POSSIBILITIES AND LIMITATIONS OF ANALYTICS FOR EFFICIENCIES IN PROJECT MANAGEMENT

by

Sarosh Iqbal

A Thesis

Submitted to the Faculty of Purdue University

In Partial Fulfillment of the Requirements for the degree of

Master of Science

Department of Computer and Information Technology

West Lafayette, Indiana

December 2021

THE PURDUE UNIVERSITY GRADUATE SCHOOL

STATEMENT OF COMMITTEE APPROVAL

Jeffrey Brewer, Chair

Department of Computer and Information Technology

Kevin Dittman

Department of Computer and Information Technology

Dr. **John Springer**

Department of Computer and Information Technology

Approved by:

Dr. John A. Springer

To my loving brother Shoaib, my little sisters Erina & Aayat, and the endearingly naughty Armaan.

ACKNOWLEDGEMENTS

This thesis might never have been written, had it not been for the dedicated guidance of Professor Jeffrey Brewer (my advisor), Professor Kevin Dittman, and Professor John Springer. You are so enjoyable to learn from and work for - Thank you for the interest you took in me and for a very memorable graduate school experience at Purdue!

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

ABSTRACT

This study aimed to identify if data and analytics are, or can be, meaningfully and extensively used for improving efficiencies in project management. The research problem was addressed using a survey, involving capture, collection, analysis and interpretation of qualitative (and some quantitative) data obtained from industry practitioners of project management.

The study was completed in two important parts. First was the laying of groundwork which involved questionnaire planning and design to ensure coverage, completeness, relevance, usefulness, and logical (and where pertinent, statistical) validity of the answers for performing analysis and drawing inferences. The second part was the actual analysis of the survey results, and compilation of the research details into this written report with a conclusion (my M.S. thesis).

The survey was mainly in the form of multiple-choice questions, along with two free form text boxes to glean additional insights from comments and notes that structured questions with fixed choices for answers could not have easily elicited.

CHAPTER 1. INTRODUCTION

This chapter provides an overview of the research project and its significance. It covers the background as a basis for conducting the research. It frames the research question, and lays out the scope, significance, and definitions. The chapter also includes the research assumptions, limitations, and delimitations.

1.1 Background

Examples of wasteful or failed projects abound. The reasons can be endogenous or exogenous, qualitative or quantitative, financial or non-financial, strategic or tactical, and so on. Data & analytics can plausibly help prevent wasted efforts and investments, and improve cost and time efficiencies in projects, as well as along other non-numbers-based dimensions such as professional satisfaction and human achievement.

A history of countless organized projects in all kinds of fields could in theory mean a treasure trove of data. But how often are key pieces of data captured and stored, to be analyzed and generate learnings from for improvements in project management?

Large organizations with multiple projects at any given time may have the motivation, infrastructure and processes for identifying, collecting and utilizing data for analytical insights and decision making in project management. Even so, such data are likely to be siloed within an organization without offering a multi organizational cross industry view.

And what about medium sized or smaller organizations which may collectively account for a great number of projects but individually may be involved in only a handful - do they have the incentives for data investments and will each of these smaller entities ever generate enough project management related data to form a critical mass for analysis?

One central question – *"Have data and analytics impacted, or have the potential to impact, the practice of project management"* – forms the purpose and substance of this study.

1.2 Research Question

Are data analytics being, or have the potential to be, utilized for improving efficiencies in project management along one or more of its dimensions of scope, time, cost and quality?

1.3 Scope

This research was meant to identify if historic data from previous projects are being captured, cleansed and used by project managers and others in project leadership roles to affect project management improvements. The research was conducted at Purdue University by means of a web-based survey distributed to project managers and other individuals who have worked in leadership roles in the field of project management.

1.4 Significance

Rapid advancements in computing through the turn of the century, including lower cost and faster data processing, has led to ever expanding applications of data analytics and statistical modelling in scientific research and business decision-making in many different fields. Think of driverless trains connecting airport terminals, and driverless cars on roads, for example.

Computer applications and tools have most certainly affected projects and project management as well. In engineering drawing, widely used in engineering projects, especially those related to infrastructure, T-squares and drafters have been rendered obsolete by computer-aided design/computer-aided manufacturing software; and project management software allows quick creation of critical path method, program evaluation and review technique and GANTT charts. But what has been, or potentially can be, the impact of *data analytics* in project management?

The research was intended to find definitive answers to the above question, relying on evidence-based insights instead of anecdotes, hearsay, or conjecture. It should provide a good basis for further work to help identify local areas, if there were not broad ones, where analytics can aid in project management improvements, and possibly afford an opportunity to learn about any blind spots or undiscovered dimensions of project management *(this was not very likely as project management as a field has been in existence for quite some time)*. Importantly, the study was expected to potentially also reveal the limits of data and analytics in project management – as not everything can be captured in standardized data fields and analyzed, statistically or otherwise.

1.5 Definitions

1. Analytics - Analytics is the process of discovering, interpreting, and communicating significant patterns in data.

2. Predictive Analytics - Predictive analytics is a branch of analytics that makes predictions about future outcomes using historical data combined with statistical modeling, data mining techniques and machine learning.

3. Large Data - Larger, more complex datasets, that despite being voluminous can be managed by traditional data processing software and can provide enough information to address business problems that cannot be tackled with regular small sized data sets.

4. Project Management Office (PMO) - A project management office is a group or department within a business, government agency, or enterprise that defines and maintains standards for project management within the organization.

1.6 Assumptions

Assumptions for this research included:

1. Survey response rate would be sufficient for effective coverage and meaningful analysis.
2. Survey respondents would thoughtfully and truthfully answer all or most questions.
3. Employers would not object to their employees taking the survey.
4. All necessary permissions (from Purdue's Institutional Review Board, IRB) for sending out the surveys would be obtained in time.
5. Purdue's surveying platform would be up and running for the duration of the research, and had been tested and could be relied on for smooth rollout of the survey and retrieval of the survey results.

1.7 Limitations

Limitations for this research include:

1. Based almost entirely on surveys, and augmented or corroborated only by review of existing theses/dissertations and other supplementary readings. The existing body of academic research work did not have significant overlap with my thesis topic.
2. Meaningful response rates were required to generate sufficient data to be studied/analyzed.
3. Sample size constraints could have affected statistical significance of (though not necessarily render invalid) the survey results and the inferences drawn.
4. While the researcher expected to be able to at least draw some broad conclusions, very detailed or granular insights were likely not feasible, as sub-samples within the survey pool would be even smaller making error margins and uncertainty too high to be ignored.
5. There existed a possibility that the results of the research would be inconclusive, either because of low response rates, or because of no discernible patterns observed in the answers to the survey questions. While that would have been less than an ideal outcome, the efforts would still not be a total waste as the learnings could still be leveraged to either inform future studies on closely related subjects, or to rule such topics out as being unviable for research.

1.8 Delimitations

Delimitations for this research include:

1. Due to reasons of practicality, the survey was limited to companies where the researcher could establish contacts through Purdue, or through online forums such as professional groups on LinkedIn, and Amazon Mechanical Turk, a ‘crowdsourcing’ platform. The Purdue based contacts resulted in some loss of randomization. LinkedIn and Amazon as outreach channels helped to an extent in expanding to a broader spectrum of companies and generating data that were somewhat more comprehensive.
2. While fundamental statistical principles were not disregarded in the analysis of the survey results, the survey itself was not designed utilizing a statistical construct such as design of experiments, or other advanced techniques, so as not to make it all overly complex and the research objective extra-specific and restrictive. This trade-off came with a downside – of not being able to assign quantitative measures of certainty (error margins, confidence levels) to metrics that could have otherwise become a part of the thesis conclusion.

