THE NEED FOR AGILITY IN CAPITAL BUDGETING OF INTELLIGENT AUTOMATIONS FOR KNOWLEDGE AND SERVICE WORK

A Dissertation
Submitted to
the Temple University Graduate Board

In Partial Fulfillment
of the Requirements for the Degree
Executive Doctorate of Business Administration

---

by
Parthasaradhy Vuppalapaty
Mar 2021

Examining Committee Members:

Dr. Subodha Kumar, Dissertation Chair, Marketing and Supply Chain Management
Dr. Sunil Wattal, Management Information Systems
Dr. Lalitha Naveen, Finance
Dr. Wang Yang, External Member, Marketing and Supply Chain Management

ABSTRACT

It is argued that the future of the workforce will be ‘humans and machines’ but not ‘humans vs machines’ due to the drift from ‘workforce planning’ to ‘work planning’. Advances in Artificial Intelligence (AI) and its sub-fields have enabled the development of a new form of automation that is described as Intelligent Automation. It is the application of AI in ways that can learn, adapt and improve over time to automate tasks that were formally undertaken by a human.

The purpose of this study is to develop a conceptual framework on the necessity of agility within the capital budgeting process for Intelligent Automations, as the traditional approaches ignore the effects of new or disruptive technologies like Artificial intelligence. This study provides advice to managers on the strategic fit of traditional capital budgeting models vs. alternatives like beyond budgeting in the context of Intelligent Automations for knowledge work (consulting, education, etc.) and service work (retail, cleaning, etc.). The approach to conduct this study will be mixed methods. From the outcomes of qualitative analysis through semi-structured interviews, the conceptual framework is formulated. This framework is tested using the survey responses data and quantitative methods.

From the preliminary analysis of the pilot study conducted with 7 participants at the c-suite level, the consistent themes that are observed in this phenomenon are a) lack of data for planning due to non-linearity in the resource models in projects where AI is applied, b) use or misuse of the discretionary pool funding model and c) lack of adoption to new ways of working due to organizational climate. The two conflicting themes are the disagreements on ethics council, whether internal vs external and the expectations on human skills that cause the burden of change in large firms.

A survey instrument is developed for data collection to analyze the conceptual model, which results from the qualitative study and literature review. A random sample of 217 respondents is chosen during the period from Nov 2020 to Mar 2021. A structural equation modeling (SEM) analysis is applied to investigate the research model. The measurement model is first examined for instrument validity, followed by an analysis of the structural model for testing associations hypothesized by the research model.

The main findings show that – a) relationship between intelligent automation and agility in capital budgeting is positively significant b) the relationship between intelligent automation and agility in capital budgeting is negatively moderated by demand unpredictability. These findings provide advice to practitioners and decision-makers that one size fits all capital budgeting models are not recommended for projects with increased levels of intelligent automation.

The novel contribution to theory is that ‘Demand unpredictability’ is a useful decision input parameter, which can be counter-intuitive at times when managers allocate capital or prioritize projects during capital budgeting cycles. This suggests that firms need to adapt to hybrid strategies by picking the best-fit approach to allocate capital towards Intelligent Automations or AI projects. It is not necessary to have one size fits all approach for capital budgeting.

This dissertation is dedicated to memory of my father Guruswamy. He always inspired me to invest quality time in gaining knowledge and get better at decision making in life. Though, my mother Sita Bhawani, never went to school, she is one of the most intelligent women I have ever met. She is my motivation for continued education efforts, hoping that I can become as intelligent as her one day. All my family members helped me throughout my academic journey. They always boosted my confidence by saying 'you can do it'. I cannot thank enough my sister Naga Sankari and brothers Hema Kumar and Bhaskar.

I feel blessed to have my lovely wife Deepika by my side as a great friend and strong support all through this journey. Thank you for always lending an ear, sharing your words of wisdom and for tirelessly cheering me on.

My daughter, Nyra, continuously inspires me to expand my knowledge of the world around me by keeping me curious.

ACKNOWLEDGMENTS

I would like to acknowledge and thank my research advisor, Dr. Subodha Kumar of Temple University's Fox School of Business, for the indispensable and invaluable direction, guidance and support he provided over the course of this research effort.

I am also sincerely grateful to my committee members, Dr. Lalitha Naveen, Dr. Sunil Wattal and Dr. Yang Wang, for their guidance, encouragement, and dedication in helping me attain a life-long professional goal.

I wish to thank my best friends Manoj, Manohar, and Raja for the support and encouragement they provided throughout my life in every endeavor.

My deep thanks to all the organizations and their leaders who supported me by participating in the interviews and the survey.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

CHAPTER 1

INTRODUCTION

The history of 'productivity gains' trace back to the concepts of division of labor in a Scottish pin factory during the beginning of industrial revolution. Humans were trained to master specific skills to improve the productivity in a manufacturing line. When industrial robots took over some of the mundane repetitive tasks, the second wave of productivity gains was observed, where human skills are distributed and shared across Humans and Mechanical Robots. Later, with the globalization economic trend, the geography boundaries of a firm are extended across multiple nations. This phenomenon created new human resource types beyond traditional employees, which are contractors, consultants, free-lancers or broadly referred to as gig-economy.

Now, with the latest advancements in technology that moved super computing power from research labs to consumer devices through mobile, cloud, big data and artificial intelligence etc., we see the extension of skills from humans to intelligent automations. An example of Intelligent Automation is the popular chatbots that we interact with, on many websites. Intelligent Automations use a wide range of AI technologies like machine learning, image processing/deep vision, natural language processing and natural language generation.

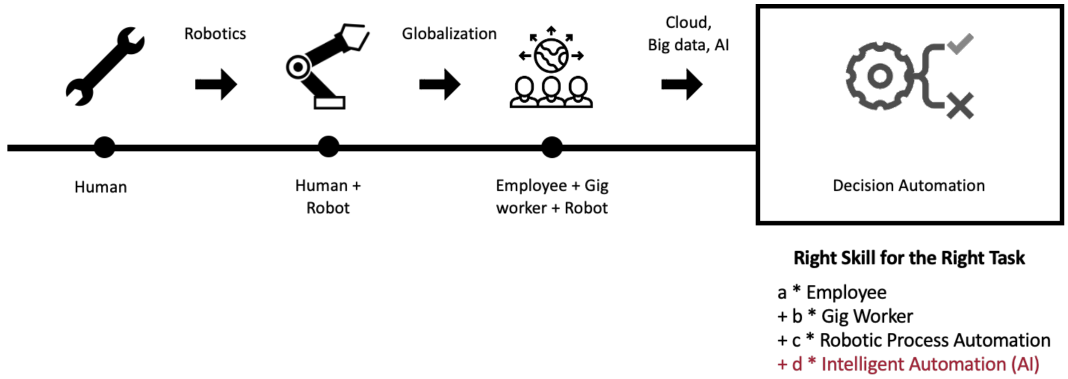


Figure 1. Evolution of Resource Types.

In corporate finance, there are two budgets company need to consider each year. Cash outflows, which are short-term expenses within the year. Capital budget is for deciding how a company wants to invest capital in growing the business long-term. Capital budgeting is the process of determining how to allocate the limited amount of money available for investment. The goal is to buy fixed assets or invest in new opportunities that generate the highest return of investment. Given the evolution of AI as a new resource type in business models, the high-level research question that is framed for this study is – to what extent, capital budgeting helps a manager in improving decision impact towards picking AI projects or intelligent automations?

Contributions

The theoretical contributions of this research would extend our knowledge on the capital budgeting processes of Intelligent Automations, as the approach provides a behavioral study viewpoint, and methodology adopted is exploratory in nature to establish hypothesis. This takes away the prior assumptions and adds new perspective to these critical corporate finance decision-making processes of a firm. From the pilot study, there are new ideas generated where leaders eluded that discretionary funding and traditional approaches are being employed at firms and they do not believe it worked for the Intelligent Automation implementations in few scenarios. This is a gap in the current literature, and it is confirmed in the literature review conducted by Busenbark, et al, (2017) on internal capital allocation research and Nguyen, et al, (2018) on Beyond Budgeting concepts.

The novel contributions to theory are the logical explanations of why traditional and discretionary funding models may not always apply to Intelligent Automations. In addition, the relevance of Beyond Budgeting will also be studied in the context of such Intelligent Automations in knowledge and service work, with key organization design factors taken into account – Flexible structure and Adaptive Processes.

In a recent interdisciplinary literature review (Coombs et al., 2020), these gaps are highlighted that are in the context of this research a) Range and type of tasks targeted for intelligent automations b) level of intelligent automation implemented and c) Linkage of intelligent automation to organizational strategy

Theory

In addition to addressing the literature gaps mentioned above, this research provides theoretical foundation for the following relationships – a) positive correlation between Intelligent Automations and Agility in Capital Budgeting. This indicates that as we increase the levels of automation towards autonomous AI, the capital allocation approach should have increased agility b) counter intuitive Interaction effect of demand unpredictability towards capital budgeting agility of intelligent automations. This suggests that managers should assess fit for purpose capital allocation approach when demand unpredictability increases.

Practice

The study also provides a simplified framework to assess key indicators as input to decide desired agility in capital budgeting – demand unpredictability and levels of automation for Intelligent Automations. This approach provides flexibility to re-allocate and re-prioritize capital during the monitoring period. Due to the cloud technology maturity, the transition of intelligent automation projects from drawing boards to minimum viable products has become faster than before.

CHAPTER 2

STUDY 1: GROUNDED THEORY APPROACH TOWARDS CAPITAL BUDGETING

Research Motivation

The key business phenomenon of interest for this research is capital budgeting in Intelligent Automations. The timing of adoption to new and disruptive technologies is often considered as a competitive action. It becomes critical and significant to understand on how to form and organize work teams in new product or software development that involves a spectrum of skills that can be augmented by humans or artificial intelligence or collective intelligence. These teams may grow or shrink in size within the firm depending on the product's perceived success. It is usually a positive sign for the managers if such teams grow due to the product success and increased demand from market situations. The challenge is when such teams need to shrink or dissolve in cases of failure. There are many internal pressures that managers face in this context. It also adds complexity to capital budget decisions to be made for such investments. An appropriate mix of humans and machines will help in handling the scalability aspect of former scenario and refocus on other priorities in later scenario. We refer to such team as a human+machine team (Paul Daugherty's book Human+Machine) in this study. A study on strategies for capital budgeting with human+machine teams could help in strategic decisions that include investment, re-investment, diversification, timing to drive change and adoption through either sustaining innovation or disruptive innovation.

The target audience for this research are both academicians and practitioners. From academia standpoint, researchers can find the integration of theories and explanations to relationships between traditional and non-traditional budgeting practices as useful tools in extending the knowledge in behavioral accounting theories and human+machine resource allocation models. From practitioner's standpoint, managers can better understand the implications of human+machine teams in strategic capital budgeting decisions and potentially extend these concepts towards evolving modern IT operating models

Research Questions

The primary research question can be stated as – How Intelligent Automations influence the Agility in Capital Budgeting that is needed in knowledge and service work? In order to conduct this study, reality could be constructed by identifying the technology transformation investments (historically) in few corporations and subsequent value realized or lessons learned through the capital budgeting cycles.

The secondary question is - What is the effect of Demand Unpredictability on the need for Agility in Capital Budgeting for Intelligent Automations in knowledge and service work? One such possible explanation could be scarcity in resources with skills needed to perform repetitive and frequently asked questions on a product or business operations, where a chatbot can augment human skills to scale up. A few additional factors could be analyzed through semi-structured interviews with managers on prior investments such as technology debt due to legacy, behavioral attributes of staff, enterprise change drivers, perceived relevance etc. Few other ancillary questions that could be explored during this study are – Can we identify any mediating effect of intelligent automations on demand unpredictability and agility in capital budgeting? What is the direct effect of demand unpredictability on Intelligent Automations? Is there any relationship between demand unpredictability and agility need in capital budgeting? To further these questions and motivation, we could consider the evolution of Artificial Intelligence (AI) technologies in knowledge and service work. As an example, in claims processing, the combination of humans and Intelligent Automation (Ex: chatbots) orchestrate the business process through human touch, machine learning and robotic process automation.

These research questions could lead to managerial insight and develop paths towards new explanations for capital budgeting decision process in the modern work environments. Traditionally, software development leveraged mixed models of employees and contractors, where the human capital can be scaled up or down to meet the software development needs through contractors. From the literature review, it is observed that there is a gap that exists in academic literature with respect to the phenomenon of human+machine teams in business operations with intelligent automations.

The study can also provide strategies and recommendations to practitioners towards a new IT operating model that can be devised with the congruence of thought capitals – humans and intelligent automations. A mixed methods approach will be employed as it will afford the opportunity to collect data in two natural settings to formulate the conceptual framework, test hypotheses (propositions), and delve deep to get a complete picture.

Literature Review

Capital Budgeting

As defined by Lee and Johnson (1998, 16), a budget is a document, or a collection of documents, that refers to the financial conditions, future plans of an organization, including information on revenues, expenditures, activities, and purposes and goals. Capital budgeting is defined as a process by which resources are allocated in the firm; it involves not only objective and quantitative approaches but also subjective and intuitive methods (Solomon, 1963). In many contemporary organizations, budgeting is an important instrument to implement companies' strategies and to fulfil a wide range of further tasks (Hansen et al., 2003)

According to (Mukherjee, 1987), capital budgeting can be viewed as a process that requires several tasks to be performed at different phases. It is a multi-faceted activity and a loopy process with several sequential stages in the process. These stages are:

- Strategic planning—Strategic planning can be defined as an organization's process of defining its strategy or direction and making decisions on allocating its resources to pursue this strategy
- Identification of investment opportunities—Profitable investments emerge from healthy suggestions, so the firms should develop a mechanism wherein the investment suggestions coming from inside the firm, such as from its employees or from outside the firm, such as from a firm's advisors are 'listened and paid attention to' by the management

- Preliminary screening of identified projects—To avoid unnecessary wastage of resources such as time, money and effort, these identified investment opportunities are subjected to a preliminary screening process by the management to isolate the marginal and unsound proposals
- Financial appraisal of screened projects—This involves a detailed analysis of the marketing, technical, financial, economic and ecological aspects of these projects. Financial appraisal involves the application of cash flow forecasting techniques, project evaluation or capital budgeting techniques, risk analysis techniques and even mathematical programming techniques
- Consideration of qualitative factors in project evaluation—This includes factors such as societal impact on employment, environmental impact, safety issues, political attitude towards the project, labor management relationships and legal hassles of the project
- Final accept/reject decision of projects—Finally acceptation or rejection of projects is done based on all collected information coming from the financial appraisal and qualitative results and data, as well as the managers' judgement
- Project implementation—The implementation phase of the project involves setting up of manufacturing facilities, project and engineering designs, negotiations and contracting, construction and training and plant commissioning is done
- Post-implementation audit/project review—Project review helps in providing useful feedback to project appraisal or strategy formulation by analyzing the past 'rights' and 'wrongs'

Investment decisions, that is, investment in new facilities, in new organizational and business processes, in new product lines and their inherent resource commitment are seen as key for the long run performance of the firm and vital in managing strategic change (Northcott, 1991; Emmanuel et al., 2010); thus, they are the basis for profit and value (Ryan and Ryan 2002; Swain and Haka, 2000). An appropriate perspective to address the "how and why" in investment decision-making is provided by institutional theory. According to Meyer and Rowan (1977) and Lawrence (1999), institutional theory is based on how organizations embrace or accept structures, procedures or ideas that are not fundamentally based on "efficiency", but rather on a source of legitimacy outside of the organizational setting. DiMaggio and Powell (1983) further suggest that organizational practices, for example, investment decision-making, may be more influenced by institutional elements (legal requirements), formal and informal pressures and mimetic processes – especially in the context of uncertainty – instead of a rational and purposeful management. Thus, a broader examination, beyond that of the focal actor or organization is mandatory. In the so-called new institutionalism, managerial actions are habits, deeply imbedded in the organization, further creating isomorphic structures (DiMaggio and Powell, 1983).

From Appendix A, although different methods have been designed to improve traditional budgets, previous research suggests that they are still unable to fully eradicate traditional budgeting's weaknesses (Hope and Fraser, 1997; Neely et al., 2003; Player, 2003). Hence, beyond budgeting has been proposed as an alternative coherent management model that enables organizations to manage performance in varying business environments (Hope and Fraser, 2003a). The beyond budgeting concept is based on the 12 principles presented in Appendix B. The first six principles are concerned with creating a flexible organizational structure. Principles 7 to 12 deal with designing an adaptive management process that allows performance management to adapt better to highly competitive environments (Hope and Fraser, 2001).

The essence of beyond budgeting is to abandon traditional budgeting's principles by focusing on relative improvement rather than fixed performance contracts and shifting from top-down control to bottom-up empowerment. Instead of adopting rigid measures and incentives, beyond budgeting focusses on providing power to front-line teams. Thus, this concept is deemed to allow companies to adapt their strategies quickly to changing market requirements. By empowering lower-level managers, the beyond budgeting concept aims to enable companies to maintain close relationships with customers (De Waal, 2005; Hope and Fraser, 2001). Hope and Fraser (2001) further propose that the concept also allows companies to attract and keep talented employees by providing a challenging work environment. In this vein, proponents of the beyond budgeting approach suggest that the performance of employees should be evaluated at the end of each year and that the evaluation should be based on the results that employees could have achieved under the given circumstances of that period (De Waal, 2005). As targets, measures and rewards are aligned with an organization's long-term value rather than short-term profits, beyond budgeting should also allow companies to focus on value creation instead of cost reduction (De Waal, 2005; Hope and Fraser, 2001).

The fact that budgetary decisions are the output of network of interactions among the different actors in the budgetary process (both external and internal) suggests that the budgetary process does not follow a linear path. In other words, the budgetary process is nonlinear though it may appear to be otherwise. This nonlinearity explains why it is so hard to rationalize the budgetary process (Hijal-Moghrabi, I., 2019). The Presence of asymmetric information (Antle, R., et al., 1985) among the several members of the firm, each with individual's own objectives and decisions causes a) organization slack (excess of resources allocated over the min. necessary to accomplish the tasks assigned), b) resource rationing (under allocation of resources i.e. an increase in the amount would generate revenues in excess of its costs) c) stated "cut off rate" for accepting capital projects in firms is often greater than the market rate of interest

Conceptual Foundation

Traditionally, capital budgeting models used human costs in assessing the investment cost against the perceived business value and rate of returns. With the technological advancements in artificial intelligence, low-cost automation is possible through AI bots. Some of the skills can be deployed and performed through autonomous decision capabilities of AI bots. When we form a new team with the combination of humans and AI bots, there are various advantages that can be observed. As an example, for creative quotient and knowledge retention, employees can be leveraged, and in cases of, mundane repetitive processes with pre-defined decision workflows, AI bots can be trained.

Firms can overcome some of the internal challenges they face in a human only team. Also, human limitations can be taken out of the equation when AI could perform the same tasks with minimal downtime and low cost, if an AI is fit for such tasks. As we observe the drift from "workforce planning" to "work planning" in modern workplaces, it becomes critical to represent the resource allocation mix as follows.

Productivity gains through optimal resource mix

Resource Allocation as a function of -

$$\left.\begin{array}{l}\text{a * Employee}\\ \text{+ b * Gig Worker}\end{array}\right\}\ \textbf{Human}$$

$$\left.\begin{array}{l}\text{+ c * Robotic Process Automation}\\ \text{+ d * Cognitive Automation (bots)}\end{array}\right\}\ \textbf{Machine}$$

Right Skill for the Right Task

Figure 2. New Age Resource Model.

In traditional capital budgeting models, the project costs are typically estimated as human full-time equivalents (which are additive in nature and grows/shrinks linearly with humans required) and technology costs (which are also sizable in currency for infrastructure, equipment, software, licenses etc.). This approach works for the a, b and c coefficients described in the above conceptual view of resource mix. When we add AI into this equation, the complexity increases from linear change to a non-linear change. This can be attributed to the facts that AI tasks have self-learning/adjusting capabilities with autonomous decision making (ex: decisions such as reducing compute resources dynamically on cloud for the specific task if it requires less compute) and elastic scalability as needed. Hence, just like humans, AI can be accounted in both liabilities and assets of the total value assessment. And just like software, it can be replicated to perform multiple similar tasks for scalability. Due to these reasons, the capital budget allocation and resource allocation becomes an interesting phenomenon to study and generate directions for new theories, as AI assume the qualities of humans and technology roles.

