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JOURNAL OF INFORMATION SYSTEMS APPLIED RESEARCH

Influence of Reporting Structure and Perception of Role of Information Technology on Decision-Making: A Qualitative Study

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Abstract

Decision-making in organizations is influenced by the perception of executives in management roles. Information Technology (IT) investment budget forms a significant portion of the overall budget in organizations. These investment decisions are made by executives who perceive IT to play certain roles in supporting organizational objectives and missions. It is critical to understand these perceptions about IT that allow resources to flow (or not) towards critical IT solutions and maintenance. This study explores the perceptions of high-level executives about the role of IT in an organization's success. A case study is performed at a financial institution in the northeast region of the United States. The results indicate that there are four types of the dominant role of IT, as suggested by the data. These are 1) IT as a strategic partner, 2) IT as a support function, 3) IT as a facilitator, and 4) IT as a business enabler. Further analysis suggests that the role of an executive in an organization is related to how they perceive IT's role. This study also suggests that the CIO reporting structure in an organization might influence how the role of IT is perceived in an organization. Implications for research and practice are drawn, and future research directions are suggested.

Keywords: IT role, strategic IT, IT enabler, IT support, IT facilitator, qualitative, case study

1. INTRODUCTION

Most business executives believe IT is critical to a firm's strategic success but are unclear about "how and where" IT actually contributes to business value. Only 30 percent of business executives engage IT leadership in developing business strategies (Worthen, 2007). IT leaders often complain that IT is not given the opportunity to shape business strategy. It clearly shows that IT leadership is not appropriately engaged in the development of the business strategy of the organizations. IT administration is historically focused on aligning IT strategies with business strategies (Strohlein and Pucciarelli, 2019). IT strategy should also inform business strategy by presenting new and unexpected opportunities and capabilities. CIOs and strategy development stakeholders must cycle back and forth between business and IT strategies to maximize synergies (Strohlein and Pucciarelli, 2019). A big part of how these strategies and alignment are conceived depends on how the executives in decision-making roles perceive IT's role in the overall business vision.

Executives' views differ on the "strategic role of IT" and "goals of IT" in the organization. These differences are significant as it influences the scale and direction of IT investment decisions and the extent to which IT investment impacts firm performance (Kiessel, 2012). Executives' positive perception of IT builds confidence and encourages leaders to focus on IT not only as an operational but also as a strategic tool (Porter, 1996). IT in organizations has evolved to the point where its goal is not only to enable the business but also to improve and transform the organization's capabilities (McDonald, 2007). IT is valuable, but the extent and dimensions are dependent upon internal and external factors, including complementary organizational resources of the firm, its stakeholders, and the competitive and macro environment (Melville et al., 2004). IT is gaining more and more strategic importance in an ever-changing computing environment. A new understanding of the role and value of IT is crucial. IT does not solely support but creates business value (Uhlig and Remané, 2022).

The executives' individual characteristics, such as personal history & values, education, etc., may vary fundamentally. Each executive brings a somewhat unique perspective to processes and evaluates an organization and its internal environments (Ireland et al,1987). Since perception plays a crucial role in individual decisions and strategy development of the firm, it is important to understand executives' perceived "role of IT" in the organization and examine whether executives' perception of it relates to their position in the organization. This research study aims to understand the executives' perception of the "role of IT" in a firm. The specific research question posed in this study is: *What are executives' perceptions of the role of IT in a firm?*

The following section presents a discussion of the current research in this domain. The literature review section is followed by the methodology adopted in the study. A description of the case and data collection and analysis mechanisms are presented. Results from the case study are presented with a discussion about the implications of the study and future research paths.

2. LITERATURE REVIEW

A critical review of research literature is presented around the main components of the study: perception in decision making, IT strategy, and the role of IT in business.

Perception in Decision-Making

Perception plays a critical role in the decision-making process. Perception is "our sensory experience of the world around us and involves both recognition of environmental stimuli and actions in response to these stimuli" (Cherry, 2015). A great degree of perception is involved in addressing a complex problem in the decision-making process. Horn (2006) observes that "all decisions require perceptual processes to extract factual information from the external world that can be used to help develop an answer to a problem." The role of perception could also depend on the nature of the decision context. Some decisions require a minimum of perceptual involvement, while other decisions of choice rely primarily on internal preferences. Wang and Chan (1995) argue that the personal attributes approach contributes to identifying characteristics that can be used to predict an individual's information-processing capability. Wang and Cha, (1995) propose a global information processing framework that demonstrates the information-processing capability of the top managers and determines the quality of information used in formulating strategic decisions.

Senior managers' information-processing activities involve three sequential steps: view, search and interpret (Wang & Chan, 1995). The "view" determines the competitive, economic, technological, and political scope of information to which managers' attention should be directed. The "search" activity involves the acquisition of specific types of information (familiar, novel, soft, or hard) that the managers are looking for. The "interpret" activity is defined as the analysis of collected information. The outcome of the analysis determines if the captured information will be perceived to be relevant and valid and be the input for the strategic decision-making process of the firm. Anderson and Paine (1975) identify three sources of bias that influence strategic decisions: Selectivity: Separation of information for further consideration; Closure: Compilation of pieces of information into a meaningful whole; Interpretation: Use of earlier experience as an aid in judging the information previously collected. Perception plays a critical role in decision making of executives in IT roles.

Executives' Perception and Information Technology

The role of the perception of executives has been extensively studied in information systems research (Fink & Neumann, 2009; Kraemer et al., 1999; Tai & Phelps, 2000; Tallon, 2010, 2013; Tallon, Kraemer, & Gurbaxani, 2000; Tallon & Kraemer, 1999). The positive perception of the executives about business value of IT in a firm strengthens the strategic role of IT in meeting business objectives. The favorable perception of IT leads to confidence in the leadership team and gains support in IT initiatives projects, and encourages leaders to focus on IT not only as an operational but also as a strategic tool (Porter, 1996). Universally, business executives differ in strategic intent or goals for IT. These differences are important because they influence the scale and direction of IT investment decisions and how these investments will impact firm performance. Organizations with more focused goals for IT perceive higher levels of IT payoffs throughout the value chain. If IT payoffs are consistent with executives' goals and expectations, executives are likely to be satisfied with IT performance. Higher satisfaction with IT performance would lead to a greater executive commitment to IT , thus leading to IT spending. Executives', who are unable to get the intended results of IT investments, might be unfavorable to IT and work towards reducing the IT budget. The payoffs from IT investments are directly related to executives' perspectives (Kraemer et al., 1999). The executives' perceived IT payoffs and management practices play a significant role in creating IT value in the organization Tallon, Kraemer, & Gurbaxani, 2000). The IT leadership reporting structure has a notable impact on the perception of IT. Tai and Phelps (2000) propose that an indirect reporting CEO/CIO relationship has negative effect on role of IT. For organizations that have shown business transformation via IT, CIOs have been an influence on members of the core executive team.

Role of Information Technology

It is essential to understand executives' perception about the role of IT in an organization as it has resource-wise implications. Analyzing the role of information technology is vital when firms' focus on streamlining business processes and cost reduction related initiatives (Stewart, Coulson, & Wilson, 2014). IT plays multiple roles in achieving an organization's business objectives. Schein (1992) proposes three strategic roles for IT in organizations: automate- replace manual tasks with the automated process; informate- collecting and disseminating information throughout the organization and transform: using IT to create new business models. Strategic intent for IT provides a broader perspective of information technology in a firm. IT in a strategic partner role improves process, increases productivity, brings efficiency at an organizational level and provides flexible and scalable resources for the business (Agarwal & Sambamurthy, 2002). Chan (2000) suggests three roles of IT in a firm: an initiator, a facilitator or an enabler. IT in an initiator role acts as an agent of change. IT in a change agent role helps firm transform itself by focusing on organizational effectiveness, improvement, and development. The role of IT as enabler has been identified by many researchers (Al-Tameem, 2004; Dewah, 2014; Kanter, 1996; Luftman, Papp, & Brier, 1999; Mitra, 2005). The role of IT as a facilitator role serve as a coordination mechanism (Dedrick, Gurbaxani, & Kraemer, 2003; Dewett & Jones, 2001). IT facilitates the expansion of the firms and improves the relationship with other firms through the outsourcing of activities (Nieto & Fernández, 2005). The availability and quality of IT support is a critical factor helping a business operate smoothly. Lack of quality IT support could have a negative impact on business operations (Peter, 2003).

Dewett and Jones (2001) argue that IT moderates the effects of organizational characteristics on outcomes through its ability to generate information efficiencies and synergies. Information efficiencies are the cost and time saving that result when IT allows individual employees to perform their current tasks at a higher level and expand their role in the firm due to advances in the ability to gather and analyze data. Information synergies are the performance gains that result when IT allows two or more individuals to collaborate across inter-organizational or inter-departmental roles in a firm. Management views IT as a scarce resource and necessary evil in the organization. In some organizations, management sees IT role in shaping different types of strategies: such as defensive strategy, aggressive strategy, moderate and development strategy. IT roles could vary in an organization based on the current and future needs of the business.

3. METHODOLOGY

Organizational Context

This case study was conducted at a financial institution located in the mid-Atlantic region. Hereafter, the organization would be referred to as Mid-Atlantic Financial Institution (MAFI) a pseudonym given to the research site for the context of this research study. MAFI is a cooperative financial institution. The customers, and other banks, are required to have a firm membership. The customers share ownership of the firm along with other member financial firms. MAFI's mission is to provide low-cost liquidity to its customers and enhance the quality of the communities it serves. The firm is governed by an independent Board of Directors and executive committee. The executive committee consists of President, Chief Executive Officer (CEO), Chief Operating Officer (COO), Chief Strategy Officer (CSO), Chief Financial Officer (CFO), Chief Risk Officer (CRO), and General Counsel (GC). The Chief Information Officer (CIO) leads the information technology (IT) department and reports the o COO of the firm. There are seven committees: Executive Committee, Audit Committee, Finance Committee, Risk Committee, Human Resource Committee, Product and Service Committee and Governance and Public Policy Committee. These seven committees report to Board of Directors and are formed by members of senior management team of the firm. Each committee is led by one of the executive committee members. Senior management's primary responsibilities are to: (1) manage the firm safely and soundly, and in accordance with the highest standards of ethics and integrity; (2) implement the strategic direction established by the Board; (3) establish and maintain a strong system of internal controls; (4) implement the policies established by the Board; and (5) ensure the firm's compliance with applicable legal and regulatory requirements."

MAFI's corporate plan reflects the firm's future direction and assists in decision making related to the allocation of resources and risk tolerances. The firm's CSO is responsible for the overall strategic planning process. The strategic plan covers a period between three and five years and is revised every three years. The firm's board of directors reviews the strategic business plan annually, establishes management reporting requirements, and monitors implementation of the strategic business plan, the operating goals, and objectives. The firm's executive committee reviews the strategic plan and financial and non-finical goals. The committee makes recommendations to the Board of Directors in terms of any changes or the creation of a new strategic plan. The current strategic plan provides a path to accomplish the firm's strategic objectives and creates a framework for evaluating the current technology environment in order to ensure that the firm has an information technology that delivers the required technology capabilities and is in alignment with the firm goals.