1.9 Chapter Summary

This chapter began by describing the background and the research question. Next, it defined the scope and highlighted the significance of the study. It concluded with discussions on assumptions, limitations, and delimitations of the research.

CHAPTER 2. REVIEW OF RELAVENT LITERATURE

The literature review targeted works of scholarship from a miscellany of academic and business writings, where the substance and essence of the proposed thesis topic *(Possibilities and Limitations of Analytics for Efficiencies in Project Management)* would permeate as a central theme, or otherwise occur whether in material measure or meaningful context, or with peripheral relevance. Not setting an overly focused or narrow criteria in the search, was meant to generate in the filtered results, a sufficient amount of literature to appraise and distil information from. A number of extraneous articles that would go on to be sifted, examined and then summarily discarded as not germane, have not been discussed or catalogued in this report.

Below is a listing of sources explored for literature selection, through keyword searches as well as scanning through content tables and glossaries. Search terms included: PMO Use of Data, Knowledge Based Systems, Machine Learning, Data Science in Project Management, Project Management Data Analytics, and some other combinations of the aforementioned terms.

1. Purdue University's thesis repository and libraries and those of other universities.
2. Purpose-built online databases and search engines like ProQuest, Google Scholar and ScienceDirect.
3. Leading business school periodicals such as the Harvard Business Review (HBR), Massachusetts Institute of Technology's (MIT) Sloan Management Review, and Stanford Business Magazine.
4. Publications from McKinsey & Company, the Boston Consulting Group (BCG), Bain & Company, Deloitte, PricewaterhouseCoopers, Ernst & Young, and KPMG.
5. Websites of national and supranational organizations of eminence, among them the National Science Foundation, the Bureau of Labor Statistics, the Federal Reserve System, and the World Bank. These institutions work with copious volumes of data, produce superior research and analysis, and (some of them) undertake or sponsor projects of all sizes in their respective domains.
6. Articles from Project Management Institute (PMI), Australian Institute of Project Management (AIPM), and United Kingdom's Association for Project Management (APM).
7. Textbooks at the intersection of project management, data, and analytics.

2.1 Deloitte's Predictive Project Analytics

Accounting and advisory firm Deloitte, in a 2019 article on its website, provides some disconcerting statistics under a rhetorical, bolded, heading '**Did you know?**': 60% of companies experience project failure, 14% of projects completely fail, 71% of projects are delayed, 21% cancelled or never deployed, and the average cost overrun is 46%. Deloitte has a database containing detailed information of over 2,000 completed projects from across multiple industry sectors, and categorized by product type, complexity, management approach, and outcomes. This database is part of the architecture of Deloitte's *Predictive Project Analytics* tool which Deloitte claims enables it to run advanced analytics to evaluate the likelihood of project success, and offer practical and actionable advice (to its paying clients). As of 2019 *Predictive Project Analytics* had been in development for over eight years, and successfully applied – proving effective in over USD 120 billion of project investment – to more than 200 projects of all types, sizes and industries around the world (Deloitte Analytics Publications).

The author of this research proposal earlier posited that project management data are likely to be siloed within individual organizations without offering multi-organizational cross industry views. Deloitte's story, prima facie, confutes that assumption, and appears to present a fairly evolved current state of, and a promising future for, analytics in project management.

Deloitte building up a database of 2,000 projects, and leveraging the data to build predictive models to be used for 200 other projects, is somewhat akin to the all-pervasive practice (and big business) in the world of finance, of third parties *(for example, credit bureaus, rating agencies, Bloomberg)* setting up the infrastructure, and gathering and making available data, and insights from the data, to end users (creditors and investors). And it is also different in an important way in that Deloitte was probably a direct participant or stakeholder in those 2,000 projects (presumably of its multiple clients) instead of an unaffiliated party interested mainly in the acquisition, processing and monetization of the data.

Deloitte's proclaimed success with *Predictive Project Analytics* needs a critical assessment and an independent validation before drawing broad and universal inferences about the use of data and analysis for efficiencies in project management. Deloitte and other advisory and consulting firms with outsized footprints, have unique visibility and access to companies, projects and information – that most organizations and project management teams will almost never have the advantage of and will find it difficult to develop the capabilities for.

Deloitte’s quantification of its success metric, USD 120 billion in project investments, is impressively large to cite for a single analytics tool, but how exactly was the figure arrived at, and what was the value contribution of Deloitte’s Analytics to the USD 120 billion? Deloitte as an accounting firm commands credibility. What it publishes is treated with respect. The reports reviewed were indeed quite informative and made for interesting reading, but also rang the tone of a sales pitch for its *Predictive Project Analytics* tool.

2.2 McKinsey - Predictive Analytics in R&D Project Scheduling

McKinsey’s Ori Ben-Moshe, Shannon Johnston, Dorian Pyle, and Alexander Silbey note that product development projects are usually late and often very late. They spent more than a decade researching scheduling challenges in research & development projects. Analyzing more than 1,100 software projects and more than 1,600 integrated circuit development projects, they attributed to the schedule (and consequently cost) overruns, two complementary root causes – underestimating project complexity, and overestimating development teams’ productivity.

Ben-Moshe, et al., further note that companies that understood and sought to address the twin issues, didn’t have the effective tools, until recently. And that powerful data-analysis and modelling have now begun to be used for estimating project resource requirements. This has been made possible with the realization that while projects are unique, many of the complexity factors are not, and can be quantified and modeled - but for which companies must first collect a significant amount of data. The McKinsey consultants conclude that organizations applying predictive analytics to their product-development and project-planning processes dramatically reduce schedule slippage, but offer examples that are too few, anonymized, and with scant details.

2.3 HBR - Data Driven Adjustments for Optimism Bias in Project Planning

Harvard Professor Yael Grushka-Cockayne in her HBR article, highlights a human psychology connection in project planning. Nobel prizewinning psychologist Daniel Kahneman, along with Amos Tversky, had decades ago observed that humans tend to suffer from a planning fallacy - they overpromise and underdeliver based on unrealistic project goals. Kahneman and Tversky had proposed a technique to forecast project duration and cost by comparing a project of interest to similar projects from the past (being grounded in actual experience would make the forecasts more objective and less susceptible to fallacious assumptions).

Guidance for project proposal appraisals in the Green Book of the UK's Her Majesty's Treasury, includes an explicit adjustment to account for systematic optimism, or optimism bias (an overstatement of benefits and understatement of durations and costs). The Green Book's guidance has been influenced and shaped by data collected by Oxford Professor Flyvbjerg, on hundreds of large-scale projects, mostly in infrastructure, construction, and information technology.

Yael's article is about a study she led for the UK Department for Transport. Her study revealed that rail infrastructure projects require optimism adjustments up to as high as 64%. The adjustments were empirically derived by analyzing data from thousands of historical projects. Yael's study wouldn't have been possible without reliable, usable data. In the UK, project performance data have been collected for over a decade now. *nPlan*, a London-based startup, uses data from tens of thousands of construction projects involving millions of tasks in conjunction with natural language processing and Artificial Intelligence (AI) to predict project durations and delays.

On this side of the Atlantic, the (United States) Program Management Improvement Accountability Act of 2016 aims to improve program and project management practices within the federal government. Among its goals is the use of cost and schedule data to support decision-making. The legislation can be a catalyst for establishing new norms in project-related data collection more broadly than just in the government sector.