Contingency theory may provide some explanation of why capital budgeting practices may vary between organizations operating in different contexts (Burns and Stalker, 1961; Otley, 1980). Contingency theory proposes that there is no universal system or operational standard suitable for all organizations in all circumstances (Otley, 1980). According to this theory, organizations operate as open systems, influenced by both external and internal variables (Tikk and Almann, 2011), and as a result, there is no single best way to operate nor is there any management accounting system that is universally applicable to all organizations (Tikk and Almann, 2011; Chen, 2008). Contingency theory can assist in identifying those specific aspects of the organization's accounting systems related to defined circumstances and highlight the suitable matching. Contingent factors can include internal and external factors such as economic constraints, competition, technology, size and type of organization. There are five underlying assumptions of the theory including fit, performance, the existence of rational actors within the organization, equilibrium and a deterministic relationship (Weill and Olson, 1989).

Many existing theories do not lay foundation for AI in the resource allocation and capital budgeting processes as this is a recent phenomenon and trend. Due to the gaps in theories, this research proposal aims to conduct interpretive qualitative study, where content analysis on the transcriptions from interviews with subject matter experts can generate valuable inputs, that can be further used to construct the reality of situations in human+machine teams' context and contribute to academic literature.

Data Collection Methodology

For this proposed research study, a mixed methods approach can be employed. Firstly, semi structured interviews can be conducted to develop the conceptual framework through content analysis. This is mostly qualitative in nature and needs IRB review and approval. Secondly, a quantitative study can be done through experimental or survey design for further data analysis and deductions in Study 2.

Qualitative Study

The perceived gaps in practice, current state understanding, and literature review will help in preparing for the semi structured interviews. Given the research questions, this qualitative study design will allow researcher to explore how capital budgeting decisions are made with human+machine teams.

To analyze data collected from semi-structured interviews, content analysis and conversation analysis will be used. To analyze interview data, the data will be transcribed first. Second, a set of categories of words and phrases (Myers, 2013) will be developed. These codes will then be applied to units of text (Myers, 2013). Third, once the texts have been coded, the researcher will be able to apply various statistical techniques (i.e., descriptive, correlational, and inferential).

The main advantage of content analysis is that it will provide researchers with a structured method for quantifying the contents of this qualitative study (McNabb, 2002). It will be useful for the researchers of this study to look at the frequencies of words and their change in frequency over time. Content analysis will also be useful to analyze historical trends found in email and corporate records at the selected firms.

To further analyze, conversation analysis will also be used to look at the use of language by IT managers. Unlike, content analysis “which tends to assume that the meaning of words is relatively straightforward,” conversation analysis does not presume the existence of fixed meaning in words and idioms (Myers, 2013, p.173). Rather, it assumes that the meanings are shaped in the context of the exchange (Myers, 2013, p. 173). To understand and explain these meanings, the researchers of this study will immerse themselves in the verbal interactions that will be digitally recorded during interview sessions.

Data Analysis

The pilot study included 7 semi-structured interviews. The interview process was kicked off after the interview protocol and consent form were reviewed and approved by IRB. After coding these interview transcripts, the key insights that are generated were three consistent themes (where general agreement on the topics exists from participants) and two conflicting themes (where there is difference in opinions from the participants) at the highest level. The key limitation of this data analysis is the generalizability due to its sample size, given it is a pilot study. The insight generated will help in further refining the interview instrument for conducting the second iteration of interviews and data collection.

Table 1. Summary from semi-structured interviews

		Consistent Themes			Conflicting Themes	
Participant's role at the time of interview	**Interview Length (min)**	**Lack of Data to support Capital Budget Decisions**	**Discretionary pool funding not recommended**	**Lack of adoption due to organization climate**	**Ethics Council to be externalized for review**	**Expectations on IT skills are mostly converging towards AI based**
Chief Data Officer	70	X		X	Both	Mostly
Partner - Business Technology Leader	64			X	Internal - IT	Either Art or AI
IT - Portfolio Manager	60			X	External	
Partner - Business Technology Leader	65	X	X	X	Internal - Business	Forced Expectation
Practice Head - AI and Analytics	67	X		X	Software like approach, no difference	Impractical to the society
Partner - Managing Director	62			X	Both	Mostly
Chief Information Officer	66		X	X	External	Not necessarily

Lack of enough data or models to support the justifications of cost and value during capital investments review process appeared as a consistent theme during this pilot study. Three out of seven participants (43%) eluded to this factor and highlighted that the current models do not take AI bots into account for decision making on cost. They mentioned that project costs are either looked through human lens or technology costs. There is no clarity on how capital expenditure or operational expenditure can be broken down into resource types that include AI bots.

The concept of discretionary pool funding (innovation funding, experimentation funding etc.) is also perceived to be dysfunctional by two out of seven (29%) participants, though they observed this to be a common approach across their clients to drive new age thinking or changes with the name tag of innovation and transformation journeys. The other participants did not bring this topic voluntarily. One of the participants from a Technology Consulting firm, highlighted that there are three underlying challenges that makes this concept less attractive from his experiences. They are

a) It is difficult to make such funding time bound in large firms and often these functions become more operational than building human+machine teams. It also takes a long duration for recruitment and internal communications to set this team up for success

b) These planning cycles are often considered to be annual and not recurring basis. This usually creates constraints to generate impact through desired change

c) The forecast of performance assumes a hockey-stick growth. It is almost impossible to predict the triggering cusp of this hockey-stick as learning abilities of AI bots depend on various factors like datasets, rules defined etc.

The human fear factors that are caused within an organization is the last consistent theme that is observed from all participants. There are 4 categories that one of the participants articulated:

1. 'Burden' of creative, decision & intuitive work
2. Displacement & speed of reskilling
3. Fear of technology hacks
4. Trust in AI

There are two conflicting themes with differences in points of view were observed during the interviews - investing on ethics council or processes and expectations on IT skills in the modern workplace. On cost inputs for ethics front, some participants believe that this should be externalized whereas some believe that it should be internalized. This appears to be a cost component that is not well defined and there are strong arguments on why there should be regulatory agency for such review, given challenges like racial bias etc. become unnoticed which could be either an unexpected bug or anticipated fraud. In software development, the features were deterministically tested, but with AI bots, as learning can be adaptive, debugging and reframing the purpose of AI bot may require advanced skills. This cannot be just considered as a contingency cost. It is articulated as a required resource cost by design.

The second conflicting point is on the expectations on human skills are narrowing towards building machines and AI to perform everything that human do and retain the design skills, arts etc. This convergence expects society and education systems to evolve greatly from the current state models. Some participants thought this is a wrong expectation and they don't see it happening as there should be an existence of human need at varying levels of intelligence and tasks. These conflicting points might need additional literature review and may provide future research recommendations.

One of the participants from Technology consulting articulated that there are three areas where embedding AI becomes relevant – repetitive processes, well-defined measurable outcomes and uncertainty/variability in inputs. As it relates to repetitive processes, the traditional approaches of Capital Budgeting appear to be a fit, where the costs are estimated to be human costs and technology costs. For the second category, well-defined measurable outcomes, the participants alluded to alternate approaches, as the traditional approach is not perceived to be a fit. When there is uncertainty or variability in inputs, the risks involved in pursuing such projects is relatively high and this area has not matured.

One of the interesting outcomes from the interviews is a measure that needs further investigation before conducting further interviews. There was a mention of measuring social interaction that might define the complexity of a human+machine team. It was explained during the interview that, every project needs some level or degree of social interaction. As an example, an AI driven surgery still needs a surgeon to take judgement on edge cases, and design of a new product may need lesser interaction between humans and machines. In either case, there is some degree of social interaction. This can be viewed as human-bot interaction, human-human interaction and bot-bot interaction. This could potentially explain the risks and variability of tasks performed in a human+machine team. Additional literature review is required to identify if there is a pre-existing instrument that can be leveraged for this approach and that can explain the theoretical underpinnings for the capital planning in a human+machine team. The underlying question that needs further exploration is “If we understand the degree of social interaction in a human+machine, to what extent will it improve our predictability and capital planning for a human+machine team”

Limitations of Study 1

The pilot study provided some direction for further analysis and themes to be reviewed regularly to evaluate the theoretical saturation. This will conclude the current study from data collection standpoint as there are no new codes anticipated with the additional interviews. The data analysis, results, discussion and logical inferences contribute to the explanations on current challenges with traditional capital budgeting approach and lay foundations to new or integrated theories/models for alternate approaches. The current literature review included the Better Budgeting and Beyond Budgeting as potential considerations to evaluate as fit for the Human+Machine teams planning cycles.

Although, the insights generated from the pilot study are in alignment with the challenges highlighted in literature review for traditional budgeting processes in the new era of human+machine teams, the size of data is limited to draw any generalizable results and inferences. The virtual/remote nature of the interviews conducted, context of covid-19 pandemic and the competing priorities of interview participants due to unprecedented times are few reasons for the constraints posed in pilot study. These limitations are required to be handled in the next study.

CHAPTER 3

STUDY 2: INTELLIGENT AUTOMATIONS AND CAPITAL BUDGETING

Introduction

The grounded theory approach towards capital planning surfaced few generalizable concepts that can be analyzed further. Instead of looking at the research questions from human+machine team models and AI angle, the new study can focus on Intelligent Automations (Coombs, et al, 2020). Advances in AI and its sub-fields have enabled the development of a new form of automation that we describe as Intelligent Automation (the application of AI in ways that can learn, adapt and improve over time to automate tasks that were formally undertaken by a human). Also, practitioners are more familiar with the concepts of agile theory which summarizes the flexibility and adaptability qualifiers of beyond budgeting. Through empirical results and interviews, it is observed the demand unpredictability has some effect on both degree of intelligent automations and need for agility in capital budgeting process. The proposed research questions for this study are:

Research Question 1: How Intelligent Automations influence the Agility in Capital Budgeting that is needed in knowledge and service work?

Research Question 2: What is the effect of Demand Unpredictability on the need for Agility in Capital Budgeting for Intelligent Automations in knowledge and service work?

From the learnings of Study 1, it is critical to analyze the key concepts – Intelligent Automations, Knowledge and Service Work, Demand Unpredictability and

Agility in capital budgeting. The scope of study II is focused on Intelligent Automations in Knowledge and Service work areas. The focus of this study is primarily to understand the effect of demand unpredictability on degrees of intelligent automations and the desired agility in an enterprise towards capital budgeting processes.

Definitions

Intelligent Automations

The application of AI in ways that can learn, adapt and improve over time to automate tasks that were formally undertaken by a human (Crispin Coombs, et al., 2020). Although automation is an established concept and reflects the replacement of humans by machines, referring to computers automating work does not encapsulate the radical transformation of work that AI may enable. Intelligent Automation differs from previous forms of automation in that AI machines can learn, adapt and improve over time.

Knowledge and Service Work

Cognitive and manual tasks are commonly found in knowledge and service work (Davenport and Kirby, 2016a). Knowledge work is defined as work which is intellectual, creative, and non-routine, and which involves the utilization and creation of knowledge (Hislop et al., 2018). Knowledge work includes work in a wide range of professional areas, such as information and communication, consulting, pharmacology, and education (Kuusisto and Meyer, 2003). Service work can be defined as the process of using one's resources (e.g., knowledge) for someone's (self or other) benefit (Barrett et al., 2015). It includes jobs as diverse as working in retail, security, office cleaning, and more knowledge-intensive work such as consulting. The definition of service work thus includes (white-collar) office and administrative work.

Demand Unpredictability

A dimension of environmental uncertainty which firms strive to reduce (Beckman et al., 2004), the difficulty firms have in predicting the future because of incomplete information or changing conditions. It is a major contributor to overall uncertainty (Davis, 1993; Chen et al., 2000). It can also be described as the degree to which a firm can anticipate or forecast sales and market trends: demand unpredictability is low when sales forecasts and market trends are easier to monitor and predict, while in a highly unpredictable demand environment, sales forecasts and market trends are more difficult to monitor and predict (Celly and Frazier, 1996).

Agility in Capital Budgeting

According to Sherehiy et al. (2007, p. 459) “adaptability”, “flexibility”, and “agility” are used in the research on how organization can cope with unpredicted and dynamically changing environment. Gartner (2006, p. 1) defined agility as “the ability of an organization to sense or create environmental change and respond efficiently and effectively to that change”. From Beyond budgeting literature, “Flexible organization structure” and “adaptive management practices” allows performance management to align better to highly competitive environments (Hope and Fraser, 2001)

Conceptual Model

The grounded theory approach from Study 1 resulted in some key themes for the exploration of Intelligent Automations and Capital Budgeting phenomenon further. An excerpt from the interviews is as follows –

“...The variability in inputs or outputs increases the need for cognitive automation in business operations…”

– Interviewee (Head of AI and Analytics)

Also, from practitioner studies, it is demonstrated how the inherent variability of network traffic can be successfully addressed by self-optimizing methodologies*. The most prominent of them, is based on artificial intelligence, but also makes use of deep modeling insights of the problem. With the above understanding, the following hypothesis can be proposed –

H1: Increase in demand unpredictability increases the levels of intelligent automation

* https://arxiv.org/pdf/1805.12090v1.pdf

As it relates to capital budgeting process, there are few comments from Study I interviews that are key to connect with the established contingent theory.

"...Traditional budgeting is not working for AI projects…"

– Interviewee (Chief Data Officer)

"...leaders are experimenting with uncertainty in capital budgeting as this new space for decision making…"

– Interviewee (Head of AI and Analytics)

To handle contingencies, firms select particular organizational structures to increase adaptability (Miller, 1987). The traditional argument is that adaptability to demand unpredictability is found in more "organic" structures, with less formal control and greater cross-functional integration (Burns and Stalker, 1966; Miles and Snow, 1978; Miller, 1991).

H2: Increase in demand unpredictability increases the need for agility in capital budgeting.

Integration of theories approach can be adopted to connect the concepts Intelligent Automations (Integrated Intelligence by Ulrich Lichtenthaler, 2018) and Agility in Capital Budgeting (Hope, J. and Fraser, R. ,1997). Due to the continued popularity and the way Agile theory evolved to fit different contexts, agile methods have fundamentally changed the way software development projects are organized (Wang et al. 2012; Stavru 2014). Weber and Linder determined in 2008 that especially the characteristic of the dynamic and complexity in the business environment and within the business itself is the crucial factor for the optimal form of budgeting. Beyond Budgeting has, according to Weber and Linder, great advantages in high dynamic conditions which are mainly generated by the fast distribution of resources with the help of internal markets. Software development agility is the ability of an information system development (ISD) method to create change, or proactively, reactively, or inherently embrace change in a timely manner, through its internal components and relationships with its environment (Conboy, 2009). Agility is an organization's ability to sense and respond swiftly to technical changes and new business opportunities (Lyytinen & Rose, 2006).

H3: Higher degree of intelligent automation requires increased agility in capital budgeting.

The Complex Adaptive System Theory (Highsmith, 1999; Vidgen & Wang, 2009) states that complex systems are like living organisms and are made up of multiple interconnected elements and have the capacity to change and learn. These systems should not be viewed as dead, mechanistic, and linear machines. The CAS theory suggests that adaptation is significantly more important than optimization because complex systems cannot be predicted because of their emergent behavior (Meso & Jain, 2006). Emergence is a property of complex adaptive systems that creates some greater property of the whole, and can, thus, cause lack of predictability. The CAS theory does not address key indicators of the projects such as meeting budgetary goals, ensuring cost-benefit of the project, and completing the project in time

H4: Demand unpredictability positively moderates the effect of Intelligent Automations on required agility in capital budgeting

H5: Intelligent Automations positively mediates the effect of Demand unpredictability on desired agility in capital budgeting

The proposed conceptual model for this study is visualized as shown in Figure 3.

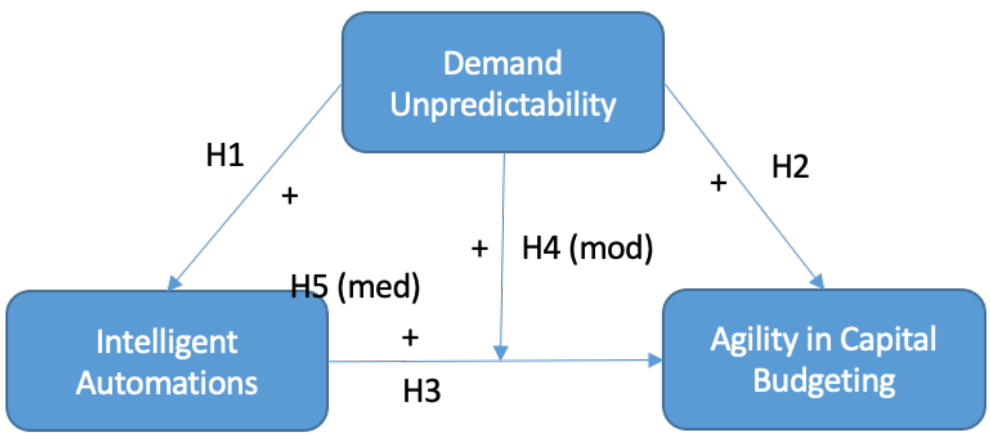


Figure 3. Conceptual Model.

Table 2. Hypothesis Summary

H1	Increase in demand unpredictability increases the levels of intelligent automations
H2	Increase in demand unpredictability increases the need for agility in capital budgeting
H3	Higher degree of intelligent automation requires increased agility in capital budgeting
H4	Demand unpredictability positively moderates the effect of Intelligent Automations on required agility in capital budgeting
H5	Intelligent Automations positively mediates the effect of Demand unpredictability on desired agility in capital budgeting

Data Collection Methodology

From the outcomes of the study, literature review and integration of prior theories discussed above, the conceptual model and the theoretical framework is developed. The proposed hypothesis is tested to validate the established conceptual model, through data collection using a survey approach. The licensed Qualtrics platform is leveraged to manage the entire life cycle of survey from design to data collection.

Measurement Model

The survey questions are developed with the aim towards collecting the data from respondents in an unbiased manner. The universe of survey targets or potential respondents will be kept random to promote fairness in the study and handle few possible biases. The respondents will be segmented based on the relevance to the topic and required behavioral parameters that are subjected to the scope of this study (Q5 and Q6 in appendix c and template 2). After collecting statistically significant responses from the survey, quantitative methods are applied to study the relationship between variables that are defined in the hypothesis. A variety of analytical methods can be applied in this study. It mostly depends on the nature of data, type of analysis, subject area and the quality of data from survey respondents. The measurement approach for the independent and dependent variables is as follows.

Demand Unpredictability

A 7-point semantic differential scales can be used to measure this independent variable (Germain et al., 2008). Respondents will be asked whether:

(1) "User demand is predictable … unpredictable,"

(2) "Demand forecasts are likely to be accurate … inaccurate," and

(3) "Market Trends are easy to monitor … difficult to monitor."

The mean of these three items was taken and the sample was then split as close as possible to the median of the composite score (Calantone et al., 2002). The variable Demand Unpredictability is measured through the above factors that are assessed through survey questions as highlighted in Appendix C - template 2 – Questions 7 through 9.

Intelligent Automations

Human-machine interaction and cooperation can be expressed by various Levels of Automation (LOA) (Sheridan and Verplank 1978) through a 10 – point Ordinal Scale -

1. Low/Remote Control; No assistance from system / Humans decide
2. System offers set of decision alternatives
3. Narrows selection down to few
4. Suggests one alternative
5. Executes the suggestion if human approves
6. Allows human restricted time to veto before automatic execution
7. Executes automatically, informs human

8. Informs human if asked
9. Informs human if the system decides to
10. High/ Fully Autonomous; System acts autonomously, ignores human

Another measurement that will could potentially contribute to the overall effect of demand unpredictability to need for intelligent automations is 'Intent of Adoption'. It is the subjective probability of an individual's engagement in a certain behavior (Fishbein and Ajzen, 1975). Behavioral intention intends to elucidate and envisage the users' acceptance of new technology (Davis, 1989; Martins et al., 2014; Fishbein and Ajzen, 1975; Venkatesh et al., 2003). It is referred to as the help provided by the technology to achieve the targets by using the technology (Burton-jones and Grange, 2013).

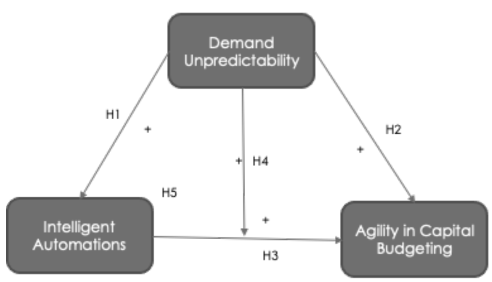
The variable Intelligent Automation is measured through the above factors that are assessed through survey questions as highlighted in the appendix c - template 2 – Questions 10 through 12.