The cost-benefit analysis, compliance, reputational risk, and operational risk are the key factors in determining the priority of the business application enhancement request. Business unit managers, business analysts, system analysts, program managers, project managers, IT managers and directors are member of the PEG. ITGC, BCAG and PEG each committee has a charter. All decisions are made by the committee reaching consensus through voting. Committee-based decision-making is a common practice in organizations. The preference of individual committee members is a distinctive element in the process of committee decision making (Noh, 2007).

Data Collection

Data for case study can come from multiple sources. Yin (2018) proposed three principles to address the construct validity and reliability-related concern in case study research. These are: using multiple sources of evidence, creating a case study database and maintaining a chain of evidence. Five data collection efforts were undertaken for this study: documents, interviews, direct observation, archival records and participant observation. Documents play an explicit role in any data collection in doing a case study. For this study, the researcher collected meeting minutes, memoranda and progress reports on projects. For interviews, an initial solicitation was sent out to 30 potential participants in the organization. Twenty-six participants volunteered to be part of this study. After the initial follow-up with participants, the researchers scheduled face-to-face interviews. For archival records, the researchers collected organization charts, participants' details such as job titles, and prior years of strategic planning documents.

Observation evidence provides additional information about the topic being studied and serves as another source of evidence in the case study. The observation could range from formal to causal data collection activities. The researcher is an employee at the case study site and observed project meetings, department and organization level meetings and usage of information technology policy and procedures. The researcher gained access to two committee meetings and participated in these monthly meetings regularly. The researcher took notes and utilized the participant-observation protocol.

Data Analysis

Creswell (2012) describes data analysis in qualitative research consist of "preparing and organizing the data (i.e., text data as in transcriptions or image data in photographs) for analysis, then reducing the data into themes through a process of coding and condensing the codes, and finally representing the data in figures, tables or discussion." (p. 180). Creswell (2012) proposed a data analysis spiral framework for qualitative analysis strategy. The data analysis spiral involves the following phases during the process: organizing, reading and memoing, describing, classifying and interpreting, and representing and visualizing the data (p. 183).

Yin (2018) argues that qualitative data analysis consists of examining, categorizing, tabulating, and testing to address the initial propositions of a study. Yin (2018) advocates for having a general analytic strategy to define priorities for what to analyze and why. For a case study, data analysis involves making a detailed description of the case and its setting (Creswell, 2012). Stake (1995) proposes four types of data analysis and interpretation technique in case study research: categorical aggregation, direct interpretation, patterns and natural generalization. In categorical aggregation, the researcher pursues a collection of instances from the data hoping to find issue-relevant meanings. In direct interpretation, the researcher looks at a single instance and draws meaning from it without looking at multiple instances. In this study, the researchers used Creswell's data analysis and representation technique and Yin's "Relying on theoretical propositions" and "developing a case description" analytic strategies.

4. RESULTS

IT can play multiple roles in achieving an organization's business objectives. Timely and proper implementation of IT in an organization may lead to broader shifts in products, markets, and society as a whole. The emergent themes about the perceived role of IT at MAFI suggest four dominant factors: IT as a Support Function (SF), IT as a Business Enabler (BE), IT as a Facilitator (Fac) and IT as a Strategic Partner (SP). A brief description of each factor is presented.

IT as a Support Function

16 out of 26 participants perceived role of IT as a Support Function (SF) at MAFI In Figure 1. In this role, IT implements and provides support for the entire underlying infrastructure such as network, desktop, laptop, mobile devices, servers, and telecommunications. IT works with business units to deploy the most effective technology solutions to better serve the internal users and customers. IT provides ongoing support to internal users and customers through helpdesk or self-service facilities via the firm's intranet.

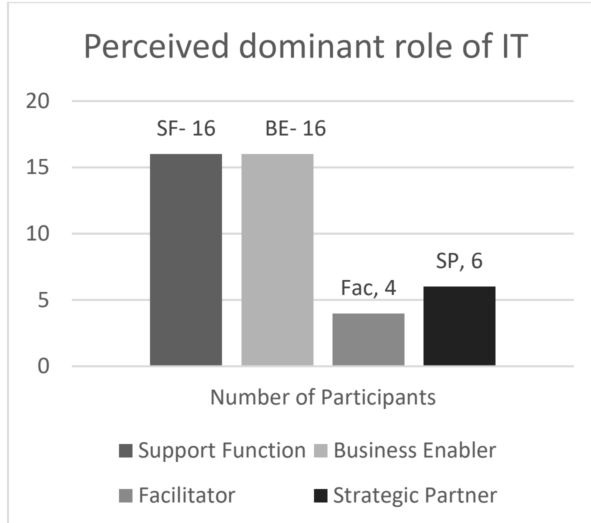

Figure 1: Perceived Role of IT

As one of the senior executives observed:

> *Support function... without business unit IT does not exist. IT is to support the needs of its client. Understand technology... What your needs are and what are your alternatives... client has to decide...Technology is a mean to get there.*

A similar view was supported by another IT manager:

> *IT is a support function. Support means not just supporting the problem, also delivery of new system, new applications. Over the past years IT has become publicly more important in organization because we automated more processes. I think business unit in this organization depends on IT.*

IT supports the business, and its role is to provide technology solutions for business problems. One of the IT managers pointed out, "It depends on the business model of the organization. For our business model, IT in a support role is the right role" and one of the senior executives said, "for us, IT is a support function... Our business model is not necessarily focused on IT." The availability and quality of IT support are a critical factor in helping a business operate smoothly. Lack of quality IT support could seriously impede business operations (Peter, 2003). The dominant perspective for this role is that IT should always ensure that infrastructure is always up and running and available for business. IT is perceived as a necessary tool for supporting the main business by running day-to-day operations smoothly. IT as a support function is widely recognized by C-level executives, business unit directors, business unit managers, and IT leaders of MAFI.

IT as a Business Enabler

The theme of the role of "IT as business enabler" clearly emerged from the data. IT is enabling the business units to do the job in a more effective way and provide solutions to business problems in an efficient way 16 out of 26 participants predominantly view the role of "IT as a business enabler" at MAFI. An enabler is an entity that offers the ability or the necessary assistance to accomplish something (Choi & Chan, 1997). There is support in the research literature for the role of information technology as an enabler of growth in firms (Mitra, 2005). As one of the business executives said the role of IT at MAFI is "to provide the ability to the firm to manage its business affairs and also communicate with our shareholders and customers as efficiently as possible." Kanter (1996) views IT as an enabler for working smarter and more productively. IT is designed for efficient data processing and analytical capabilities for better decisions making. Alavi and Yoo (1995) point out that IT acts as an enabler that provides rapid processing and analytical capabilities, parallel access, and information capture. A similar view is presented by one of the business executives about the role of IT at MAFI. As per the business executive, "IT helps us in processing data and creating reports. It enables us to communicate with people in the most effective fashion."

IT as a Facilitator

Data suggest that IT as a facilitator, serves as a liaison between various business units to promote smooth and timely delivery of software products or updates. At MAFI, IT works with various business units to gather and define business and technical requirements for a variety of business initiatives. Four out of twenty-six participants viewed role of "IT as a facilitator" at MAFI in Figure 1. A crucial role of IT within organizations is to serve as a coordination mechanism (Gurbaxani, & Kraemer, 2003). One of the business executives describes, "IT role is to help facilitate the business and business people should define what that means and technology is a way to facilitate or accomplish those goals." IT facilitates collecting business requirements, system changes and system upgrades. IT works with various business units to determine the system dependency or gap between the external and internal systems. One senior executive said about the role of IT, "IT facilitates our business model and helps guide non-IT people in terms of thing we should be thinking about and to help our control structure."

IT as a Strategic Partner

Six out of twenty-six participants perceived the role of IT as a strategic partner at MAFI in Figure 1. IT brings efficiency, improves processes, and increases productivity at the organizational level. IT as a strategic partner role provides flexible and scalable resources for the business (Agarwal & Sambamurthy, 2002). At MFAI, one of the senior executives views the role of IT as:

> *IT brings efficiency across organizations. IT works with a whole organization in a much more detailed manner than any other business unit. In theory, executive management has a certain perspective; audit has a certain perspective as they see the whole organization, but IT works with the whole organization in a much more detailed manner the way the other two do not. IT works with other business unit's day-to-day basis. There is a long-term relationship. IT is in a position to provide opinions or value-added concepts.*

IT has the ability to solve large and complex problems across organizations. IT is a means to provide flexibility, improve the process, and increase productivity at the organizational level. Another senior executive puts her thought on the role of IT as:

> *IT is fundamental to everything we do from a business perspective. IT is a skeleton system and may be a brain function and framework of the organization. Without IT, we cannot function. IT is the heartbeat of the organization.*

5. DISCUSSION

Table 1 presents the mapping of the organizational positions of the participant at MFAI and identifies the dominant perceived role of IT. The management column in table 1 represents the participants' current position in the organization. Participants with C-level job title such as CEO, CIO, CFO and COO are grouped here as "Senior". Participants with job title "Director" are grouped here as "Mid-level". Participants with job title "Manager" are grouped here as "Lower". The senior management group clearly identifies with three out of four dominant roles of IT as proposed in this study. The senior management group views the roles of IT as a Business Enabler, Support Function, and Strategic Partner. The mid-level management group identified two out of four dominant roles of IT as proposed in this study. The mid-level management group views the roles of IT as a Business Enabler and Support Function. In contrast, the lower management group views the role of IT as a Business Enabler, Support Function and Facilitator.

Business function	Perceived dominant role of IT			
	SP	BP	SF	Fac
Senior	✓	✓	✓	
Mid-level		✓	✓	
Lower		✓	✓	✓

Table 1: Organization Position and Role

The perceived role of IT is classified based on the two-dominant groups: IT and non-IT. The group defined as "IT" comprised participants who have job titles such as IT Director, IT Manager, Program Manager, CIO and also workers in the IT department in an organization. The non-IT group consist of participants with job titles such as CFO, COO, CEO, directors, and managers. Table 2 presents the mapping of the business functionality of the participants and the identified dominant perceived role of IT. The IT group predominantly identified with two perceived roles of IT: Business Enabler and Support Function. The "non-IT" group identified with all the four dominant roles of IT: Strategic Partner, Business Enabler, Support Function and Facilitator.

Business Function	**Perceived dominant role of IT**			
	SP	BE	SF	Fac
IT		✓	✓	
Non-IT	✓	✓	✓	✓

Table 2: Business Function and perceived dominant role of IT

At MAFI, IT plays multiple roles in achieving business goals. Four broad themes emerged as the perceived roles of IT in this firm: Strategic Partner, Business Enabler, Support Function, and Facilitator.
The above findings are consistent with Schein (1992) categorization of roles of IT in a firm: automate, informate or transform. "Automate" relates to the perceived role of IT as a "Support Function" as identified in this study, "Informate" relates to the perceived role of IT as "Business Enabler" and "Transform" relates to the perceived role of IT as "Strategic Partner" as identified in this study. Chan (2000) identifies the role of IT as an initiator, a facilitator or an enabler in a firm. The perceived role of IT "Strategic Partner", as identified in this study is consistent with the role of IT as initiator. The perceived role of IT as a "Business Enabler" is similar to role of IT as an enabler. The perceived role of IT as a "Facilitator" is parallel to role of IT a facilitator.