2.4 UK APM - AI in Project Management

A UK APM paper (Project Data Analytics: The State of the Art and Science) describes current research into project data analytics as in its infancy, although reviews and surveys in the field of project management have begun to ask questions about project data analytics. APM itself has commissioned three studies researching project data analytics, all related to AI, the results of which are expected to be published sometime this year (2021). The ensuing paragraphs are a synopsis of the objectives of the three studies.

Leveraging the value of lessons learnt through the power of intelligent agents: In this investigation, University of Sheffield's Dr Ronald Dyer will examine the application of intelligent agents to learning lessons across projects. It will investigate the use of chatbots (a software that emulates human chatting to identify and disseminate lessons learnt) as an AI tool in project management.

To what extent can project management as a profession be 'black-boxed'; Can AI learn to be a professional project manager? In this investigation, University of Manchester's Dr Ian Stewart and Dr Kun Wang will attempt to uncover if and how AI can be used to replicate the knowledge and functionality of human project managers.

AI in project management - how to leverage big data for project complexity mitigation: University of Southampton's Dr Nicholas Dacre will identify the potential for AI in projects particularly through a big data perspective, and examine the priorities of organizations that are faced with applying and implementing such new technologies in practice for project success.

APM's assessment of research into project data analytics being in its infancy reflects a view which is visibly divergent from other works such as that of Professor Yael's. Differing perspectives are not necessarily rooted in fallacies, and each of these studies should be evaluated on its own merits. Herdthink can create big bad blind spots and systemic risks, and great minds need not always think alike (quantum physics and classical physics, anyone?).

In all three of the APM sponsored studies currently underway, not gone unnoticed is the emphasis on AI. AI surely has proven itself in many of its diverse applications. But are some researchers getting caught up in the fad? Data analytics in project management itself is an intersection of two disciplines. Narrowing in on AI in project management makes it even more specialized. How broadly can then AI be deployed in project management? A 2021 International Business Machine survey found that only 21% of 5,501 companies had deployed AI across their businesses. According to a VentureBeat analysis, 87% of AI models are never put into production. And in a 2019 MIT Sloan Management Review / BCG survey, 70% companies reported zero value from their AI investments – it is only logical that there can be no economic value when there is no production deployment, whether in project management or in other business functions.

2.5 Large Data in Mega Engineering Projects & Broader Impacts on PMOs

Aerospace giant Airbus, London's Crossrail project, and the European nuclear research organization CERN *(for the French, conseil européen pour la recherche nuléaire),* have been featured in a white paper authored by Jennifer Whyte, Angelos Stasis, and Carmel Lindkvist, and published in the International Journal of Project Management. These organizations work on engineering projects that are high-tech, capital intensive, of significant scales and long durations, and require collaboration across multiple firms for project delivery. They rely on digital technologies to manage large datasets for delivering (even larger) projects of great complexity. Their projects are emblematic of digital technologies breaking the mold of established approaches to project management and bringing about speed and flexibility in project organizing. Large data can positively impact the PMO function within organizations in several ways affording insights into customer preferences and project portfolio performance, enabling introduction of new project metrics that support agile project practices, and helping improve project manager performance through qualitative interventions. Large Data is disrupting PMOs. Digitization will affect paradigm shifts and, according to Capgemini's Priya Patra, the journey is an uncertain one. PMOs will need to be on their toes.

2.6 Doctor of Engineering Praxes from ProQuest & ResearchGate

In their respective Doctor of Engineering praxes, George Washington University's Anya Medenhall (Forecasting Schedule Delays in IT Project Management Using Predictive Analytics Model, 2018) and Mohammad Altaf Hossain (Utilizing Predictive Analytics to Aid Project Continuity Decision Making, 2019) discuss data driven approaches for forecasting project initiation delays and predicting project failures.

Medenhall in her research presents a Random Forest (RF) method based predictive model to forecast initiation time for IT projects based on 'various identified project issues', along with a cluster analysis tool for uncovering root causes of project schedule delays. Hossain in his research demonstrates predicting project failure based on past performance of similar projects using Decision Tree, Linear Discriminant Analysis, Quadratic Discriminant Analysis, and Support Vector Machine models. Mendenhall and Hossain are among the only graduate student researchers whose work related to data and analytics in project management could be easily found in thesis repositories.

2.7 All Things Considered – *Sorry (and thanks), NPR!*

The articles discussed in this literature review are *indicative* of opening of new horizons, of transformative changes, of possibilities far in reach, all brought about by harnessing the power of data and analytics in project management. *Indicative,* but far from conclusive. Professor Yael's study appears the most rigorous, and the important details in her paper should mostly be verifiable. Deloitte's *Predictive Project Analytics* is a powerful tool that has impacted 100s of projects worth over a hundred billion dollars, has been widely referenced in other articles, but as mentioned earlier, Deloitte's essays on the subject have the tone and tenor of an advertisement. The McKinsey report is somewhat ambivalent on key points, as McKinsey reports often are, but could still be considered instructive.

While private capital and individual enterprise are often thought to be a catalyst for innovation and trailblazing, why is it quasi-governmental Airbus, city of London owned Crossrail and supranational CERN that appear to form a quintessential case in point on large data in projects? That may have to do with private corporations keeping their cards close to their chests to protect proprietary information and competitive advantage, and governmental organizations subjecting themselves to higher disclosure requirements in the broader public interest.

More examples are needed to form a clearer and definitive idea of to what extent data and analytics are being used for efficiencies in project management. But the researcher is also cognizant and wary of going down a rabbit hole (O Alice!) and seeing a pattern where it might not exist (patternicity bug), crafting coherent explanations for that illusory pattern (storytelling bug), and then searching for yet additional information that would fit and not refute those explanations (confirmation bug). While additional relevant material can be helpful and so will continue to be researched and reviewed, the planned survey assumes greater significance and will be a critical source of, and central to, the thesis.

CHAPTER 3. METHODS

This chapter describes the method and procedure to be used in this research project to answer the question: *Are data analytics being, or have the potential to be, utilized for improving efficiencies in project management along one or more of its dimensions of scope, time, cost and quality?* An online survey of project management practitioners in the industry was conducted to answer this central question and its corollaries. Discussed in this chapter are survey target population selection, survey design and plan for rollout, approvals obtained, and retrieval and analysis of the survey responses.

3.1 Selection of Survey Participants

The survey targeted project managers and other individuals in project leadership roles. Participants included industry professionals from companies where contacts existed through Purdue University's Computer and Information Technology (C&IT) department, primarily the researcher's thesis advisory committee, members of the C&IT Industrial Advisory Council, which is comprised of notable Purdue C&IT alumni in an array of companies, online forums of professional groups on LinkedIn, and Amazon Mechanical Turk, a 'crowdsourcing' platform.

The survey would generate thirty-two sets of responses that were either a hundred percent or nearly hundred percent complete from individuals in twelve distinct industry sectors. While not a very broad-based survey campaign, the multiple channels of outreach ensured that an adequate number of responses were generated resulting in sample size not becoming an insurmountable constraint. Sample size was a risk that needed to be carefully monitored, assessed and adapted to, to mitigate the risk of potential sample size limitations.

3.2 Procedure

A questionnaire (summary in the next section; details in appendix) for the survey was first created offline. This questionnaire was then programmed into the Purdue Qualtrics internet-based surveying platform, and after approvals were obtained, made available to survey participants in the later part of Fall 2021. The survey was kept open for a month to allow participants ample time to thoughtfully respond. The responses were electronically retrieved, analyzed, and the findings incorporated into this M.S. thesis.