Agility in Capital Budgeting

All items from beyond budgeting principles (Appendix B) that result in agility score can be measured on a 7-point Likert scale. Overall, research suggests that a 7-point scale obtains the most reliable and valid results (Preston and Colman, pp. 2000, 12 f.) and also helps to obtain more variance in responses (Sarstedt and Mooi, 2014, p. 69).

The following are four measurements that will be used for the independent variable – Agility in Capital Budgeting. First, Adaptability measure is derived from Libby et al., 2010, where Beyond Budgeting and Traditional budgeting approaches are evaluated through a survey design. A 7-point semantic differential scale will be used to explain the extent to which it is difficult to set accurate budgets due to unpredictability of factors and increase in obsoleteness as time passes by.

Accountability, Market Awareness and Flexibility are the other 3 measures that are derived from both beyond budgeting literature (Libby et al., 2010) and Enterprise Agility framework (Gunsberg et al., 2018) which is used in software development. These measures also use 7-point semantic differential scale that ranges from strongly disagree to strongly agree. The variable Agility in Capital Budgeting is measured through the above factors that are assessed through survey questions in Appendix C - template 2 – Questions 13 through 18.



Hypothesis	Equation
H1	IA = a0 + a1(DU)
H2	ACB = b0 + b1(DU)
H3	ACB = c0 + c1(IA)
H4	ACB = d0 + d1(DU) + d2(IA) + d3(DU)(IA)
H5	ACB = e0 + e1(IA)

Variable	Type	Description
DU	Independent	Demand Unpredictability
IA	Dependent / Moderator	Level of Intelligent Automations
ACB	Dependent	Agility in Capital Budgeting

Figure 4. Conceptual Model with Linear Regression Equations.

The measurements and survey questions are derived from prior research to ensure the construct validity. The linkage table is provided in appendix d that shows the link between survey instrument and prior literature.

Structural Equation Model

Structural Equation Model (SEM) approach is a series of statistical methods that allow complex relationships between one or more independent variables and one or more dependent variables. Though there are many ways to describe SEM, it is most commonly thought of as a hybrid between some form of analysis of variance (ANOVA)/regression and some form of factor analysis.

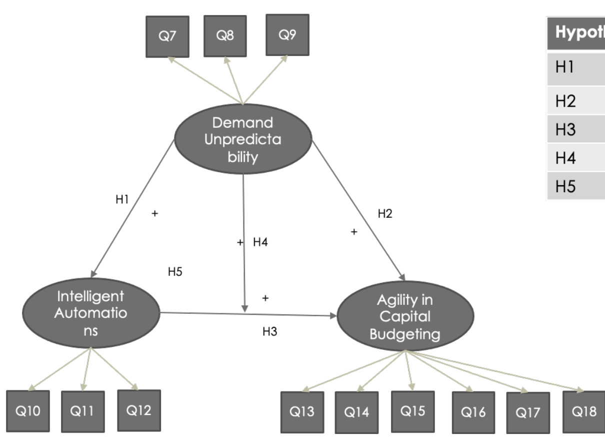
Variables that are not influenced by other variables in a model are called exogenous variables. In this study's measurement model, demand unpredictability (du) and intelligent automations (ia) are exogenous variables. Variables that are influenced by other variables in a model are called endogenous variables, which is agility in capital budgeting (acb) in this study. Variable that is directly observed and measured is called an indicator variable. The indicators in this study are measured through survey questions Q7 through Q18. A variable that is not directly measured is a latent variable. The "factors" in a factor analysis are latent variables. There are 2 latent variables in this study – 'du', 'ia' and 'acb'.

For the purposes of SEM, specifically, moderation refers to a situation that includes three or more variables, such that the presence of one of those variables changes the relationship between the other two. In other words, moderation exists when the association between two variables is not the same at all levels of a third variable. One way to think of moderation is when you observe an interaction between two variables. H4 is required to be setup accordingly to test such interaction. Mediation refers to a situation that includes three or more variables, such that there is a causal process between all three variables. Generally, a mediation model like the one above can be implemented by doing a series of separate regressions.

The primary goal of SEM is to determine and validate a proposed conceptual model. Therefore, SEM is a confirmatory technique. The empirical question of SEM is therefore whether the proposed model produces a population covariance matrix that is consistent with the sample covariance matrix.

Goodness of fit statistics indicates whether the proposed model is appropriate or needs further revision. SEM summarizes if the amount of variance in the DVs – both manifest and latent DVs – is accounted for by the IVs. It also generates the reliability of each measured variables.

The detailed linkage table that provides references to each survey question, construct / latent variable, prior literature and the corresponding hypothesis is provided in Appendix E.



Hypothesis	Equation
H1	IA = a0 + a1(DU)
H2	ACB = b0 + b1(DU)
H3	ACB = c0 + c1(IA)
H4	ACB = d0 + d1(DU) + d2(IA) + d3(DU)(IA)
H5	ACB = e0 + e1(IA)

Latent Variable	Description
DU	Demand Unpredictability
IA	Level of Intelligent Automations
ACB	Agility in Capital Budgeting

Figure 5. Measurement Model for SEM

Data Analysis

The survey responses dataset, which is collected from Qualtrics as comma separated file is imported into r dataframe for data analysis. The survey responses are captured from 21-Nov-2020 to 26-Mar-2021. Total responses in the dataset are 217.

df <- read.csv(file = 'SurveyResponseData_Dissertation_Defense_20201121-20210326.csv')

The dataset is filtered for a) finished survey responses using the Boolean flag field 'Finished'. A value of 1 indicates that the survey is marked as finished by Qualtrics b) non preview survey responses that are used during survey design (Status = 0). This resulted in 166 survey responses after the filtering.

df_finish <- df[which(df$Finished==1 & df$Status==0),]

Sample Size

A CFA/SEM rule of thumb is the ratio of cases to free parameters, or N:q is commonly used for minimum recommendations and 10:1 to 20:1 is a commonly suggested ratio (Schumacker & Lomax, 2015;Kline, 2016;Jackson, 2003). The N:q ratio for this study is 166/12 = 13.83.

Descriptive Statistics

All the survey responses are analyzed by generating summary tables in SPSS without filtering the data. The total survey responses are 217. This summary table provides a quick view of the measured indicators to inspect any unusual responses behavior. There are no specific observations of interest from this table.

Table 3. Descriptive Statistics on Survey Responses

Statistics

		Q7	Q8	Q9	Q10	Q11	Q12	Q13	Q14	Q15	Q16	Q17	Q18
N	Valid	183	179	176	172	170	168	169	168	168	167	167	165
	Missing	34	38	41	45	47	49	48	49	49	50	50	52
Mean		3.37	3.50	3.72	5.31	5.60	4.77	4.82	4.43	5.56	5.59	5.87	5.92
Std. Error of Mean		.118	.125	.129	.105	.096	.168	.105	.126	.090	.099	.083	.081
Std. Deviation		1.598	1.667	1.713	1.382	1.256	2.174	1.370	1.629	1.162	1.281	1.076	1.042
Variance		2.552	2.779	2.933	1.910	1.579	4.727	1.877	2.654	1.350	1.640	1.159	1.085
Skewness		.610	.300	.117	-1.430	-1.669	.309	-.662	-.422	-1.259	-1.411	-1.477	-1.839
Std. Error of Skewness		.180	.182	.183	.185	.186	.187	.187	.187	.187	.188	.188	.189
Kurtosis		-.804	-1.260	-1.284	2.174	3.413	-.562	-.004	-.893	2.476	2.267	3.926	5.613
Std. Error of Kurtosis		.357	.361	.364	.368	.370	.373	.371	.373	.373	.374	.374	.376
Range		6	6	6	6	6	9	6	6	6	6	6	6
Minimum		1	1	1	1	1	1	1	1	1	1	1	1
Maximum		7	7	7	7	7	10	7	7	7	7	7	7
Percentiles	25	2.00	2.00	2.00	5.00	5.00	3.00	4.00	3.00	5.00	5.00	5.00	6.00
	50	3.00	3.00	3.00	6.00	6.00	5.00	5.00	5.00	6.00	6.00	6.00	6.00
	75	5.00	5.00	5.00	6.00	6.00	7.00	6.00	6.00	6.00	6.00	7.00	7.00

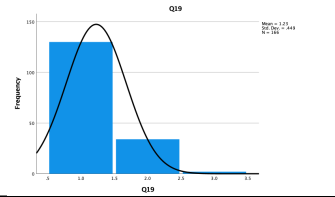
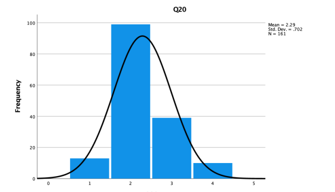
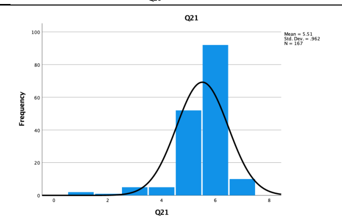
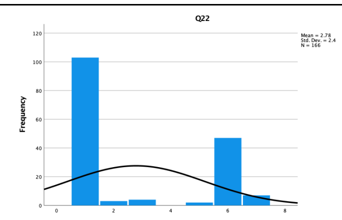
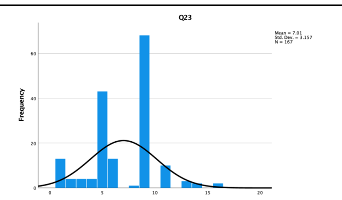
Demographics

The demographic slicing of data is done based on the survey questions related to respondent's gender (Q19), generation (Q20), education level (Q21), ethnicity (Q22) and Industry (Q23). It is observed that majority of the respondents are male under gender, genY under generation, master's degree holders under education level, Asians under ethnicity, and information technology under industry categories. This is self-reported data and not used for testing any additional hypothesis on how these variables could possibly control the proposed model.

The following table shows these survey question responses as summary tables and histograms that helps in visual inspection for any interesting observations. No such observations are made from these survey questions.

Table 4.

Summary Table for Demography Questions

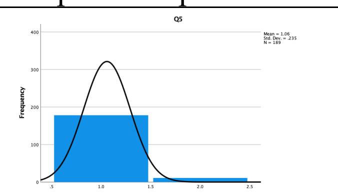
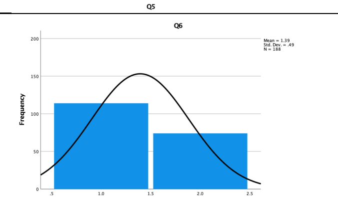
Variable	Survey Question	Summary Table	Graphical Representation
Gender (Q19)	Q19 What Gender do you identify with? Male Female Other	**Q19** N % 1 130 59.9% 2 34 15.7% 3 2 0.9% Missing System 51 23.5% Total 217 100.0%	
Generation (Q20)	Q20 What Generation do you identify with? GenZ: born 1995-2012 GenY: born 1977-1994 GenX: born 1966-1976 Baby Boomer: born 1944-1965 × None of the above	**Q20** N % 1 13 6.0% 2 99 45.6% 3 39 18.0% 4 10 4.6% Missing System 56 25.8% Total 217 100.0%	
Education (Q21)	Q21 What is the highest level of education? Some high school High School Some College Associates Bachelors Masters Doctorate	**Q21** N % 1 2 0.9% 2 1 0.5% 3 5 2.3% 4 5 2.3% 5 52 24.0% 6 92 42.4% 7 10 4.6% Missing System 50 23.0% Total 217 100.0%	
Ethnicity (Q22)	Q22 Ethnicity Asian Black Hispanic Native American Two or More Races White Other	**Q22** N % 1 103 47.5% 2 3 1.4% 3 4 1.8% 5 2 0.9% 6 47 21.7% 7 7 3.2% Missing System 51 23.5% Total 217 100.0%	
Industry (Q23)	Q23 Industry Accounting, Banking, Finance Communications, Marketing, Public Relations Education Government Life Sciences / Pharmaceuticals Healthcare Hospitality Human Capital Consulting Information Technology Legal Management Consulting, Professional Services Non-profit, Charity Sales Shipping, Supply Chain and Logistics Social Services and Assistance None of the above	**Q23** N % 1 13 6.0% 2 4 1.8% 3 4 1.8% 4 4 1.8% 5 43 19.8% 6 13 6.0% 8 1 0.5% 9 68 31.3% 11 10 4.6% 13 3 1.4% 14 2 0.9% 16 2 0.9% Missing System 50 23.0% Total 217 100.0%	

Control Variables

There are two questions that aim to understand the quality of survey responses against the subject matter awareness on intelligent automations and capital budgeting. This data is self-reported, and the assumption is made that it is true for the hypothesis testing. The following table provides summary tables and histograms.

Table 4.

Summary Table to assess subject matter awareness from respondents

<table>
<tr><th>Variable</th><th>Survey Question</th><th>Summary Table</th><th>Graphical Representation</th></tr>
<tr><td>Experience with Intelligent Automations (Q5)</td><td>Q5 Have you ever experienced Intelligent Automations (Artificial Intelligence based automations ex: Chatbots)?
Yes
No</td><td>Q5
<table><tr><th></th><th></th><th>N</th><th>%</th></tr><tr><td>1</td><td></td><td>178</td><td>82.0%</td></tr><tr><td>2</td><td></td><td>11</td><td>5.1%</td></tr><tr><td>Missing</td><td>System</td><td>28</td><td>12.9%</td></tr><tr><td>Total</td><td></td><td>217</td><td>100.0%</td></tr></table></td><td>
</td></tr>
<tr><td>Experience with Capital Budgeting (Q6)</td><td>Q6 Have you ever participated in any firm's capital budgeting process?
Yes
No</td><td>Q6
<table><tr><th></th><th></th><th>N</th><th>%</th></tr><tr><td>1</td><td></td><td>114</td><td>52.5%</td></tr><tr><td>2</td><td></td><td>74</td><td>34.1%</td></tr><tr><td>Missing</td><td>System</td><td>29</td><td>13.4%</td></tr><tr><td>Total</td><td></td><td>217</td><td>100.0%</td></tr></table></td><td>
</td></tr>
</table>

If we drill down into completed and non-preview survey responses (below summary tables), there are 96% of respondents who have experienced an intelligent automation (Q5) and 61% of respondents who have participated in capital budgeting process. Also, 60% (99 out of 166 cases), of the total valid survey responses have experience with both intelligent automations and capital budgeting. This indicates the efforts to generate subject relevant dataset by reaching out to managers via LinkedIn messaging, emails and mturk (special criteria-based HIT), has helped.

Table 5. Cross tabulation of Q6 (ia) and Q7 (acb)

	Q5 - Experience with Intelligent Automations		
Q6 - Involved in Capital Budgeting	No	Yes	Grand Total
No	4	61	65
Yes	2	99	101
Grand Total	6	160	166

	Q5 - Experience with Intelligent Automations		
Q6 - Involved in Capital Budgeting	No	Yes	Grand Total
No	2%	37%	39%
Yes	1%	60%	61%
Grand Total	4%	96%	100%

Dataset Filters

Finished	True
Distribution Channel	anonymous

IV – Demand Predictability (du)

The measured indicators for demand unpredictability follow a 7-point differential semantic scale. The range of values is 1-7. Higher response value (towards 7) indicates higher unpredictability of user demand, forecast accuracy and market trends.

Q7

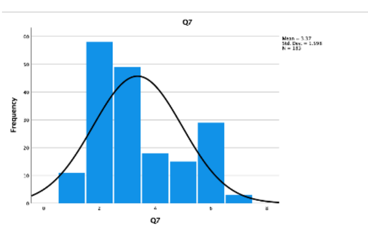
		N	%
1		11	5.1%
2		58	26.7%
3		49	22.6%
4		18	8.3%
5		15	6.9%
6		29	13.4%
7		3	1.4%
Missing	System	34	15.7%
Total		217	100.0%

Q8

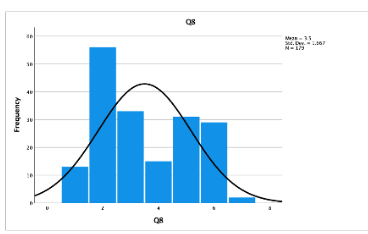
		N	%
1		13	6.0%
2		56	25.8%
3		33	15.2%
4		15	6.9%
5		31	14.3%
6		29	13.4%
7		2	0.9%
Missing	System	38	17.5%
Total		217	100.0%

Q9

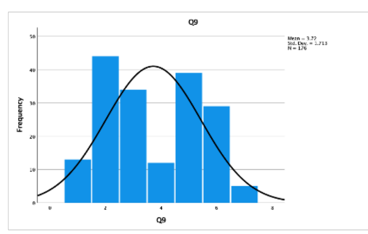
		N	%
1		13	6.0%
2		44	20.3%
3		34	15.7%
4		12	5.5%
5		39	18.0%
6		29	13.4%
7		5	2.3%
Missing	System	41	18.9%
Total		217	100.0%



User Demand



Forecasts Accuracy



Market Trends

Figure 6. Latent Variable - Demand Unpredictability - Descriptive Statistics

IV – Intelligent Automations (ia)

The measured indicators intent to adopt and intent to recommend for intelligent automations follow a 7-point differential semantic scale. The range of values is 1-7. Higher response value (towards 7) indicates higher intent for intelligent automations.

The level of automation is measured on a 10-point scale where highest value indicates autonomous behavior where AI leads the work.

Q10

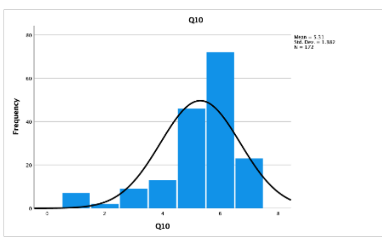
		N	%
1		7	3.2%
2		2	0.9%
3		9	4.1%
4		13	6.0%
5		46	21.2%
6		72	33.2%
7		23	10.6%
Missing	System	45	20.7%
Total		217	100.0%

Q11

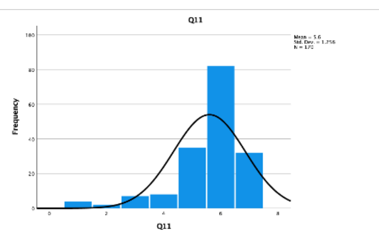
		N	%
1		4	1.8%
2		2	0.9%
3		7	3.2%
4		8	3.7%
5		35	16.1%
6		82	37.8%
7		32	14.7%
Missing	System	47	21.7%
Total		217	100.0%

Q12

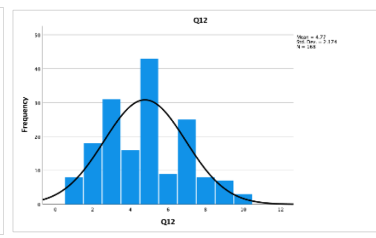
		N	%
1		8	3.7%
2		18	8.3%
3		31	14.3%
4		16	7.4%
5		43	19.8%
6		9	4.1%
7		25	11.5%
8		8	3.7%
9		7	3.2%
10		3	1.4%
Missing	System	49	22.6%
Total		217	100.0%



Intent to Adopt



Intent to Recommend



Level of Automation

Figure 7. Latent Variable - Intelligent Automations Descriptive Statistics

DV – Agility in Capital Budgeting (acb)

The measured indicators Q13 through Q18, for agility in capital budgeting follow a 7-point differential semantic scale. The range of values is 1-7. Higher response value (towards 7) indicates higher agreement on the question.