The CIO reporting structure plays a significant role in determining the role of IT in a firm. Research literature suggests that indirect reporting CEO/CIO relationship has a negative effect on the perception of IT in the organization. At MAFI, data show that 70% of participants believe that the CIO reporting structure does have an impact on determining the role of IT in a firm. This finding is consistent with Tai and Phelps (2000) argument that CIO plays a critical role in business transformation through IT. Figure 2 presents the impact of the CIO's reporting structure in determining the role of IT in a firm.

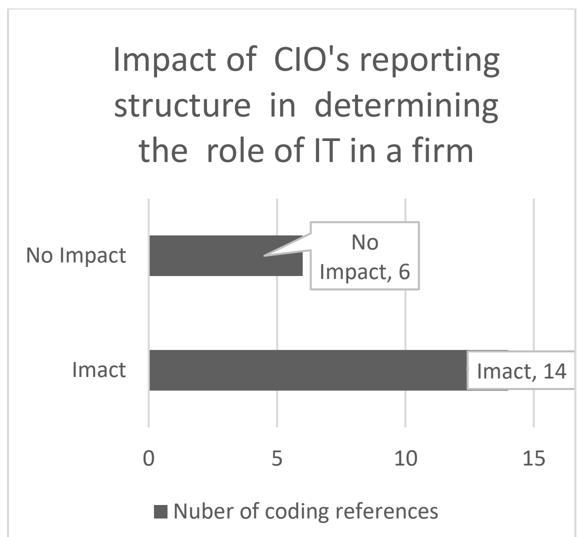

Figure 1: Impact of CIO's reporting structure

Porter (1996) argues that a positive perception of IT leads to confidence in the leadership team and gains support for IT initiatives, and encourages leaders to focus on IT not only as an operational tool but also as a strategic tool. Tai and Phelps (2000) find that an indirect reporting CEO/CIO relationship has a negative impact on the perception of IT. At MAFI, 62% of participants agree that CIO should directly report to the CEO. As one of the business managers said:

I think IT is strictly looked at as operational when CIO reports to the COO. Once things are labeled operational, that does not perceive as strategic. Reporting back to the CEO, just elevate IT in much more than operational. IT should be viewed as strategic in the firm that cuts across all the business units.

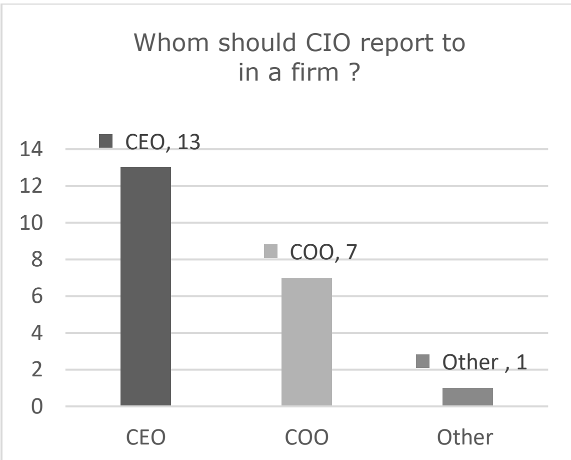

Figure 2: Whom should CIO report to in a firm?

This study has several implications for research and practice. This study contributes to research by suggesting the perceived role of IT is related to reporting structure of IT leadership in an organization. The perceived role of IT forms the basis of strategies and initiatives for alignment with business goals and it is critical to understand these perceptions of IT for better alignment. More studies in this area about how different reporting structures support alignment is warranted. On the practice side, IT executives could use this as a guide to check how their perceptions are shaping organizational IT effectiveness. If the perception of IT is limited, it cannot lead to deeper synergies with business.

6. CONCLUSION

This study shows that the perception of executives in decision-making roles in an enterprise, about the role of IT in an organization, is important in shaping how IT is consumed. The four dominant roles of IT that have emerged in this study show how IT decisions such as investments are influenced by the perception of executives. This study also suggests that the reporting structure of IT leadership is important in determining how IT is perceived. Future research on this should be conducted to compare the effectiveness of different reporting structures in organizations and their correlations with IT perception.

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Impact of Emergent Technologies on US Workforce: Exploratory Analysis

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Abstract

As new technologies continue to evolve and take center stage in organizations, workers will experience disruption and change. They might wonder what the future holds for them. This study presents an exploratory analysis on the impact of new technologies such as artificial intelligence, cloud-based computing, and robotics on the US workforce. Findings reveal that a majority of US companies which deploy these technologies do not report a decrease in the number of workers employed. In fact, more workers are employed after the technologies are utilized. Additionally, most companies report an increase in the skill level of their workforce. Practical and academic implications are also discussed.

Keywords: Artificial intelligence, cloud-based, robotics, technology, workforce

1. INTRODUCTION

New technologies such as artificial intelligence (AI), cloud-based computing, and robotics, are evolving at a rapid pace both in capabilities and widespread utilization. This trend is predicted to continue. According to McKinsey 2021 Global Survey, 57 % of organizations have adapted AI, compared to 45 % of organizations just a year prior (McKinsey, 2021). The top business functions that most frequently utilize AI include service-based operations, AI based product enhancements, and contact center automation (McKinsey, 2021). McKinsey's survey also reveals that organizations utilizing AI are able to reduce cost in service operations, manufacturing, human resources, and other functions.

As organizations realize returns on their AI investment, they will continue to invest and expand its deployment. This newest digital evolution will affect everyone involved including the workforce. As stated by Atanasoff & Venable (2017, p.333-334), "the global workforce can expect that the technological disruptions to industry and business structure will continue with new technologies on the horizon (e.g., artificial intelligence, robotics, 3-D printing)." Furthermore, Stone et al. (2016) posit that these disruptions will affect the way workers are either augmented or replaced by this latest technology. But how exactly will these disruptions affect the workforce? And what should we expect in the years to come? More specifically, what does this mean for the US workforce? To provide insight to these questions, this study explores the impact of emergent technologies such as AI, cloud-based, and robotics technology on employment trends within US based firms. The next section discusses key findings from the literature on technology and its impact on workforce.

2. LITERATURE REVIEW

There are mixed perspectives in the literature regarding the effects of technology on the workforce. The first one focuses on individual outcomes and the adverse effects of technology on employees ranging from technostress to job elimination or loss. Technostress refers to the "inability to cope with the new computer technologies in a healthy way" (Brod, 1984, p. 16). Furthermore, Tarafdar et al., (2011) suggest that technostress is caused by five conditions: techno-overload (being pressured to work more and/or faster), techno-invasion (feeling of always being online and easily reachable), techno-complexity (needing to devote extra time to learn and understand the new technology), techno-insecurity (fear of losing a job to better skilled workers), and techno-uncertainty (lack of opportunity to build experience due to quickly changing technologies).

Techno-insecurity especially has significant implications for the workforce. Zhou, et al. (2020) predicted that 278 million jobs will be replaced by AI by 2049 in China. Additionally, this topic of human labor being replaced by machines has been discussed in literature for a few decades now. Rifkin (1996) postulated that although critical to the capitalist economy, new technology often eliminates jobs leading to "near-workerless world". However, economists argued that productivity gained from new technology leads to higher national income, ultimately generating new jobs and opportunities for workers. Subsequently Pew Research Center (2016) reported that employment has been steadily increasing over the last three decades. More specifically, jobs with higher social and analytical skills have been increasing much faster than jobs with physical or manual skills.

Other scholars also acknowledge that as the digital transformation continues, organizations need to play a critical role in mediating the stress and implementing various interventions. Atanasoff & Venable (2017, p. 332) stated "…The problem can be reframed as an opportunity for self-evaluation, including what knowledge, skills, and abilities the client wants to develop for future work. It is an opportunity to reevaluate general career direction." Such approach is intended to help employees cope and even prepare them for new opportunities by assisting with new career development and upskilling opportunities. Bughin et al. (2018) predict that the need for technological, social, and emotional skills will increase despite the decrease in need for manual and physical skills. These changes will require workers everywhere to strengthen their existing skill sets or acquire new ones.

Another perspective looks primarily through the economic and organizational lens. It presents technology as an opportunity to increase efficiency, value, and evolutionary benefits. Davenport et al. (2020) discuss how AI will transform marketing strategies, human behaviors and create new business models. Additional benefits of technology discussed in the literature relate directly to workers themselves in cases where technology enhances their own work and allows them to produce more superior output (Colbert et al., 2016; Lauande Rodrigues & De Minicis, 2021). This allows employees to switch focus from trivial to more impactful and complex tasks. As a result, increasing their own self efficacy, sense of accomplishment, and job satisfaction. Historically, technology created changes in employment but at the same time it has also created new jobs especially in countries that have higher levels of innovation and economic growth such as the US (Manyika et al., 2017). The aim of this study is to conduct an exploratory analysis and to investigate the impact of firms' technology use on its workforce.

3. METHOD

This study used the US Census Annual Business Survey (ABS) data collected in 2019 (United States Census Bureau, 2019). This survey captured data regarding the extent to which US firms used emergent technologies and their impact on workforce during 2016-2018 time period. The exact name of the data set used was titled "AB1800TCB03A Annual Business Survey: Impact of Technology Use on the Workforce of Employer Firms by 2-digit NAICS for the United States and States: 2018" and contained information about firms with paid employees and receipts of $1,000 or more grouped by industry using a 2-digit NAICS (North American Industry Classification System) code. The data set also included aggregate data for all sectors. Since Census suppresses certain data to maintain confidentiality, only the aggregate level data was used to perform the analyses.

Measures

The ABS survey captured information about the following five technology groups:

- Artificial Intelligence
- Cloud-based
- Robotics
- Specialized Software
- Specialized Equipment

For each technology group the participants were asked to rate the extent to which they used each technology (in the 2016-2018 timeframe). Those companies which selected low, moderate, or high usage of these technologies were directed to answer subsequent questions about employment impact.

The response choices for employment impact were presented for each technology group.

Participants were asked to identify the effects of adopting or using each specific technology (between 2016-2018) on workforce based on the following ten answer choices:

Number of Workers:

- Increased
- Decreased
- Did not change

Skill Level of Workers:

- Increased overall
- Decreased overall
- Did not change overall

Science, Technology, Engineering, and Mathematical (STEM) skills of workers:

- Increased overall
- Decreased overall
- Did not change overall
- Not applicable, did not employ workers with STEM skills

Hence if an organization utilized more than one technology, they were directed to answer the corresponding employment impact questions for each technology group they reported.

Table 1 below lists the total number of employer firms included in the survey per each technology group.

Technology Group	Total Number of Employer Firms
Artificial Intelligence	141,731
Cloud-Based	1,550,716
Robotics	88,657
Specialized Software	1,821,368
Specialized Equipment	855,657

Table 1: Total Number of Firms Included in the Survey Per Each Technology Group

4. FINDINGS

The data was analyzed using Tableau Desktop version 22.2.0 and Microsoft Excel 365 software. The results focus on AI, cloud–based, and robotics technology groups. However, graphs for the remaining two groups (specialized software and specialized equipment) are provided for reference in the Appendix. All graphs represent the percentages of firms based on the total number of employer firms included in the sample as reported in Table 1.

