP) grouped into two factors, Factor 1 (PM's LB and PM's PP grouped) and Factor 2 (PM's LMR and PM's TS grouped) on the probability of completing the DT projects successfully by the PMs through the BLR analysis method with bootstrapped (> 1000) samples. I performed separate BLR analyses by the three PMs' situational favorability: (a) favorable, (b) moderately favorable, and (c) unfavorable. Table 13 illustrates the results from the BLR analysis in the three situational favorability. I included the interaction effect of the relationship between the two factors (Factor 1 * Factor 2) on the probability of successfully completing the DT projects by the PMs as a predictor in the analysis. In a BLR analysis, an interaction effect (X * Z) between two predictors (ex., X and Z) occurs when the relationship between one predictor, X, and the outcome (response) variable, Y, depends on the value of the other predictor variable, Z; an X * Z interaction term means that the X moderates the effect of Z on Y and Z moderates the effect of X on Y(Fisher, 1992). A significant ($p < .05$) interaction coefficient indicates that the association between X and the probability that Y = 1 depends on the values of Z and vice versa, where X and Z may be binary or continuous; in this case, the individual effects of the two predictors become less critical (Fisher, 1992).

The nonsignificant p-value, almost close to 1 of the Hosmer and Lemeshow test, which assesses the goodness of fit of the BLR model (Boateng & Abaye, 2019), for the three situations: (a) favorable (χ^2 = .01, p = .94), (b) moderately favorable (χ^2 = .00, p = 1.00), and (c) unfavorable (χ^2 = .13, p = .99) indicated, that the model predicted the data exceptionally well in all three situations. The negative and significant value of β for the interaction effect between Factor 1 and Factor 2 (Factor 1 * Factor 2) in the favorable (β

= -.99, p = .025) and unfavorable (β = -90.73, p = .040) situations (Table 13) indicated that the two factors were dependent on each other, moderated the effect of each other, and together interactively significantly decreased the chances of PMs successfully completing the DT project in these two situations (favorable and unfavorable). Most of PMs in the favorable (94.50%) and unfavorable (81.80%) situations scored high on the LPC scale displaying ROLB. In other words, when the situation was favorable (octant I, octant II, and octant III) or unfavorable (octant VII and octant VIII) to the PMs with ROLB, the odds of the PMs successfully completing the DT projects became less likely. As indicated by Fiedler (1967) and Fiedler and Chemers (1984) in the CTL model these two situations are best for the PMs with TOLB.

The odds ratio values less than 1 for the Factor 1 * Factor 2 interaction term (.37 [.14, .99]) under favorable conditions (Table 13) indicated that Factor 1 and Factor 2 interactively decreased the likelihood of the PMs successfully completing the DT projects by 63 percent ([.37 - 1.00] * 100) when the factors' values increased from 0 to 1. The almost zero odds ratio of the interaction term under unfavorable conditions (Table 13) indicated that the factors interactively decreased the likelihood of the PMs successfully completing the DT projects by almost 100 percent ([.00 - 1.00] * 100) when the factors' values increased from 0 to 1.

The positive significant (p < .05) coefficient estimates (β) of the individual effects of Factor 1 (.90, p = .047) and Factor 2 (.91, p = .032), and the larger than one odds ratio for Factor 1 (2.47 [.78, 7.81]) and Factor 2 (2 .49 [.98, 6.35]) in the favorable situation

(Table 13) indicated that the factors individually increased the successful completion of the DT projects by the PMs. However, the significant and negative β for the interaction effect of the two factors (β = -.99, p = .025) in this situation indicated that the two factors moderated the effect of each other and significantly and jointly decreased the chances of PMs completing the DT projects successfully in the favorable situation. The negative significant ($p < .05$) of β and the almost zero odds ratio for the individual effect of Factor 1 and Factor 2 in the unfavorable situation (Table 13) indicated that the factors individually decreased the successful completion of the DT projects by the PMs in the unfavorable situation. Also, the significant and negative β for the interaction effect of the two factors (β = -90.73, p = .040) in this situation indicated that the two factors moderated the effect of each other and significantly and jointly decreased the chances of PMs completing the DT projects successfully. It is important to note that when the interaction effect of two predictors is significant, the individual effects of the two predictors become less critical (Fisher, 1992). However, the significance of the individual effects of predictors in these situations provides additional insights regarding the effects of these factors.

The nonsignificant β for the interaction effect of Factor 1 and Factor 2 (Factor 1 * Factor 2) in the moderately favorable (β = .58, p = .532) situation (Table 13) indicated that the two factors did not moderate the effect of each other or significantly impact the successful completion of DT projects by the PMs in the moderately favorable situation. The nonsignificant ($p > .05$) coefficient estimates (β) of the individual effects of Factor 1

(.15, p = .639) and Factor 2 (-.67, p = .585) in the moderately favorable situation (Table 13) also indicated that changing values of Factor 1 (PM’s LB and PM’s PP grouped) or Factor 2 (PM’s LMR and PM’s TS grouped) individually from 0 to 1 had no impact on the chances of PMs successfully completing the DT project in the moderately favorable situation. The PMs from the moderately favorable situation indicated a mix of ROLB and TOLB.

Overall, results indicated that the PMs' LB and the PMs' contingency situation (represented by PM's LMR, PM's PP, and PM's TS) moderated each other's effect and together determined the successful completion of the DT project by the PMs in the favorable and the unfavorable situation. Most PMs in the favorable situation (95.50%) and unfavorable situation (81.80%) were RO leaders who, according to this study’s results, were unable to complete the DT projects successfully, as indicated by the negative and significant interaction effects of the four independent variables grouped into the two factors (Table 13). The negative and significant interaction effect in the favorable and unfavorable situations further indicated that the two factors (the four independent variables) together interactively significantly decreased the chances of PMs completing the DT project successfully in these two situations when the values of factors (the values of variables associated with the factors) changed from 0 to 1, which indicated that PMs with ROLB (high LPC) could not complete the DT projects successfully in the favorable and unfavorable situations. These results confirmed the CTL theory that RO leaders perform the least in favorable and unfavorable situations (Fiedler, 1967).

Managers who display a TOLB focus on details, give directions, and prescribe the work to team members. Conversely, managers who display a ROLB create trust and respect for the team members, allowing them to be part of project decisions (Fiedler, 1967; Henkel et al., 2019). According to Fiedler and Chemers (1984), the socio independent leaders (middle LPC score leaders) also performed well in the favorable and the moderately favorable situations. This study's findings and the above results by Fiedler and Chemers (1984) indicate that a balance between a PM's TOLB and ROLB based on the team members' readiness and skill level for specific tasks, experience, and maturity might be appropriate in moderately favorable situations. Any concrete conclusions in the moderately favorable situation would need more investigation with additional data and predictors.

Table 13

BLR Analysis Results

Situational favorability	Predictor	β	Bootstrap significance of β (2-tailed)[a]	Exp(β)	95% CI of exp(β)	
					LL	UL
Favorable	Factor 1	.90	.047[b]	2.47	.78	7.81
	Factor 2	.91	.032[b]	2.49	.98	6.35
	Factor 1 * Factor 2	-.99	.025[b]	.37	.14	.99
	Constant	-.40	.187[b]	.67	-[e]	-[e]
Unfavorable	Factor 1	-177.81	.044[c]	.00	.00	.00
	Factor 2	-154.52	.040[c]	.00	.00	.00
	Factor 1 * Factor 2	-90.73	.040[c]	.00	.00	.00
	Constant	-325.59	.043[c]	.00	-[e]	-[e]
Moderately favorable	Factor 1	.15	.639[d]	1.16	.42	3.24
	Factor 2	-.67	.585[d]	.51	.01	27.10
	Factor 1 * Factor 2	.58	.532[d]	1.79	.13	23.92
	Constant	-.43	.597[d]	.65	-[e]	-[e]

Note. CI = Confidence interval. LL = Lower level, UL = Upper level, Exp = Exponential, β = coefficient estimate. Exp(β) is the odds ratio.

[a] Bootstrap result are based on 4000 bootstrap samples, [b] based on 3203 samples, [c] based on 846 samples, [d] based on 3206 samples, [e] – indicates no CI can be estimated for a constant.

Cluster Analysis Results

The dendrogram (the graphical display of the merging of the clusters) obtained from the HC analysis (Figure 9) indicated the existence of three distinct clusters in the data (portrayed by the red circles in Figure 9). The mean (*M*) ± standard deviation (*SD*) of cluster distance of the members in each cluster: (a) Cluster 1 ($M = 0.95 \pm SD = 0.19$), (b) Cluster 2 ($M = 0.51 \pm SD= 0.32$), and (c) Cluster 3 ($M = 0.46 \pm SD = 0.32$) indicated that members of Cluster 3 were closer to the center followed by members in Cluster 2 and Cluster 1. Results from the ANOVA with the cluster mean square, error mean square, *F* values, and the significant *p*-value ($p < .05$) indicated that all variables contributed equally and significantly in forming the three clusters (Table 14). ANOVA results from CA revealed significant differences among the three clusters for all variables: (a) PM's LB ($F = 5.33$, $p = .006$), (b) PM's LMR ($F = 78.60$, $p< .001$), (c) PM's PP ($F = 3.38$, $p < .001$), and (d) project completion status ($F = 534.74$, $p < .001$). Across the entire sample of 214 cases, the total mean Silhouette score > .50 (total mean Silhouette score = .54) indicated that the chosen number of three clusters was correct, and the grouping of data points into clusters was meaningful and displayed acceptable quality.

In Table 15, I have displayed the final cluster centers of variables and the total number of cases in each cluster resulting from the k-means clustering. In Table 16, I have displayed the frequency analysis results by variable categories (0, 1) in the three clusters. There were 35 PMs in Cluster 1, 78 in Cluster 2, and 101 in Cluster 3 (Table 15). Most of the PMs in Cluster 2 and 3 displayed ROLB, with cluster centers for PM's LB closer to 1 (Table 15). They also experienced similar and favorable situations with cluster centers closer to 1 for all contingency predictor variables (Table 15).