Q13

		N	%
1		3	1.4%
2		8	3.7%
3		21	9.7%
4		23	10.6%
5		56	25.8%
6		46	21.2%
7		12	5.5%
Missing	System	48	22.1%
Total		217	100.0%

Q14

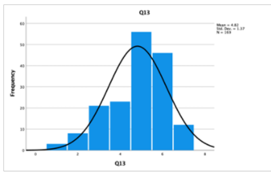
		N	%
1		6	2.8%
2		23	10.6%
3		25	11.5%
4		13	6.0%
5		52	24.0%
6		38	17.5%
7		11	5.1%
Missing	System	49	22.6%
Total		217	100.0%

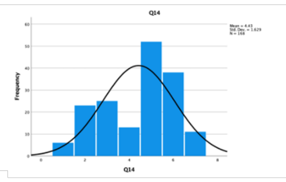
Q15

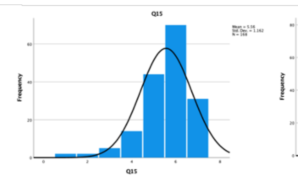
		N	%
1		2	0.9%
2		2	0.9%
3		5	2.3%
4		14	6.5%
5		44	20.3%
6		70	32.3%
7		31	14.3%
Missing	System	49	22.6%
Total		217	100.0%

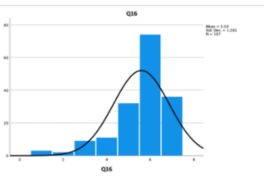
Q16

		N	%
1		3	1.4%
2		2	0.9%
3		9	4.1%
4		11	5.1%
5		32	14.7%
6		74	34.1%
7		36	16.6%
Missing	System	50	23.0%
Total		217	100.0%









Difficulty in accurate allocations

Decreased relevancy over time

"Fast Track" Approvals for unplanned but relevant projects

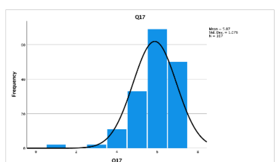
Accountability delegation downwards

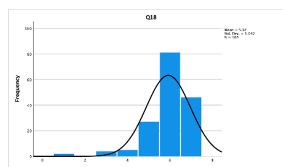
Q17

		N	%
1		2	0.9%
3		2	0.9%
4		11	5.1%
5		33	15.2%
6		69	31.8%
7		50	23.0%
Missing	System	50	23.0%
Total		217	100.0%

Q18

		N	%
1		2	0.9%
3		4	1.8%
4		5	2.3%
5		27	12.4%
6		81	37.3%
7		46	21.2%
Missing	System	52	24.0%
Total		217	100.0%





Resource allocation by quality criteria over cost

Flexibility in deploying resources

Figure 8. Latent Variable - Agility in Capital Budgeting Descriptive Statistics

Indicators – Normality Tests

The multivariate and univariate normality test results indicate that the data is not normal (last column is YES, if it is normal, otherwise NO).

Multi-variate Normality

Description: df[,4] [3 × 4]

Test <chr>	Statistic <fctr>	p value <fctr>	Result <chr>
Mardia Skewness	849.295510467164	8.51833133478445e-41	NO
Mardia Kurtosis	11.4032776789098	0	NO
MVN	NA	NA	NO

3 rows

Univariate Normality

Description: df[,5] [12 × 5]

	Test <S3: AsIs>	Variable <S3: AsIs>	Statistic <S3: AsIs>	p value <S3: AsIs>	Normality <S3: AsIs>
1	Shapiro-Wilk	Q7	0.8669	<0.001	NO
2	Shapiro-Wilk	Q8	0.8826	<0.001	NO
3	Shapiro-Wilk	Q9	0.9042	<0.001	NO
4	Shapiro-Wilk	Q10	0.8228	<0.001	NO
5	Shapiro-Wilk	Q11	0.7908	<0.001	NO
6	Shapiro-Wilk	Q12	0.9522	<0.001	NO
7	Shapiro-Wilk	Q13	0.9156	<0.001	NO
8	Shapiro-Wilk	Q14	0.9100	<0.001	NO
9	Shapiro-Wilk	Q15	0.8583	<0.001	NO
10	Shapiro-Wilk	Q16	0.8350	<0.001	NO
11	Shapiro-Wilk	Q17	0.8358	<0.001	NO
12	Shapiro-Wilk	Q18	0.7919	<0.001	NO

Figure 9. Normality Test of Survey Questions

To achieve normality, there are multiple strategies like filter out outliers etc. As SEM is used in this study that can help analyze non-normal data, there is no need to remove any survey responses or cases to achieve normality.

Indicators - Box Plots

The box plots present a quick summary of the five-point estimates for all measured indicators for the proposed model. The dots indicate outliers (far away from mean). They are observed for six questions - Q10, Q11, Q15, Q16, Q17 and Q18.

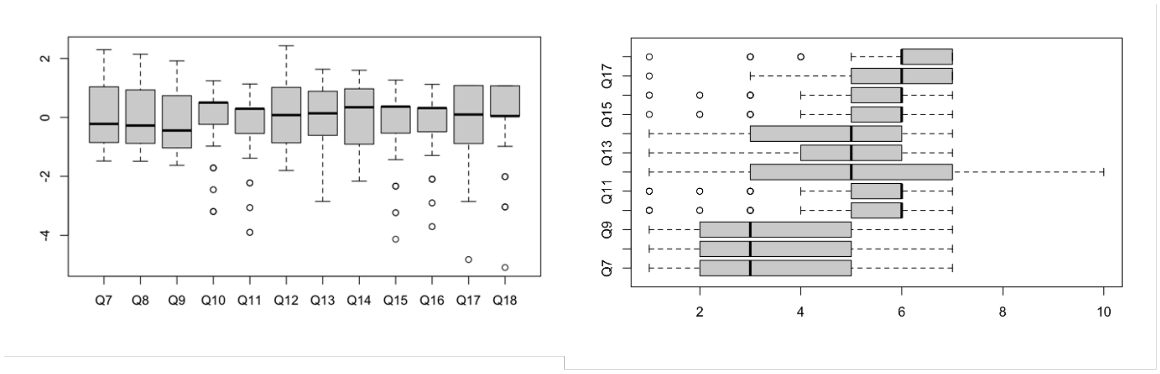


Figure 10. Box Plots of Survey Responses.

Indicators – Histograms

The histograms visually represent the frequencies of survey responses by each question under investigation. This helps in understanding if the data is skewed to right or left by visually inspecting each graph.

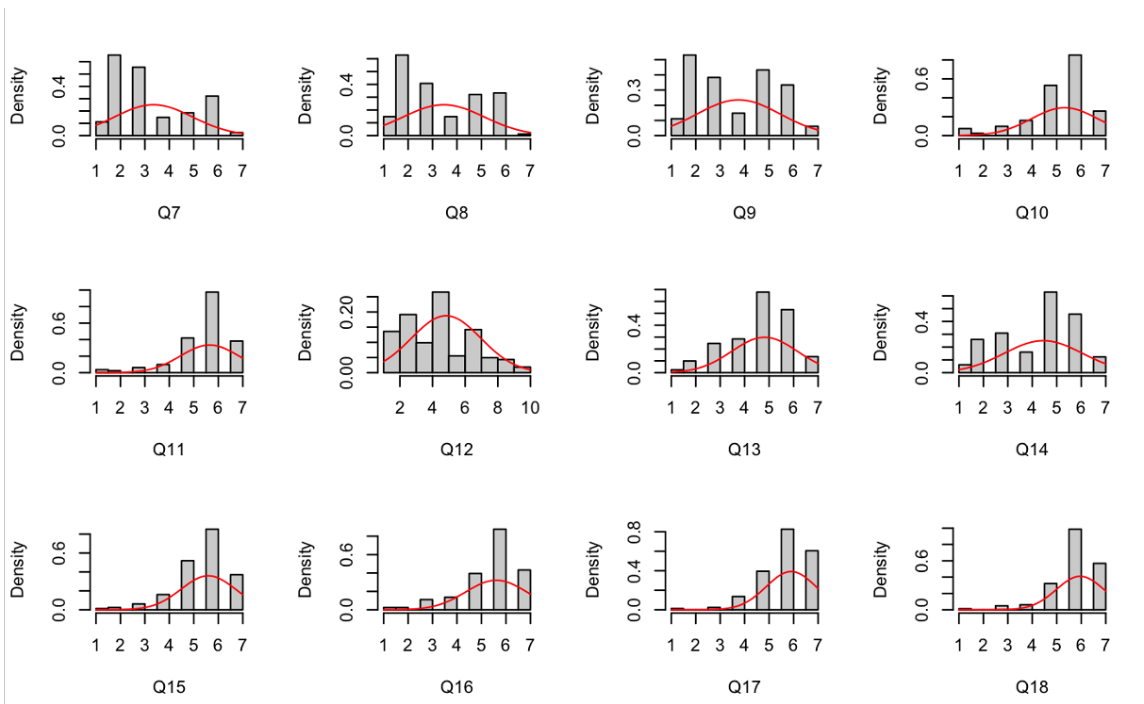


Figure 11. Histograms of Survey Responses.

Indicators - Q-Q Plots

The Q-Q plot, or quantile-quantile plot, is a graphical tool to assess if a set of data plausibly came from some theoretical distribution such as a Normal or exponential. For example, if we run a statistical analysis that assumes our dependent variable is Normally distributed, we can use a Normal Q-Q plot to check that assumption. It's just a visual check, not an air-tight proof, so it is somewhat subjective. But it allows us to see at-a-glance if our assumption is plausible, and if not, how the assumption is violated and what data points contribute to the violation.

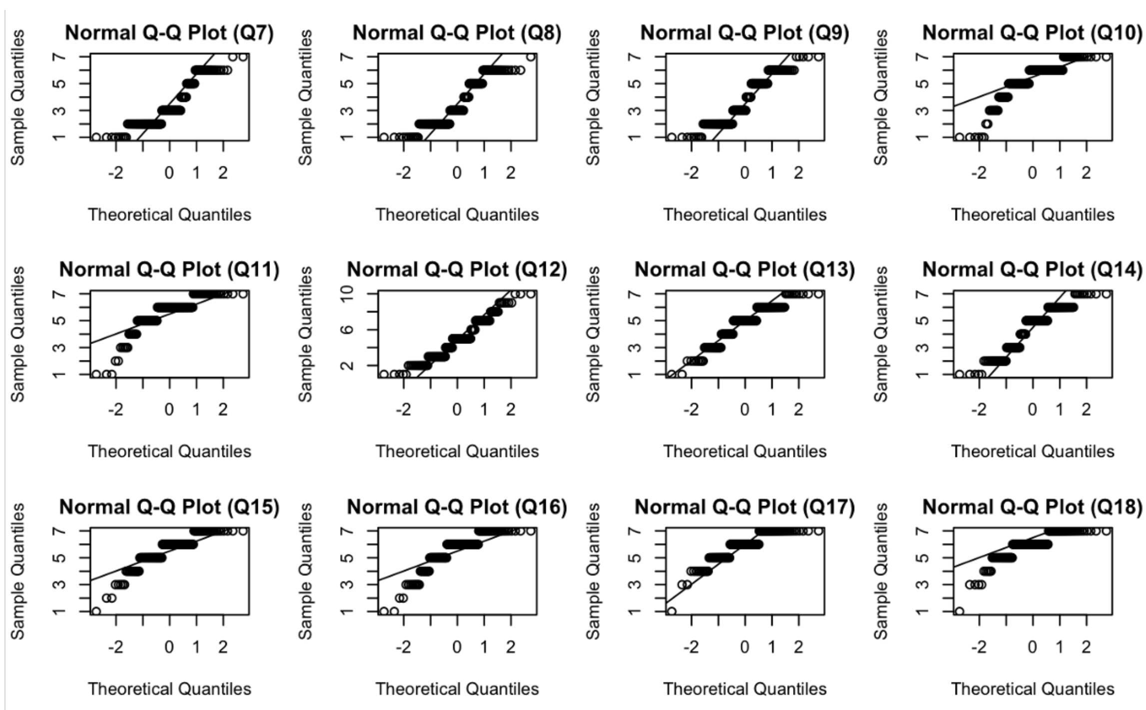


Figure 12. QQ Plots of Survey Responses.

Latent Variables - Normality Test

By adding the predicted values for latent variables from the confirmatory factor analysis (CFA) into dataset, the analysis on latent variables is performed.

idx <- lavInspect(fit, "case.idx")

fscores <- lavPredict(fit)

for (fs in colnames(fscores)) { df_finish.orth[idx, fs] <- fscores[, fs] }

The multivariate and univariate normality test results indicate that the data is not normal, as shown below.

Multi-variate Normality

Description: df[,4] [3 × 4]

Test <chr>	Statistic <fctr>	p value <fctr>	Result <chr>
Mardia Skewness	708.499513253269	3.51926585623413e-137	NO
Mardia Kurtosis	40.7878246085838	0	NO
MVN	NA	NA	NO

3 rows

Univariate Normality

Description: df[,5] [4 × 5]

	Test <S3: AsIs>	Variable <S3: AsIs>	Statistic <S3: AsIs>	p value <S3: AsIs>	Normality <S3: AsIs>
1	Shapiro-Wilk	du	0.9437	<0.001	NO
2	Shapiro-Wilk	ia	0.8644	<0.001	NO
3	Shapiro-Wilk	acb	0.8797	<0.001	NO
4	Shapiro-Wilk	mod	0.8019	<0.001	NO

4 rows

Figure 13. Normality test for latent variables

Latent Variables – Box Plots

The box plots demonstrates that the independent variable ia, dependent variable acb and the interaction effect of (ia * du) have outliers in the estimates from CFA.

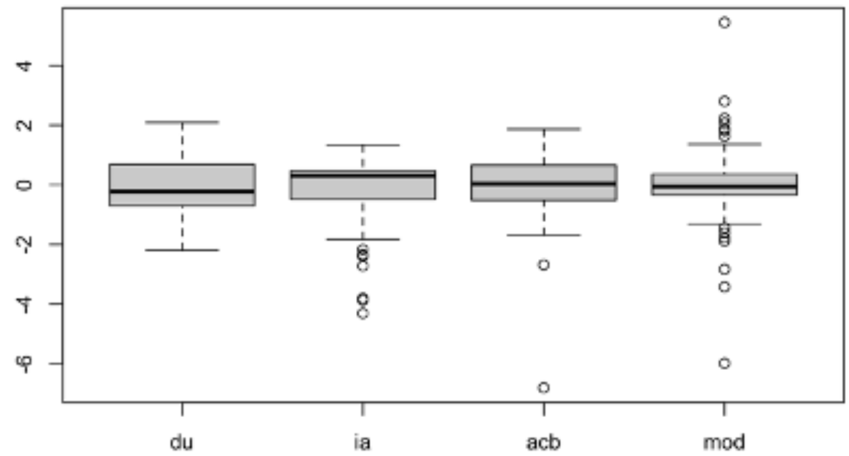


Figure 14. Box Plot of Latent Variables

Latent Variables -Histograms

The histograms for ia, du, acb and moderator confirm the non-normality of these variables in the conceptual model.

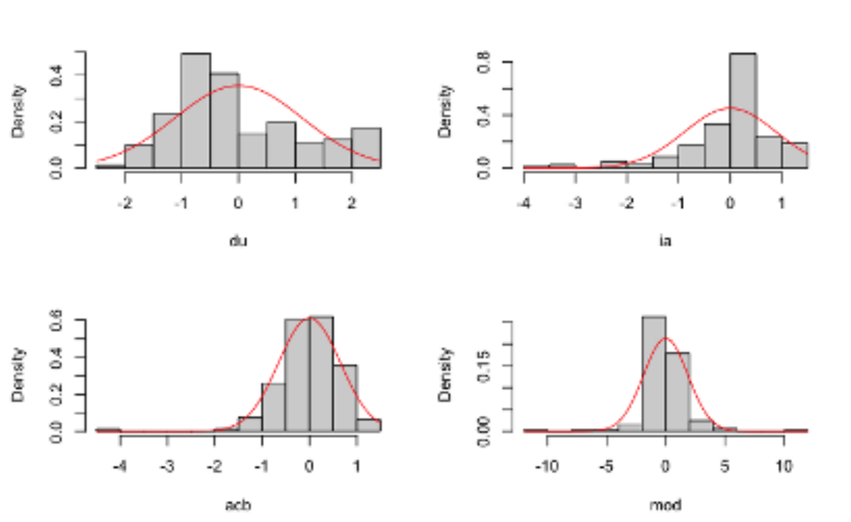


Figure 15. Histograms of Latent Variables

Latent Variables – Q-Q Plots

The Q-Q plot shows stronger correlation between theoretical and sample quantiles for acb only. If required, this variable can be converted into a normal indicator. Given the SEM approach adopted, there is no such need to remove any outliers. Normality is preferable but not a mandatory assumption for SEM.

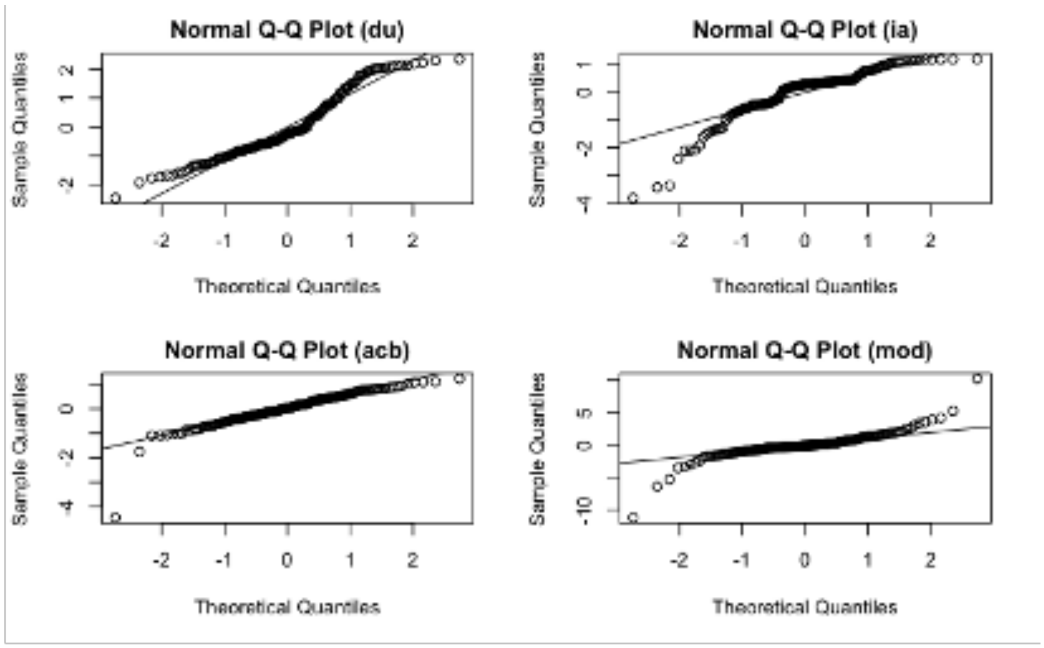


Figure 16. QQ Plots of Latent Variables.

Reliability Test

Cronbach's α is a measure of internal consistency, that is, how closely related a set of items are as a group. It is considered to be a measure of scale reliability. Cronbach's α of the identified constructs is above the threshold value of 0.6 suggested by Nunally (1978) for all constructs, therefore confirming convergent validity.

Scale: ALL VARIABLES

Case Processing Summary

		N	%
Cases	Valid	163	75.1
	Excluded[a]	54	24.9
	Total	217	100.0

a. Listwise deletion based on all variables in the procedure.

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.700	.746	12

Item Statistics

	Mean	Std. Deviation	N
Q7	3.34	1.596	163
Q8	3.44	1.660	163
Q9	3.74	1.703	163
Q10	5.29	1.392	163
Q11	5.62	1.243	163
Q12	4.81	2.142	163
Q13	4.79	1.367	163
Q14	4.43	1.614	163
Q15	5.56	1.166	163
Q16	5.58	1.290	163
Q17	5.87	1.084	163
Q18	5.93	1.046	163

Figure 17. Reliability Test and Cronbach's alpha.

The questions Q7 – Q18 have relatively high internal consistency. This is acceptable in most social sciences research situations.

SEM Path Analysis

The survey response dataset is filtered for completed survey responses. To test the moderation effect that is hypothesized in the conceptual model, the latent variables 'demand unpredictability' and 'intelligent automation' are orthogonalized (Little, T.D., et al (2006)). This will later help in testing the interaction of demand unpredictability on the intelligent automation's effect on desired agility in capital budgeting.

The R Package Lavaan is used to conducted SEM path analysis. It is a 2 -step process. First, the conceptual model is required to be setup for measurements, regressions, defined variables etc.

````
```{r conceptualModel, echo=FALSE}
model <- '
 # Measurement Model - Latent Variables
  du =~ Q7 + Q8 + Q9
  ia =~ Q10 + Q11 + Q12
  acb =~ Q13 + Q14 + Q15 + Q16 + Q17 + Q18
  mod =~ Q7.Q10 + Q7.Q11  + Q8.Q10 + Q8.Q11  + Q9.Q10 + Q9.Q11  + Q9.Q12 + Q7.Q12 + Q8.Q12
 # Regressions
  ia ~ a*du
  acb ~ b1*ia + b2*du + b3*mod
 # Direct Effect of du on acb
  direct := b2
 # Indirect Effect (a*b1)
  indirect := a*b1
 # Total Effect
  total := b2+(a*b1)
'
```
````

Figure 18. Measurement Model setup in R Program.