Table 2 contains percentages of employer firms broken down by the three foci technology groups and ten employment impact codes. In addition, Figures 1-3 present corresponding bar graphs for each technology group sorted by employment impact code in descending order.

	AI	Cloud-based	Robotics
Number of Workers			
Increased	15.0	12.5	10.0
Decreased	6.3	3.7	8.1
Did not change	78.8	83.8	81.9
Skill Level of Workers			
Increased	40.9	28.2	23.6
Decreased	1.8	0.8	2.3
Did not change	57.3	70.9	74.1
STEM Skills of Workers			
Increased	31.2	15.8	20.3
Decreased	1.1	0.5	1.6
Did not change	39.8	42.3	54.4
Not applicable	27.9	41.4	23.7

Table 2: Percentages of Firms by Technology and Employment Impact Code.

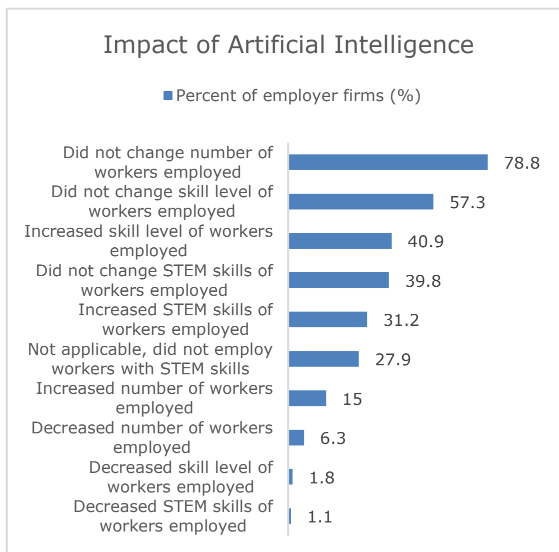

Figure 1: Impact of Artificial Intelligence Technology on Firms' Workers

The first graph in Figure 1 represents the impact of AI on individual employment impact codes. The data shows that implementation of artificial intelligence did not change the number of workers employed in almost 79 % of the firms utilizing AI. In fact, the number of workers increased in 15 % of those organizations. In addition, the skill level of workers increased in 41 % of firms, with STEM skills being higher in 31 % of the organizations. Approximately 6 % of the firms incurred a decrease in the number of workers and 2%

reported decrease in the skill level of their workers.

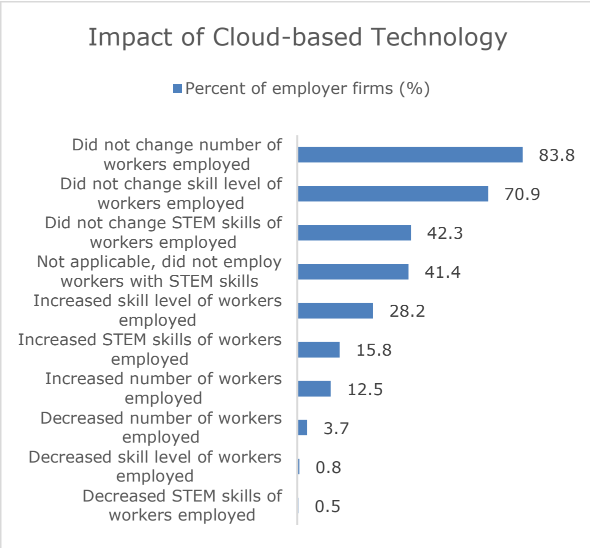

Figure 2: Impact of Cloud-based Technology on Firms' Workers

Similarly, 84% of the firms utilizing the cloud-based technology, did not change the number of workers employed as presented in in Figure 2. Number of workers employed increased in 13% of the firms. Although the increase in skill level was not as high as in case of AI, it still generated an increase in skill level of workers in 28 % of the firms. About 4 % of firms reduced the size of their workforce as a result of the cloud-based technology and only less than 1 % reported a decrease in workers' skill levels.

A comparable trend was observed in robotics where 82 % of organizations reported no change to the number of workers employed as presented in Figure 3. Additionally, 24% of firms which utilized robotics, reported increase in the skill level of their employees, and 10% of firms reported increase in the number of workers employed. About 8% of firms reported a decrease in the number of workers. Compared to AI (6%) and cloud-based technologies (4%), robotics (at 8%) presented the largest percent of firms with a reduction in workforce and the smallest percent of firms (10%) with an expansion of the workforce.

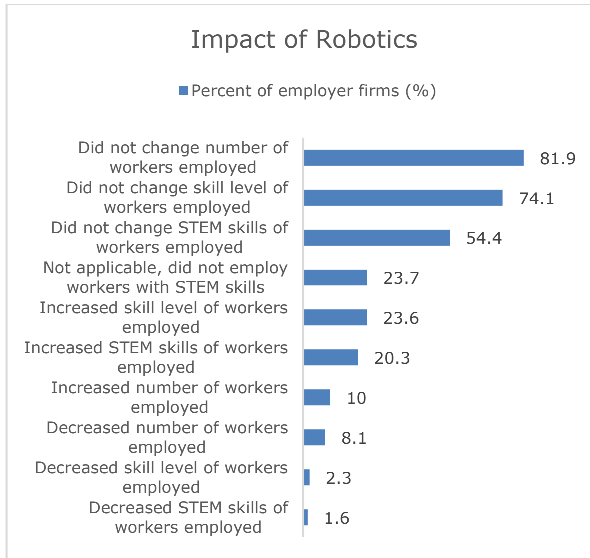

Figure 3: Impact of Robotics Technology on Firms' Workers

Figures for specialized software and specialized equipment technologies provided in the Appendix present similar findings. More specifically the number of workers did not change in majority (87%) of the firms utilizing these technologies.

The next graph in Figure 4, demonstrates a different view of the data where each employment impact code is broken down by the technology group. All technologies appear to

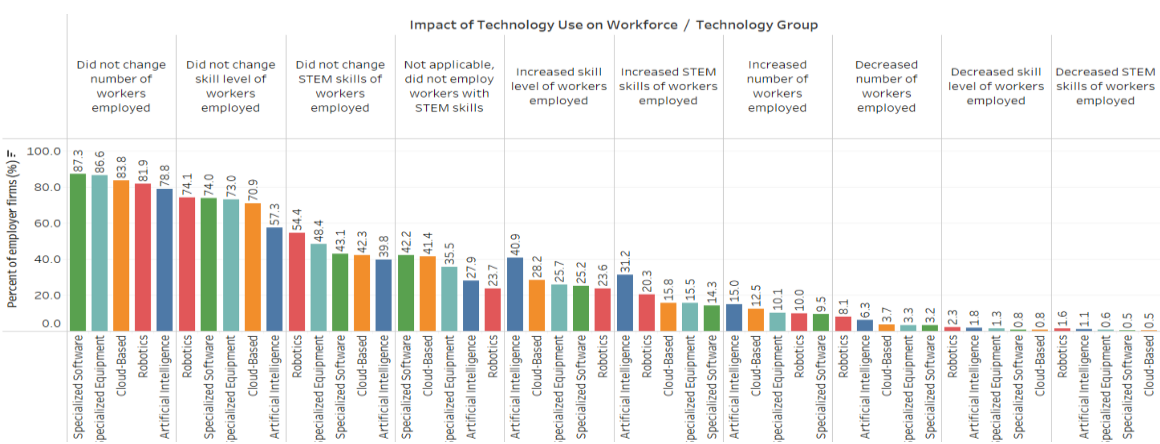

Figure 4: Employment Impact Code by Technology Group

demonstrate a similar pattern in terms of the impact on the workforce. One technology that stands out in terms of skill set is AI. Out of the five technologies, artificial intelligence shows the largest impact on workers new skill development (41%), including STEM skills (31%). Companies using AI also led in terms of the increase in the number of workers employed (15%).

5. DISCUSSION AND CONCLUSION

This study investigated the effects of emergent technologies on US workforce. More specifically it used Census data that captured changes to the workforce within a three year period of adapting the new technology. These changes were measured in terms of the increase or decrease, skill level, and STEM skills of workers employed by the US firms.

The results reveal that majority of firms which utilized the emergent technologies did not change the number of workers employed. In fact, the organizations that implemented these technologies showed an increase in the number of workers employed. This is most likely attributed to the complexities and challenges associated with implementing new technologies (Berente, 2021; Devonport et al., 2020; Stone et al., 2016). Additionally, workers whose tasks have been automated are often reassigned to new tasks within the organization (Manyika et al., 2017). However, organizations might also be replacing unskilled workers with more skilled workers instead of upskilling internally. Therefore, these numbers might represent a net effect of various employment changes within organizations. Findings in this study are similar to the survey results reported by Bughin et al. (2018) who indicated that approximately 77 % of organizations do not anticipate changes in the net size of their workforce in the US, and approximately 17 % of firms anticipate their workforce to grow. Nonetheless, causality cannot be established in this paper and findings should be interpreted with caution.

This paper has important implications for employees, employers, and educators. As organizations continue to utilize emergent technologies, employees should stay abreast of these trends and create development plans to help employees maintain or develop new skills for roles that are being created in support of such technologies. These roles are hard to automate and consist of non-routine tasks which require creativity and strong problem solving skills (Bughin et al., 2018; Lauande Rodrigues & De Minicis, 2021). Information Systems (IS) professionals especially should continue to stay current in their field and seek opportunities to gain exposure in new technologies. Findings in this paper revealed that considerable number of firms which utilize AI, cloud-based, and robotics technologies reported an increase in the skill level of their employees. This suggests that employees might have access to in house opportunities for exposure or development of new skills. IS professionals in particular might not only be comfortable but also excited about such opportunities. Prior literature shows that IS professionals demonstrate certain common occupational propensities that include high preference for intrinsic rewards at work such as an interesting job, opportunities to learn new skills, skills that do not go out of style, as well as creative and impactful work (Toskin & McCarthy, 2021).

Employers also have an important part in this digital transformation. As suggested by other scholars (Atanasoff & Venable, 2017), they should play an active role in mitigating employee stress due to new technology adaptation, as well as provide training and growth opportunities to upskill and reskill their workforce.

Last but not least educators, especially those in the IS discipline, should feel empowered to revise curriculum that will prepare students for successful careers in AI, cloud-based, and robotics technologies. Findings in this study also emphasize the importance of STEM skills. Manyika et al., (2017) predict that the employment for IS professionals such as computer engineers and computer specialists is expected to grow by 34 % by 2030. More specifically, employers will be looking for advanced IS and programming skills, high cognitive skills, social and emotional skills as well as creativity (Bughin et al., 2018; Lauande Rodrigues & De Minicis, 2021).