Frequency analysis indicated that 89.70% of PMs in Cluster 2 and 94.10% in Cluster 3 experienced favorable situations (belonged to Octants I, II, and III). Only 10.30% of PMs in Cluster 2 and 5.90% of PMs in Cluster 3 experienced moderately favorable situation (belonged to Octant V). Besides, all PMs (100%) in Cluster 3 and none of the PMs (0%) in Cluster 2 completed their DT projects successfully (Table 15 and Table 16). A significant percentage (77%) of the PMs in Cluster 1 were RO leaders, out of which 62.90% experienced unfavorable situation (belonged to the octants VII and VIII) and a 37.10% experienced moderately favorable situation (belonged to the octants IV and VI). About half (54.30%) of PMs in Cluster 1 completed their DT projects successfully and 45.71% did not (Table 15 and Table 16). Out of the PMs who did not complete their DT projects in Cluster 1, 31.25% experienced moderately favorable situation and 68.75% experienced unfavorable situation. Out of the PMs who completed their DT projects in Cluster 1, 42.11% experienced moderately favorable situation and 57.89% experienced unfavorable situation. The final cluster center in Cluster 1, for PM's PP was = .49, PM's TS was = .14, and PM's LMR was = .23.

Figure 9

Dendrogram From Hierarchical Cluster Analysis

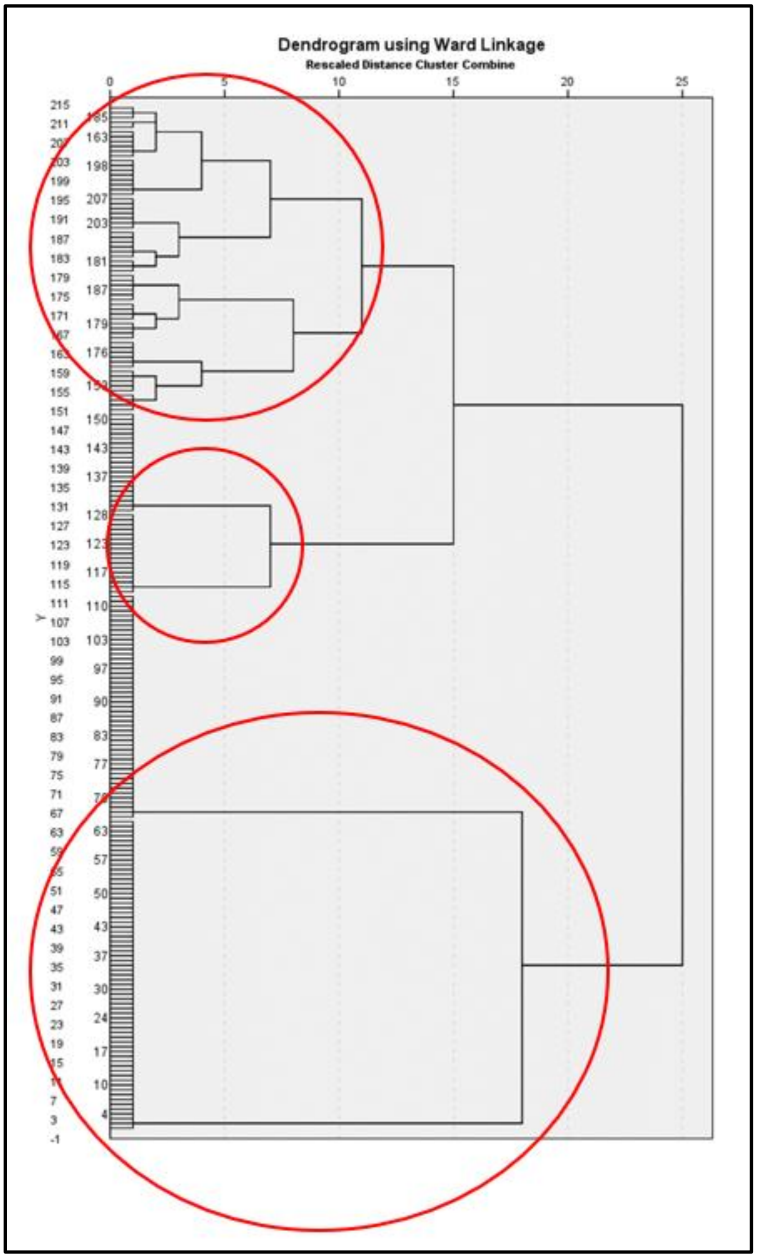


Table 14

Results of Dispersion Analysis of Cluster Formation

Variable	Cluster mean square	df	Error mean square	df	*F*	Significance
Project completion status	22.01	2	.041	211	534.74	<.001
PM’s LB	.42	2	.078	211	5.33	.006

PM's LMR	7.08	2	.090	211	78.60	<.001
PM's TS	5.99	2	.165	211	36.38	<.001
PM's PP	3.32	2	.073	211	45.28	<.001

Note. PM = Project manager, LB = Leadership behaviors, LMR = Leader member relations, TS = Task structure, PP =Position power.

Table 15

Final Cluster Centers and Number of Cases in Each Cluster

Variable	Cluster centers		
	Cluster 1	Cluster 2	Cluster 3
Project completion status	.54	.00	1.00
PM's LB	.77	.95	.93
PM's LMR	.23	.90	.94
PM's TS	.14	.77	.79
PM's PP	.49	.95	.97
Total cases	35	78	101

Note. PM = Project manager, LB = Leadership behaviors, LMR = Leader member relations, TS = Task structure, PP =Position power.

Table 16

Frequency Analysis of Variables by Clusters

Variable	Category	Cluster 1		Cluster 2		Cluster 3	
		Frequency	Valid percent	Frequency	Valid percent	Frequency	Valid percent
Project completion status	0	16	45.7	78	100.0	0	0.0
	1	19	54.3	0	0.0	101	100.0
PM's LB	0	8	22.9	4	5.1	7	6.9
	1	27	77.1	74	94.9	94	93.1
PM's LMR	0	27	77.1	8	10.3	6	5.9
	1	8	22.9	70	89.7	95	94.1
PM's TS	0	30	85.7	18	23.1	21	20.8
	1	5	14.3	60	76.9	80	79.2
PM's PP	0	18	51.4	4	5.1	3	3.0
	1	17	48.6	74	94.9	98	97.0
Total	-	35	100.0	78	100.0	101	100.0

Note. PM = Project manager, LB = Leadership behaviors, LMR = Leader member relations, TS = Task structure, PP =Position power.

BLR Analysis Results by Cluster Membership. I performed BLR analysis of the data by the cluster membership. In Cluster 2 and Cluster 3, the dependent variable had only one category and a constant (Table 15); hence, a BLR analysis was impossible. I performed BLR on the member PMs in Cluster. Some of Cluster 1 member PMs experienced unfavorable and others moderately favorable situational control. The nonsignificant *p*-value, of 1 of the Hosmer and Lemeshow test for the two situations: (a) unfavorable (χ^2 = .00, *p* = .1.00) and (b) moderately favorable (χ^2 = .00, *p* = 1.00) indicated, that the BLR model predicted the data exceptionally well in both situations. Within Cluster 1 members, the β for the interaction effects of the independent variables (Factor 1 * Factor 2) were not significant at the 5% level in both unfavorable (β = -77.70, *p* = .055) and moderately favorable situations (β = .00, *p* = .999). However, the interaction effect was almost significant (*p* = .055) and negative in the unfavorable situation. The negative value of the coefficient estimate (β) with a *p*-value less than .05 of Factor 1 (-152.27, *p* = .049) and Factor 2 (-132.23, *p* = .040) and the zero odds ratio for the individual effects in the unfavorable situation (Table 17) indicated that changing values individually of Factor 1 (PM's LB and PM's PP grouped) or Factor 2 (PM's TS and PM's LMR grouped) from 0 to 1 would significantly decrease (by 100%) the chances of PMs successfully completing the DT project in unfavorable situation.

In the moderately favorable situation, the positive value with a *p*-value less than .05 of β (.77, *p* = .043) and the odds ratio larger than 1 (exp(β) = 2.16) for the individual effect of Factor 1 indicated that changing values of Factor 1 (PM's LB and PM's PP grouped) individually from 0 to 1 would significantly increase the chances of PMs completing the DT project successfully. The positive value with a *p*-value almost close to .05 of β (1.61, $p = .053$) (Table 17) and the odds ratio larger than 1 (exp(β) = 5.02) for the individual effect of Factor 2 in the moderately favorable situation indicated that changing values of Factor 2 (PM's LMR and PM's TS grouped) individually from 0 to 1 would almost significantly increase the chances of PMs successfully completing the DT project in the moderately favorable situation. As indicated by Fiedler (1967) and Fiedler and Chemers (1984) in the CTL model, this study's results indicated that PMs with ROLB have better chances of completing the DT projects successfully in moderately favorable situations. Also indicated by the results is that in the moderately favorable situation, improving the PM's PP, PM's LMR, and PM's TS would significantly improve the chances of the PMs completing the DT projects successfully.

Table 17

BLR Analysis Results of Cluster Members

Situational favorability	Predictor	β	Std. Error	Bootstrap significance of β (2-tailed)[a]	95% CI of β[a]	
					LL	UL
Unfavorable	Factor 1	-152.27	137.14	.049[b]	-435.00[b]	7.40[b]
	Factor 2	-132.23	125.08	.040[b]	-379.89[b]	25.52[b]
	Factor 1 * Factor 2	-77.70	72.52	.055[b]	-227.67[b]	6.55[b]
	Constant	-278.66	264.97	.041[b]	-804.06[b]	53.79[b]
Moderately favorable	Factor 1	.77	29.89	.043[d]	-41.87[c]	63.49[c]
	Factor 2	1.61	88.51	.053[d]	-143.61[c]	184.39[c]
	Factor 1 * Factor 2	.00	15.39	.999[d]	-25.10[c]	25.10[c]
	Constant	3.27	129.74	.044[d]	-201.08[c]	274.59[c]

Note. CI = Confidence interval. LL = Lower level, UL = Upper level, β = coefficient estimate.