Second, the model is run against the dataset by leveraging the function sem() and store the results (fit) for further analysis or inspection.

fit <- sem(model, data=df_finish.orth, estimator = "DWLS")

In confirmatory factor analysis (CFA), the use of maximum likelihood (ML) as default estimator, assumes that the observed indicators follow a continuous and multivariate normal distribution, which is not appropriate for ordinal observed variables. Diagonally weighted least squares (DWLS), on the other hand, is specifically designed for ordinal data. Due to the nature of survey response data (Li, CH (2016)), default estimator 'ML' does not give meaningful results. The measured values are ordinal and continuous data.

semPaths(fit, "std", "hide")

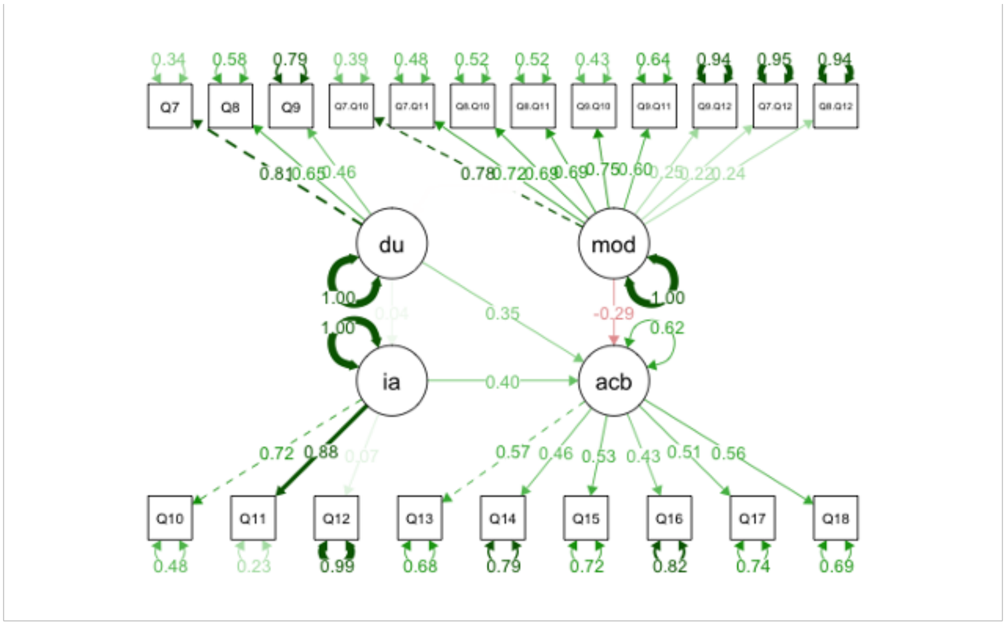
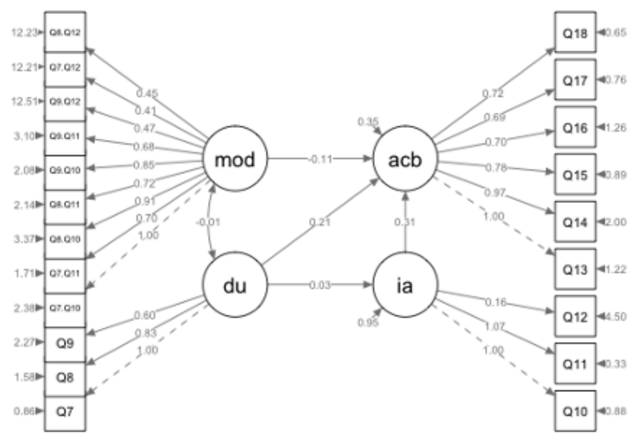


Figure 19. SEM output

Christine, et al (2014) study compared diagonal weighted least squares robust estimation techniques available in 2 popular statistical programs: diagonal weighted least squares (DWLS; LISREL version 8.80) and weighted least squares–mean (WLSM) and weighted least squares—mean and variance adjusted (WLSMV; Mplus version 6.11). Both DWLS and WLSMV produced accurate parameter estimates

semPaths(fit, what="paths",whatLabels="par",style="lisrel",layout="tree", rotation=2)



Construct's Convergent Validity

Construct validity will be assessed in terms of significance of factor loadings and magnitude of factor loadings (Mahapatra et al., 2012). To confirm Convergent validity, the loadings should indicate that all standardized loadings are greater than 0.5 and highly significant (p-value < 0.05).

```
lavaan 0.6-8 ended normally after 99 iterations

  Estimator                                         DWLS
  Optimization method                             NLMINB
  Number of model parameters                          47

                                                    Used       Total
  Number of observations                             162         166

Model Test User Model:

  Test statistic                                 128.556
  Degrees of freedom                                 184
  P-value (Chi-square)                             0.999

Model Test Baseline Model:

  Test statistic                                 538.379
  Degrees of freedom                                 210
  P-value                                          0.000

User Model versus Baseline Model:

  Comparative Fit Index (CFI)                      1.000
  Tucker-Lewis Index (TLI)                         1.193

Root Mean Square Error of Approximation:

  RMSEA                                            0.000
  90 Percent confidence interval - lower           0.000
  90 Percent confidence interval - upper           0.000
  P-value RMSEA <= 0.05                            1.000

Standardized Root Mean Square Residual:

  SRMR                                             0.088
```

Latent Variables:

	Estimate	Std.Err	z-value	P(>|z|)	Std.lv	Std.all
du =~						
Q7	1.000				1.292	0.813
Q8	0.830	0.203	4.082	0.000	1.073	0.649
Q9	0.602	0.150	4.015	0.000	0.778	0.459
ia =~						
Q10	1.000				0.975	0.720
Q11	1.071	0.415	2.580	0.010	1.045	0.876
Q12	0.162	0.168	0.965	0.335	0.158	0.074
acb =~						
Q13	1.000				0.758	0.566
Q14	0.974	0.206	4.727	0.000	0.738	0.462
Q15	0.781	0.172	4.530	0.000	0.592	0.532
Q16	0.703	0.167	4.212	0.000	0.533	0.429
Q17	0.689	0.156	4.410	0.000	0.522	0.513
Q18	0.717	0.162	4.419	0.000	0.543	0.558
mod =~						
Q7.Q10	1.000				1.936	0.782
Q7.Q11	0.701	0.164	4.263	0.000	1.357	0.720
Q8.Q10	0.911	0.196	4.653	0.000	1.763	0.693
Q8.Q11	0.720	0.171	4.213	0.000	1.393	0.689
Q9.Q10	0.850	0.187	4.549	0.000	1.645	0.752
Q9.Q11	0.675	0.160	4.210	0.000	1.308	0.596
Q9.Q12	0.466	0.134	3.487	0.000	0.902	0.247
Q7.Q12	0.412	0.131	3.145	0.002	0.797	0.222
Q8.Q12	0.449	0.134	3.343	0.001	0.870	0.241

Figure 20. Convergent Validity.

Construct's Discriminant Validity

To confirm Discriminant validity, the correlations are calculated among latent variables. If there are some high values in the correlations of independent variables, variance inflation factor (VIF) helps to confirm multi-collinearity.

Description: df[,3] [3 × 3]

Variables <chr>	Tolerance <dbl>	VIF <dbl>
du	0.9977724	1.002233
ia	0.9977738	1.002231
mod	0.9999971	1.000003

3 rows

Figure 21. Discriminant Validity and multi-collinearity test.

From the above table, both tolerance and VIF are not a concern between du, ia and mod (interaction effect du*ia).

The below correlation matrix provides ability to visually inspect the data for any patterns and subsequent plots provide inside into influencer data points, outlier data points etc. Due to SEM approach, there is no further filtering of data applied.

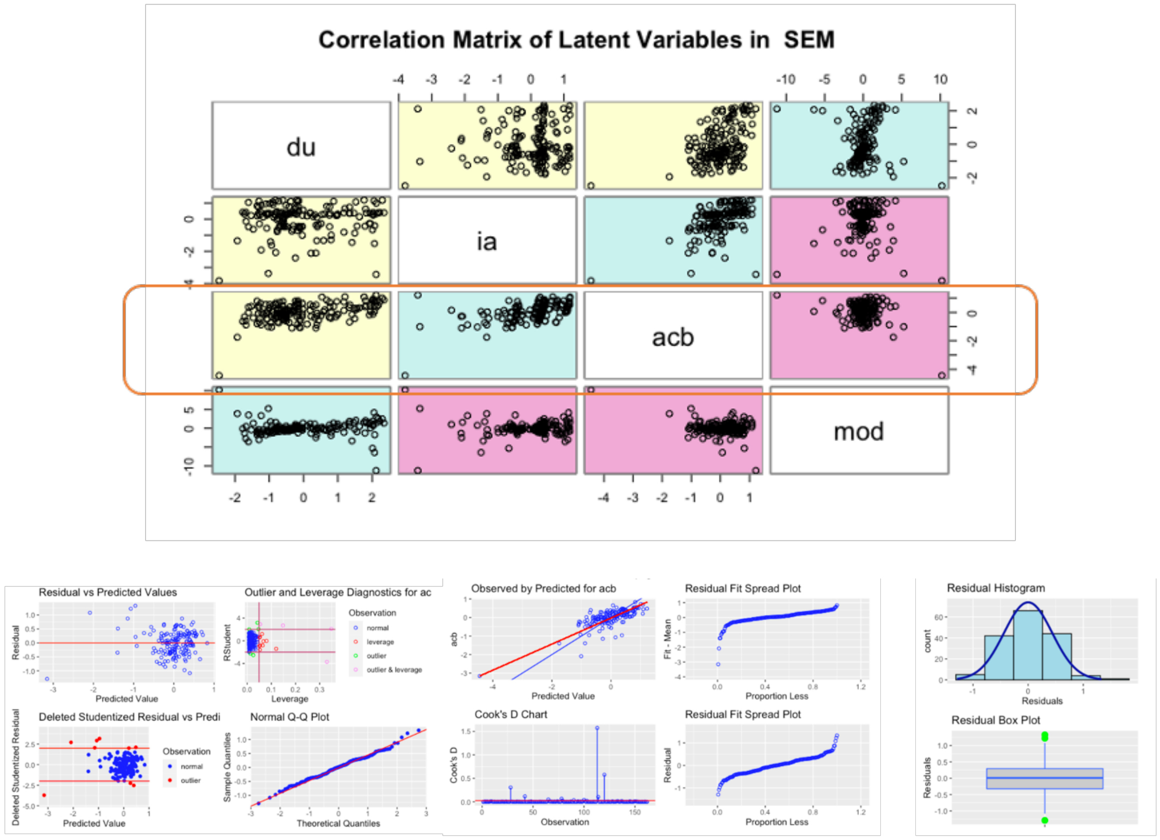


Figure 22. Correlations between latent variables.

Correlations

The following table provides correlation coefficients that explain the strength and direction of correlation between the latent variables. The correlation between ia and du is 0.05 which indicates that there is almost no correlation between these variables.

The dependent variable acb is positively and moderately correlated to both ia and du. At the same time, acb is negatively and moderately correlated to the interaction effect of ia * du. From the prior VIF values, there is no multi-collinearity between these three variables – ia, du and mod.

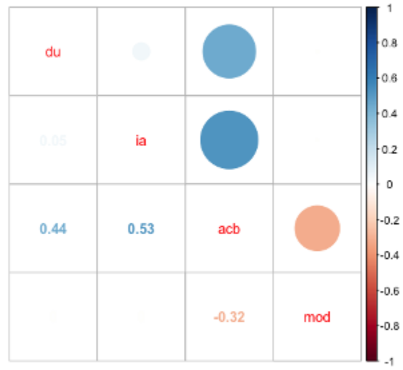


Figure 23. Correlation Summary between latent variables.

The +ve correlation of ia on acb is visually confirmed by the following xy scatter plot.

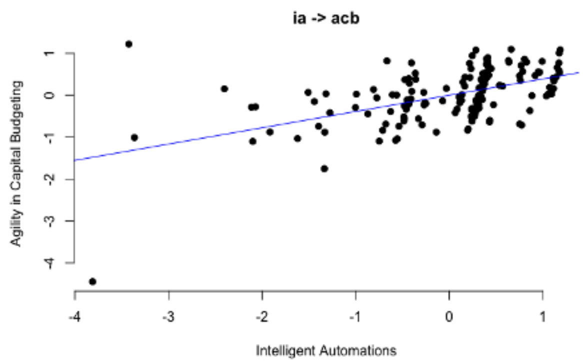


Figure 24. Correlation between Intelligent Automations and Agility in Capital Budgeting.

The lack of correlation between du and ia is visually confirmed by the following xy scatter plot.

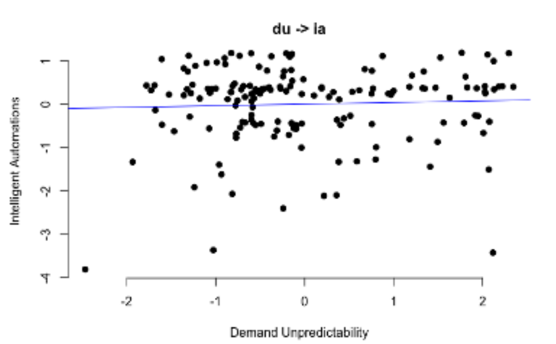


Figure 25. Correlation between Demand Unpredictability and Intelligent Automations.

The +ve correlation of du on acb is visually confirmed by the following xy scatter plot.

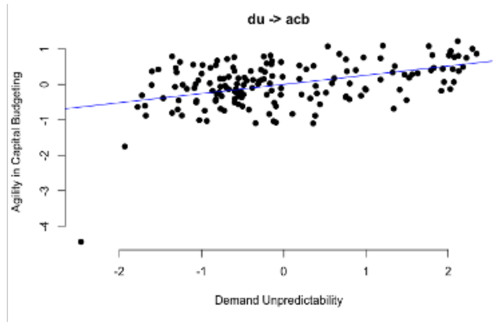


Figure 26. Correlation between Demand Unpredictability and Agility in Capital Budgeting.

The -ve correlation of du*ia on acb is visually confirmed by the following xy scatter plot.

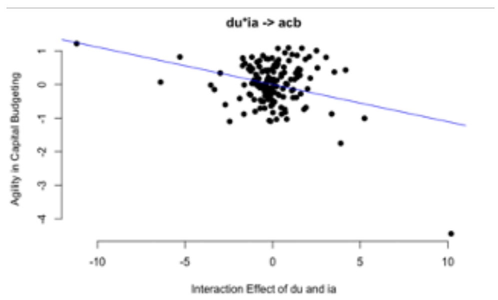


Figure 27. Correlation between integration effect of du and ia against Agility in Capital Budgeting.

Hypothesis Testing

From the summary of SEM path analysis, the regression outputs can be interpreted to evaluate the established hypothesis.

print(summary(fit, fit.measures=TRUE, standardized=TRUE))

For simplicity, the below table is constructed from the sem() output that shows hypothesis, regression, coefficient estimate from sem analysis, p-value and the inferences on hypothesis testing.

Table 6. Hypothesis Testing - Results

	Regression	Estimate	P(>|z|)	Statistical Correlation
h1	Ia ~ a*du	a = 0.031	0.543	
h2	acb ~ b2*du	b2 = 0.207	0.001	Positive and Moderate correlation
h3	acb ~ b1*ia	b1 = 0.314	0.008	Positive and Moderate correlation
h4	acb ~ b2*du + b1*ia + b3*du*ia	b3 = -0.113	0.001	Negative and Moderate correlation
h5	Indirect effect: a*b1	a*b1 = 0.010	0.533	

For H1 and H5, the p-value > 0.05. This indicates that the data suggests rejecting these hypotheses. This means, it is unable to establish statistical evidence that demand unpredictability positively correlates to intelligent automations (H1). It is also unable to establish statistical significance that intelligent automations mediate the effect of demand unpredictability on agility in capital budgeting.

For H2, H3 and H4, the p-value < 0.05. This indicates that the data suggests that we cannot reject these hypotheses. The coefficient for moderation effect is -ve which indicates that increase in demand unpredictability reduces the effect of intelligent automations on the agility in capital budgeting.

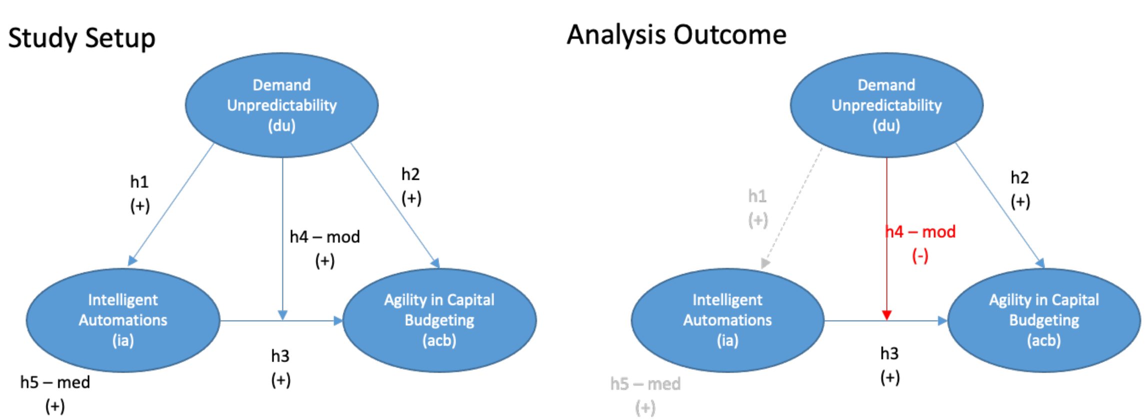


Figure 28. Study Results – Hypothesis.

Goodness of Fit

For analysis of fit measures, Kline suggests that at a minimum the following indices should be reported: 1) The model chi-square 2) RMSEA 3) CFI 4) SRMR

```
➢ fitMeasures(fit, c("chisq","df","pvalue","gfi","agfi","nfi", "nnfi","cfi","rmsea","srmr"))
```

chisq	df	pvalue	gfi	agfi	nfi	nnfi	cfi	rmsea	srmr
128.556	184.000	0.999	0.934	0.917	0.761	1.193	1.000	0.000	0.088

To inspect all the fit measures, following r command can be used.

fitMeasures(fit)

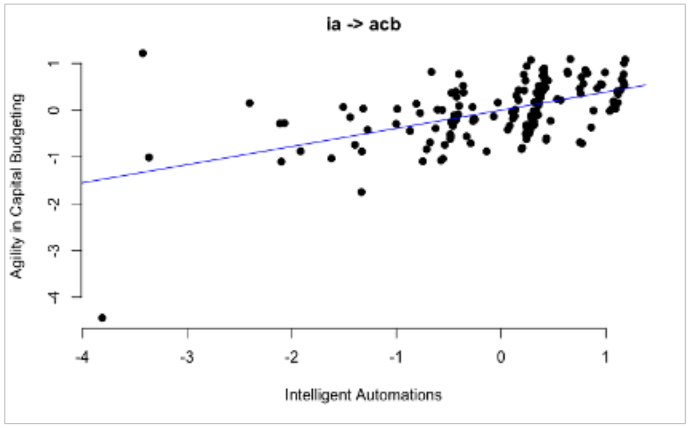
Measure	Name	Description	Cut-off for good fit	Model Output
X_2	Model Chi- Square	Assess overall fit and the discrepancy between the sample and fitted covariance matrices. Sensitive to sample size. H_0: The model fits perfectly.	p-value> 0.05	pvalue = 0.999
(A)GFI	(Adjusted) Goodness of Fit	GFI is the proportion of variance accounted for by the estimated population covariance. Analogous to R_2. AGFI favors parsimony.	GFI ≥ 0.95 AGFI ≥0.90	GFI = 0.934 AGFI = 0.917
(N)NFI TLI	(Non) Normed- Fit Index Tucker Lewis index	An NFI of .95, indicates the model of interest improves the fit by 95% relative to the null model. NNFI is preferable for smaller samples. Sometimes the NNFI is called the Tucker Lewis index (TLI)	NFI ≥ 0.95 NNFI ≥ 0.95	NFI = 0.761 NNFI = 1.193
CFI	Comparative Fit Index	A revised form of NFI. Not very sensitive to sample size. Compares the fit of a target model to the fit of an independent, or null, model.	CFI ≥.90	CFI = 1.000
RMSEA	Root Mean Square Error of Approximation	A parsimony-adjusted index. Values closer to 0 represent a good fit.	RMSEA < 0.08	RMSEA = 0.000
(S)RMR	(Standardized) Root Mean Square Residual	The square-root of the difference between the residuals of the sample covariance matrix and the hypothesized model. If items vary in range (i.e. some items are 1-5, others 1-7) then RMR is hard to interpret, better to use SRMR.	SRMR <0.08	SRMR = 0.088

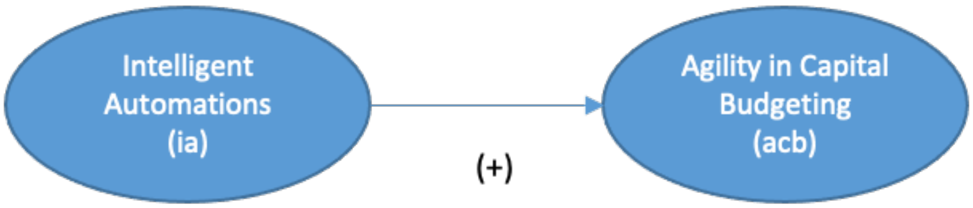
Figure 29. Goodness of Fit for SEM.