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Appendix A.
Additional Figures

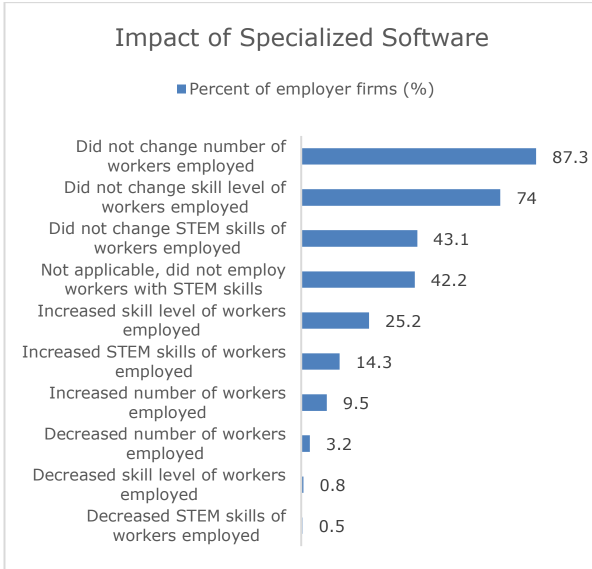

Figure 5: Impact of Specialized Software Technology on Firms' Workers

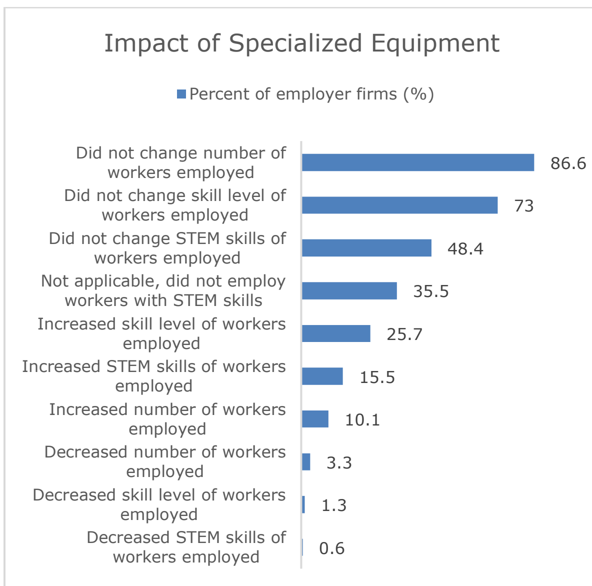

Figure 6: Impact of Specialized Equipment Technology on Firms' Workers

A Predictive Unmanned Aerial Vehicle Maintenance Method: Using Low-Code and Cloud-Based Data Visualization

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Abstract

Demand for Unmanned Aerial Vehicle (UAV) usage in various industries rapidly increases from one year to another. The Federal Aviation Administration (FAA) anticipates that the number of commercial drones will increase to 1.44 million by 2025. But at the same time, there is a growing concern about UAVs' electrical, mechanical, and system reliability. The problem is that those reliability issues can interfere with safe operations and may lead to accidents due to malfunctions during flight. One of the effective ways to solve the reliability issues is to improve the UAV maintenance method. For this purpose, we first review existing UAV maintenance methods and investigate technologies utilized for the current maintenance in the aviation industry. Second, we propose a Cloud-based and Low-Code Predictive Maintenance Method (CLPMM) that uses a low code development platform and Azure Cloud Services. Third, we compare each technology of the existing maintenance methods with the CLPMM to verify the benefits. Lastly, we discuss the strengths and weaknesses of the CLPMM.

Keywords: Low-Code Development Platform, Cloud Computing, Cloud-based Predictive UAV Maintenance Method

1. INTRODUCTION

Unmanned Aerial Vehicles (UAV) have been widely used for monitoring, delivery, and field management tasks because they bring significant benefits in decreasing workload and fixed costs and increasing work efficiency and productivity. For that reason, logistics, agriculture, and other industries are taking advantage of UAVs, which is accelerating the UAV industry's growth (FAA Aerospace Forecasts, 2020).

From a report by the Federal Aviation Administration (FAA), 351,244 of 868,838 commercial UAVs are registered in the United States and the number is growing (FAA, 2021).

And another FAA report notes that the number of commercial drones will increase to 1.44 million by 2025 (FAA Aerospace Forecasts, 2020). Although the number of companies operating UAVs is rising in various industries, the existing maintenance method that is one of the key factors that directly influence UAV reliability remains without improvement (Mrusek, Kiernan, & Clark, 2018).

Studies on UAV reliability and risk analysis highlight that mechanical and system failures are still risk factors (Lum & Tsukada, 2010), and improvement of system reliability and standardization is necessary for safe UAV operation (Belzer, 2017). But issues of UAV reliability still have not been solved, and the question of reliability in UAV has been continuously raised.

For ensuring that all components are operating the required functions as designed for safe UAV operation, we challenge a question in this paper – How can we improve UAV maintenance reliability even while a UAV is being operated? For this purpose, first, we review existing UAV preventive or predictive maintenance methods and investigate technologies utilized for the current maintenance in the UAV industry. Second, we propose and describe a cloud-based low-code predictive maintenance method for UAVs (CLPMM) that uses a low-code development platform, Microsoft Power Platforms, and cloud computing, Azure Cloud Services. Third, we compare current preventive and predictive maintenance methods with the CLPMM to verify the benefits. Lastly, we discuss how CLPMM improves UAV maintenance reliability even while a UAV is being operated.

2. BACKGROUND

UAV Maintenance Methods

There are two types of maintenance - preventive and predictive maintenance. Preventive maintenance is to repair parts at a scheduled interval. On the other hand, predictive maintenance is to repair parts before they fail (Barlow, 2015).

Cloud Computing for IoT

Internet of Things (IoT) is the network of connecting smart devices and allows to exchange data in real-time with other devices using sensors on the devices over the internet. The Azure IoT Central platform of Microsoft is a Software as a Service (SaaS) and plug & play IoT application platform. It provides various built-in functions that include templates, data analytics, data management, auto-scaling, recovery, and protocol. This platform also offers a built-in GUI dashboard that allows users to manage, customize, and visualize data for monitoring (Microsoft, 2021, March 29).

Low-Code Development Platform

The Microsoft Power Platform consists of Power Apps, Power Automate, Power BI, and Power Virtual Agents and offers solutions with low-code and no-code development platform for building and developing the application.

- Power Apps provides a friendly development environment that allows developers to easily build custom mobile and web applications that run on any device and connect and interact with existing data.
- Power Automate is used to create an automated workflow to reduce the workload on repetitive processes such as communication, data collections, and task assignments. Also, it provides an auto-notification function that sends notifications via email when the event occurs.
- Power BI, which is a data analysis software and Software as a Service (SaaS), allows users to easily connect to a broad set of data sources and process and visualize data to discover valuable information in the cloud, hybrid cloud, or on-premises environment.

3. RELATED WORK

Table 1 shows three related work - Su and Yon's (2018), Berbente et al. (2020), and Massaro, Selicato, and Galiano's (2020).

Su and Yon's (2018) study presented a Predictive

Criteria	Su & Yon, 2018	Berbente et al., 2020	Massaro, Selicato, & Galiano, 2020
Maintenance Method	Predictive	Preventive /Predictive	Predictive
Data Collection Location	Cloud Computing/On Premise	N/A	Cloud Computing
Data Storage	On Premise	On Premise	On Premise
Dev.	High code dev.	Low and High code dev.	Low and High code dev.
Capital Cost	High	High	High
Difficulty for Dev.	High	Intermediate	High
Data Visualization	Low (text only)	High	High
Auto & Timely Notification	Warning message	No	No

Table 1: Summary of Previous Work

Analytics Framework (PAF-HD) system to detect a sign of Hard Disk Drive (HDD) failure in the data center using a Machine Learning (ML) and Hadoop with Apache Spark. This architecture used a Random Forest algorithm and Hadoop with Apache Spark to distribute and process data and predict HDD failures. Also, this system includes a warning system to report HDD failures to a user, and raw data is manually uploaded to the system or is received from cloud storage.

Su and Yon (2018) utilize a Smartmontools software to provide the status of HDD health information for monitoring. The data is displayed in text only, and a user can only access data through a computer that is installed with this software.

Su and Yon (2018) build a system with complementary software to reduce development costs. But the system develops with high-code, and data is stored in an on-premise database. Furthermore, the paper provides two approaches for data connection with the system. One approach is to manually upload HDD historical health data to the system, which leads to high development and capital cost.

Bernente et al. (2020) highlighted that monitoring tooling, maintenance procedures, and analyzing components' data are crucial to detect equipment failures proactively. For that reason, the paper suggested an advanced Engine Health Management that is added a pro-active system and Business Intelligence from existing Engine Health Management. The pro-active system with predictive algorithms compares current patterns with historical data to predict component failures. Business Intelligence in engine condition monitoring detects impending failures by monitoring key parameters, such as temperature, engine thrust, oil temperature, and others.

Bernente et al. (2020) use business intelligence that offers a user-friendly environment for creating a data pipeline with an on-premise database and generating new valuable information from existing data. Furthermore, the business intelligence provides enriched templates and features to visualize the engine's key parameters based on user selection and allow users to share and access a dashboard and report with others for monitoring.

Massaro, Selicato, and Galiano's (2020) study proposed a new maintenance method that anticipates the timing of maintenance for a bus fleet through classifying the driver behavior and bus engine status using a hybrid cloud. This method is used for the Internet of Things (IoT), multilayer perceptron artificial neural network, and data visualization to collect, transfer, analyze, and display data. The data from internal sensors and OBD-II transfers to Raspberry Pi and is streamed to a company's on-premise database using the IoT cloud. Artificial intelligence algorithms process collected data to indicate engine stress and key performance indicators of driver behaviors. This information links to a cloud platform with a graphical dashboard for monitoring.

The system suggested includes a cloud platform with dashboards to visualize vehicle health status, fuel consumption, and key performance indicators of driver behaviors using various templates and visual aids for monitoring. This system uses a hybrid cloud. Data is transferred using the IoT cloud platform. But, data is sent to an on premise database, so capital cost is expensive.

4. DESIGN & IMPLEMENTATION

The concept of CLPMM can be classified into three main sections: data collection, data processing, and data visualization, and the steps of CLPMM are as follows (Figure 1):

1) Massive telemetry data from sensors on the device of drone parts is received in real-time via Azure IoT Central (Microsoft, 2021, May 3).
2) Azure Steam Analytics structures the telemetry data and stores it in Azure Storage (Microsoft, 2021, November 12).
3) The data is transferred to Power BI for real-time monitoring of the status of the drone's parts to detect the imminent part failure and is also utilized to predict the part life and part failure for predictive maintenance using Azure machine learning.
4) Power BI visualizes key parameters of drone parts in real-time.
5) Power Apps allows mechanics to access Power BI dashboard on mobile and upload maintenance records to Azure Storage.
6) Azure Automate automatically sends an email to assigned mechanics when the data shows that the part function is lower than standard.

In order to demonstrate the concept of CLPMM, a Tello drone and artificial flight data are used to show data processing and data visualization. Telemetry data from the Tello drone is transferred to IoT central in real-time using IoT and DJI Tello SDK in Figure 2.