[a] Bootstrap result are based on 6000 bootstrap samples. [b] based on 4378 samples. [c] based on 4473 samples.

Summary of Findings

The reliability and validity analysis results confirmed that the instruments used in this study had good psychometric properties, and the data collected based on these instruments were of adequate quality. Given the validity and reliability of the instruments, the inferential results based on the collected data were valid and reliable. The nonparametric Spearman's rho correlations as well as the categorical Phi correlations between the DT project completion status and PM's LB indicated that the relationship was nonrandom as shown by Fiedler (1964, 1967) in his CTL model. The successful DT project completion status was negative and decreased (moved from 1 towards 0) as PM's LB became more RO (higher PM's LB indicate higher LPC scores) at favorable and unfavorable situations. The successful DT project completion status was positive and increased as PM's LB became more RO and remained high and positive in moderately favorable situations (Figure 2). Results agreed with the CTL theory for DT projects in LICs in the United States.

FA with the PCA component extraction method resulted in a superior factor model with significant factor loadings (> .40) for all the independent variables, significant communalities (> .50) of all the variables in the factors, highly nonsignificant Pearson correlation coefficient (.000, $p = 1.00$) between the two factors, anti-image correlation coefficients ≥ .57 for all variables in the factors, adequate KMO test measure (.59) indicating sampling adequacy, and highly significant Bartlett's sphericity test measure (χ^2 [6, $N = 214$] = 39.14, $p < .001$) indicating adequate correlations for FA.

Factor 1 combined PM’s LB and PM’s PP, with PM’s LB as the major variable in the factor with a .85 loading and explained 38.05% of the total variation in the dependent variable. Factor 2 combined PM’s TS and PM’s LMR and explained 24.83% of the total variation in the dependent variable. FA allowed the detection of relevant combinations of variables without multicollinearity and the extraction of two valuable factors from the data set.

BLR analysis of data with the extracted factors indicated that the PMs' LB and the PMs' contingency situation (represented by PM's LMR, PM's PP, and PM's TS) moderated each other's effect and determined together the PMs' successful completion of the DT projects in LICs. Significant relationship existed between PM’s LB and the DT project completion status, dependent on the contingency situation of the PM leading to rejection of the null hypothesis for the RQ1 ($H_0 1_1$) and acceptance of the alternate hypothesis ($H_1 1_1$) with 95% confidence. In the favorable and unfavorable contingency situations, the PMs with ROLB did not complete their DT projects successfully as indicated by the negative and significant ($p < .05$) regression coefficients for interaction effects. The results indicated that these two situations depend on PMs with TOLB to successfully complete the DT projects, supported, and confirmed the application of CTL theory by Fiedler (1967) for DT projects in LICs in the United States.

Cluster analysis of data revealed the existence of three distinct clusters: (a) PMs with ROLB who experienced favorable contingency situations but did not complete their DT projects successfully (Cluster 2), (b) PMs with ROLB who experienced favorable contingency situations and completed their DT projects successfully (Cluster 3), and (c) PMs who experienced moderately favorable to unfavorable contingency situations whom 54% completed their DT projects successfully (Cluster 1). The significant *p*-value ($p < .05$) for all variables from the dispersion analysis indicated that all variables contributed significantly to forming the clusters. Thus, the results led to the rejection of the null hypothesis ($H_0 2_1$) and the acceptance of the alternate hypothesis ($H_1 2_1$) for RQ2 with 95% confidence. The favorable contingency situation helped some PMs with ROLB (PMs in Cluster 2) complete their DT projects successfully but did not help some other PMs with ROLB (PMs in Cluster 3) complete their DT projects successfully. Results indicated the possible influence of situational variables other than the three variables indicated in the CTL on the PMs completing the DT projects successfully.

Further analysis indicated that in Cluster 1 in the unfavorable situation, the situational variables almost significantly moderated the PMs' LB and decreased the chances of PMs with ROLB successfully completing their DT projects. In the moderately favorable situation in Cluster 1, the PMs' LB and the situational control individually contributed significantly and positively to enhancing the ability of PMs with ROLB to successfully complete the DT projects. The situational variables and PMs' LB did not interact significantly in the moderately favorable situation. Seventy-seven percent (77%) of the PMs in Cluster 1 displayed ROLB. The above results indicated that CTL theory applies to DT projects in LICs in the United States.

Discussion on Findings

This study provided important information regarding the relationship between PMs' LB and the DT project completion status under the three contingency situation (favorable, unfavorable, and moderately favorable to the PMs) described in the CTL model by Fiedler (1967). Most PMs (91%) in this current study who responded to the survey questions on the Fiedler's LPC self-assessment scale indicated that they were RO leaders. According to the BLR results, ROLB (high LPC) of DT PMs significantly decreased the successful completion of DT projects in LICs in favorable and unfavorable situations of the leader. It is imperative from this study's results that the TOLB (low LPC) of DT PMs are preferred and the best LB in favorable and unfavorable situations of the leader for the successful completion of DT projects in LICs in the United States. BLR analysis of participants in Cluster 1 indicated that in the moderately favorable situation, PM's ROLB and PM's PP significantly increased the chances of PMs successfully completing the DT projects in LICs in the United States. This study's results indicated that PMs with ROLB have better chances of completing the DT projects successfully in moderately favorable situations. Also indicated by the results of this study is that in the favorable and moderately favorable situations, improving the PM's PP, PM's LMR, and PM's TS would significantly improve the chances of the PMs completing the DT projects successfully. Overall, the results supported the application of the CTL theory by Fiedler (1964, 1967) for DT projects in LICs in the United States.

According to the cluster analysis results of this study, a group of PMs with ROLB did not complete their DT projects successfully in favorable situation. In contrast, another group of PMs with ROLB completed DT projects successfully in similar favorable situation. When managing complex projects involving DT, some team members might expect their leaders to engage more in TOLB (i.e., clarifying purpose, defining goals, setting direction, and training coaching to accomplish DT tasks), especially at the beginning. When the project cycle progressed, team members might expect leaders to express more ROLB (i.e., listening, showing interest, consideration, and autonomy-delegation) from leaders. Therefore, PMs with a socio-independent (middle LPC) LB might be appropriate to enforce the most effective LB at the right time to successfully complete the evolving, task-intensive, and volatile DT projects. According to Fiedler (1967) and Fiedler and Chemers (1984), socio-independent leaders also performed well in favorable and moderately favorable situations. According to Henkel et al. (2019), a situational LB approach of PMs with a distribution pattern of the TOLB and ROLB and not an either-or LB is helpful for successful project completion. Future research of socio-independent PM’s LB on the successful completion of DT projects would benefit business leaders in LICs to devise strategies for the successful completion of DT projects applicable for all situations.

Chemers et al. (1985) in their study have shown that measures of group effectiveness such as (a) leader's job satisfaction, (b) leaders' job stress, and (c) leaders' supervisory performance impacted the LB of the leaders, thereby, the strength of the

Fiedler’s CTL model. According to Chemers et al. (1985), leaders' member relationships correlated significantly with leaders' experience of stress with their subordinates and leaders' other perceived job stress. According to Chemers and Ayman (1985), low LPC leaders showed a significantly stronger relationship between performance measures and job satisfaction than high LPC leaders. Fiedler and Chemers (1984) and Fiedler and Garcia (1987) found that the leaders’ experience and training correlated with the leaders' LPC scores. According to Albadawi and Salha (2022), males and females differed in their LB, implying that gender impacts the type of LB; female supervisors scored less than males on the LPC scale, indicating TOLB, while males were motivated by ROLB. Female supervisors prioritized getting work done and controlled and directed the subordinates to accomplish tasks over human relationships than male counterparts; females also used more power to protect their stand with the subordinates (Albadawi & Salha, 2022). Scholars and IT practitioners must consider incorporating measures of group effectiveness (leader's job satisfaction, leaders' job stress, and leaders' supervisory performance, leader's experience), group members' job satisfaction, and gender of PMs along with the contingency situational variables into Fiedler's CTL model in future research of PMs’ LB on successful completion of DT projects in LICs in the United States.

According to Fiedler (1967), high LPC leaders (RO leaders) behaved more considerately toward group members in moderately favorable conditions where there was a need for maintaining relationships and not in favorable or unfavorable situations than low LPC leaders (TO leaders). The TO leaders behaved more considerately than RO leaders in favorable and unfavorable situations where they felt in control and challenged. The above results and results from this study indicate that the PM's LB reflected the PM's values and goals (i.e., the need for task accomplishment and maintaining relationships with people), which served as the motivational forces behind the PM's actions in a situation. Many LICs in the United States lack PMs with effective LBs who can lead their team to the desired level of productivity by providing supportiveness and directness according to the given situation of subordinates and their level of motivation when different situations need handling differently since every situation has its characteristics, as indicated by Fiedler (1967) in CTL.

Henkel et al. (2019), using Fiedler's CTL model and the LPC scale, found that effective PMs adapt their LB to meet the needs of the project team members and the situational environment. Their results indicated that most leaders have primary and secondary LB when influencing team members, and they revealed both TO leadership and RO leadership behaviors as needed during the life cycle of a project. The goals may differ for highly volatile and complex DT projects at different stages. When task interdependence is high, leaders' ROLB is necessary to enhance both the team and individual processes and outcomes; in contrast, when the task complexity is high, leaders' TOLB is essential to strengthen both the team and individual processes and projects (Brown et al., 2021; Warner & Wager, 2019). Future studies using Fiedler's CTL model to identify the PM's LB requirements at different stages of DT projects would benefit the business community in LICs in the United States.