In summary, the model demonstrates a good fit as per the fit measures reported through lavaan package output.

Empirical Findings

The relationship between intelligent automation and agility in capital budgeting is positively significant (p-value < 0.05), indicating that the hypothesis (ia -> acb) cannot be rejected. The correlation coefficient is 0.53. This indicates a positive and moderate effect (which is between 0.3 and 0.7) of intelligent automations on agility in capital budgeting for knowledge and service work. This interpretation addresses the research question - *How Intelligent Automations influence the Agility in Capital Budgeting that is needed in knowledge and service work?*





Regressions:

		Estimate	Std.Err	z-value	P(>|z|)	Std.lv	Std.all
ia ~							
du	(a)	0.031	0.051	0.608	0.543	0.041	0.041
acb ~							
ia	(b1)	0.314	0.119	2.633	0.008	0.404	0.404
du	(b2)	0.207	0.061	3.367	0.001	0.353	0.353
mod	(b3)	-0.113	0.033	-3.399	0.001	-0.288	-0.288

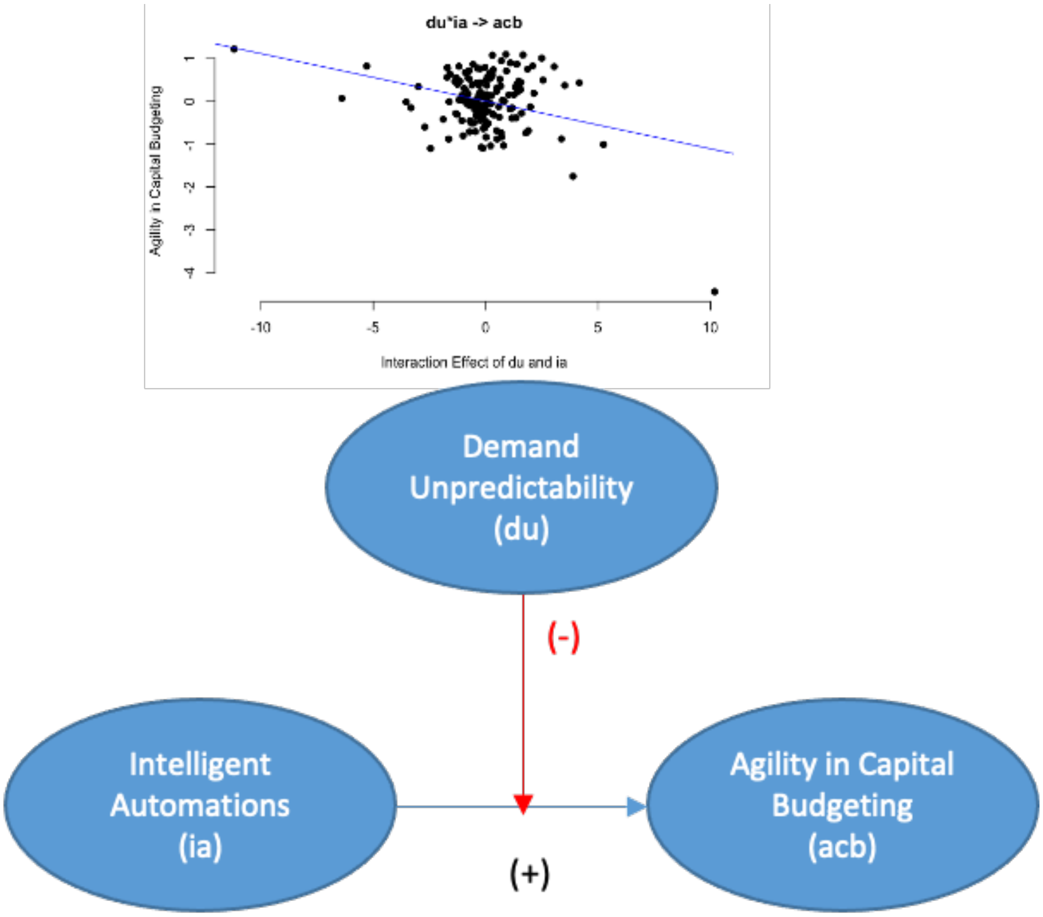
Defined Parameters:

	Estimate	Std.Err	z-value	P(>|z|)	Std.lv	Std.all
direct	0.207	0.061	3.367	0.001	0.353	0.353
indirect	0.010	0.016	0.623	0.533	0.017	0.017
total	0.217	0.061	3.541	0.000	0.369	0.369

Figure 30. Finding 1 - Positive correlation effect of Intelligent Automations on Agility in Capital Budgeting.

The study did not result in sufficient evidence for a positive mediating effect of Intelligent Automations on Demand unpredictability and agility in capital budgeting (du -> ia -> acb).

The relationship between intelligent automation and agility in capital budgeting is negatively moderated by demand unpredictability (p-value < 0.05), indicating that the hypothesis (du moderates, ia -> acb) cannot be rejected. The correlation coefficient is -.32. This indicates a negative and moderate effect (which is between 0.3 and 0.7) of demand unpredictability on intelligent automations and agility in capital budgeting for knowledge and service work. This interpretation addresses the research question - *What is the effect of Demand Unpredictability on the need for Agility in Capital Budgeting for Intelligent Automations in knowledge and service work?*



Regressions:

		Estimate	Std.Err	z-value	P(>|z|)	Std.lv	Std.all
ia ~							
du	(a)	0.031	0.051	0.608	0.543	0.041	0.041
acb ~							
ia	(b1)	0.314	0.119	2.633	0.008	0.404	0.404
du	(b2)	0.207	0.061	3.367	0.001	0.353	0.353
mod	(b3)	-0.113	0.033	-3.399	0.001	-0.288	-0.288

Figure 31. Finding 2 - Negative Interaction effect of Demand unpredictability on agility in capital budgeting of Intelligent Automations.

CHAPTER 4

DISCUSSION

Effect of Intelligent Automations on Agility in Capital Budgeting

The project proposals for capital budgeting decisions involve few cost components that have become obsolete over time. This is due to the maturity in cloud technologies. In earlier days, when complex computing is required (super computers) to accomplish an automation task, then the costs involved buying hardware, setting up staff to manage the hardware and related software etc. Most of these cost components have transitioned to pay per use models with cloud computing. A data scientist can spin up a cluster of supercomputing with few clicks and payment card details. This also provides flexibility towards using such expensive compute resources for the needed duration only. Why is it possible to have agility in capital budgeting now, as opposed to in past?

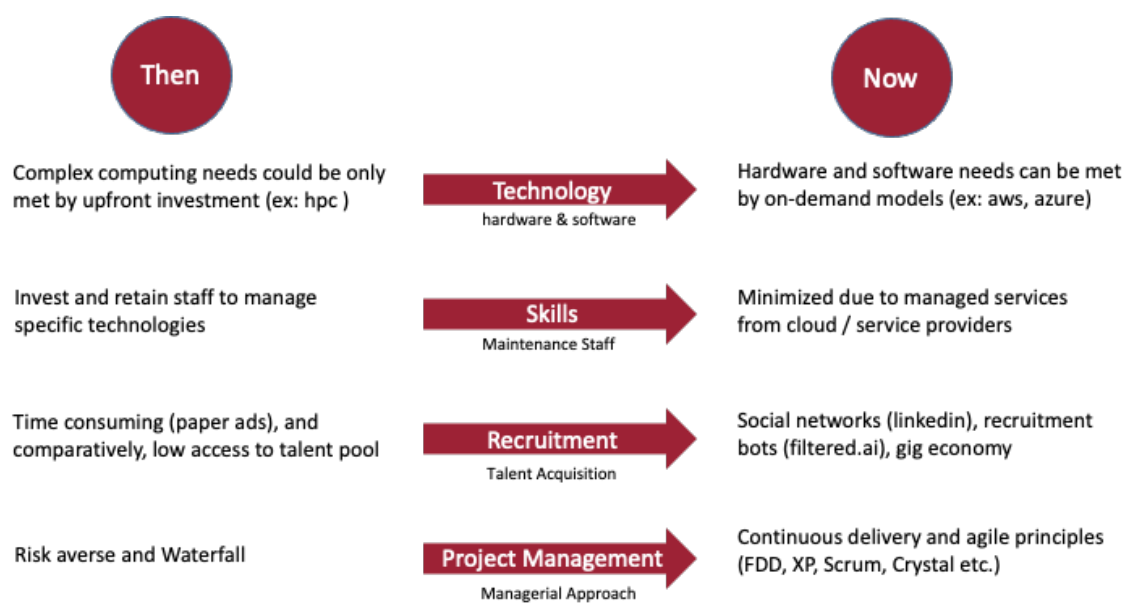


Figure 32. Explanation on Finding 1 (figure 30)

Given the circumstances described above, it builds a case to embrace agility in capital budgeting for increased intelligent automation levels. An illustration of this relationship is depicted below.

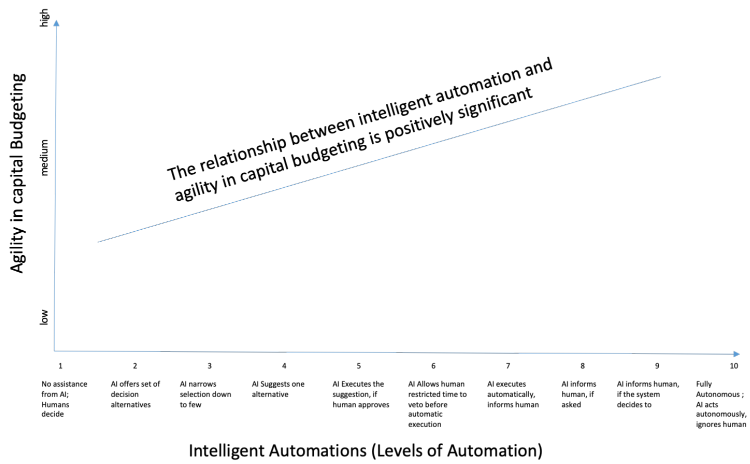


Figure 33. Theoretical interpretation from Finding 1 (figure 30).

Interaction of Demand Unpredictability on Intelligent automation's effect on Agility in capital Budgeting

George Fairbanks proposed an approach in which the amount of architecture design is determined entirely by the need to reduce risk to a satisfactory level. The classic definition of risk is the product of the probability of failure and the impact of that failure. The main reason for a high probability of failure is severity of perceived risks and system complexity.

If two AI projects are considered with same level of automation, how do we decide if agility is needed in capital allocation. The following table shows the risk factors against predictability of user demand, forecast accuracy and market trends. Practically, the risks are usually high when there is higher unpredictability in these factors.

Risk Category	Risk	Predictable	Unpredictable
Demand	User Demand	Low Risk	High Risk
Demand	Forecast Accuracy	Low Risk	High Risk
Demand	Market Trends	Low Risk	High Risk

Figure 34. Explanation on Finding 2 (figure 31).

Complexity has three facets: scale (the number of things being considered), diversity (the number of different things), and connectivity (the number of relationships between the things). Other sources of failure include unique problems that haven't yet been solved and the use of unknown or new and unproven technologies.

For critical systems, the cost of failure is high—perhaps people might be harmed or even lives lost. So, teams put in more architecture design effort to reduce risk. For example, compared to a team building a corporate website, a team building a medical system on which lives depend will require significantly more architectural effort and scrutiny to ensure that the ASRs (architecturally significant requirements) are met before development starts.

In such cases, where more upfront time is needed to develop a new product from an unproven technology or unsolved market need, it is reasonable to take risk mitigating, contingent planning and traditional approach with fixed performance contracts. Thus, the negative moderation effect provides practical advice on when to be less agile and when does one size fits all breaks. As per this discussion, it builds a case to lessen agility in capital budgeting for increased intelligent automation levels where demand unpredictability plays in. An illustration of this relationship is depicted below.

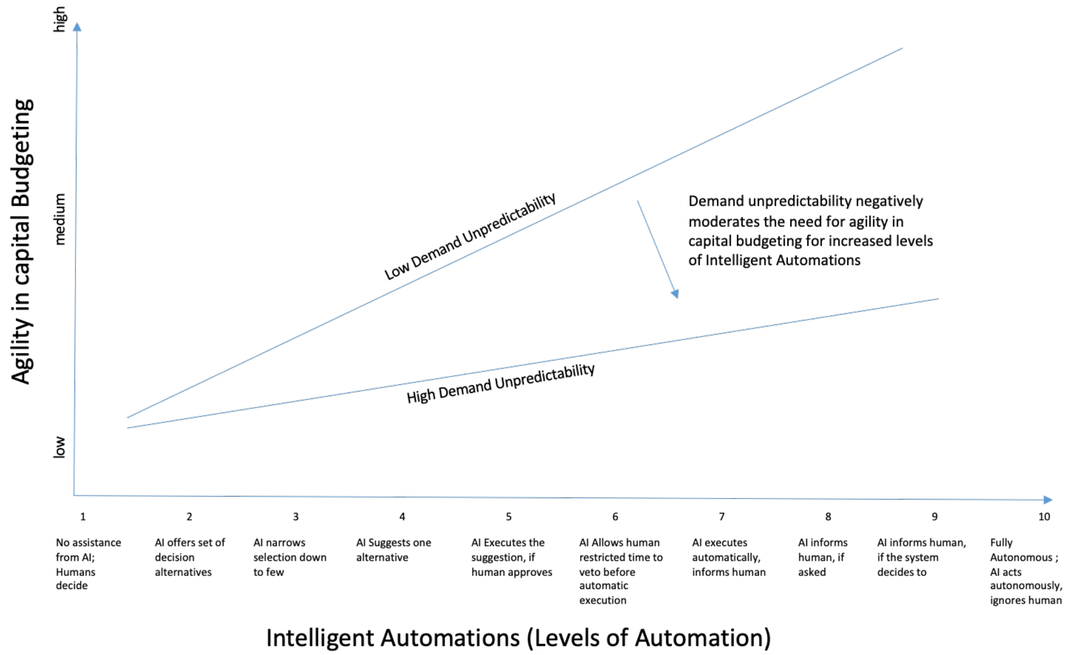


Figure 35. Theoretical Interpretation from Finding 2 (figure 31).

Practical and Managerial Implications

The key insight from this study is that managers can use at least the two factors – type of automation (intelligent automation) and demand unpredictability (low) to identify the agility need in capital budgeting (Beyond Budgeting).

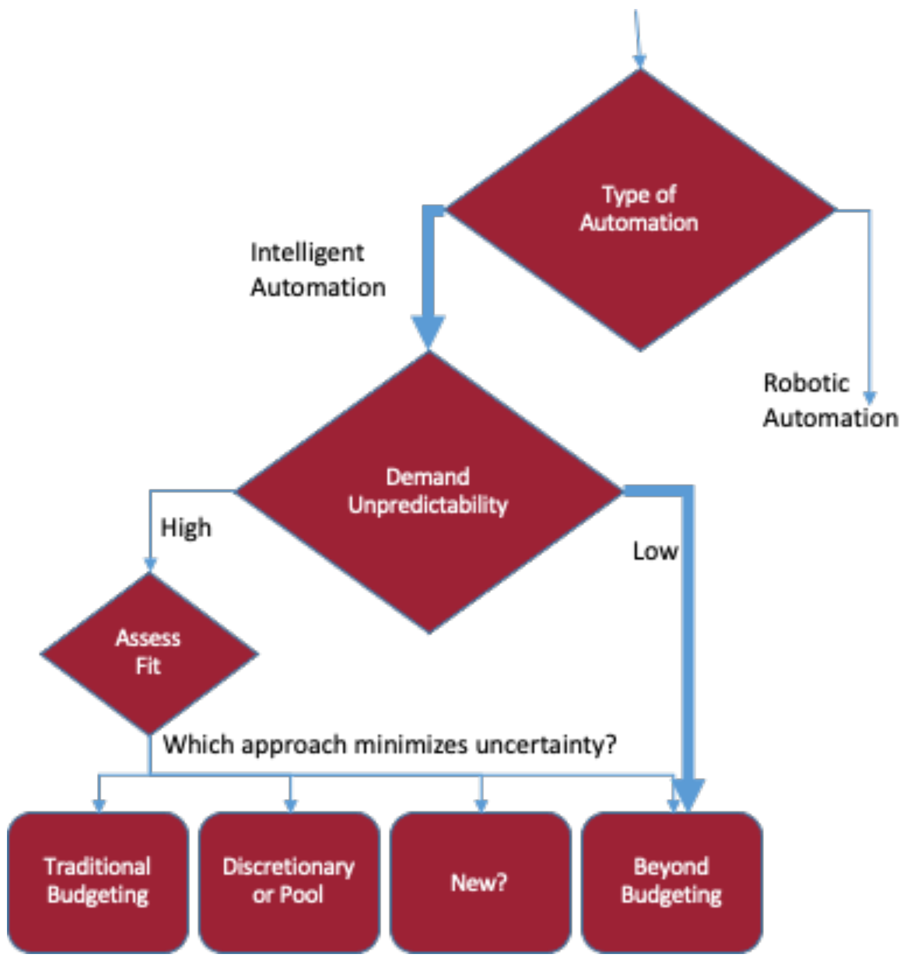


Figure 36. Managerial Implication and Advice.

This leads to a key question that needs further explanation. How can we explain the negative interaction effect of demand unpredictability and intelligent automations on the agility in capital budgeting? The major difference between a robotic automations and intelligent automations is that the expected output is known in robotic automations that could be rules driven, whereas intelligent automations deliver systems that are complex adaptive systems in nature. Emergence is a property of complex adaptive systems that creates some greater property of the whole, and can, thus cause lack of predictability.

Emergent phenomena often behave in surprising and unpredictable ways. A classic example is Braess's Paradox, named after the German engineer Dietrich Braess, who identified it in 1968. From extensive traffic studies, Braess found that adding new lanes to a highway does not necessarily reduce rush-hour grid lock but often makes it far worse. Indeed, emergent phenomenon frequently exhibit counterintuitive behavior that can be difficult to understand. This is similar to our results; high demand unpredictability does not necessarily need higher agility in capital budgeting for intelligent automations.

From beyond budgeting literature, the agility principles are grouped into two categories – leadership styles and management processes. Ewing Theory and Cobra Effect could explain the warning signals on why team performance and processes respectively could be suboptimal, if intelligent automations with high demand unpredictability are approached with higher agility.

In the mid-90s, ESPN analyst Bill Simmons and his friend Dave Cirilli made a pretty surprising observation: the New York Knicks seemed to play much better when their superstar center, Patrick Ewing, was out with either an injury or some type of foul trouble. This theory is an extension of Braess's paradox in Basketball. A high-volume player might hold the ball for longer time and encounter more misses. The second principle of Beyond Budgeting (appendix B) is performance responsibility, to make managers responsible for competitive results, not for meeting the budget. In a high demand unpredictable scenario, the time lost in recognizing such problem could become expensive. This trap is usually avoided in traditional budgeting approach as the fixed performance contracts are based on expected outcomes and not intermediatory results.

Cobra effect is a famous anecdote that describes a scheme the British Colonial Government implemented in India in an attempt to control the population of venomous cobras that were plaguing the citizens of Delhi that offered a bounty to be paid for every dead cobra brought to the administration officials. The policy initially appeared successful, intrepid snake catchers claiming their bounties and fewer cobras being seen in the city. Yet, instead of tapering off over time, there was a steady increase in the number of dead cobras being presented for bounty payment each month. This is due to the cobra farming that led to more cobras. Most of the cause–effect experiences involve very simple, direct relationships in terms of 'linear' behavior. In reality, this may not apply to Intelligent automations that are complex adaptive systems. The twelfth principle of Beyond Budgeting (appendix B) is motivation and rewards, to base rewards at unit level competitive performance, not predetermined targets. The end goal for most intelligent automations is to deliver the value (lifting sales) and competitive advantage (discover new antigen) in long term. The solutions with myopic view should neither multiply the problem nor create new problems to solve. Agility without alignment on how uncertainty of solution risks is explored could lead to a trap.

Conclusions

Capital budgeting is the process of determining how to allocate the limited amount of money available for investment. The goal is to buy fixed assets or invest in new opportunities that generate the highest return on investment. Because capital is limited, capital budgeting decisions require finding the right combination of investments that create a well-balanced portfolio.