3.3 Data Collection

Data in the form of answers to twenty-eight survey questions, twenty-six of them multiple choice, were gathered along the dimensions of: i) industry sector, project size, and geography; ii) organizational environment for data & analytics in project management; iii) how extensively data & analytics are used in project management; iv) efficiency gains from data & analytics in project management; and v) miscellaneous free text comments

3.4 Qualitative and Quantitative Analysis of the Data

The data captured were exported from within Qualtrics to Excel. The researcher was able to perform all of the analysis in Excel given the relative simplicity and low volumes of the data that were generated from the survey. The free form text responses with qualitative information were individually reviewed.

The researcher is adept in computer programming and also has a SAS certification (for performing advanced analysis if that were to be a value-add). However, the functions, tools and features present in Excel were sufficient for analyzing the survey data. This research was not so much about building overly complicated or esoteric (and often indecipherable) models, as it was about discerning trends and patterns in data, and drawing insights based on facts, scientific reasoning, logic and judgment. The highlights of the analysis, along with the conclusions and recommendations are presented in the following chapters.

3.5 Chapter Summary

This chapter began by restating the research question and describing the participants. Next, it defined the procedures and data collection method. It concluded with a discussion on the data analysis mechanisms.

CHAPTER 4. RESEARCH FINDINGS

This chapter discusses the survey results. Section 4.1 summarizes the main findings. Section 4.2 and its subsections describe in greater details the underlying analysis.

4.1 Key Findings Summary

Data and Analytics in Project Management are used, and the benefits realized, more for Quality and Time monitoring and improvements, and not as much for Cost or Scope. These occur in the backdrop of broad management support for the use of analytics in project management. Further, most organizations, and especially the larger ones, have the infrastructure and capabilities to meet basic or advanced analytics in project management.

The main findings are graphically depicted on the next page. The graph to the left is for the Extent of Use of Analytics in Project Management, and the one on the right for Gains from Using Analytics for Project Management. The graphs show the distribution of respondents who reported values (for the extent of use or gains) that are grouped into Low, Medium and High for each of Cost, Quality, Time, and Scope, with the categories along the X axes. The Y axes in each of the two graphs are the number of respondents. The details supporting these high-level conclusions are elaborated in a later section.

4.1.1 Key Findings Summary in Charts

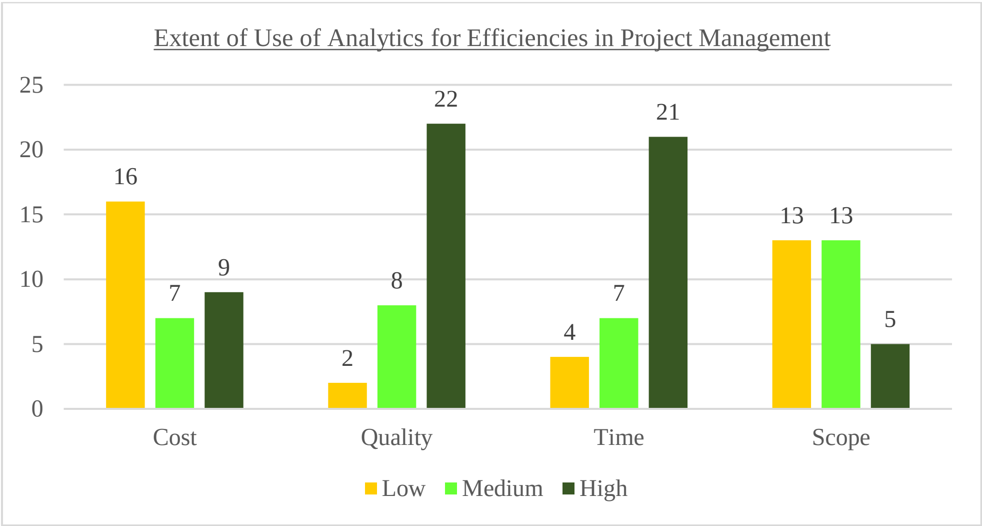

Figure 1. Extent of Use of Analytics for Efficiencies in Project Management

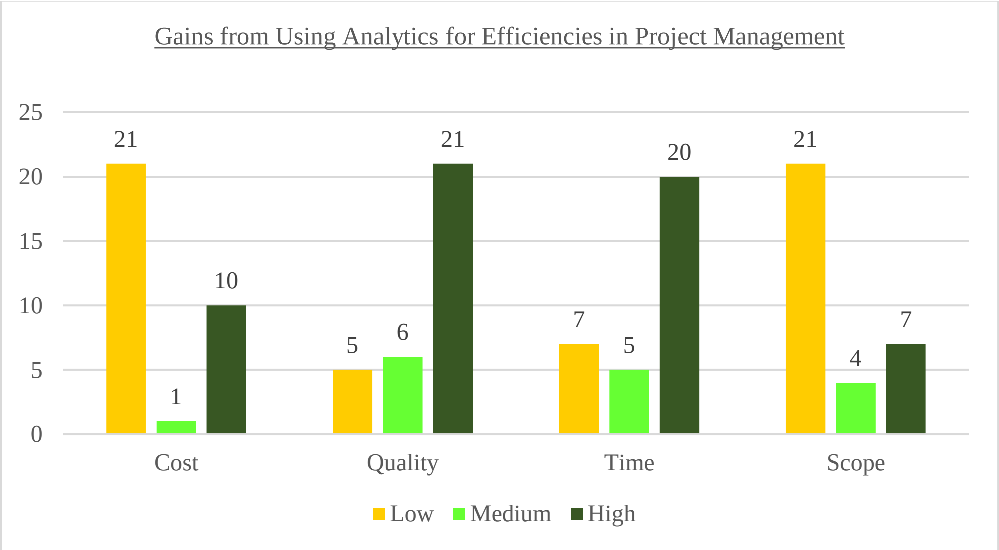

Figure 2. Gains from Using Analytics for Efficiencies in Project Management

Notes:

– Response groupings for Extent of Use of Analytics were *predefined* in the survey as: Low (up to 30), Medium (between 30 and 70), and High (70 and above) on a sliding scale of 0 to 100

– Response groupings for Gains from Use of Analytics, were further aggregated, for simplifying the graphical depiction, *after* receiving the survey responses as: Low (~0% or ~5%), Medium (~10%), High (~20% or significantly greater than 20%)

4.2 Analysis of Findings

The survey results reveal that data and analytics in project management are used, and the benefits realized, more for quality and time monitoring and improvements, and not as much for cost or scope. The researcher, in addition to the core measures of the extent of data analytics usage and the magnitude of benefits realized, had also collected some other demographic and business variables (such as respondents' gender, age and experience, industry sector, organization size, regions of the world) that could be used for segment level analysis. The analysis of findings in the following sections are for the overall sample, along with univariate breakdowns by industry sector and organization size (number of employees). The researcher did look for patterns along other segmentation variables, but those were not meaningful because some of the univariate segmentation showed clustering or concentration (for example, North America for regions of the world), and a multivariate analysis of just 32 respondents would spread the sample far too thin in the resulting granular segments.

4.2.1 Analytical Infrastructure and Organizational Culture for Data Analytics in Project Management

Analytical Infrastructure: A majority (66%) of survey participants reported existing infrastructure at their organizations to meet basic (41%) or advanced (25%) analytics in project management. The data reveals a high direct correlation (correlation coefficient 0.93) between organization size and the state of analytical infrastructure. The coefficient was computed by ranking organization size, and the corresponding percentages of respondents reporting existing infrastructure for either basic or advanced project management analytics.