Also indicated by the results in this study, is that in the favorable and moderately favorable situations, improving the situation through improving PM’s PP, PM’s LMR, and PM’s TS would significantly improve the chances of the PMs completing the DT projects successfully. Therefore, leaders should possess the skills to manage followers at different hierarchical levels, stages of projects, and individual characteristics of followers for DT projects' success. Therefore, always, PMs must understand the complexity of their DT projects and their employees' skill level and design projects' task structures effectively. They must set clear project goals, maintain good relationships with team members, motivate, coach, and control the team to accomplish tasks and successfully implement the DT projects (Popp & Hadwich, 2018). Past research indicated that no single situation equally applied to DT projects in all organizations; still, DT projects' effectiveness in organizations depends on a fit or match between the technology, culture, people, environmental volatility, and the organizational structure's features (Makhlouf & Allal-Chérif, 2019). Leaders must understand and handle these factors together for the successful completion of the DT projects.

Application to Professional Practice

The results of this study are significant to the business leaders of the LICs in the United States, as they enhance their understanding of the relationship between the LB of the PMs managing DT projects and the successful completion of the DT projects in the

LICs. Approximately 76% of DT projects fail to achieve the desired results, and of the $1.3 trillion spent on DT in 2018, $900 billion went to waste (Correani et al., 2020; McCarthy et al., 2024; Reeves et al., 2018) primarily in LICs. LICs operate in the industrial environment where digital technologies such as software, AI, cloud computing, IoT, big data, and intelligent manufacturing are major driving forces for growth, innovation, and product differentiation is a competitive necessity (Ghosh et al., 2022; Reeves et al., 2018), and survival of LICs depends mainly on their DT capabilities. The unsuccessful DT project implementation negatively impacts business performance, leading to significant inefficiency and losses in financial and product quality (C.-H. Lee et al., 2021). The successful completion of the DT projects is a big challenge as the volatile and highly competitive business environment calls for effective and proactive strategies for successfully implementing DT projects in LICs' for continued viability. Therefore, this study's findings on leadership effectiveness for successful DT project implementation in LICs may provide valuable insight that informs organizational strategy and business practice.

Using this study's results, organizations can successfully complete their DT projects, enhancing their competitive business landscape to grow and expand their businesses. Successful completion of DT projects can enable organizations to make the concurrent rise of speed and complexity of processes possible and manageable, quickly overcome the hard limits to scaling and coordinate efficiently across many organizations and value chains, break the rigid boundaries between engineering domains and vertical specializations, and leverage data analytics horizontally across siloed categories (Benbya et al., 2020; Russ, 2021). Successful completion of DT projects also can help organizations enhance resiliency (Nkomo & Kalisz, 2023), improve competitiveness (Cennamo, 2021; Kraus et al., 2021a; Llopis-Albert et al., 2021), reduce costs, and increase revenue (Bush, 2020; Llopis-Albert et al., 2021) in a challenging economic environment. The successful DT completion and the associated structural transformation and improved work processes in the LICs will create safer work environments for employees, especially those with disabilities through smart and enhanced technologies (Albukhitan, 2020; Llopis-Albert et al., 2021; Sousa & Rocha, 2019).

Results from this study indicated that the DT PMs' project situation, including DT project tasks' structure set forth by task complexity and project goals, PMs' member relations set forth by the organizational culture, and the team member's ability to support their PM per members' skill level, training, and readiness, and the PMs' PP vested by the organization significantly mediated DT PMs' LB impacting PMs completing the DT projects successfully. One of the critical success factors for the successful completion of DT projects is the capabilities of the acting people, especially of the managing people of the DT projects, the first imperative of DT (Brunner et al., 2023; Dubey et al., 2020; Klein, 2020; Müller et al., 2024; Shao, 2019). Completing an organization's DT projects is primarily driven by the project managers' LB and the group members' skills, training, commitment, and well-being (Leavy, 2020; Nkomo & Kalisz, 2023). Using this study's results, business leaders in LICs can devise strategies to match the DT PMs' LB and their project situation and enhance team performance and output (supported by studies, Fernandez-Vidal et al., 2022; Fiedler, 1967; Fiedler & Chemers, 1984; Müller et al., 2024), resulting in the successful completion of the DT projects leading to significant growth, expansion, competence, and survival in LICs in the United States.

This study's results further indicated that the PMs with ROLB could not complete (indicated by the statistically significant negative coefficients) their DT projects successfully in the favorable (strong PM's PP, good PM's LMR, and structured or unambiguous tasks) and unfavorable (weak PM's PP, poor PM's LMR, and unstructured or ambiguous tasks) situations. Results indicated that these situations require TOLB PMs to complete DT projects successfully. Thus, there is a need for business leaders in organizations to identify and match PMs' effective LB per situation for successful DT project completion for organizational growth and survival (supported by studies [Henkel et al., 2019; Klein, 2020; Müller et al., 2024]). The potential negative impacts and substantial losses of unsuccessful DT project completion and the potential benefits of successful DT project completion create a need for business leaders to have the knowledge and capabilities to devise strategies to apply leadership match for successful DT project completion per the leaders' PP, TS, and LMR. Because most of the LICs are still at the beginning of their DT process, there is a lack of a shared understanding and a standard model of effective LB of leaders of DT projects related to the leaders' project situation (Kane et al., 2019; Klein, 2020; Philip & Gavrilova Aguilar, 2022). Business leaders in LICs can use this study's results to determine the type of PMs' LB required based on the PMs' project situation to complete the DT projects successfully for organizational growth, improvement, and survival.

This study's results also indicated that the contingency situational variables and PMs' LB did not interact significantly in situations moderately favorable to the PMs. However, the PMs' LB and the situation individually contributed significantly and positively to enhancing the ability of PMs with ROLB to successfully complete the DT projects. According to this study's results, (a) engagement and participation of team members with relevant skill sets and expertise are necessary for the complex and volatile DT project's success (Gilli et al., 2024; Guinan et al., 2019; Radhakrishnan et al., 2022) and (b) DT PMs must understand the complexity of DT projects and design their task structures effectively, set clear project goals, maintain good relationships with team members, and motivate, direct, coach, and control the team members to accomplish tasks to complete the DT projects successfully (Fernandez-Vidal et al., 2022; Popp & Hadwich, 2018). Concern over the successful completion of DT projects in LICs is increasing as the higher levels of internationalization and the bigger dimensions of businesses that require more advanced stages of DT demand more effective management characteristics (McCarthy et al., 2024) in LICs. In recent years, business leaders, IT practitioners, and researchers of DT projects' success emphasized the importance and influence of leadership in DT projects' successful implementation, suggesting that leadership, especially in middle project management where the action mostly is (Nadkarni & Prügl, 2021) plays a crucial role in DT's success and without which the rest of the DT efforts will be rendered meaningless (McCarthy et al., 2024; Nadkarni & Prügl, 2021; Porfírio et al., 2021). This study's results can help business leaders in LICs in the United States devise effective strategies to improve PMs' DT project situation and successfully complete their DT projects.

Implications for Social Change

Global technological changes evolve rapidly, transforming operations, customer preferences, and market shares, necessitating organizations to transform digitally to stay competitive. Subsequently, DT shapes organizations, work environments, and processes, creating new management challenges for leaders (Brunner et al., 2023; Müller et al., 2024). The results from this study might help LICs in the United States to complete the DT projects on time, within an approved budget, and per quality expectations significantly enhancing the processing power of LICs in the United States through increased productivity and revenue (Albukhitan, 2020; Peng & Tao, 2022; Sousa & Rocha, 2019), reduced cost, enhanced processing efficiency and faster time-to-market, improved product and service quality, and added value through dedicated services (Sousa & Rocha, 2019) reshaping industry competition, and allowing these companies to stay competitive (Albukhitan, 2020; Sousa & Rocha, 2019; Zhai et al., 2022). Subsequently, the LICs will become more digitally advanced and offer the scope to generate new projects (Albukhitan, 2020; Sousa & Rocha, 2019), allowing them to transform their structure of supply chains to deliver advanced higher-quality digital products and services (Faruquee et al., 2021; Kraus et al., 2021a; Sousa & Rocha, 2019). These LICs can attract more customers by gaining their trust and increasing market share (Doukidis et al., 2020; Nasiri et al., 2020; Verhoef et al., 2021).

The improved productivity and efficiency of business processes in these organizations, and the subsequent higher revenue growth by increased sales (Albukhitan, 2020; Sousa & Rocha, 2019; Zhai et al., 2022), and expanded market coverage (Kraus et al., 2021a; Zaki, 2019), can enhance their ability to provide services remotely, through outsourcing and the deployment of virtual customer care centers (Doukidis et al., 2020; Kraus et al., 2021a) allowing the LICs to effectively manage contingent emergencies such as pandemics and natural disasters and prevent economic decline by leveraging digital technologies such as electronic commerce (e-commerce) channels, remote working, and intelligent manufacturing (Datta & Nwankpa, 2021).

The increased productivity of digital products and services can improve the living standards of people because of the introduction of advanced services and applications such as Internet information searches, e-commerce, distance education, digital healthcare, digital financial and other services, more broadband services, the IoT, AI, and other innovative products, and social networks. Subsequently, work, commerce, entertainment, and social interactions will undergo technological transformation, shifting from physical to virtual platforms and digital technologies. This physical-to-digital transformation will enable the LICs to secure a better business position, increase productivity, and minimize financial losses (Zhai et al., 2022), enhancing community living standards.