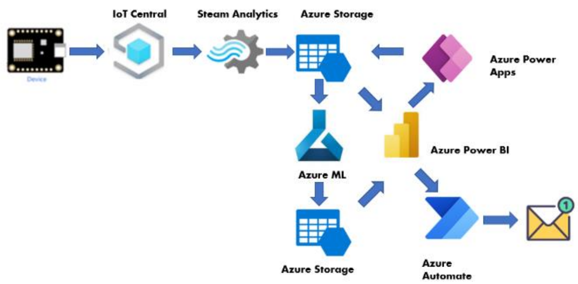

Figure 1: Architecture of CLPMM

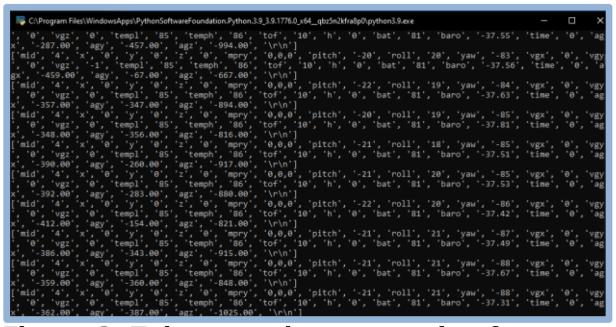

Figure 2: Telemetry data streaming from Tello Drone

Using IoT central service, telemetry data processes and displays on a dashboard in IoT central in Figure 3. The data is stored in Azure table storage.

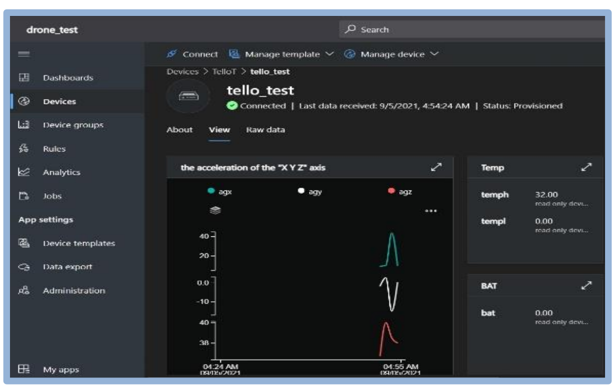

Figure 3: Telemetry data received through Azure IoT

Power BI connects with the storage and visualizes key data to detect impending failures of drone components in Figure 4.

From Figure 5, UAV just took off on Walnut St in Everett, WA at 12:17 PM to return home, and data showed that motor #one's rpm suddenly dropped on a line chart. Mechanics could easily recognize the abnormal condition of motor #one during monitoring the UAV's key indicators and quickly determine that it needs to replace. Furthermore, assigned mechanics would receive an email notification through the CLPMM.

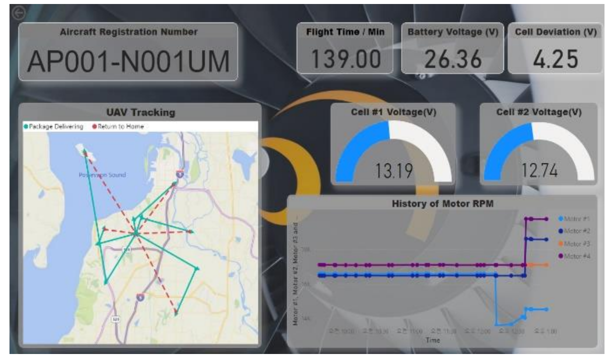

Figure 4: Key indicators of drone components

Figure 5. Monitoring abnormal behavior

Time series data in Azure storage are pulled from the storage and down into Azure notebooks. And then, it needs to set Azure subscription id and IoT hub name, storage account name, key, container, and others, and data is loaded using pandas. Lastly, a regression model is trained with Azure Auto ML. Azure Power Apps that connects with the storage and Power BI allows mechanics to access the dashboard in Power BI via mobile devices, so the mechanics can access it at any time for monitoring. Also, mechanics can easily upload the maintenance data to the storage. Using Azure Automate, supervisors or assigned mechanics automatically receive notification of impending component failure.

5. FINDINGS

From architecture and technology, cost, and data visualization and monitoring perspectives, the features of each architecture and the CLPMM will be analyzed and compared. Furthermore, the following requirements are considered to compare with each architecture.

- Allow mechanics to access the report and dashboard at any time for increasing collaboration and maintenance efficiency.
- Enable to flexibly expand IT resources depending on the workload in a short time to respond to massive data from UAVs.
- Need to consider operating costs.
- Require enriched features and templates to visualize data for providing insights to UAV mechanics.
- Provide strong security and recovery system to satisfy FAA maintenance records regulations.

CLPMM uses a PaaS and SaaS cloud architecture. Telemetry data is received from drones through Azure IoT, and Azure Stream Analytics processes and routes data to a dataset in Power BI. The Power BI performs to visualize data using templates and tools. Azure ML is used to predict drone component lifetime for predictive maintenance, and Azure Power Apps provides enhancement of mobile experience for access Power BI dashboard and uploading maintenance record to cloud storage. So, this environment satisfies FAA FAR part 91 which is maintenance record storage requirement. Lastly, Azure Automate automatically send notification to assigned mechanics or supervisors when the part function is lower than normal standard. These features of CLPMM bring several advantages over other existing architectures for UAV maintenance, as given below.

Architecture
- Low downtime
- High availability and scalability
- Easy to backup data
- Disaster recovery available

Cost
- No initial large investment
- Various pricing models available, such as Pay as you go, Monthly, and 1- 3 year reserved upfront plan

Data Visualization and Monitoring
- Easy to share and access reports and dashboard with others
- Enriched features and templates
- Intuitive dashboard and high accessibility

However, the concept of CLPMM is not free from the inherent limitations of the cloud and other drawbacks.
- Possibility of cloud outage
- Level of control
- Long-term costs (Increasing the total cost of ownership)
- requirement of reliable connection
- Risk of IoT security

Overall, architectures that are used on-premise and hybrid cloud have strengths. However, in the light of the above requirements for improvement of predictive UAV maintenance, the CLPMM has more benefits and satisfy more requirements than other architectures. In other words, those technological advantages from CLPMM help mechanics efficiently monitor critical indicators of UAV components to maintain the airworthiness condition and contribute to improving UAV reliability. Furthermore, existing UAV companies or start-up companies just jumping into the UAV industry can quickly launch their UAV maintenance program and flexibly manage and store flight data depending on the amounts of data using CLPMM. On the other hand, reliable connection and the risk of IoT security might be hurdles to adopting and operating CLPMM because the meaning of a lost connection is unable to receive flight data from a drone. Therefore, a reliable connection should guarantee. Also, vulnerabilities of IoT security should remove to avoid hacking or data breaches.

6. CONCLUSIONS

The Cloud-Based and Low-Code Predictive Maintenance Method (CLPMM) that uses cloud services is designed to receive data from UAV in real-time and process and visualize the data for providing valuable information for predictive UAV maintenance. Azure IoT Hub receives data in real-time from UAV, and the Azure Steam Analytics processes and routes the data to a dataset in Power BI, Azure Table storage, and Azure ML.

This architecture has the ability to handle resources depending on demands without impacting performance and availability, so it can flexibly respond to growing UAV data during flight. Furthermore, a large initial investment in IT equipment is not necessary as a cloud provider services software, storages, operating systems, and other resources. Moreover, the cloud provider offers various types of pricing models, so there is an opportunity to optimize the operating cost.

The Power BI in the CLPMM architecture furnishes an intuitive visualization dashboard that consists of significant data to UAV technicians using Power BI enriched features and templates, and the UAV mechanics are able to access the latest updated dashboard at any time for monitoring the status of UAV components and detecting impending component failures. Azure ML is used to predict part lifetime and timing of maintenance, and Power Apps offers a good mobile experience to mechanics to access Power BI dashboard and upload maintenance record to the cloud storage.

Furthermore, Azure Automate provides automatic notification that send email to assigned mechanics when the component's performance is below the normal standard. These features show that the CLPMM is improved and reduces maintenance efforts more than other architectures, and it is suitable for improving predictive UAV maintenance and reliability.

7. FUTURE WORK

First, this paper could only test the CLPMM using a single drone due to the limited resources. Accordingly, an examination to check that this concept flexibly deals with unexpected network overload, processing power, and a sudden increase of telemetry data for smooth and stable data transfer when connected to multiple drones is needed.

Second, the main required future work will be researching IoT technologies because the CLPMM has utilized IoT technology to receive telemetry data from a drone. In other words, the data connectivity between UAV and IoT is essential to get the data stably. Therefore, it is necessary to research types of IoT networking technologies to find what technology is suitable, such as wireless mesh network systems or Long-Range Radio (LoRa).

Last, IoT security cannot be neglected. IoT vulnerabilities lead to allowing unauthorized access and may cause a hijacking. Additionally, an unauthorized person who obtains data during the streaming can get information about the shipping destination based on data and steal packages. The data is from sensors of UAV components, so it is unable to detect UAV structure problems using CLPMM. For that reason, the future work may involve in investigating a method to get structural data from the drone in real-time. In addition, the data collected from the failed components may be used to influence the current or future policy on preventive and predictive maintenance. This work does not focus on this topic but finding the improved window for maintenance intervals can be an area for future addition.

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Measuring Analytics Maturity and Culture: The LDIS+™ Analytics Impact Framework

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Abstract

Measures of analytics maturity in companies and organizations often include a reference to culture, but do not go further than a surface-level examination. The relationship between occupational cultures—that is, the work styles of various divisions within an organization—and analytics maturity is not known. The purpose of this quantitative correlational study was to examine the relationship between occupational culture and data analytics maturity. The problem addressed in the study is that the relationship between occupational culture and data analytics maturity has not been identified. Quantitative methods were used to identify occupational cultures within organizations using the Competing Values Framework (CVF) quadrants, rank priorities and challenges, and quantify data analytics maturity. Enough significant relationships were found within the companies that participated in the study to suggest that the differences within occupational groups impact a company's data strategy, analytics maturity, and adoption readiness. These results demonstrate the need to consider occupational cultures when assessing an organization's data analytics maturity. Simply declaring a company's overall culture is not sufficient. Companies are not monolithic cultures, and any assessment of analytics maturity must take these differences into account.

Keywords: data analytics, analytics maturity, data culture, data literacy, occupational culture, organizational culture

1. INTRODUCTION

In 2019 a new approach to business intelligence and analytics (BI&A) maturity was proposed (Fowler, 2019), tying together previous research in organizational theory, occupational culture, data analytics strengths, and analytics maturity. This approach was investigated in a doctoral dissertation and produced four data culture archetypes. Along with these findings, recommendations for further research are presented.

The problem addressed in the study is that the relationship between occupational culture and BI&A maturity has not been identified (Bach, Jaklic, & Vugec, 2018; Bhatt, 2001; Mardiana, Tjakraatmadja, & Aprianingsih, 2018; Shao, Wang, & Feng, 2015; Sheng, Pearson, & Crosby, 2003; S. Wang & Yeoh, 2009; Watson, 2016). The plurality of occupational cultures within an organization have been acknowledged in prior research but not in relation to BI&A maturity (Bellot, 2011; Guzman & Stanton, 2009; Jacks, 2012; Jacks & Palvia, 2014; Mallet, 2014; Schein, 1996; Trice, 1993). Because culture is a primary driver in a successful BI&A implementation (Bara & Knežević, 2013; Clark & Wiesenfeld, 2017; Frisk & Bannister, 2017; Grublješič & Jaklič, 2015; LaValle, Lesser, Shockley, Hopkins, & Kruschwitz, 2011; Smith, 2015; Teixeira, Oliveira, & Varajão, 2019), a more robust evaluation of organizational culture that includes its occupational cultures must be made. A BI&A solution that only considers an organization's dominant culture and its drivers for implementation is certain to meet the needs of some and leave others unengaged, underserved, and disappointed.