Table 1. State of Analytical Infrastructure for Project Management

Organization Size (No. of Employees) →	**Not Reported**	**11 - 50**	**51 - 200**	**201 - 1,000**	**1,001 - 5,000**	**5,001 - 20,000**	**20,001 - 40,000**	**> 40,000**	**Grand Total**
Minimal at present and no serious investment planned for the foreseeable future	1	1	1	1					**4**
Limited analytical activity without standardized data and analytics methods and tools					2			1	**3**
Uncoordinated pockets of analytical activity with investments to adopt it more broadly		1		1	1	1			**4**
Infrastructure & capabilities exist & are sufficient to meet basic analytics utilized in project management						1	5	7	**13**
Infrastructure and capabilities exist to support advanced analytics utilized in project management					1	2	1	4	**8**
Grand Total	**1**	**2**	**1**	**2**	**4**	**4**	**6**	**12**	**32**

<u>Organizational Culture:</u> Notably, a hundred percent of respondents reported either Medium or High for the prevailing culture and management support *(how conducive is the environment?)* at their organizations for the use of data and analytics in project management.

Table 2. Management Support for Project Management, by Organization Size

Org. Size ↓	Low	Medium	High	Total
Not Reported			1	**1**
11 to 50		1	1	**2**
51 to 200			1	**1**
201 to 1,000		1	1	**2**
1,001 to 5,000		2	2	**4**
5,001 to 20,000		2	2	**4**
20,001 to 40,000		1	5	**6**
>40,000		3	9	**12**
Total		**10**	**22**	**32**

Table 3. Management Support for Project Management, by Industry Sector

Industry Sector ↓	Low	Medium	High	Total
Banking/Finance/Asset Management		4	7	**11**
Computing / Information Technology		1	9	**10**
Heavy Industrial / Manufacturing		1	1	**2**
Oil and Gas		1		**1**
Scientific Research			1	**1**
Construction		1		**1**
Telecom			1	**1**
Government		1		**1**
Consulting			1	**1**
Public Utility		1		**1**
Consumer Goods			1	**1**
Pharmaceutical			1	**1**
Total		**10**	**22**	**32**

4.2.2 Extent of Use of Analytics in Project Management

This subsection has four pairs of tabulated summaries (each on its own page) for the extent of use of analytics in project management for each of cost, quality, time and scope – along the segmentation variables of organization size and industry sector.

Costs: A majority of participants reported a lower extent of the use of analytics for project costs. The lower skew is driven by larger organizations. Cost efficiencies through analytics may be less important for larger organizations, or this could be a spurious pattern from noise in the data.

Table 4. Extent of Use of Data Analytics in PM for Costs, by Organization Size

Org. Size ↓	**Low**	**Medium**	**High**	**Total**
Not Reported			1	**1**
11 - 50		1	1	**2**
51 - 200			1	**1**
201 - 1,000			2	**2**
1,001 - 5,000		3	1	**4**
5,001 - 20,000	1	2	1	**4**
20,001 - 40,000	6			**6**
>40,000	9	1	2	**12**
Total	**16**	**7**	**9**	**32**

Table 5. Extent of Use of Data Analytics in PM for Costs, by Industry Sector

Industry Sector ↓	**Low**	**Medium**	**High**	**Total**
Banking/Finance/Asset Management	7	2	2	11
Computing / Information Technology	5	1	4	10
Heavy Industrial / Manufacturing	1		1	2
Oil and Gas	1			1
Scientific Research		1		1
Construction			1	1
Telecom		1		1
Government		1		1
Consulting	1			1
Public Utility		1		1
Consumer Goods	1			1
Pharmaceutical	1			1
Total	**16**	**7**	**9**	**32**

Quality: A great majority of survey participants, across most industry sectors and organizations small or big, reported a high extent of the use of data and analytics for project quality.

Table 6. Extent of Use of Data Analytics in PM for Quality, by Organization Size

Org. Size ↓	Low	Medium	High	Total
Not Reported	1			**1**
11 - 50			2	**2**
51 - 200			1	**1**
201 - 1,000		1	1	**2**
1,001 - 5,000		2	2	**4**
5,001 - 20,000		2	2	**4**
20,001 - 40,000			6	**6**
>40,000	1	3	8	**12**
Total	**2**	**8**	**22**	**32**

Table 7. Extent of Use of Data Analytics in PM for Quality, by Industry Sector

Industry Sector ↓	Low	Medium	High	Total
Banking/Finance/Asset Management	1	2	8	**11**
Computing / Information Technology	1	2	7	**10**
Heavy Industrial / Manufacturing			2	**2**
Oil and Gas		1		**1**
Scientific Research		1		**1**
Construction			1	**1**
Telecom			1	**1**
Government			1	**1**
Consulting			1	**1**
Public Utility		1		**1**
Consumer Goods			1	**1**
Pharmaceutical		1		**1**
Total	**2**	**8**	**22**	**32**

Time: A great majority of survey participants reported a high extent of the use of data analytics for project time. This is observed for most industry sectors. There also exists a high correlation (correlation coefficient 0.94) between organization size and a survey response of 'High'.

Table 8. Extent of Use of Data Analytics in PM for Time, by Organization Size

Org. Size ↓	Low	Medium	High	Total
Not Reported	1			**1**
11 - 50	2			**2**
51 - 200	1			**1**
201 - 1,000		2		**2**
1,001 - 5,000		3	1	**4**
5,001 - 20,000		2	2	**4**
20,001 - 40,000			6	**6**
>40,000			12	**12**
Total	**4**	**7**	**21**	**32**

Table 9. Extent of Use of Data Analytics in PM for Time, by Industry Sector

Industry Sector ↓	Low	Medium	High	Total
Banking/Finance/Asset Management	1	3	7	**11**
Computing / Information Technology	2	2	6	**10**
Heavy Industrial / Manufacturing	1		1	**2**
Oil and Gas			1	**1**
Scientific Research		1		**1**
Construction			1	**1**
Telecom			1	**1**
Government			1	**1**
Consulting			1	**1**
Public Utility		1		**1**
Consumer Goods			1	**1**
Pharmaceutical			1	1
Total	**4**	**7**	**21**	**32**

<u>Scope:</u> Relatively very few participants reported high use of data analytics for project scope. This makes sense, as while scope creep can sometimes (or often times!) be a concern, scope is driven by business needs or 'wishes', and not as much influenced by patterns in project management data.

Table 10. Extent of Use of Data Analytics in PM for Scope, by Organization Size

Org. Size ↓	Low	Medium	High	Total
Not Reported	1			**1**
11 - 50		1	1	**2**
51 - 200			1	**1**
201 - 1,000		2		**2**
1,001 - 5,000	1	2	1	**4**
5,001 - 20,000	1	2		**3**
20,001 - 40,000	3	1	2	**6**
>40,000	7	5		**12**
Total	**13**	**13**	**5**	**31**

Table 11. Extent of Use of Data Analytics in PM for Scope, by Industry Sector

Industry Sector ↓	Low	Medium	High	Total
Banking/Finance/Asset Management	5	3	3	**11**
Computing / Information Technology	4	4	1	**9**
Heavy Industrial / Manufacturing		1	1	**2**
Oil and Gas		1		**1**
Scientific Research		1		**1**
Construction		1		**1**
Telecom		1		**1**
Government	1			**1**
Consulting	1			**1**
Public Utility		1		**1**
Consumer Goods	1			**1**
Pharmaceutical	1			**1**
Total	**13**	**13**	**5**	**31**

4.2.3 Gains from Using Analytics in Project Management

This subsection has four pairs of tabulated summaries for the gains from using analytics in project management for each of cost, quality, time and scope – along the segmentation variables of organization size and industry sector.