The increased revenue in digitally transformed companies can attract several high-tech jobs locally and from other regions, thereby significantly increasing employment creation in the United States. Additional demand for skilled workers in advanced digital product and service development may result in an increase in compensation, spending power, and increasing the economy in the United States. Improved employee satisfaction, performance growth, and productivity in LICs would translate to enhanced income and socio-economic empowerment of the employees, their families, and others in the community (Trenerry et al., 2021). Improved growth and productivity also translate into enhanced employment effects, thus reducing unemployment through long-term sustainable employment practices. Improved employment conditions and well-being can boost employee morale and family relationships, leading to healthy societies.

Technological changes in organizations impact employees at both personal and professional levels, necessitating the strategic implementation of DT rollouts and DT projects effectively managed to lower the impact of technostress on employees, strengthen resilience, and improve their performance (Nkomo & Kalisz, 2023). Subsequently, the LB of DT PMs play a critical role in strategizing tasks and influencing the employees (Bunjak et al., 2022; N. T. Nguyen & Hooi, 2020) and encouraging, coaching, and motivating employees during the challenge of technological change (Wolff et al., 2019; Zulu & Khosrowshahi, 2021). Besides, according to Cortellazzo et al. (2019), some of the most common problems generated by organizations' DT are worker alienation and weak social bonding; therefore, leaders must support and help followers deal with the challenges of DT, such as greater autonomy and increased job demands, by adopting LB, such as coaching, motivating, promoting employee development, and providing resources for better task handling.

Results from this study can help PMs manage DT projects effectively per employees' readiness level and situation by strategizing tasks and encouraging, coaching, and motivating employees, reducing technostress and employee alienation, and improving employees' performance (Bunjak et al., 2022), driving the continued successful completion of DT projects. Employee financial stability caused by sustainable employment practices, improved working and living conditions, and a more innovative and collaborative culture caused by reduced job stress and advanced digital processing and communication infrastructures may create highly engaged and motivated employees, support their families, and actively build a sustainable society.

Recommendations for Action

This study’s results indicated that both the PMs’ LB and the contingency situation of the PMs (measured as PM’s PP, PM’s LMR, and PM’s TS) significantly moderated the effect of each other and significantly interactively impacted the successful completion of DT projects in LICs in the United States. According to this study’s results, the ROLB of DT PMs significantly decreased the successful completion of DT projects in LICs in the United States in favorable and unfavorable situations. Therefore, I recommend the following to the business leaders in LICs in the United States when hiring, training, and evaluating PMs for the DT projects and when devising strategies for continued successful completion of the DT projects to improve their business practices.

1. When the situation is favorable to the DT leader, that is, when DT projects are with tasks that are structured and highly interdependent, DT employees are trained, with appropriate skill sets, and know what to do, and DT PMs are vested with relatively strong position power and have the support of their group members, PMs must be quick to reward and punish team members, act authoritatively, focused on task completion, give directions and prescribe the work to team members, and not concerned with or sensitive to the feelings of their team members to influence and control the team members to get the DT projects' tasks completed (Fiedler, 1967; Fiedler & Chemers, 1984); this situation is best for PMs with TOLB and business leaders from LICs in this situation must consider hiring or assigning PMs with TOLB (low LPC) to manage the DT projects.
2. When the situation is unfavorable to the DT PM, that is, when the DT projects' task complexity is high, and tasks are unstructured, the leader's authority or vested position power is weak, and the group members are untrained, beginners, and unable to support their PMs, PMs must be diplomatic, subject matter experts, able to initiate tasks, clarify purpose, define goals, forceful and give directions to team members, and enjoy the challenge; this situation is best, and organizations must consider hiring or

assigning PMs with TOLB (low LPC) who would be best at training and coaching their team members, providing the needed directions, and influencing the team members on task accomplishments (Fiedler, 1967; Fiedler & Chemers, 1984; Warner & Wager, 2019).

3. When the situations have mixed problems such as: (i) where the group members are supportive, have appropriate skills, and trained but the DT projects' tasks are relatively ambiguous and unstructured, and the PM's vested position power is weak, or (ii) where tasks are structured and precise cut and the PMs have high position power, but the group members are unskilled, untrained, and unsupportive; this situation is best for the relationship-motivated (high LPC) leaders (Fiedler, 1967; Fiedler & Chemers, 1984) and organizations in this situation must consider hiring or assigning PMs with ROLB (high LPC) with the following traits, who are diplomatic and concerned with the feelings and readiness level of group members to get their corporation for task accomplishment, treat their group members like they are significant, include team members in decision making, act like a peer with team members, speak positively, reward team members for their excellent work ethic but do not punish frequently, and always have an open-door policy; these strategies can increase employee morale and corporation which can improve DT productivity (Fernandez-Vidal et al., 2022). According to

Fiedler and Chemers (1984), a socio-independent (middle LPC) leader may also perform well in this situation.

4. According to this study's results favorable situation represented by strong PP, good LMR, and high TS can enhance the DT projects' successful completion. Therefore, business leaders from the LICs in the United States must ensure the following strategies are in place to improve the contingency situation of the DT PMs for continued DT projects' success.
   a. Ensure that the DT PMs continuously improve their LMR through effective employee communication, such as one-on-one meetings, corporate meetings, and weekly, monthly, and yearly performance evaluations. Improved LMR can enhance the PMs' and the group members' satisfaction at work, foster collaboration, enhance productivity, and lead to the successful completion of the DT projects.
   b. Ensure an excellent recognition and reward program exists for the employees' continued dedication. Reward them with intrinsic and extrinsic gifts to motivate them to perform their best when accomplishing tasks to complete DT projects successfully. Also, render appropriate position powers to DT PMs to reward or punish the employees; this can keep the PMs feeling in control of the situation.
   c. Ensure a continuous performance monitoring program exists for the PMs managing the DT projects, along with a clear articulation of goals,

objectives, and expected outcomes, for evaluating and monitoring their projects' TS and performance.

   d. Ensure a coaching and mentorship program exists to develop DT employees' DT-related skills and practices and encourage their creativity and willingness to contribute to the organization's DT objectives.

5. I further recommend that the business leaders of LICs in the United States have scales or indicators to measure the LB of PMs who manage DT projects and monitor their LB continually. I strongly suggest using Fiedler's (1967) LPC scale for measuring PM's LB.

The findings of this doctoral study will be disseminated in the following ways to enhance knowledge among the business and academic community. Upon request for consideration and potential adoption within business practice, the participants will receive a high-level summary of the findings. Walden University will publish the results of this study in the University's ScholarWorks and ProQuest databases for the benefit of future scholars. Along with my doctoral study chair and second committee member, I will work to publish this study's research results in a peer-reviewed, reputable journal.

Recommendations for Further Research

While several limitations existed within this doctoral study, other researchers may expand on the findings and contribute to the literature. I have discussed some ways in which future researchers can expand the findings of this study to contribute to the literature and improve the knowledge of leadership for successful DT project completion.

First, in this study, I investigated the effect of PM's LB, and the contingency situational variables Fiedler (1967) introduced, namely, PM's LMR, PM's PP, and PM's TS, on completing the DT projects successfully. Future research could broaden the scope of this study by including additional variables such as PMs' education, experience, gender, job stress, and job satisfaction in a quantitative study within the same CTL framework that may explain additional variation in the dependent variable, successful completion of the DT projects in LICs in the United States. Investigators from previous studies have shown that measures of leaders' group effectiveness such as (a) leader's job satisfaction, (b) leaders' job stress, and (c) leaders' supervisory performance (Chemers & Ayman, 1985; Chemers et al., 1985; Fiedler & Chemers, 1984), leaders' gender (Albadawi & Salha, 2022), and leaders' experience and training (Fiedler & Garcia, 1987) correlated with the leaders' LB and impacted the leaders' project management capabilities. Adding these as additional independent variables may provide more insights and structural models about the influence of the PM's LB on the successful completion of the DT projects in LICs in the United States, applicable for all contingency situations of the PMs (favorable, unfavorable, and moderately favorable) and at different stages of the DT project (beginning, middle, end) to help build dynamic capabilities for DT.

Second, in this study, I investigated the contingency leadership of the PMs of DT projects using the CTL by Fiedler (1967) as the framework. Future studies should investigate the effect of other leadership styles of PMs on DT projects, such as transformational leadership of PMs using the transformational leadership theory by Burns

(1978) and situational leadership of PMs using the situational leadership theory by Hersey and Blanchard (1970, as cited in Benmira & Agboola, 2021), along with the contingency leadership of the PMs using Fiedler's (1967) CTL in LICs in the United States. Situational leaders are flexible and change and adapt their LB to meet the needs of employees and display a distribution pattern of the TOLB and ROLB and not an either-or LB to manage projects depending on the followers' maturity and readiness levels (Henkel et al., 2019). Transformational leaders efficiently manage external crises and events that could lead a company to transform, such as forceful DT (Philip, 2021), and inspire followers using the strength of their vision, personality, and charismatic behavior, motivating them to work toward completing the DT project's tasks for successful transformations (Schiuma et al., 2022). Together or separately, these different leadership styles may help PMs manage and complete DT projects effectively at different stages, with team members' diverse skills, readiness levels, and varying contingency situations.

Third, the selection of samples in this study was limited to the industrial sector within the United States. As DT impacts various other sectors such as sales (Alavi & Habel, 2021), pharmaceutical (Kulkov, 2021; Ma et al., 2023), food and beverage (I. Ali & Aboelmaged, 2022), banking and financial services (Tsindeliani et al., 2022), healthcare (Kraus et al., 2021b), and many more, investigating the influence LB of PMs on successful completion of DT projects including these sectors may be of increasing relevance and concern for both scholars and practitioners in the field; future research should leverage the insights from this study in other sectors within the United States and a broader global context.