The purpose of the quantitative correlational study was to examine the relationship between occupational culture and data analytics maturity. The occupational cultures are measured by the Competing Values Framework (Cameron, n.d.; Cameron & Quinn, n.d.). The metrics for BI&A—priorities, challenges, maturity level, and maturity characterization—are measured by an assessment instrument developed specifically for this research.

2. REVIEW OF THE LITERATURE

Maturity Models

LaValle et al. (2011) stands as a seminal study in BI&A maturity. The authors sought to quantify how businesses use analytics in different functional areas of the organization and create a framework for BI maturity within companies. They acknowledged that many businesses are "still looking for better ways to obtain value from their data and compete in the marketplace," and that in the emerging business intelligence market, "knowing what happened and why it happened are no longer adequate" (LaValle et al., 2011, p. 21).

Prior to 2011, the available research on BI&A was less dense; the articles reflected a field that was in its infancy and were restricted to specific applications rather than a meta view of the industry itself (Apte et al., 2010; Bolton & Drew, 1991; Bose, 2009; Chan, 2007; Gessner & Scott Jr., 2009; Hair Jr, 2007; J. K. Kim, Song, Kim, & Kim, 2005; Liberatore & Luo, 2010; Morita, Lee, & Mowday, 1993; Mosley, 2005; Noori & Hossein Salimi, 2005; Sahay & Ranjan, 2008; Somers & Birnbaum, 1999; J. Wang, Hu, Hollister, & Zhu, 2008). Becker, Knackstedt, and Pöppelbuß (2009) surveyed maturity models for IT in a broader sense and introduced the IT Performance Measurement model, which did include the TDWI Maturity Model from 2007, comparing stages in business intelligence adoption to stages in child and adolescent development (Eckerson, 2007).

The taxonomy that emerged from LaValle et al. (2011) included three distinct levels of BI&A maturity: Aspirational, Experienced, and Transformed. Organizations fall into one of these three categories by way of six key areas: motive, functional proficiency, business challenges, key obstacles, data management, and analytics in action. Among challenges and obstacles, the most common impediment to successful analytics adoption was found to be cultural, not technical—that is, companies were not able to effectively understand how to utilize their data, or management did not prioritize, or the company lacked internal skills. Key areas of differentiation between Aspirational and Transformed saw the more successful organizations functioning anywhere from four to ten times more proficiently in end-to-end data processes.

Competing Values

Any organization has an implicit culture comprised of "fundamental values, assumptions and beliefs held in common" by its members (Helfrich, Li, Mohr, Meterko, & Sales, 2007, p. 2). The culture grows as the company transitions from startup to incumbent, and new members are acclimated to the culture as they are brought into the organization. As it affects every part of member interaction and organizational operation, culture has been cited as a critical barrier to innovation and implementation (Helfrich et al., 2007). Much has been written about organizational culture, how to assess it, and how to deal with it; likewise, many models of organizational culture have emerged as researchers attempt to make sense of an otherwise abstract phenomenon.

Schein (1997) introduced a three-level model that has been a valuable resource in organizational analysis. The surface level of the model is concerned with artifacts: things that represent both tacit and explicit knowledge and are most easily discovered. However, the ability to *discover* these artifacts doesn't assume the ability to *understand* their meanings. This mirrors the Access/Usability difference discussed by Popovic et al. (2012). Meanings are found in the intermediate and foundational levels. At the intermediate level, organizational goals and philosophies define "what ought to be done in an organization" and "visible and debatable with individuals" (Aier, 2014, p. 49). Under that, at the foundational level, are the underlying assumptions that define belief systems, truth, behavior, and reality (Schein, 1997).

At the intermediate level of values and beliefs, the Competing Values Framework (CVF) focuses on these "core constituents of organizational culture" (Aier, 2014, p. 50). The CVF was introduced in 1981 by Quinn and Rohrbaugh; since that time, it has served in many capacities from peer-reviewed research to industry tools and white papers (Cameron, n.d.; Cameron & Quinn, n.d.). Its concise methodology and ease of reporting has made it a favorite of organizational culture analysts (Aier, 2014; Büschgens, Bausch, & Balkin, 2013; Helfrich et al., 2007; K. Kim & Kim, 2015; Pakdil & Leonard, 2015; Rabelo et al., 2015; Shao et al., 2015; Yu & Wu, 2009).

The CVF is a basic two-axis, four-quadrant system; one axis represents the change vs. stability spectrum, the other represents internal vs. external focus (Aier, 2014). The two axes converge to make the four quadrants of culture: Group, Developmental, Rational, and Hierarchal (R. E. Quinn & Rohrbaugh, 1983). The four quadrants have different names depending on the application. An organization will exhibit traits of all four, most often lean towards one or two, and exhibit these especially when it grows and experiences "external environment pressure" (Rabelo et al., 2015, p. 90).

BI&A and Culture Interplay

By 2014, the idea of cloud-based BI&A services was coming in the mainstream, and one of the primary advantages of cloud architecture was the lack of physical infrastructure to maintain (Bonthu, Thammiraju, & Murthy, 2014). More organizations were shifting focus from the deliverables of BI&A to how the supporting culture could enable more valuable insight. That is, BI&A shifted from something the organization *drew from* to an asset the organization *fed into*. The absence of a physical reminder as cost center signified the shifting role of data.

Although any database programmer understands the idea of *garbage in, garbage out*, that concept is more difficult to understand when applied to cultural elements. In other words, organizations had not thought of the interplay between culture and BI&A. Sweetwood (2016) summed it up thusly: "The problem is that while [companies] are thinking differently about their data, in many cases they're not acting differently based on what the data is telling them." This gap has persisted a number of years with little sign of improvement (Davenport & Bean, 2018).

This is not actually about delivering specific analytics insights, but about crafting how the organization supports analytics efforts and arrives at them. Think of this analogy. In the book *The Death of Expertise*, Nichols (2017) discusses the importance of our metacognitive ability—that is, the ability to think about our thinking. Metacognition is the wisdom and ability to evaluate our own shortcomings, thought patterns, logic, and biases. It's one thing to not know something, but *not knowing that we should, and don't, know something* is dangerous. An organization that is not mature enough to identify its pedestrian BI&A culture has a different disadvantage than one that understands its own shortcomings and wants to improve. Ignorance and willful ignorance are not the same.

Maturity indices that include culture have already made a significant contribution to the field in allowing organizations to codify their adoption progress and speak a common language about BI&A implementation (Gudfinnsson, Strand, & Berndtsson, 2015; LaValle et al., 2011). As culture is a significant part of adoption and maturity, these go hand in hand. Organizational culture has already been a popular topic for a long time, particularly around leadership circles, but the confluence of culture and analytics is a new research area ripe for further research and knowledge creation.

Grublješič and Jaklič (2015) discussed organizational factors directly influencing BI&A acceptance. The authors drew a distinction between operational information services (IS) acceptance and BI&A acceptance. These differences came into play as the authors introduced the Technology Acceptance Model and Unified Theory of Acceptance and Use of Technology. Social influence and facilitating conditions were two of the four major influencing factors, rooted in environment. In their literature review, they summarized the factors in five major environmental characteristics: individual, technological, organizational, social, and macro. The authors examined four specific cases of acceptance across different organizations and were able to make several general conclusions.

All interviewees noted that BI&A was "not accepted as planned" and "did not achieve expectations of acceptance" (Grublješič & Jaklič, 2015, p. 306). The authors did not find this surprising, as implementation of BI&A tends to carry an expectation of solving business problems by itself and automatic acceptance. It is necessary to build a culture of BI&A use and management support—in many cases a "transfer of responsibility," delegation and trust (Grublješič & Jaklič, 2015, p. 306). Such a level of delegation and responsibility includes a direct top-level sponsor and business users' active participation in the process of building the BI&A capabilities. It also engenders a "proactive information culture" (Grublješič & Jaklič, 2015, p. 307).

Beyond organizational characteristics, individual and social characteristics played no small part. These call attention to the different divisional/occupational determinants within an organization and acknowledge the organization is comprised of the sum of its parts, not a monolithic entity. Of the individual characteristics discussed in previous literature, Grublješič and Jaklič (2015) found age, computer literacy/self-efficacy/anxiety, prior experience, and attitude to be the major determinants (p. 309). A reciprocal relationship exists between the soft organizational factors, individual characteristics, and BI&A culture.

Villamarín García and Díaz Pinzón (2017) echoed many of the findings of Grublješič & Jaklič in their study of BI&A success factors. A sponsor is key, acting as a "champion" for the project and demonstrating its value to the business users (p. 60). The authors acknowledged this person must wield influence and possess ability to form alliances amongst the various stakeholders in the organization. They must be respectful of different occupational cultures and exhibit tactical empathy.

The authors linked BI&A success with organizational culture, through business strategy. This is defined as the "mission, vision, strategies, objectives, needs and, generally, all issues than have led the organization to think about a BI solution" (Villamarín García & Díaz Pinzón, 2017, p. 60). These elements sound very close to how Schein (1997) defined culture. The authors referred to these as the conditions an organization operates in both internally and externally. Any new BI&A process introduces a new set of norms and processes that may meet resistance from the established culture, either at the organizational, divisional, or individual level. Environmental conditions especially affect project implementation success. These generate both barriers and benefits "as joint problem solutions on behalf of positive issues formed by the organizational culture" (Villamarín García & Díaz Pinzón, 2017, p. 65).

BI&A project implementation carries its own culture, as Villamarín García and Díaz Pinzón (2017) suggested in the six characteristics that impact the team's performance and development: collaboration, engagement, communication, trust, cooperation, and coordination. Technology tools serve to improve and empower these skills, complementing organizational processes and individual edification. This concept re-emerged in Moreno, Vieira da Silva, Ferreira, and Filardi (2019).

Moreno et al. (2019) acknowledged the difficulty of evaluating the often-intangible benefits BI&A implementations with methods built for traditional project management approaches. The authors introduced the idea of complementarity, or the pairing of IT resources with organizational resources to produce business value. This, according to the authors, is absolutely necessary for IT investments. The authors also discussed BI&A absorbability, a collection of mostly intangible factors introduced by Popovič, Turk, and Jaklič (2010). These factors include "strategy alignment, a culture of continuous process improvement, a culture of information use and analysis, decision process management, cooperation between IT, and business and technological readiness" (Moreno et al., 2019, p. 62). The authors called out an adoption strategy that met a number of obstacles from the outset. Neither management nor stakeholders were engaged, and the organization seemed more interested in "gaining information, not the matter in which it was obtained" (Moreno et al., 2019, p. 64). This was a very managerial view of BI&A, concerned mostly with access and not application.