The results show a strong linkage between how extensively data and analytics are deployed in project management along its four dimensions (the traditional triple constraints, plus quality), and the benefits realized. Both the extent of use and benefits are higher for quality and time, and lower for cost and scope. The researcher finds the low use of analytics for project costs, somewhat surprising, especially because of the higher levels of use of analytics reported for quality and time. One could construe that the focus on project quality and time through data analytics would also have affirmative impacts on project costs. The existing survey questionnaire and its results, however, are not sufficient to allow for testing the presumption of positive second order effects of data analytics on costs.

<u>Costs:</u> Consistent with reported low level of analytics usage for project costs, most survey participants reported only small levels of benefits attributed to analytics along the cost dimension.

Table 12. Gains from Using Data Analytics in PM for Costs, by Organization Size

Org. Size ↓	~0%	~5%	~10%	~20%	>20%	Total
Not Reported		1				**1**
11 - 50			1	1		**2**
51 - 200				1		**1**
201 - 1,000		1		1		**2**
1,001 - 5,000		2			2	**4**
5,001 - 20,000		1		3		**4**
20,000 - 40,000		6				**6**
>40,000	1	9		1	1	**12**
Total	**1**	**20**	**1**	**7**	**3**	**32**

Table 13. Gains from Using Data Analytics in PM for Costs, by Industry Sector

Industry Sector ↓	~0%	~5%	~10%	~20%	>20%	Total
Banking/Finance/Asset Management		8	1	1	1	11
Computing / Information Technology		4		5	1	10
Heavy Industrial / Manufacturing		1		1		2
Oil and Gas		1				1
Scientific Research		1				1
Construction		1				1
Telecom		1				1
Government		1				1
Consulting		1				1
Public Utility					1	1
Consumer Goods		1				1
Pharmaceutical	1					1
Total	**1**	**20**	**1**	**7**	**3**	**32**

Quality: A majority reported materially high benefits from the use of data and analytics in project management along the dimension of Quality.

Table 14. Gains from Using Data Analytics in PM for Quality, by Organization Size

Org. Size ↓	**~0%**	**~5%**	**~10%**	**~20%**	**>20%**	**Total**
Not Reported		1				**1**
11 - 50				1	1	**2**
51 - 200				1		**1**
201 - 1,000			1	1		**2**
1,001 - 5,000		1	1		2	**4**
5,001 - 20,000			1	2	1	**4**
20,000 - 40,000		1		5		**6**
>40,000		2	3	4	3	**12**
Total		**5**	**6**	**14**	**7**	**32**

Table 15. Gains from Using Data Analytics in PM for Quality, by Industry Sector

Industry Sector ↓	**~0%**	**~5%**	**~10%**	**~20%**	**>20%**	**Total**
Banking/Finance/Asset Management		1	2	7	1	**11**
Computing / Information Technology		1	1	5	3	**10**
Heavy Industrial / Manufacturing		1		1		**2**
Oil and Gas			1			**1**
Scientific Research			1			**1**
Construction		1				**1**
Telecom			1			**1**
Government		1				**1**
Consulting				1		**1**
Public Utility					1	**1**
Consumer Goods					1	**1**
Pharmaceutical						
Total		**5**	**6**	**14**	**7**	**32**

Time: Respondents reported varying degrees of benefits for time from the use of analytics in project management. The Banking and I.T. sectors appear to realize higher levels of time gains.

Table 16. Gains from Using Data Analytics in PM for Time, by Organization Size

Org. Size ↓	~0%	~5%	~10%	~20%	>20%	Total
Not Reported		1				**1**
11 - 50				1	1	**2**
51 - 200				1		**1**
201 - 1,000				2		**2**
1,001 - 5,000		1	2		1	**4**
5,001 - 20,000			1	3		**4**
20,000 - 40,000		1		4	1	**6**
>40,000	1	3	2	3	3	**12**
Total	**1**	**6**	**5**	**14**	**6**	**32**

Table 17. Gains from Using Data Analytics in PM for Time, by Industry Sector

Industry Sector ↓	~0%	~5%	~10%	~20%	>20%	Total
Banking/Finance/Asset Management		1	3	5	2	**11**
Computing / Information Technology		2		6	2	**10**
Heavy Industrial / Manufacturing		1		1		**2**
Oil and Gas			1			**1**
Scientific Research			1			**1**
Construction	1					**1**
Telecom		1				**1**
Government		1				**1**
Consulting				1		**1**
Public Utility					1	**1**
Consumer Goods					1	**1**
Pharmaceutical				1		**1**
Total	**1**	**6**	**5**	**14**	**6**	**32**

Scope: Unsurprisingly, few survey participants reported scope benefits of analytics in project management - which is consistent with analytics not being much used for project management scope objectives in the first place.

Table 18. Gains from Using Data Analytics in PM for Scope, by Organization Size

Org. Size ↓	~0%	~5%	~10%	~20%	>20%	Total
Not Reported		1				**1**
11 - 50		1		1		**2**
51 - 200				1		**1**
201 - 1,000			1		1	**2**
1,001 - 5,000		2			2	**4**
5,001 - 20,000	1	1	1	1		**4**
20,000 - 40,000		6				**6**
>40,000	1	8	2	1		**12**
Total	**2**	**19**	**4**	**4**	**3**	**32**

Table 19. Gains from Using Data Analytics in PM for Scope, by Industry Sector

Industry Sector ↓	~0%	~5%	~10%	~20%	>20%	Total
Banking/Finance/Asset Management		5	3	1	2	**11**
Computing / Information Technology	1	7	1	1		**10**
Heavy Industrial / Manufacturing		1		1		**2**
Oil and Gas		1				**1**
Scientific Research		1				**1**
Construction				1		**1**
Telecom		1				**1**
Government		1				**1**
Consulting		1				**1**
Public Utility					1	**1**
Consumer Goods		1				**1**
Pharmaceutical	1					**1**
Total	**2**	**19**	**4**	**4**	**3**	**32**

4.2.4 Miscellaneous Observations from Survey Results

Following are some minutiae, the trifling details *(Trifles make perfection, and perfection is no trifle – Michael Angelo):*

- Most of the 32 respondents are from North America (25), the others being from Europe (3), South Asia (2), Asia Pacific, Australia or New Zealand (1), and Central or South America (1).
- The Banking/Finance and Computing/I.T. sectors form a great bulk of the survey respondents (that is where so many of the professional jobs are!) and these sectors therefore weigh on the overall results.
- There is an apparent correlation between how extensively data and analytics are used and the benefits realized (each is higher for quality and time, and lower for cost and scope). While there can be logical explanations, a definitive causal relationship cannot be drawn from the survey results.
- About a fourth of the respondents indicated that their answers to questions on the benefits from analytics in project management were conjectured estimates (as opposed to approximated quantifications based on actual experience). This minority subgroup, in general, somewhat overestimated the benefits of analytics in project management (compared to the rest, they chose relatively higher values for benefits for cost, time and scope)!
- Only one of the 32 respondents chose experience and intuition over data and analytics for project management, 19 chose hard data and advanced analytics alone, and 12 a balance of both.
- 10 of 32 respondents from across the world are females (or 31%). For North America, 7 of the 25 are females (or 28%). For comparison, 47% of the overall U.S. workforce is female (U.S. Department of Labor).