Fourth, DT imposes tremendous challenges not only for individual companies but also for national economies (Švarc et al., 2021). The global scale issues make DT complex and difficult to comprehend (Ćukušić, 2021; Hanelt et al., 2021). At the same time, DT also presents tremendous opportunities for growth at the global level, where digital societies and smart cities interact to improve the lives of people of all nations and benefit national governments and global companies (Ćukušić, 2021; Hanelt et al., 2021). Additional research involving more extensive samples of participants from around the globe might help enhance the national economy in the United States and help validate this study’s findings.

Fifth, the LB of the PMs managing the DT projects was analyzed only through the lens of the PMs who managed or were managing the DT projects during the data collection for this study. Future research should include the perceptions of business leaders in the supervisory positions of the DT PMs and the project team members in the subordinate positions of the DT PMs, of the PMs' LB on the successful completion of the DT projects. The followers' and supervisors' perceptions of the PM's LB may differ and have different influencing effects (Philip, 2021). Montenegro et al. (2021) found that PMs' internal and external stakeholder relationships linked to PMs completing construction projects successfully. Future research, including the PMs' supervisors' perceptions, PMs' perceptions, and group members' perceptions interactively on the DT

PMs' LB in a mixed method study approach, may provide significantly better insight into the effective PM's LB (Müller et al., 2024) for the DT projects' successful completion and help devise effective strategies for the DT's success at varying project cycles and circumstances for organizational growth and survival in the LICs in the United States.

Sixth, there is little systematic insight into the application of DT in the public sector. Very little is known about the effects of PMs’ LB on the successful implementation of DT projects in the public sector (Demircioglu & Chowdhury, 2021), although the effect of LB on the successful completion of DT projects in the public sector is becoming critical. DT initiatives in the public sector can help government agencies deliver high-value, real-time digital services and satisfy the growing people's expectations for advanced digital services in the public sector (Mergel et al., 2019). In response to people's changing expectations, governments increasingly invest in DT to improve public service delivery (Mergel et al., 2019). Finally, future studies could also encompass controlled conditions in an experimental or quasi-experimental design to gain better insights into the causal agents of the successful completion of DT projects.

Reflections

The DBA journey significantly shaped my personal, academic, and career life and fulfilled my dream of a doctorate. I realize that accomplishing a DBA degree is a significant life achievement. I share my reflections as a testament to the power of perseverance, resilience, commitment, and hard work in navigating the doctoral journey. The DBA journey was a very fulfilling and rewarding self-discovery that widened my mind, enriched my intellectual faculties, and transformed me emotionally and spiritually to be a better and able person who could be a positive example for future scholars.

The doctoral journey has provided a wealth of knowledge and valuable and rewarding experience, a mix of scholarly and practical, and enhanced my positive energy, determination, and dedication toward accomplishing anything challenging but rewarding. I further realize that pursuing a DBA degree requires an unrelenting spirit, a healthy appetite for learning, a positive mindset, and commitment to the process. The valuable and suitable support network full of enthusiastic and knowledgeable mentors, loving family members and friends, and colleagues I gathered during the journey facilitated and significantly contributed to a positive outcome. I recognize that my mental, emotional, and physical health has been intrinsically linked and contributed to my success.

This doctoral study gave me significant knowledge, insights, and comprehension of the research topic. Through this study, I gained significant knowledge and insights into leadership's importance and value in the success of DT projects. Further, the doctoral journey enhanced my research, learning, analysis, communication, and presentation skills and contributed to my professional development as a scholar-practitioner. I intend to disseminate the knowledge and skills acquired through teaching and mentoring scholar-practitioners and informing business leaders, project managers, and other stakeholders in the industry. Through applying quantitative research methodology, I learned to collect large amounts of reliable data from multiple participants using existing instruments, carefully checked their reliability and validity, and inferred the results from the data to a broader audience. I learned to use survey tools for data collection for a doctoral study through anonymous surveys, thereby minimizing researcher bias; through conducting an anonymous survey, I ensured that my beliefs did not influence the study's findings, promoting objectivity in the research processes. By practicing constant reflexivity and carefully self-examining biases and assumptions during design, analysis, and interpretation, I further eliminated preconceived personal biases creeping into the research.

I learned to analyze large amounts of data meticulously through advanced statistical methods, test pre-defined hypotheses, confirm research theories, and answer research questions, which enhanced my critical analysis, logical reasoning, and presentation skills and provided critical guidance in producing trustworthy predictions. I became exposed to choosing the proper methods to collect the data, employ the correct analysis methods, perform stringent statistical analyses, and effectively present the results. Statistics allowed me to make decisions based on data, make predictions from the results, learn from the data reliably, use significance levels to differentiate between reasonable and erroneous conclusions, challenge assumptions, and understand the subject much more deeply.

Conclusion

Global technological changes evolve rapidly, transforming operations, customer preferences, and market shares, necessitating organizations to transform digitally to stay competitive. LICs operate in the industrial environment where globalization, rapid technological advancement, and subsequent product differentiation are a competitive necessity. According to a recent trend, over 70% of the DT initiatives failed in LICs, negatively impacting profitability, competitive advantage, and companies' sustainability, demonstrating that most LICs lack DT competency. As found within this research study, successfully completing an organization's DT projects is primarily driven by a match between the PMs' LB and the project situation, including DT project tasks' structure set forth by task complexity and project goals, PMs' member relations set forth by the organizational culture, and the team member's ability to support their PM per members' skill level, training, motivation, and readiness, and the PMs' PP vested by the organization. Using the results of this study might assist business leaders in improving the successful completion of DT projects that can enhance economic growth and profitability, deliver enhanced digital products and services to communities, and make informed decisions about successful digital leadership aligned with business improvement and continuity. Successful business leaders might return value to society through stable and increased employment in the sector, improved financial health, and better quality of people's lives.

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Appendix A: Participant Eligibility Criteria Statements and Questions

This Appendix consists of 'four' questions about participants' eligibility for this study. The potential participant must answer 'Yes' to the four eligibility criteria questions to be eligible. Suppose the answer is 'No' to any of the four eligibility criteria questions. In that case, the potential participant does not meet the eligibility criteria for this study and does not need to proceed or answer the survey questions. If the answer to all the four eligibility criteria questions listed below is 'Yes,' the potential participant can participate in this study and must proceed and read the 'Anonymous Survey Consent Form for DBA Survey Study' statement and answer the survey questions if the potential participant consents to the terms in the 'Anonymous Survey Consent Form for DBA Survey Study.' The four eligibility criteria questions are listed below. Participants must circle their choice.

Eligibility Criteria Question 1

Are you between 18 and 80 years old (≥ 18 and ≤ 80 years)? Yes: No:

Eligibility Criteria Question 2

Do you live in the United States of America? Yes: No:

Eligibility Criteria Question 3

Have you worked or are you currently working for a Unit~~ed St~~ates of A~~merica~~-based company that employs 500 or more (≥ 500) employees? Yes: No:

Eligibility Criteria Question 4

Have you managed (or supervised) or are you currently managing (or supervising) a digital transformation project for the company you have worked for or are currently working for? A definition of digital transformation is provided below.

Yes: No:

Definition of Digital Transformation

Digital transformation is the process of replacing or improving manual processes in the company with advanced digital tools and techniques, including but not limited to artificial intelligence, machine learning, cloud computing, Internet of Things (IoT), big data analytics, IoT analytics, edge computing, blockchain, 5G networking, eCommerce, intelligent manufacturing, and similar digital technologies, for one or more of the following benefits including improving internal (ex., stakeholders, employees) and external (ex., customers, sellers) communication, improving the efficiency of internal (ex., business, production) and external (ex., sales, marketing) processes, boosting customer satisfaction and retention, increasing sales and revenue, time optimization of processes, faster time to market and the like.

Appendix B: Anonymous Survey Consent Form for DBA Survey Study

This Appendix contains of the *'Anonymous Survey Consent Form for DBA Study* (*ASCFDS*).' The potential participants must read the *ASCFDS* displayed below before proceeding to answer the survey questions and answer the survey questions only if they agree to the terms in it.

Anonymous Survey Consent Form for DBA Survey Study

You are invited to complete an anonymous online questionnaire for a Walden University doctoral study. To provide your informed consent, please review the information below and continue on to the survey if you choose to proceed.

Your role

· is completely voluntary and can end at any time you wish

· is anonymous (your name will not be requested)

· involves completing a questionnaire

· involves little or no risk

Privacy

To protect your privacy, the researcher will not collect, track, or store your identity or contact info. In place of a consent signature, your completion of the questionnaire would indicate that you consent to your responses being analyzed in the study.

Data will be kept secure by using password-protected devices and platforms. Data will be kept for a period of at least 5 years, as required by the university.

Once the doctoral student graduates, the study's results will be posted online in

Scholarworks (a searchable publication of Walden University research).

Contacts and Questions

Questions about the study can be emailed to the student researcher via anpalaki.ragavan@waldenu.edu or ragaann@gmail.com. If you want to talk privately about your rights as a participant or any negative parts of the study, you can call Walden University's Research Participant Advocate at 612-312-1210 or email IRB@mail.waldenu.edu. Walden University's ethics approval number for this study is 10-13-23-1017545.

You might wish to retain this consent form for your records. You may ask the researcher or Walden University for a copy at any time using the contact info above.

Appendix C: Project Completion Status Survey Questions

This Appendix contains two questions used to collect data for the dependent variable (DT project completion status) related to the DT project(s) the participants managed or are currently managing. Participants must select 'Yes' to question 1 if the DT project they managed or supervised was 'successfully completed.' Participants can choose 'Yes' if they are confident of meeting all the deadlines, budget, and quality criteria in successfully completing the DT project(s) they are currently managing. Participants may select 'No' if the DT project(s) they managed or supervised were 'not completed' or 'not successfully completed' and if the DT project that they are currently managing has already exceeded budget, surpassed the scheduled deadline, or do not meet quality criteria set forth, and therefore, may not be completed successfully.