When there are multiple competing projects that need capital allocation and prioritization, Study 1 indicated that one size fits all approach is not recommended. There are benefits in following traditional capital budgeting strategies for specific project types like building a new plant, upgrading site network for faster transfer rates etc. Also, there are benefits in following strategies like beyond budgeting, where capital allocation can be increased or decreased over time, depending on the performance of the projects. The nature of projects and the complexity in achieving outcomes are required to be considered.

From Study 2, if the nature of a project that is being implemented is automation using AI, then the need for agility in capital budgeting is high. This means, strategies like beyond budgeting are applicable for prioritizing and allocating capital for such projects. But, if such projects have high unpredictability in user demand, forecast accuracy or market trends, then it needs careful evaluation of which budgeting model works best. To explain this phenomenon, let's take 2 projects of similar AI technology, where one project aims to distribute network bandwidth from office location to home networks using Machine Learning for future pandemic readiness, and another project aims to generate an automated reporting AI bot for regulatory submissions using machine learning and natural language processing. Both projects might use similar AI technology by design. Now, if we evaluate the unpredictability of user demand, forecast accuracy and market trend, they are highly unpredictable in pandemic readiness project, compared to regulatory submissions project. Though valuable assets are anticipated to get built in both projects, it makes it easy to manage capital allocation for pandemic readiness project using traditional approach, whereas regulatory submission AI bot could adhere to beyond budgeting approach.

In conclusion, there is no magic pill to address all scenarios of capital budgeting. Managers are required to evaluate certain criteria like demand unpredictability to assess the fit for purpose capital allocation model. For AI projects, it makes sense to follow higher agility in capital budgeting when demand unpredictability is low. Whereas an evaluation is needed between multiple capital allocation approaches if demand unpredictability is high.

Recommendations for Future Research

This study tried to identify relationships between demand unpredictability, intelligent automations and agility in capital budgeting in knowledge and service work. The findings revealed that intelligent automations are not considered as a vital moderator in the relationship between demand unpredictability and agility in capital budgeting. Accordingly, further research might be directed to use other project and planning dimensions.

During study 1, two conflicting ideas from interviewees were captured. They are the disagreements on ethics council whether it should be internal vs external and the high expectations on human skills to stay relevant that causes burden of change in large firms. There is gap in literature that needs further exploration towards these research questions – a) What is the effect of ethic's council setup on intelligent automation's performance? b) How can manager's deal with burden of skills transformation due to paradigm shift of intelligent automations?

Intelligent automation is still an evolving discipline and not much of academic research is published on managerial insights and viewpoints. There are multiple opportunities to explore insights through qualitative approaches, such as, how much does strategic partnerships for technology skills play in the success of intelligent automations? What is the effect of incentive plan types on the performance and quality of intelligent automations? To what extent the overhead costs can be justified if hybrid capital budgeting strategies are adopted for intelligent automations?

While this research aimed to provide empirically supported recommendations for both capital budgeting decision makers as well as project managers, this research can be built upon to develop strategic advice towards improving project prioritization, capital reallocation in the middle of monitoring period based on evolving priorities etc. Exploring additional influencing variables beyond the demand unpredictability, such as perceived usefulness from technology adoption management theory may add new insights to this construct.

REFERENCES

(Gartner) Daryl, Plummer, David McCoy. (2006). Achieving agility: Defining agility in an IT context. Retrieved from https://www.gartner.com/en/documents/491393

Al Ani, M. K. (2015). A strategic framework to use payback period (PBP) in evaluating the capital budgeting in energy and oil and gas sectors in oman. *International Journal of Economics and Financial Issues, 5*(2), n/a. Retrieved from http://libproxy.temple.edu/login?url=https://search-proquest-com.libproxy.temple.edu/docview/1678821795?accountid=14270

Alam, M. (2015). Resource allocation and service design in local government: A case study. *The International Journal of Public Sector Management, 28*(1), 29-41. doi:http://dx.doi.org.libproxy.temple.edu/10.1108/IJPSM-01-2014-0013

AlKulaib, Y. A., Al-Jassar, S. A., & Al-Saad, K. (2016). Theory and practice in capital budgeting: Evidence from kuwait. *Journal of Applied Business Research, 32*(4), 1273-1286. doi:http://dx.doi.org.libproxy.temple.edu/10.19030/jabr.v32i4.9736

Alleyne, P., Armstrong, S., & Chandler, M. (2018). A survey of capital budgeting practices used by firms in barbados. *Journal of Financial Reporting and Accounting, 16*(4), 564-584. doi:http://dx.doi.org.libproxy.temple.edu/10.1108/JFRA-07-2017-0061

Antle, R., & Eppen, G. D. (1985). Capital rationing and organizational slack in capital budgeting. *Management Science (Pre-1986), 31*(2), 163. Retrieved from http://libproxy.temple.edu/login?url=https://search-proquest-com.libproxy.temple.edu/docview/205853411?accountid=14270

Arya, A., Glover, J., & Sivaramakrishnan, K. (1997). Commitment issues in budgeting. *Journal of Accounting Research, 35*(2), 273-278. doi:10.2307/2491365

Arya, A., & Mittendorf, B. (2006). Project assignments when budget padding taints resource allocation. *Management Science, 52*(9), 1345-1358. Retrieved from http://libproxy.temple.edu/login?url=https://search-proquest-com.libproxy.temple.edu/docview/213192373?accountid=14270

Awad, I. M., & Amro, A. A. (2017). The effect of clustering on competitiveness improvement in hebron: IMS. *Journal of Manufacturing Technology Management, 28*(5), 631-654. doi:http://dx.doi.org.libproxy.temple.edu/10.1108/JMTM-12-2016-0181

Batra, D., VanderMeer, D., & Dutta, K. (2011). Extending agile principles to larger, dynamic software projects: A theoretical assessment. *Journal of Database Management, 22*, 73+. Retrieved from https://link-gale-com.libproxy.temple.edu/apps/doc/A294896157/AONE?u=temple_main&sid=AONE&xid=acb33510

Batra, R., & Verma, S. (2014). An empirical insight into different stages of capital budgeting. *Global Business Review, 15*(2), 339-362. doi:10.1177/0972150914523588

Beckman, C. M., Haunschild, P. R., & Phillips, D. J. (2004). Friends or strangers? firm-specific uncertainty, market uncertainty, and network partner selection. *Organization Science, 15*(3), 259-275. Retrieved from http://libproxy.temple.edu/login?url=https://www-proquest-com.libproxy.temple.edu/docview/213831899?accountid=14270

Bourmistrov, A., & Kaarbøe, K. (2017). Tensions in managerial attention in a company in crisis. *Journal of Accounting & Organizational Change, 13*(2), 239-261. doi:http://dx.doi.org.libproxy.temple.edu/10.1108/JAOC-08-2015-0066

Brennan, M. J. (1995). Corporate finance over the past 25 years. *Financial Management, 24*(2), 9. Retrieved from http://libproxy.temple.edu/login?url=https://search-proquest-com.libproxy.temple.edu/docview/208185884?accountid=14270

Burggräf, P., Wagner, J., Dannapfel, M., Fluchs, S., Müller, K., & Koke, B. (2019). Automation decisions in flow-line assembly systems based on a cost-benefit analysis. *Procedia CIRP, 81*, 529-534. https://doi.org/10.1016/j.procir.2019.03.150

Busenbark, J. R., Wiseman, R. M., Arrfelt, M., & Woo, H. (2017). A review of the internal capital allocation literature: Piecing together the capital allocation puzzle. *Journal of Management, 43*(8), 2430-2455. doi:10.1177/0149206316671584

Calantone, R., Drö, C., ge, & Vickery, S. (2002). *Investigating the manufacturing–marketing interface in new product development: Does context affect the strength of relationships?*. Amsterdam] :

Chao, R. O., Kavadias, S., & Gaimon, C. (2009). Revenue driven resource allocation: Funding authority, incentives, and new product development portfolio management. *Management Science, 55*(9), 1556-1569. Retrieved from http://libproxy.temple.edu/login?url=https://search-proquest-com.libproxy.temple.edu/docview/213272434?accountid=14270

Chen, F., Drezner, Z., Ryan, J., Simchi‐, D., & Levi. (2000). *Quantifying the bullwhip effect in a simple supply chain: The impact of forecasting, lead times and information*. Providence, R.I., etc.,:

Conboy, K. (2009a). Agility from first principles: Reconstructing the concept of agility in information systems development. *Information Systems Research, 20*, 329+. Retrieved from https://link-gale-com.libproxy.temple.edu/apps/doc/A209539589/AONE?u=temple_main&sid=AONE&xid=b40aa16e

Conboy, K. (2009b). Agility from first principles: Reconstructing the concept of agility in information systems development. *Information Systems Research, 20*, 329+. Retrieved from https://link-gale-com.libproxy.temple.edu/apps/doc/A209539589/AONE?u=temple_main&sid=AONE&xid=b40aa16e

Coombs, C., Hislop, D., Taneva, S. K., & Barnard, S. (2020). The strategic impacts of intelligent automation for knowledge and service work: An interdisciplinary review. *The Journal of Strategic Information Systems,* , 101600. https://doi-org.libproxy.temple.edu/10.1016/j.jsis.2020.101600

Covaleski, M. A., Evans,John H., I.,II, Luft, J. L., & Shields, M. D. (2003). Budgeting research: Three theoretical perspectives and criteria for selective integration. *Journal of Management Accounting Research, 15*, 3+. Retrieved from https://bi-gale-com.libproxy.temple.edu/global/article/GALE%7CA112905009/e9f4bc21eaeb78881d9be4f7cf3871ee?u=temple_main

Davis, T. (1993). *Effective supply chain management*. Cambridge, Mass.

de Waal, A. A. (2005). Is your organisation ready for beyond budgeting? *Measuring Business Excellence, 9*(2), 56-67. doi:http://dx.doi.org.libproxy.temple.edu/10.1108/13683040510602885

De With, E., & Dijkman, A. (2008). Budgeting practices of listed companies in the netherlands. *Management Accounting Quarterly, 10*, 26. Retrieved from https://link-gale-com.libproxy.temple.edu/apps/doc/A192001237/AONE?u=temple_main&sid=AONE&xid=b3fddb84

Dunk, A. S. (1993). The effect of budget emphasis and information asymmetry on the relation between budgetary participation and slack. *The Accounting Review, 68*(2), 400. Retrieved from http://libproxy.temple.edu/login?url=https://search-proquest-com.libproxy.temple.edu/docview/1301346064?accountid=14270

Dunk, A. S., & Nouri, H. (1998). Antecedents of budgetary slack: A literature review and synthesis. *Journal of Accounting Literature, 17*, 72. Retrieved from http://libproxy.temple.edu/login?url=https://search-proquest-com.libproxy.temple.edu/docview/216307240?accountid=14270

Fairbanks, G. (2010). *Just enough software architecture: A risk-driven approach*

Germain, R., Claycomb, C., & Dröge, C. (2008). Supply chain variability, organizational structure, and performance: The moderating effect of demand unpredictability. *Journal of Operations Management, 26*(5), 557-570. doi:10.1016/j.jom.2007.10.002

Ghiyasi Mojtaba. (2018). Performance assessment and capital budgeting based on performance. *Benchmarking, 25*(6), 1729-1745. doi:http://dx.doi.org.libproxy.temple.edu/10.1108/BIJ-07-2016-0116

Graham, P. J., & Sathye, M. (2017). Does national culture impact capital budgeting systems? *Australasian Accounting Business & Finance Journal, 11*(2), 43-60. Retrieved from http://libproxy.temple.edu/login?url=https://search-proquest-com.libproxy.temple.edu/docview/1920036844?accountid=14270

Gunsberg, D., Callow, B., Ryan, B., Suthers, J., Baker, P. A., & Richardson, J. (2018). Applying an organisational agility maturity model. *Journal of Organizational Change Management, 31*(6), 1315-1343. doi:http://dx.doi.org.libproxy.temple.edu/10.1108/JOCM-10-2017-0398

Harris, M., & Raviv, A. (1996). The capital budgeting process: Incentives and information. *The Journal of Finance, 51*(4), 1139-1174. doi:10.2307/2329390

Henseler, J. ö, & Chin, W. W. (2010). A comparison of approaches for the analysis of interaction effects between latent variables using partial least squares path modeling. *Null, 17*(1), 82-109. doi:10.1080/10705510903439003

Hijal-Moghrabi, I. (2017). The current practice of performance-based budgeting in the largest U.S. cities: An innovation theory perspective. *Public Performance & Management Review, 40*(4), 652-675. doi:10.1080/15309576.2017.1313168

Hijal-Moghrabi, I. (2019). Why is it so hard to rationalize the budgetary process? A behavioral analysis of performance-based budgeting. *Public Organization Review, 19*(3), 387-406. doi:10.1007/s11115-018-0410-1

Hope, J., & Fraser, R. (1997, Beyond budgeting..*75*, 20+. Retrieved from https://link-gale-com.libproxy.temple.edu/apps/doc/A20163244/AONE?u=temple_main&sid=AONE&xid=75f4ee21

K.S. Celly, & Frazier, G. (1996). *Outcome - based and behavior - based coordination efforts in channel relationships*. Chicago :

Kengatharan, L. (2016). Capital budgeting theory and practice: A review and agenda for future research. *Applied Economics and Finance, 3*(2) doi:10.11114/aef.v3i2.1261

Kruchten, P., & Kruchten, P. (2013). *Complexity made simple* doi:10.24908/pceea.v0i0.4705; info:doi/10.24908/pceea.v0i0.4705

Laux, C. (2001). Delegated information acquisition and capital budgeting: On the separation of project evaluation and project management. *Journal of Institutional* *and Theoretical Economics (JITE) / Zeitschrift Für Die Gesamte Staatswissenschaft, 157*(4), 591-607. Retrieved from http://www.jstor.org.libproxy.temple.edu/stable/40752296

Lengnick-Hall, C., & Beck, T. E. (2005). Adaptive fit versus robust transformation: How organizations respond to environmental change. *Journal of Management, 31*(5), 738-757. doi:10.1177/0149206305279367

Libby, T., & Lindsay, R. M. (2010). Beyond budgeting or budgeting reconsidered? A survey of north-american budgeting practice. *Management Accounting Research, 21*(1), 56-75. doi:https://doi.org/10.1016/j.mar.2009.10.003

Lichtenthaler, U. (2018). Substitute or synthesis: The interplay between human and artificial intelligence. *Null, 61*(5), 12-14. doi:10.1080/08956308.2018.1495962

Lima, A. C., da Silveira, José Augusto Giesbrecht, Matos, F. R. N., & Xavier, A. M. (2017). A qualitative analysis of capital budgeting in cotton ginning plants. *Qualitative Research in Accounting and Management, 14*(3), 210-229. doi:http://dx.doi.org.libproxy.temple.edu/10.1108/QRAM-07-2016-0055

Little, T. D., Bovaird, J. A., & Widaman, K. F. (2006). On the merits of orthogonalizing powered and product terms: Implications for modeling interactions among latent variables. *Null, 13*(4), 497-519. doi:10.1207/s15328007sem1304_1

M. Waterman. (2018). *Agility, risk, and uncertainty, part 2: How risk impacts agile architecture* doi:10.1109/MS.2018.2141017

Marko Sarstedt, E. M.*A concise guide to market research* https://link.springer.com/book/10.1007%2F978-3-642-53965-7.

Martínez-López, F. J., Gázquez-Abad, J. C., & Carlos M.P. Sousa. (2013). Structural equation modelling in marketing and business research: Critical issues and practical recommendations. *European Journal of Marketing, 47*(1/2), 115-152. doi:http://dx.doi.org.libproxy.temple.edu/10.1108/03090561311285484

Meso, P., & Jain, R. (2006). Agile software development: Adaptive systems principles and best practices. *Information Systems Management, 23*(3), 19-30. Retrieved from http://libproxy.temple.edu/login?url=https://www-proquest-com.libproxy.temple.edu/docview/214124079?accountid=14270

Miller, D. (1987). Strategy making and structure: Analysis and implications for performance. *Academy of Management Journal, 30*(1), 7. Retrieved from http://libproxy.temple.edu/login?url=https://www-proquest-com.libproxy.temple.edu/docview/199801742?accountid=14270

Nguyen, D. H., Weigel, C., & Hiebl, M. R. (2018). Beyond budgeting: Review and research agenda. *Journal of Accounting & Organizational Change, 14*(3), 314-337. doi:http://dx.doi.org.libproxy.temple.edu/10.1108/JAOC-03-2017-0028

Preston, C. C., & Colman, A. M. (2000). Optimal number of response categories in rating scales: Reliability, validity, discriminating power, and respondent preferences. *Acta Psychologica, 104*(1), 1-15. doi:https://doi.org/10.1016/S0001-6918(99)00050-5

Rosseel, Y. (2012). Lavaan: An R package for structural equation modeling. *Journal of Statistical Software, 48*(2) doi:10.18637/jss.v048.i02

Sandalgaard, N. (2012). Uncertainty and budgets: An empirical investigation. *Baltic Journal of Management, 7*(4), 397-415. doi:http://dx.doi.org.libproxy.temple.edu/10.1108/17465261211272157

Shukla, S. K., & Sushil. (2020). *Evaluating the practices of flexibility maturity for the software product and service organizations* doi:https://doi-org.libproxy.temple.edu/10.1016/j.ijinfomgt.2019.05.005

Singh, S., Jain, P. K., & Yadav, S. S. (2012). Capital budgeting decisions: Evidence from india. *Journal of Advances in Management Research, 9*(1), 96-112. doi:http://dx.doi.org.libproxy.temple.edu/10.1108/09727981211225671

Soltwisch, B. W., & Krahnke, K. (2017). Maximizing decision making style and managerial effectiveness: Understanding how maximizing and locus of control impact managers' performance on the job. *Managing Global Transitions, 15*(3), 215-230. doi:http://dx.doi.org.libproxy.temple.edu/10.26493/18s4-693s.15.21s-230

Subhash Asanga Abhayawansa, Guthrie, J., & Bernardi, C. (2019). Intellectual capital accounting in the age of integrated reporting: A commentary. *Journal of Intellectual Capital, 20*(1), 2-10. doi:http://dx.doi.org.libproxy.temple.edu/10.1108/JIC-01-2019-223

Tysiac, K. (2018, The benefits of 'budgeting for results': Beginning with detailed, specific outcomes when building the budget can help not-for-profits attract impact-driven donors.*226*, 29+. Retrieved from https://link-gale-com.libproxy.temple.edu/apps/doc/A562689994/AONE?u=temple_main&sid=AONE&xid=a1b23b3e

Ulrich, L. (2020). Beyond artificial intelligence: Why companies need to go the extra step. *Journal of Business Strategy, 41*(1), 19-26. doi:10.1108/JBS-05-2018-0086

Vagia, M., Transeth, A. A., & Fjerdingen, S. A. (2016). A literature review on the levels of automation during the years. what are the different taxonomies that have been proposed? *Applied Ergonomics, 53*, 190-202. doi:https://doi-org.libproxy.temple.edu/10.1016/j.apergo.2015.09.013

Valuckas, D. (2019). Budgeting reconsidered: Exploring change initiative in a bank. *Journal of Accounting & Organizational Change, 15*(1), 100-126. doi:http://dx.doi.org.libproxy.temple.edu/10.1108/JAOC-10-2016-0060

Waterman, M., Waterman, M., Noble, J., & Allan, G. (2015). *How much up-front? A grounded theory of agile architecture*. Piscataway, New Jersey : doi:10.1109/ICSE.2015.54; info:doi/10.1109/ICSE.2015.54

Wendler, R. (2014). *Computer science and information systems (FedCSIS), 2014 federated conference on* doi:nfo:doi/

Zoni, L., & Pippo, F. (2017). CFO and finance function: What matters in value creation. *Journal of Accounting & Organizational Change, 13*(2), 216-238. doi:http://dx.doi.org.libproxy.temple.edu/10.1108/JAOC-12-2014-0059

APPENDIX A

CRITICISM OF TRADITIONAL BUDGETING

		Supporting studies / Author(s), year	
Cluster	**Finding**	**Conceptual studies**	**Empirical studies**
Expenses	The expenses represent a significant disadvantage of traditional budgeting	Hansen *et al.* (2003); Hope and Fraser (2003a); Libby and Lindsay (2003a); Neely *et al.* (2003)	Sandalgaard and Bukh (2014)
	The expenses do not represent a significant disadvantage of traditional budgeting	Libby and Lindsay (2007, 2010); Lidia (2014)	
Gaming behavior	Gaming behavior represents a significant disadvantage of traditional budgeting	Hansen *et al.* (2003); Hope and Fraser (2003a); Libby and Lindsay (2003a); Neely *et al.* (2003); Rickards (2006)	Libby and Lindsay (2010)
	Gaming behavior does not represent a significant disadvantage of traditional budgeting	Libby and Lindsay (2007); Lidia (2014)	
Low adaptability in dynamic business environments	Low adaptability in dynamic business environments represents a significant disadvantage of traditional budgeting	Hansen *et al.* (2003); Hope and Fraser (2003a); Libby and Lindsay (2003a); Neely *et al.* (2003); Rickards (2006)	Ekholm and Wallin (2000); Sandalgaard and Bukh (2014)
	Low adaptability in dynamic business environments does not represent a significant disadvantage of traditional budgeting		Libby and Lindsay (2007, 2010); Lidia (2014)
Misalignment with the company's strategy	Misalignment with the company's strategy represents a significant disadvantage of traditional budgeting	Hansen *et al.* (2003); Libby and Lindsay (2003a); Neely *et al.* (2003); Rickards (2006)	

	Misalignment with the company's strategy does not represent a significant disadvantage of traditional budgeting	Libby and Lindsay (2007, 2010); Lidia (2014)	
Vertical command-and-control	Vertical command-and-control represents a significant disadvantage of traditional budgeting	Hansen *et al.* (2003); Libby and Lindsay (2003a); Neely *et al.* (2003)	Ekholm and Wallin (2000); Lidia (2014)
	Vertical command-and-control does not represent a significant disadvantage of traditional budgeting		Libby and Lindsay (2007)

APPENDIX B

PRINCIPLES OF BEYOND BUDGETING

Governance	Use clear values and boundaries as a basis for action, not mission statements and plans
Performance responsibility	Make managers responsible for competitive results, not for meeting the budget
Delegation	Give people the freedom and ability to act, do not control and constrain them
Structure	Organize around the networks and processes, not functions and departments
Coordination	Coordinate cross-company interactions through process design and fast information systems, not detailed actions through budgets
Leadership	Challenge and coach people, do not command-and-control them
Goal setting	Beat competitors, not budgets
Strategy process	Make the strategy process a continuous and inclusive process, not a top-down annual event
Anticipatory management	Use anticipatory systems for managing strategy, not for making short-term corrections
Resource management	Make resources available to operations when required at a fair cost, don't allocate them from the center
Measurement and control	Use a few key indicators to control the business, not a mass of detailed reports
Motivation and rewards	Base rewards on a company and unit-level competitive performance, not predetermined targets

APPENDIX C

PILOT STUDY DATA COLLECTION TEMPLATE

Template 1. Interview Protocol

Our goal is to let the interviewee describe their strategies towards capital budget planning for human+machine teams.