CHAPTER 5. CONCLUSION

The aim of this research was to identify if data and analytics are, or can be, meaningfully and extensively used for improving efficiencies in project management. The research reveals that data and analytics are used in project management, and the benefits realized, more along the dimensions of quality and time, and not as much for cost or scope. These occur in the backdrop of broad management support for the use of analytics in project management. Further, most organizations, and especially the larger ones, have the infrastructure and capabilities to meet basic or advanced analytics in project management.

The relatively very few participants reporting high use of data analytics for project scope makes sense, as while scope creep can sometimes (or often times!) be a concern, scope is driven by business needs or 'wishes', and not as much influenced by patterns in project management data.

The researcher, however, finds the low use of analytics for project costs somewhat surprising, especially because of the higher levels of use of analytics reported for quality and time. One could construe that the focus on project quality and time through data analytics would also have affirmative impacts on project costs. The existing survey questionnaire and its results, however, are not sufficient to allow for testing the presumption of positive second order effects of data analytics on costs.

Future researchers in this area may consider narrowing in on the impact of analytics on ‘big data’ projects as their research topic, building out on the survey questionnaire, and potentially supplementing their surveys with interviews of subjects, expanding their outreach to have a greater number of participants from across a broader range of industry sectors, and lastly and perhaps more importantly, focusing on other important dimensions such as risk governance, controls and mitigation in projects and project management.

The conclusions of this research can be a useful reference while validating or refuting fundamental feasibility assumptions about using data analytics in the practice of project management. The survey results directly address the research question, building on and adding to other germane learnings discussed in the literature review section of this thesis. Nevertheless, the applicability of the research findings must be contextually evaluated while attempting to seek data analytics solutions to very complex or vexing project management dilemmas.

REFERENCES

Alexander, M. (2021, March 23). *The data-driven project manager: Using analytics to improve outcomes*. CIO. https://www.cio.com/article/3612317/the-data-driven-project-manager-using-analytics-to-improve-outcomes.html

A.P.M. (2021, February 25). *What is project data analytics? | APM*. Association for Project Management. https://www.apm.org.uk/resources/what-is-project-management/what-is-project-data-analytics/

A.W. (2020, December 11). *4 Ways Big Data is Disrupting the PMO*. Adobe Workfront. https://www.workfront.com/blog/4-ways-big-data-is-disrupting-the-pmo

Ben-Moshe, O., Johnston, S. J., Pyle, D., & Silbey, A. (2020, October 20). *R&D that's on time and on budget? Yes, with predictive analytics*. McKinsey & Company. https://www.mckinsey.com/business-functions/operations/our-insights/rd-thats-on-time-and-on-budget-yes-with-predictive-analytics

Brynjolfsson., E. (2017, September 15). *Data-driven decision making: an adoption framework*. MIT DSpace. https://dspace.mit.edu/handle/1721.1/111450

Davenport, T., & R.Z. (2021, July 20). *Achieving Return on AI Projects*. MIT Sloan Management Review. https://sloanreview.mit.edu/article/achieving-return-on-ai-projects/?og=Home+Editors+Picks

Deloitte. (2017). Predictive Project Analytics. https://www.google.com/url?sa=t&rct=j&q=&esrc=s&source=web&cd=&cad=rja&uact=8&ved=2ahUKEwjWq8COrZvyAhXPWc0KHSH7DqgQFnoECBQQAw&url=https%3A%2F%2Fwww2.deloitte.com%2Fcontent%2Fdam%2FDeloitte%2Fca%2FDocuments%2Frisk%2Fca-en-ers-predictive-project-analytics.pdf&usg=AOvVaw01pmEbMHYTXM74642fQ6gT

Deloitte. (2019). Predictive Project Analytics 2.0. https://www.google.com/url?sa=t&rct=j&q=&esrc=s&source=web&cd=&cad=rja&uact=8&ved=2ahUKEwjWq8COrZvyAhXPWc0KHSH7DqgQFnoECC8QAw&url=https%3A%2F%2Fwww2.deloitte.com%2Fcontent%2Fdam%2FDeloitte%2Fbe%2FDocuments%2Frisk%2Fbe-ara-predictive-project-analytics-2-0.pdf&usg=AOvVaw3FhfirdLag2cfyB_Qzn35Q

Deloitte. (2017). Predictive Project Analytics – Planning for success. https://www2.deloitte.com/ca/en/pages/deloitte-analytics/articles/predictive-project-analytics.html

Gottlieb, J., & Weinberg, A. (2019, October 4). *Catch them if you can: How leaders in data and analytics have pulled ahead*. McKinsey & Company. https://www.mckinsey.com/business-functions/mckinsey-analytics/our-insights/catch-them-if-you-can-how-leaders-in-data-and-analytics-have-pulled-ahead

Grushka-Cockayne, Y. (2020, February 26). *Use Data to Revolutionize Project Planning*. Harvard Business Review. https://hbr.org/2020/02/use-data-to-revolutionize-project-planning

Hossain, M. (2019, May 19). *Utilizing Predictive Analytics to Aid Project Continuity Decision Making*. GW ScholarSpace. https://scholarspace.library.gwu.edu/concern/gw_etds/h702q7035?locale=es

Hürtgen, H., & Mohr, N. (2019, May 11). *Achieving business impact with data*. McKinsey & Company. https://www.mckinsey.com/business-functions/mckinsey-analytics/our-insights/achieving-business-impact-with-data

IBM. (2021). *Global Data from IBM Points to AI Growth as Businesses Strive for Resilience*. IBM Newsroom. https://newsroom.ibm.com/IBMs-Global-AI-Adoption-Index-2021

Jain, A. (17–12). *Analytics Protocol for Data-Driven Decision-Making in the Construction Industry*. Purdue E-Pubs. https://docs.lib.purdue.edu/dissertations/AAI10684724/

Kudyba, S., & D'Cruz, A. (2021, July 16). *Build a Better Dashboard for Your Agile Project*. Harvard Business Review. https://hbr.org/2021/07/build-a-better-dashboard-for-your-agile-project

Mendenhall, A. (2018). *Forecasting Schedule Delays in IT Project Management Using Predictive Analytics Model*. Hyrax. https://scholarspace.library.gwu.edu/concern/gw_etds/44558d50p?locale=de

Priya, P. (2017, October 6). *Projects in the Real World: Agile and Beyond*. PMI. https://www.projectmanagement.com/articles/494595/Projects-in-the-Real-World--Agile-and-Beyond

Ross., J. W. (2017, March 10). *Data-Centric Business Transformation*. MIT Libraries. https://dspace.mit.edu/handle/1721.1/107344

Spalek, S. (2018, October 24). *Data Analytics in Project Management*. Routledge & CRC Press. https://www.routledge.com/Data-Analytics-in-Project-Management/Spalek/p/book/9781138307285

van Maanen., J. (2017, September 15). *Leading data analytics transformations*. MIT DSpace. https://dspace.mit.edu/handle/1721.1/111472

Viaene, S., & Bunder, A. V. (2011, September 21). *The Secrets to Managing Business Analytics Projects*. MIT Sloan Management Review. https://sloanreview.mit.edu/article/the-secrets-to-managing-business-analytics-projects/

Whyte, J., Stasis, A., & Lindkvist, C. (2016). Managing change in the delivery of complex projects: Configuration management, asset information and 'big data.' *International Journal of Project Management*, *34*(2), 339–351. https://doi.org/10.1016/j.ijproman.2015.02.006

Wiggers, K. (2021, May 11). *One-third of organizations are using AI, IBM survey finds*. VentureBeat. https://venturebeat.com/2021/05/10/one-third-of-organizations-are-using-ai-ibm-survey-finds/

APPENDIX A: SCHEDULE

Below are the target dates for key events in the research process:

- 08/09/2021 – Present Thesis Proposal
- 10/28/2021 – Obtain IRB Approval
- 10/29/2021 – Open Survey
- 11/26/2021 – Close Survey
- 11/16/2021 – Analyze Survey Report and Compile Report
- 11/30/2021 – Submit Thesis to Committee
- 12/01/2021 – Defend Thesis

APPENDIX B: SURVEY

Thank you for agreeing to participate in this study of “Impact of data and analytics in project management”. Your participation is valuable and much appreciated. However, it is completely voluntary and you may stop at any time if you choose to.