A project successfully completed implies completing the project within the planned and allocated budget, on or before the scheduled completion time, and per pre-defined quality expectations and satisfaction to the stakeholders (stakeholders are company leaders and customers). The participant's company may have project completion criteria other than those specified in this note (on time, within budget, and per specified quality criteria). If the project meets or has met the company's project completion criteria, the project should be considered successfully completed.

A project not successfully completed can mean one of the following: (i) the project was either completed not within the schedule, not within the allocated budget, not per agreed quality criteria, or any combination of these, (ii) participants never completed the project or the project is in progress after five years of initiation or initially agreed on completion date, or (iii) the project was abandoned due to causes such as inadequate resources, a flaw in the design or the like. The participants must circle the option that best answers ('Yes' or 'No') Question 1. There are no right or wrong answers.

The second question (Question 2) on DT project completion criteria refers to any of the DT projects that the participant had trouble managing or completing due to one or many of the reasons mentioned above including (a) the project was either completed not within the schedule, not within the allocated budget, not per agreed quality criteria, or any combination of these, (b) the project was never completed and in progress after five years of initiation or initially agreed on completion date, or (c) the project was abandoned due to causes such as inadequate resources, a flaw in the design or the like, or a combination of a, b, and c. The participants must select all options that apply to the project that they managed or are currently managing. If the participant selected any of the options listed under Question 2, the DT project they managed or are currently managing will be considered not completed successfully.

Question 1

Did you successfully complete the digital transformation project(s) you managed or are you on a path to successfully completing the digital transformation project you are currently managing? Yes: No:

Question 2

Did you experience the following when managing any of the digital transformation project(s)?

_____ Project cost exceeded the allocated budget

_____ Some or all of project tasks not completed within initially defined schedule

_____ Some or all project tasks did not meet the agreed quality criteria or stakeholder expectations

_____ Project was never completed or in progress after 5 years of initiation

_____ Project was abandoned due to causes such as inadequate resources, a flaw in the design, or the like

_____ Project was not completed due to other reasons

Appendix D: Survey Scales for Independent Variables

This Appendix consists of survey scales used to collect the data for the four independent variables (PM's LB, PM's PP, PM's TS, PM's LMR) from the eligible participants recruited for this study. I used the following four existing survey scales associated with the contingency theory of leadership, developed and used initially by Fiedler (1967) and published in the book chapter by Ayman et al. (1998), to collect data for the four independent variables of the study. I purchased permission from the book publisher (Emerald Group Publishing Limited; license number =1412887-1, Appendix F) of Ayman et al. (1998) to use and reproduce the survey scales in this study. The following four survey scales are included in this Appendix as tables: (a) leader-member relations scale (Table D1) used to collect data for PM 's LMR, (b) task structure rating scale (Table D2) used to collect data for PM's TS, (c) position power rating scale (Table D3) used to collect data for PM's PP, and (d) least preferred coworker (LPC) scale (Table D4) used to collect data for PM's LB. The scoring scheme used for each scale appears at the bottom of the table as notes.

Table D1

Leader–Member Relations (LMR) Scale

Circle the number which best represents your response to each item Item #		Strongly Agree	Agree	Neither Agree nor Disagree	Disagree	Strongly Disagree
1.	The people I supervise have trouble getting along with each other.	1	2	3	4	5
2.	My subordinates are reliable and trustworthy.	5	4	3	2	1
3.	There seems to be a friendly atmosphere among the people I supervise.	5	4	3	2	1
4.	My subordinates always cooperate with me in getting the job done.	5	4	3	2	1
5.	There is friction between my subordinates and myself.	1	2	3	4	5
6.	My subordinates give me a good deal of help and support in getting the job done.	5	4	3	2	1
7.	The people I supervise work well together in getting the job done.	5	4	3	2	1
8.	I have good relations with the people I supervise.	5	4	3	2	1

Note. Reproduced with permission from the publisher, Emerald Publishing Group (license number =1412887-1). Scoring Method: The participant's combined score for the eight questions on the LMR sale (maximum possible = 40) indicates if the participant's member relationship is '*good*' or '*poor*.' A combined score of 19 or below (≤ 19) on the LMR scale indicates '*poor*' leader-member relations and *'moderate to poor*' otherwise (Fiedler, 1967; Fiedler & Chemers, 1984).

Table D2

Task Structure Rating (TSR) Scale

Circle the number in the appropriate column.	Usually True	Sometimes True	Seldom True
Is the Goal Clarity Stated or Known?			
1. Is there a blueprint, picture, model, or detailed description available of the finished product or service?	2	1	0
2. Is there a person available to advise and give a description of the finished product or service, or how the job should be done?	2	1	0
Is There Only One Way to Accomplish the Task?			
3. Is there a step-by-step procedure, or a standard operating procedure which indicates in detail the process which is to be followed?	2	1	0
4. Is there a specific way to subdivide the task into separate parts or steps?	2	1	0
5. Are there some ways which are clearly recognized as better than others for performing the task?	2	1	0
Is There Only One Correct Answer or Solution?			
6. Is it obvious when the task is finished and the correct solution has been found?	2	1	0
7. Is there a book, manual, or job description which indicates the best solution or the best outcome for the task?	2	1	0
Is It Easy to Check Whether the Job Was Done Right?			
8. Is there a generally agreed upon understanding about the standards the particular product or service has to meet to be considered acceptable?	2	1	0
9. Is the evaluation of the task generally made on some quantitative basis?	2	1	0
10. Can the leader and the group find out how well the task has been accomplished in enough time to improve future performance?	2	1	0

Note. Reproduced with permission from the publisher, Emerald Publishing Group (license number =1412887-1, Appendix F). Scoring Method: The participant's combined score for the ten questions on the TS rating scale (maximum possible = 20) indicates if the participant's tasks are '*structured*' or '*unstructured*.' A combined score of 14 or above (≥ 14) on the TS rating scale indicates the participant leader has '*structured*' tasks and '*moderate to unstructured*' otherwise (Fiedler, 1967; Fiedler & Chemers, 1984).

Table D3

Position Power (PP) Rating Scale

Circle the number which best represents your answer.

1. Can the leader directly or by recommendation administer rewards and punishments to subordinates?

2	1	0
Can act directly or can recommend with high effectiveness	Can recommend but with mixed results	No

2. Can the leader directly or by recommendation affect the promotion, demotion, hiring or firing of subordinates?

2	1	0
Can act directly or can recommend with high effectiveness	Can recommend but with mixed results	No

3. Does the leader have the knowledge necessary to assign tasks to subordinates and instruct them in task completion?

2	1	0
Yes	Sometimes or in some aspects	No

4. Is it the leader's job to evaluate the performance of subordinates?

2	1	0
Yes	Sometimes or in some aspects	No

5. Has the leader been given some official title of authority by the organization (e.g., foreman, department head, platoon)?

2	0
Yes	No

Note. Reproduced with permission from the publisher, Emerald Publishing Group (license number =1412887-1, Appendix F). Scoring Method: The participant's combined score for the five questions on the PP rating scale (maximum possible = 10) indicates if the participant's position power is '*strong*' or '*weak*.' A combined score of 7 or above (≥ 7) on the PP rating scale indicates the participant leader has '*strong*' position power and '*moderate to weak*' otherwise (Fiedler, 1967; Fiedler & Chemers, 1984).

Table D4

Least Preferred Coworker (LPC) Scale

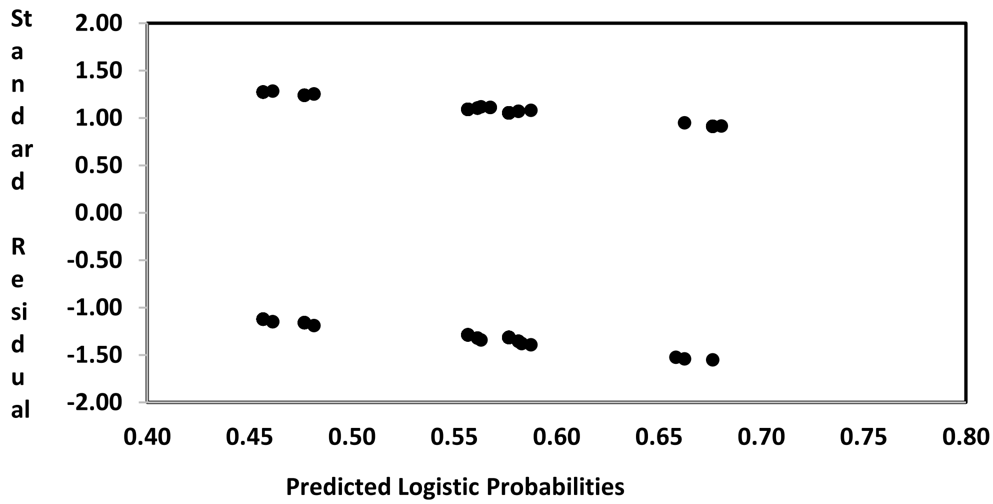
Item #	*Put an X in the space provided above the number which best rates your LPC*										Scoring
1	Pleasant	8	7	6	5	4	3	2	1	Unpleasant	______
2	Friendly	8	7	6	5	4	3	2	1	Unfriendly	______
3	Rejecting	1	2	3	4	5	6	7	8	Accepting	______
4	Tense	1	2	3	4	5	6	7	8	Relaxed	______
5	Distant	1	2	3	4	5	6	7	8	Close	______
6	Cold	1	2	3	4	5	6	7	8	Warm	______
7	Supportive	8	7	6	5	4	3	2	1	Hostile	______
8	Boring	1	2	3	4	5	6	7	8	Interesting	______
9	Quarrelsome	1	2	3	4	5	6	7	8	Harmonious	______
10	Gloomy	1	2	3	4	5	6	7	8	Cheerful	______
11	Open	8	7	6	5	4	3	2	1	Guarded	______
12	Backbiting	1	2	3	4	5	6	7	8	Loyal	______
13	Untrustworth y	1	2	3	4	5	6	7	8	Trustworthy	______
14	Considerate	8	7	6	5	4	3	2	1	Inconsiderate	______
15	Nasty	1	2	3	4	5	6	7	8	Nice	______
16	Agreeable	8	7	6	5	4	3	2	1	Disagreeable	______
17	Insincere	1	2	3	4	5	6	7	8	Sincere	______
18	Kind	8	7	6	5	4	3	2	1	Unkind	______

Note. Reproduced with permission from the publisher, Emerald Publishing Group (license number =1412887-1 Appendix F). Scoring Method: The participant's combined score for the 18 checklist items (maximum possible = 144) indicates the participant's leadership behavior as 'task-oriented' or 'relationship-oriented.' A combined score of 73 or above (≥ 73) on the LPC scale indicates the leader is a 'relationship-oriented' leader and 'task-oriented' otherwise (Fiedler, 1964, 1967).