Introduction

Thank you for agreeing to this interview. The purpose of this interview is to help in my doctoral dissertation. My aim is to understand the managerial implications of human+machine teams in Capital Budgeting processes. The interview will take about 45 minutes.

Part I: Motivation, Business Case & Problem:

- What are your thoughts on the data availability during budget allocations for human+machine teams?
- On a scale of high, medium and low, to what extent do you believe discretionary, or pool funding works well to allocate capital for human+machine teams or projects?
- On a scale of high, medium and low, to what extent do you believe traditional capital budgeting processes apply for human+machine teams or projects?
- On a scale of high, medium and low, to what extent do you believe traditional capital budgeting processes apply for human+machine teams or projects?

Part II: Flexible Organization Design

- To what extent "clear values and boundaries as a basis for action, not mission statements and plans" impact the capital decision framework?
- What are your thoughts on "Make managers responsible for competitive results, not for meeting the budget"?
- To what extend do you agree with "Give managers the freedom and ability to act, do not control and constrain them"
- What do you think about "Organize around the networks and processes, not functions and departments"?

Part III: Adaptive Management Processes

- How does "Make the strategy process a continuous and inclusive process, not a top-down annual event" work for Human+machine teams?
- To what extent do you agree with "Use a few key indicators to control the business, not a mass of detailed reports" for capital decisions.
- What are some key risks, ethical concerns, compliance issues etc. that are critical for resource planning?

Part IV: General

- General thoughts around the subject matter.
- What does your leadership think on business impact/performance due to human-robot teams on organizations and overall industry?
- How do they handle change and communication strategies?

- What do you think is going to be the role of HR department in this context of Human-Machine teams?
- Are there any additional managerial implications that you would like to share on this subject that we might not have covered so far?

Closing statement:

Thank you for your participation. To reiterate, your information will be kept anonymous and confidential. Your answers will help me understand managerial implications of human-robot teams in modern workplaces.

Template 2. Survey Design for Study 2

Start of Block: Default Question Block

Q1 **Participant Consent (page 1 of 3)** By selecting "CONTINUE" you are consenting to participate in this survey and for your inputs to be used in the data analysis and reporting for the stated doctoral dissertation and possible follow-on publishing. It is estimated this survey will take approximately **10 minutes** to complete. Your participation in the survey is completely anonymous and all data will be confidentially managed. No personally identifiable information collected will be associated with your identity or as a participant in the survey. Data from this survey will be maintained by the student investigator through the duration of the dissertation and will be deleted from the record by December 2021. Information obtained will be utilized for data analysis and reporting purposes of the doctoral dissertation and possible future publishing. Anonymous survey data and reporting will be shared with individuals and organizations that conduct or watch over this research only where applicable and required, including:

- The Institutional Review Board (IRB) that reviewed this research
- Temple University Fox School of Business program management

Select continue to complete your review of the consent.

Q2 **Participant Consent (page 2 of 3)** This research and results may be published post-dissertation. However, all data collected is anonymous and results will only be shared in aggregate reporting. All data and reporting will be held confidential for this dissertation and publication pursuits. No identifying information will be collected or reported. Loss of confidentiality is a risk of participating in the study. I will protect your information from disclosure to others to the extent required by law. However, I cannot promise complete secrecy. You may withdraw from the survey at any point in time. Once you complete the survey, your data will be recorded and analyzed along with all other participant inputs.

Select continue to complete your review of the consent.

Q3 **Participant Consent (page 3 of 3)** This research is being overseen by an Institutional Review Board ("IRB"). An IRB is a group of people who perform an independent review of research studies. You may talk to them at (215) 707-3390 or irb@temple.edu if:

You have questions, concerns, or complaints that are not being answered by the research team

- You are not getting answers from the research team
- You cannot reach the research team
- You want to talk to someone else about the research
- You have questions about your rights as a research subject

If you have any questions regarding the research or information management protocol, please contact me at tuj75908@temple.edu or Temple IRB at irb@temple.edu.

By selecting continue you acknowledge consent to participate in this survey.

Q4 Definition of Terms:

Intelligent Automation: Advances in Artificial Intelligence (AI) and its sub-fields have enabled the development of a new form of automation that is described as "Intelligent Automation". It is the application of AI in ways that can learn, adapt, and improve over time to automate tasks that were formally undertaken by a human.

Capital Budgeting: Capital budgeting is defined as a process by which resources are allocated in the firm; it involves not only objective and quantitative approaches but also subjective and intuitive methods. In many contemporary organizations, budgeting is an important instrument to implement companies' strategies and to fulfill a wide range of further tasks.

Knowledge Work: Knowledge work is defined as work that is intellectual, creative, and non-routine, and which involves the utilization and creation of knowledge. Knowledge work includes work in a wide range of professional areas, such as information and communication, consulting, pharmacology, and education.

Service Work: Service work can be defined as the process of using one's resources (e.g., knowledge) for someone's (self or other) benefit. It includes jobs as diverse as working in retail, security, office cleaning, and more knowledge-intensive work such as consulting. The definition of service work thus includes (white-collar) office and administrative work.

Q5 Have you ever experienced Intelligent Automations (Artificial Intelligence based automations ex: Chatbots)?

- Yes
- No

Q6 Have you ever participated in any firm's capital budgeting process?

- Yes
- No

Q7 To what extent, do you rate the unpredictability in user demand for Intelligent Automations in knowledge and service work?

- Extremely Predictable
- Moderately Predictable
- Slightly Predictable
- Neither Predictable nor Predictable
- Slightly Unpredictable
- Moderately Unpredictable
- Extremely Unpredictable

Q8 How likely, do you think the demand forecasts be inaccurate for Intelligent Automations in knowledge and service work?

- Extremely Accurate
- Moderately Accurate
- Slightly Accurate
- Neither Accurate nor Inaccurate
- Slightly Inaccurate
- Moderately Inaccurate
- Extremely Inaccurate

Q9 How difficult is the monitoring of market trends and events for Intelligent Automations in knowledge and service work?

- Extremely Easy
- Moderately Easy
- Slightly Easy
- Neither Easy nor Difficult
- Slightly Difficult
- Moderately Difficult
- Extremely Difficult

Q10 To what extent, do you agree with the intention to use Intelligent Automations in knowledge and service work with high demand variability?

- Strongly disagree
- Disagree
- Somewhat disagree
- Neither agree nor disagree
- Somewhat agree
- Agree
- Strongly agree

Q11 How likely would you recommend the use of Intelligent Automations to others in knowledge and service work with high demand variability?

- Strongly disagree
- Disagree
- Somewhat disagree
- Neither agree nor disagree
- Somewhat agree
- Agree
- Strongly agree

Q12 What is the highest level of Intelligent automation that you have experienced in knowledge and service work with high demand variability?

- 1. No assistance from AI; Humans decide
- 2. AI offers set of decision alternatives
- 3. AI narrows selection down to few
- 4. AI Suggests one alternative
- 5. AI Executes the suggestion, if human approves
- 6. AI Allows human restricted time to veto before automatic execution
- 7. AI executes automatically, informs human
- 8. AI informs human, if asked
- 9. AI informs human, if the system decides to
- 10. Fully Autonomous; AI acts autonomously, ignores human

Q13 To what extent, do you agree that it is difficult to set accurate budgets because of the unpredictability of factors influencing the Intelligent Automations?

- Strongly disagree
- Disagree
- Somewhat disagree
- Neither agree nor disagree
- Somewhat agree
- Agree
- Strongly agree

Q14 How much do you agree that annual budgets for Intelligent Automations become obsolete or outdated as the year goes by?

- Strongly disagree
- Disagree
- Somewhat disagree
- Neither agree nor disagree
- Somewhat agree
- Agree
- Strongly agree

Q15 To what extent do you agree that, "Fast Track" approval process is desired to ensure timely availability for initiatives requiring significant resources that were not incorporated in the approved budget for Intelligent Automations

- Strongly disagree
- Disagree
- Somewhat disagree
- Neither agree nor disagree
- Somewhat agree
- Agree
- Strongly agree

Q16 To what extent do you agree that, Managers are required to be empowered to make budget decisions needed to improve Intelligent Automations

- Strongly disagree
- Disagree
- Somewhat disagree
- Neither agree nor disagree
- Somewhat agree
- Agree
- Strongly agree

Q17 How much do you agree that managers should select resources by quality criteria, rather than pure cost-based decisions during budget allocations for Intelligent Automations

- Strongly disagree
- Disagree
- Somewhat disagree
- Neither agree nor disagree
- Somewhat agree
- Agree
- Strongly agree

Q18 To what extent do you agree that flexibility is desired to deploy resources for Intelligent Automations (material, financial, human etc.) to make use of opportunities and minimize threats

- Strongly disagree
- Disagree
- Somewhat disagree
- Neither agree nor disagree
- Somewhat agree
- Agree
- Strongly agree

Q19 Gender

- Male
- Female
- Other

Q20 What generation do you identify with?

- GenZ: born 1995-2012
- GenY: born 1977-1994
- GenX: born 1966-1976
- Baby Boomer: born 1944-1965
- None of the above

Q21 What is the highest level of education?

- Some high school
- High School
- Some College
- Associates
- Bachelors
- Masters
- Doctorate

Q22 Ethnicity

- Asian
- Black
- Hispanic
- Native American
- Two or More Races
- White
- Other

Q23 Industry

- Accounting. Banking, Finance
- Communications, Marketing, Public Relations
- Education
- Government
- Life Sciences / Pharmaceuticals
- Healthcare
- Hospitality
- Human Capital Consulting
- Information Technology
- Legal
- Management Consulting, Professional Services
- Non-profit, Charity
- Sales
- Shipping, Supply Chain and Logistics
- Social Services and Assistance
- None of the above

End of Block: Default Question Block

APPENDIX D

LINKING TABLE BETWEEN SURVEY INSTRUMENT AND LITERATURE

Hypothesis	Construct	Measure(s)	Reference	Survey Questions (column A in spreadsheet)
H1: Increase in demand unpredictability increases the need for intelligent automations in knowledge and service work	Intelligent Automations	User Demand, Demand Forecasts, Market Trends, And Intention to Adopt (On 7-point semantic differential scale) Levels of Automation (On 10-point ordinal scale)	Germain et al., 2008, Pillai et al., 2020., Burggräf et al., 2019	7, 8, 9, 10, 11, 12
H2: Increase in demand unpredictability increases the necessity for agility in capital budgeting	Agility in Capital budgeting	Adaptability (On 7-point scale)	Libby et al., 2010	13, 14
H3: Intelligent automations require increased agility in capital budgeting process	Agility in Capital Budgeting	Adaptability, Accountability, Market Awareness and Flexibility (All on 7-point scale)	Libby et al., 2010., Gunsberg et al., 2018	15, 16, 17, 18

APPENDIX E.

LINKAGE TABLE BETWEEN SURVEY QUESTIONS & LITERATURE

#	Measure	Construct	Survey Question	Response Examples	Measurement	Qualtrics Response Type / Wizard	Related Literature (citation)	Related Literature (short form)	Originally from (citation)	Originally from (short form)	Hypothesis	Hypothesis Description
5	--	Control Variable	Have you ever experienced Intelligent Automations (Artificial Intelligence based automations ex: Chatbots)?	yes/no	boolean / dichotomous	Multiple Choices, single selection						
6	--	Control Variable	Have you ever participated in any firm's capital budgeting process?	yes/no	boolean / dichotomous	Multiple Choices, single selection						
7	User Demand	Demand Unpredictability	To what extent, do you rate the unpredictability in user scalability where Intelligent Automations are applicable / needed in knowledge and service work?	Extremely Predictable to Extremely Unpredictable	7 point likert scale	Multiple Choices, single selection	Germain, R., Claycomb, C. and Dröge, C. (2008), Supply chain variability, organizational structure, and performance: The moderating effect of demand unpredictability. Journal of Operations Management, 26: 557-570. https://doi-org.libproxy.temple.edu/10.1016/j.jom.2007.10.002	Germain et al., 2008	K.S.Celly, G.Frazier. Outcome-based and behavior-based coordination efforts in channel relationships. Journal of Marketing Research. 1996; 33(2): 200–210.	Celly and Frazier, 1996	H1	Increase in demand unpredictability increases the need for intelligent automations in knowledge and service work
8	Demand forecasts	Demand Unpredictability	How likely, do you think the demand forecasts be inaccurate, where Intelligent Automations are applicable / needed in knowledge and service work?	Extremely Accurate to Extremely Inaccurate	7 point likert scale	Multiple Choices, single selection						
9	Market Trends	Demand Unpredictability	How difficult is the monitoring of market trends and events, where Intelligent Automations are applicable / needed in knowledge and service work?	Extremely Easy to Extremely Difficult	7 point likert scale	Multiple Choices, single selection						
10	Intention to adopt / Behavioural Intention	Intelligent Automations	How much do you agree that you intent to use Intelligent Automations in knowledge and service work with high demand variability?	Strongly disagree to Strongly Agree	7 point likert scale	Multiple Choices, single selection	Pillai, R. and Sivathanu, B. (2020), "Adoption of AI-based chatbots for hospitality and tourism", International Journal of Contemporary Hospitality Management, Vol. 32 No. 10, pp. 3199-3226. https://doi-org.libproxy.temple.edu/10.1108/IJCHM-04-2020-0259	Pillai et al., 2020	J.S.C. Lin, P.L. Hsieh The role of technology readiness in customers' perception and adoption of self-service technologies International Journal of Service Industry Management, 17 (5) (2006), pp. 497-517 T. Lam, V. Cho, H. Qu	Lin & Hsieh (2006), Lam et al. (2007)		
11	Intention to adopt / Behavioural Intention	Intelligent Automations	How likely would you recommend the use of Intelligent Automations to others in knowledge and service work with high demand variability?	Strongly disagree to Strongly Agree	7 point likert scale	Multiple Choices, single selection						
12	Levels of Automation	Intelligent Automations	What is the highest level of Intelligent automation that you have experienced in knowledge and service work with high demand variability?	1(Fully Manual) - 10 (Fully Autonomous)	10 point ordinal scale	Multiple Choices, single selection	Burggräf, P., Wagner, J., Dannapfel, M., Fluchs, S., Müller, K., & Koke, B. (2019). Automation decisions in flow-line assembly systems based on a cost-benefit analysis. Procedia CIRP, 81, 529-534. doi:https://doi.org/10.1016/j.procir.2019.03.150	Burggräf et al., 2019	T.B. Sheridan, W.L. Verplank Human and Computer Control of Undersea Teleoperators Massachussetts Institute of Technology, Cambridge, Massachussetts: Man-Machine Systems Laboratory, Department of Mechanical Engineering (1978)	Sheridan and Verplank 1978		
13	Adaptability	Agility in Capital Budgeting	To what extent, do you agree that it is difficult to set accurate budgets because of the unpredictability of factors influencing the Intelligent Automations?	Strongly disagree to Strongly Agree	7 point likert scale	Multiple Choices, single selection	Libby, T., & Lindsay, R. M. (2010). Beyond budgeting or budgeting reconsidered? A survey of north-american budgeting practice. Management Accounting Research, 21(1), 56-75. doi:https://doi.org/10.1016/j.mar.2009.10.003	Libby et al., 2010	Govindarajan, V., 1984. Appropriateness of accounting data in performance evaluation: an empirical examination of environmental uncertainty as an intervening variable. Accounting, Organizations and Society 9 (2), 125–135. Umapathy, S., 1987. Current Budgeting Practices in US Industry. Quorum Books, New York.	Govindarajan, V., 1984 and Umapathy, S., 1987	H2	Increase in demand unpredictability increases the necessity for agility in capital budgeting
14	Adaptability	Agility in Capital Budgeting	How much do you agree that budgets for intelligent automations become obselete or outdated as the year goes by	Strongly disagree to Strongly Agree	7 point likert scale	Multiple Choices, single selection						
15	Adaptability	Agility in Capital Budgeting	To what extent do you agree that, "Fast Track" approval process is desired to ensure timely availability for initiatives requiring significant resources that were not incorporated in the approved budget for Intelligent Automations	Strongly disagree to Strongly Agree	7 point likert scale	Multiple Choices, single selection					H3	Intelligent automations require increased agility in capital budgeting process
16	Accountability	Agility in Capital Budgeting	To what extent do you agree that, Managers are required to be empowered to make budget decisions needed to improve Intelligent Automations	Strongly disagree to Strongly Agree	7 point likert scale	Multiple Choices, single selection	Gunsberg, D., Callow, B., Ryan, B., Suthers, J., Baker, P. A., & Richardson, J. (2018). Applying an organisational agility maturity model. Journal of Organizational Change Management, 31(6), 1315-1343. doi:http://dx.doi.org.libproxy.temple.edu/10.1108/JOCM-10-2017-0398	Gunsberg et al., 2018	Wendler, R. and Stahlke, T. (2014), "What constitutes an agile organization? Descriptive results of an empirical investigation", Dresdner Beiträge zur Wirtschaftsinformatik No. 68/14, Technische Universität Dresden, Dresden, available at: http://nbn-resolving.de/urn:nbn:de:bsz:14-qucosa-130916	Wendler et al., 2014		
17	Market Awareness	Agility in Capital Budgeting	How much do you agree that managers should select resources by quality criteria, rathen than pure cost based decisions during budget allocations for intelligent automations	Strongly disagree to Strongly Agree	7 point likert scale	Multiple Choices, single selection						
18	Flexibility	Agility in Capital Budgeting	To what extent do you agree that flexibility is desired to deploy resources for intelligent automations (material, financial, human etc.) to make use of opportunities and minimise threats	Strongly disagree to Strongly Agree	7 point likert scale	Multiple Choices, single selection						
19	--	Demography	Gender	Male, Female, Other	3	Multiple Choices, single selection						
20	--	Demography	What generation do you identify with?	Baby Boomers, None	5	Multiple Choices, single selection						
21	--	Demography	What is the highest level of education?	School, Some College, Associates, Bachelors, Masters, Doctorate	7	Multiple Choices, single selection						
22	--	Demography	Ethnicity	Native American, Two or More races, White,	7	Multiple Choices, single selection						
23	--	Demography	Industry		16	Multiple Choices, single selection						