Demographics

1. Please indicate your age in years

   a. Up to 25
   b. 25-29
   c. 30-39
   d. 40-49
   e. Above 50

2. Gender
   a. Male
   b. Female
   c. Do not wish to identify

3. Please indicate the level of project management experience you have by recording the total number of years you have been engaged at each level (Matrix Table)

   Scale points: (1 - 3, 4 - 6, 7 - 9, 10 - 12, 13 - 15, < 16)

   Statements:

   a. Team Manager
   b. Project Manager
   c. Program Manager
   d. Other roles in project management

4. What is your current primary role? (select one only)
   a. Project Team Member
   b. Project Manager
   c. Program Manager / Director
   d. Other - please specify (Textbox)

5. How many employees work in your entire organization?

   a. 1 to 10
   b. 11 to 50

c. 51-200
d. 201-1000
e. 1001-5000
f. 5001-20,000
g. 20,000-40,000
h. >40000

6. How many employees work in your division?

   a. 1 to 10
   b. 11 to 50
   c. 51-200
   d. 201-1000
   e. 1001-5000

PAGE BREAK

Industry Sector, Project Budget & Duration, Geography

1. Which of the following areas are your typical projects in? If your projects span multiple areas or sectors, choose the one that is the most relevant or dominant.
    a. Aerospace
    b. Banking/Finance
    c. Heavy Industrial / Manufacturing
    d. Computing / Information Technology
    e. Construction
    f. Scientific Research
    g. Government
    h. Other (specify) [Include Text Box]

2. In which of the following regions **you** do most of your work? (*Not necessarily the same as where your organization has most of its operations.)*
    a. North America
    b. Central or South America
    c. Europe
    d. Middle East or North Africa
    e. Central or Southern Africa
    f. South Asia
    g. Asia Pacific, Australia or New Zealand

3. What is the typical scale of projects, in terms of budget, you are generally involved in?
    a. < USD 100,000
    b. USD 100,001 – USD 500,000
    c. USD 500,001 – USD 1,000,000
    d. USD 1,000,001 – USD 5,000,000
    e. USD 5,000,001 – USD 10,000 000
    f. USD 10,000,001 – USD 25,000,000
    g. USD 25,000,001 – USD 50,000,000
    h. >USD 50,000,001

4. What is the typical scale of projects, in terms of duration, you are generally involved in?
    a. Up to 3 months
    b. Longer than 3 months and up to 6 months
    c. Longer than 6 months and up to 1 year
    d. Longer than 1 year and up to 2 years
    e. Longer than 2 years

PAGE BREAK

Organizational Environment for Data & Analytics in Project Management

5. What is the state of **data and analytics** infrastructure and processes in your organization as it relates to ***project management****?* If an exact description does not appear below, select the one that is the closest
    a. Minimal at present, and no serious investment planned for the foreseeable
    b. Uncoordinated pockets of analytical activity with investments to adopt it more broadly
    c. Limited analytical activity without standardized data and analysis methods and tools
    d. Infrastructure and capabilities exist and are sufficient to meet ***basic analytics*** utilized in project management in our organization
    e. Infrastructure and capabilities exist to support ***advanced analytics*** utilized in project management in our organization

6. How supportive are management and colleagues in your organization for using data and analytics in project management? (Sliding Scale / High [70% and above], Medium [between 30% and 70%], Low [30% and below])

7. What in your view or experience is more important in achieving efficiencies in project management **Sliding Scale (Experience and Intuition / Balance of both / Hard Data & Advanced Analytics)**

PAGE BREAK

How extensively are Data & Analytics used in Project Management

1. To what extent *data analytics* (different from using software tools) has been used in planning or managing **any material component** of your project? Note – Data analytics as directly related to the project planning or execution – not for other tasks, functions, or processes in your organization.
    a. More than 75% of projects
    b. 50% - 75% of projects
    c. 25%-50% of projects
    d. 5% -25% of projects
    e. Less than 5% of projects (or never)

2. To what extent in recent times has data analytics actually been used for monitoring or improving project **Costs** (Sliding Scale / High [70% and above], Medium [between 30% and 70%], Low [30% and below])

3. To what extent in recent times has data analytics been used for monitoring or improving project **Quality** (Sliding Scale / High [70% and above], Medium [between 30% and 70%], Low [30% and below])

4. To what extent in recent times has data analytics been used for monitoring or improving project **Time** (Sliding Scale / High [70% and above], Medium [between 30% and 70%], Low [30% and below])

5. To what extent in recent times has data analytics been used for monitoring or improving project **Scope** (Sliding Scale / High [70% and above], Medium [between 30% and 70%], Low [30% and below])

PAGE BREAK

<u>Efficiency Gains from Data & Analytics in Project Management</u>

1. What are the actual or expected future state project efficiency gains / improvements from the use of data and analytics along the dimension of **Cost**?
    a. Zero or negative - no cost savings or negative because of resource diversion, added complexity, or waste
    b. 5%
    c. 10%
    d. 20%
    e. Significantly greater than 20%

    Is the above answer based on actual realization or is your estimate if data and analytics were to be in project management at your organization?

    a) Based on actual experience
    b) Is an estimate, if data and analytics were to be used in project management

2. What are the actual or expected future state project efficiency gains / improvements from the use of data and analytics along the dimension of **Quality**?
    a. Zero or negative - no quality improvements or negative because of resource diversion, added complexity or waste
    b. 5%
    c. 10%
    d. 20%
    e. Significantly greater than 20%

    Is the above answer based on actual realization, or is your estimate if data and analytics were to be in project management at your organization?

    a) Based on actual experience
    b) Is an estimate, if data and analytics were to be used in project management

3. What are the actual or expected future state project efficiency gains / improvements from the use of data and analytics along the dimension of **Time**?
    a. Zero or negative - no time gains or negative because of resource diversion, added complexity or waste
    b. 5%

c. 10%
d. 20%
e. Significantly greater than 20%

Is the above answer based on actual realization, or is your estimate if data and analytics were to be in project management at your organization?

a) Based on actual experience
b) Is an estimate, if data and analytics were to be used in project management

4. What are the actual or expected future state project efficiency gains / improvements from the use of data and analytics along the dimension of **Scope**?
   a. Zero or negative - no gains in scope/coverage or negative because of resource diversion, added complexity and waste
   b. 5%
   c. 10%
   d. 20%
   e. Significantly greater than 20%

Is the above answer based on actual realization, or is your estimate if data and analytics were to be in project management at your organization?

a) Based on actual experience
b) Is an estimate, if data and analytics were to be used in project management

PAGE BREAK

Miscellaneous – Free Text Box

1. Free form text box: What in your view are, or from your experience have been, the impediments to using large data and advanced analytics in project management?

2. Free form text box: Please share anything else meaningful and pertinent from your knowledge and/or experience on the possibilities and limitations of using large data and analytics for efficiencies in project management along one or more of the dimensions of cost, scope, time and quality.

This concludes the study. Thank you very much for your participation.