Appendix E: Supplemental Data Including Figures and Tables

Figure E1

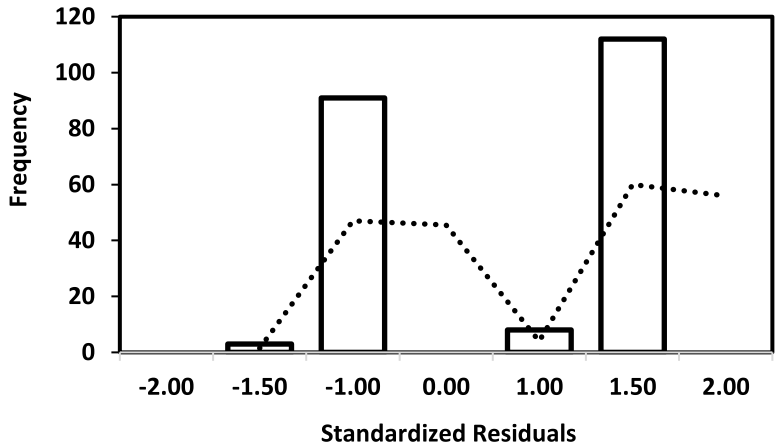
Standardized Residuals Plotted Against Predicted Probabilities From Initial BLR Model



Note. Dependent variable is project completion status. Independent variables are PM's LMR, PM's PP, PM's TS, and PM's LB. *N*=214.

Figure E2

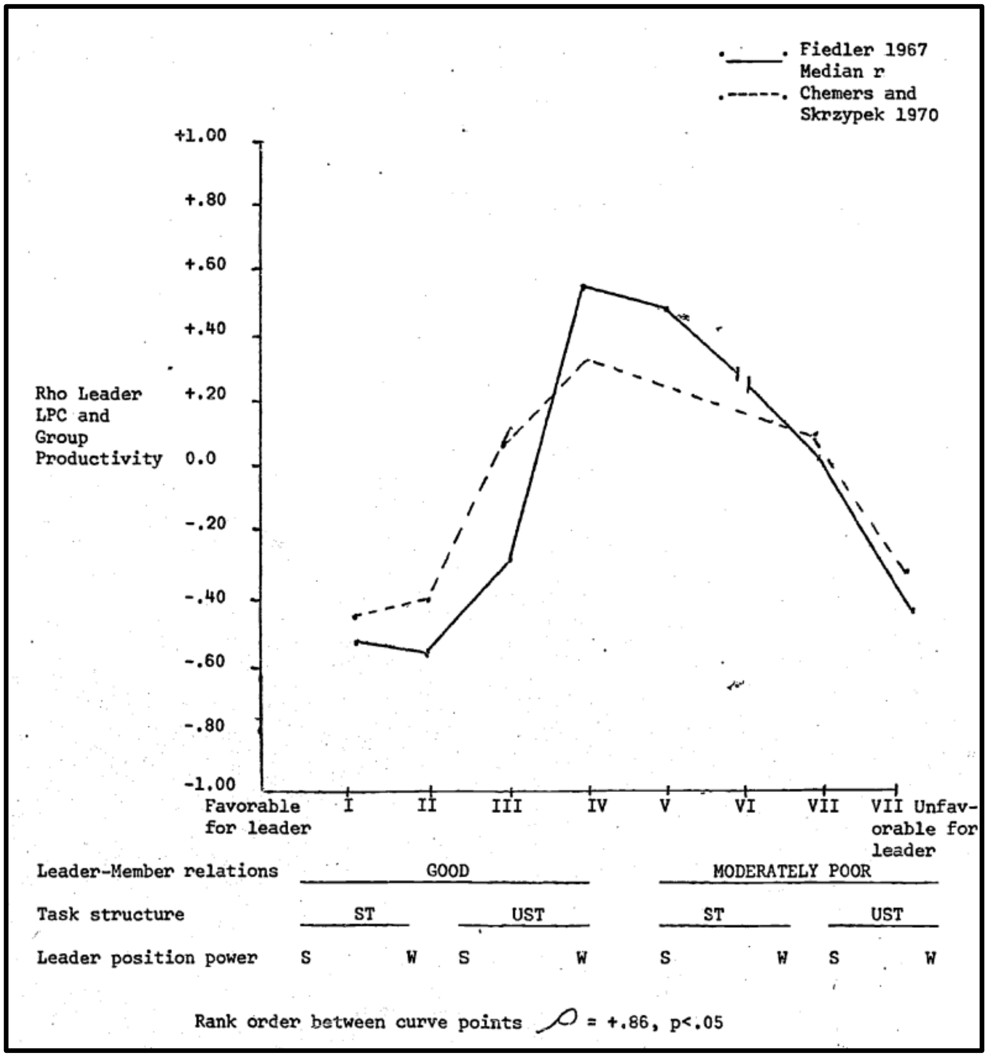
Frequency Histogram of Standardized Residuals From Initial BLR Model



Note. Dependent variable is project completion status. Independent variables are PM's LMR, PM's PP, PM's TS, and PM's LB. *N*=214.

Figure E3

Comparison of Predicted and Obtained Curves for LPC and Group Effectiveness



Source: Chemers, M., & Skrzypek, G. J. (1971). *An experimental test of the contingency model of leadership effectiveness*. https://eric.ed.gov/?id=ED057381

Note: Rho (r) is the Spearman's correlation coefficient between leader's LPC and group effectiveness. $p < .01$.

Table E1

Median rho Correlations for the Development Studies of the Contingency Model of Leadership

	Situation classification			Most effective leadership behavior (orientation)	Median rho	*N*
Octant	Group atmosphere	Task structure	Position power			
I	Good	High	Strong	Task	-.52	8
II	Good	High	Weak	Task	-.58	3
III	Good	Low	Strong	Task	-.33	12
IV	Good	Low	Weak	Relationship	.47	10
V	Poor	High	Strong	Relationship	.42	6
VI	Poor	High	Weak	Relationship	-	0
VII	Poor	Low	Strong	Relationship	.05	12
VIII	Poor	Low	Weak	Task	-.43	12

Note. Median rho is the median Spearman's correlation between the least preferred co-worker (LPC) measure of leadership behavior and group performance. Favorability of the situation for the leader is assumed to decrease from octant I to octant VIII. The N is the number of relationships included in the calculation of the median correlation.

Source: Graen, G., Alvares, K., Orris, J. B., and Martella, J. A. (1970). Contingency model of leadership effectiveness: Antecedent and evidential results. *Psychological Bulletin*, *74*(4), 285-296. https://doi.org/10.1037/h0029775

Table E2

Descriptive Statistics of Z-Normalized Independent Variables

Variable	*N*	Mean	Standard deviation	Minimum	Maximum	Variance
Z_PM’s LMR	214	.000	1.00	-2.05	.49	1.00
Z_PM’s PP	214	.000	1.00	-2.74	.36	1.00
Z_PM’s TS	214	.000	1.00	-1.45	.69	1.00
Z_PM’s LB	214	.000	1.00	-3.20	.31	1.00

Note. PM = Project manager, LB = Leadership behavior, LMR = Leader member relations, PP = Position power, TS= Task structure.

Table E3

One Sample Kolmogorov-Smirnov Test for Normality

Variable	*N*	Test statistic	Asymptotic significance (two-tailed)	Monte Carlo significance (two-tailed)		
					99% Confidence interval	
				Significance	Lower bound	Upper bound
PM’s LMR	214	.50	<.001	.000	.000	.000
PM’s PP	214	.53	<.001	.000	.000	.000
PM’s TS	214	.43	<.001	.000	.000	.000
PM’s LB	214	.53	<.001	.000	.000	.000

Table E4

Pearson Bivariate Correlations Among Z-Normalized Independent Variables

Variable Pair		*N*	Pearson correlation coefficient (PCC)	Significance	95% CI for PCC	
					LL	UL
1.	Z_PM's LMR vs. Z_PM's LB	214	.18**	.008	.05	.31
2.	Z_PM's LMR vs. Z_PM's PP	214	.19**	.005	.06	.32
3.	Z_PM's LMR vs. Z_PM's TS	214	.22**	.001	.09	.35
4.	Z_PM's LB vs. Z_PM's PP	214	.25**	<.001	.11	.37
5.	Z_PM's LB vs. Z_PM's TS	214	.03	.655	-.10	.16
6.	Z_PM's PP vs. Z_PM's TS	214	.15*	.025	.02	.28

Note. CI = Confidence interval, LL = Lower level, UL = Upper level, PM = Project manager,

LB = Leadership behaviors, LMR = Leader member relations, PP = Position power, TS = Task structure.

** Correlation is significant at the .01 level (two-tailed).

* Correlation is significant at .05 level (two-tailed).

Appendix F: License to use and Reproduce Survey Scales

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Instructor Name	Walden University	Expected Presentation Date	2023-11-15

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