There was effort to promote integration and standardization prior to BI implementation. This groundwork did help the efforts gain more traction as a cultural engagement rather than a bolt-on solution. Furthermore, "customized training that matched the different needs of the various groups of business users" and "additional organizational structures, business processes, policies, roles and norms" increased complementarity and value generation (Moreno et al., 2019, p. 67). This is a clear acknowledgement of cultural relevance to BI&A.

Specific to BI&A implementation, Perkins (2017) found that the BI capabilities affect the organization as a whole and must be viewed as "an amalgamation of strategic decision support capabilities that advance the needs of the business" (p. 137). To that end, a "strong partnership" between IT and business divisions helps bring a BI&A implementation to fruition (p. 138). The mixed-methods study provided a comprehensive look at attitudes towards BI&A goals and sometimes disparate occupational cultures within an organization. When those come together and work in harmony, great things are often accomplished. Kurzweil and Wu (2015) profiled a student success initiative at Georgia State University that involved key players across the institution, and the final report acknowledged the success was due to "the accumulated impact of a dozen or more relatively modest programs. As it turns out, the recipe for GSU's success is not a particular solution, but rather a particular approach to problem-solving" (p. 3). In other words, it was about the culture and not the tools.

Graham (2017) and J. J. Quinn (2016) both offered case studies on the interplay of BI&A and culture in the pharmaceutical industry. McCarthy, Sammon, and Murphy (2017) examined how BI&A impacts specific leadership styles in organizations. Power (2016) identified "Competitor Information Culture" (p. 350) but warned against leveraging this too quickly for justifying actions, something already identified in an Aspirational-only BI&A maturity stage. S. Wang and Yeoh (2009) crafted a comprehensive framework that matches organizational culture quadrants on the Competing Values Framework with IT effectiveness in organizations.

Gaps in the Literature

The literature around data-driven culture over the past three years has shown that the development of BI&A capabilities has focused mostly on the tangible elements of those capabilities (e.g., systems, deliverables, and personnel) rather than the intangible elements (e.g., data literacy, culture, and engagement) that are unseen but critical. This is not surprising, as new capabilities are often first implemented with the deliverables prioritized. When BI&A was first identified as an interdisciplinary field, the deliverables were what defined the field itself: reports, dashboards, aggregates, and products that were ultimately used to justify the actions of the business units that used them. Organizations that remain in this phase of BI utilization are labeled "Aspirational" in the common BI&A maturity framework (LaValle et al., 2011, p. 23). Those organizations remain unchanged in deeper levels of BI&A adoption. There is still a lack of systemic integration, no organization-wide implementation of data culture, and an absence of executive sponsorship (p. 24). The opportunity ahead involves the examination of different occupational cultures within an organization and how they affect the perceived data analytics maturity in that organization.

3. METHODS

Quantitative analysis shows concrete relationships between variables and allows generalizations about populations (Bernard, 2013; Castellan, 2010). The research method selected for this study was descriptive correlational research. This method is nonexperimental. There are no control or comparison groups, no random assignments, and no manipulation of independent variables (Cantrell, 2011).

The descriptive correlational method is useful for examining the relationship between variables for explanatory purposes (Welford, Murphy, & Casey, 2012). Rather than a traditional independent and dependent variable, descriptive correlational research typically utilizes the terms predictor and criterion variables. In this study, the Competing Values Framework culture quadrants are the predictor variables, and the criterion variables include data priorities, data challenges, and data analytics maturity scores.

Population and Sampling

The target population for the study was small to medium size companies in North America. A company with fewer than 100 employees and annual revenue less than $50 million is considered a small business, while a company with 100-999 employees and annual revenue between $50 million and $1 billion is considered medium (Gartner, 2020). This population is aware of the value that BI&A brings. Implementation is considered mandatory, and companies are sensitive to what competitive edge a proper implementation can bring (Durcevic, 2020).

Purposeful Sampling was used. In Purposeful Sampling, participants are chosen based on their experience, knowledge, or interest in the phenomenon of interest (Creswell & Plano Clark, 2011). Four companies were available during the study time period. The instrumentation involved a comprehensive Business Intelligence Maturity Assessment (BIMA) assembled from various research-based methods (Cameron & Quinn, n.d.; LaValle et al., 2011; Oficina de Cooperacion Universitaria, 2013). Collection was done through a secure online portal, and quantitative analysis was done with R.

Data Collection Instrumentation and Procedures

Informed consent was obtained from the Colorado Technical University Institutional Review Board (IRB) prior to selection of organizations for the study. As organizations are selected, a representative of each organization was given a letter identifying the purpose of the study, how the individual participants are protected, and what data the organization will receive at the completion of the study. Every individual who participated signed an individual informed consent notice that identified the purpose of the study, how they were protected, and what data would be made available at the conclusion of the study.

The collection instrument was the Comprehensive CVA-BIMA Instrument. The assessment includes four components, three of which were used for this study. The first part is the Competing Values Assessment, which is a quantitative instrument. This gave us a broad-brush idea of a division's approach to processes and outcomes, or the why behind what gets done and how it gets done. The second part is a semi-structured qualitative interview, not used for this study. The third part of the instrument is a quantitative assessment that identifies top priorities and challenges in working with data in the organization. The fourth and final part of the instrument is a quantitative assessment that identifies specific maturity levels in different areas of BI implementation.

Due to the COVID-19 pandemic, in-person assessments were not possible. Participants were interviewed via Zoom with the assessment instrument shown on the screen and the interviewer guiding the participant through each question.

The author added all collected data into a simple central database through a web portal developed specifically for this purpose. This data resided entirely within this study's IT environment and was only accessible via on-premise or VPN connection. The findings were shared with participants' respective companies by request via a prepared report and strategy document. Individual data points were not shared with companies so that anonymity of the individual respondents was preserved. This data will persist beyond the dissertation research in order to continuously improve and question the theories established through this research.

Data Analysis Procedures

Scores from the Competing Values Assessment were tabulated as instructed in the original instrument and a scale score was produced for each culture quadrant. The dominant culture (the highest scoring of the four) was identified for each participant. Culture scores for each division were identified by averaging the culture scores for all participants within a division. Much like Competing Values Framework scores, maturity scores were tabulated as instructed in the original instrument. Each subscale has its own integer score and these combine to make an overall integer score. For the data priorities and challenges, the options chosen by each participant were identified by a 1 (and those not chosen, by a 0).

Independent (or predictor) variables included the CVF culture scores (Collaborative, Creative, Competitive, Controlling). Dependent (or criterion) variables included chosen data priorities, data challenges, and data analytics maturity subscales. Inferential statistics were used for analyses, and specific tests depended on the nature of the data. Because the total number of participants was small, assumptions of normality could not be met, and non-parametric tests were utilized. In addition, descriptive statistics such as measures of central tendency were performed in order to understand the general characteristics of the data. The CVF culture scores (scale data) were compared to the maturity scores, priority choices, and challenge choices (all ordinal data) through point bi-serial correlation.

4. RESULTS & DISCUSSION

Forty-four participants were interviewed for this study. All participants were employed in the private sector and worked for companies that matched the target population. The majority of participants were female, at 79%; only 21% were male. Table 1 indicates the breakout of dominant CVF quadrant scores by gender. Tables 2 and 3 (Appendix A) indicate significant relationships found via correlation and *t*-tests, respectively.

Dominant Quadrant	**Female**		**Male**		**All**	
	n	**%**	***n***	**%**	***n***	**%**
Collaborative	23	52	7	16	30	68
Creative	4	9	0	0	4	9
Competitive	6	14	2	4	8	18
Controlling	2	4	0	0	2	4

Table 1: Demographics of Research Sample

Collaborative Quadrant

Each of the four CVF quadrants were significantly correlated to at least one priority, challenge, or maturity index. The only significant relationship found between the four cultures and all data priorities was Access, having a moderately positive correlation with the Competitive quadrant. Next, we examine the relationship between the four CVF cultures and data challenges. The Creative quadrant had a moderately positive correlation with Ownership of Data, and the Controlling quadrant had a moderately negative correlation with both Ownership of Data and Inability to Get the Data.

Finally, the relationship between the maturity matrix and CVF cultures contained several significant finds. The Scope subscale was moderately positively correlated with the Collaborative quadrant, while the Data Governance subscale was moderately positively correlated with the Controlling quadrant. The Competitive quadrant had significantly negative relationships with the Scope, User Engagement, and Overall subscales. These findings are summarized in Figure 1 (Appendix A).

In this study, the Collaborative culture aligned with data products covering a wide scope, which is consistent with the purpose of a Collaborative data culture encouraging participation and buy-in. The Creative culture called out challenges around not knowing how to use analytics to improve the business and a lack of data governance. Given that the purpose of Creative data culture is to innovate and explore, this makes sense, as innovation requires clear direction.

Although there are no overwhelming patterns connecting the CVF quadrants and maturity measures, we can identify four major themes that emerge from the results. First, Data Management/Governance appeared in quadrants opposite of each other (Controlling and Creative). Second, Scope appeared in quadrants opposite of each other (Collaborative and Competitive). Third, the quadrants focused internally had more positive measures of analytics maturity. Fourth, the most significant findings were found in the Competitive data culture.

5. CONCLUSIONS

The central research questions were structured around the CVF scores being predictor variables and the various analytics maturity subscales being criterion variables. The previous section includes the findings that answer these research questions specifically. This section will examine the themes that emerged from the study as a whole.

Theme One

The challenge of Data Management/Governance was significantly associated with the Controlling and Creative quadrants, which are opposite each other on the Competing Values Framework. Those in the Controlling quadrant were more likely to say it was not a challenge, whereas those in the Creative quadrant were more likely to say that it was.

Based on the characteristics of these two quadrants, we can infer that respondents who were internally focused and valued stability found data governance to be satisfactory, whereas those who were externally focused and valued flexibility found data governance to be lacking.

On the surface, these scores seem completely opposite of what we might expect. Wouldn’t respondents who value internal focus and stability be more critical of data governance measures? A few things could be happening here. The item on the assessment specifically says “Ownership of data is unclear or governance is ineffective (too hard to resolve conflicts across silos).” The Controlling quadrant is also known as the Hierarchal model quadrant, associated with bureaucracy and organizational continuity (J. K. Kim et al., 2005). Perhaps the respondents see the data environment through that hierarchal lens, or they have influenced the environment to have sufficient data governance in place. On the other hand, the Creative quadrant (also known as the Open Systems quadrant) respondents may be so focused on growth and creativity that these measures have been neglected.

Theme Two

The Scope maturity subscale was significantly associated with the Collaborative and Competitive quadrants, which are opposite each other on the Competing Values Framework. Those in the Collaborative quadrant were more likely to rate it higher, whereas those in the Competitive quadrant were more likely to rate it lower. The Collaborative quadrant is a combination of internal focus and flexibility, encouraging company participation and sharing (J. K. Kim et al., 2005); without all users in scope, this participation cannot thrive. Perhaps these organizations prioritized Scope based on their information culture. This is a reflection of the “proactive information culture” discussed by Grublješič and Jaklič (2015).

Theme Three

The Collaborative and Controlling quadrants, while opposite each other with respect to stability and flexibility, are both internally-focused quadrants. Both quadrants were significantly associated with positive measures: less likely to cite certain challenges and more likely to rate maturity subscales higher. Given the internal focus of these quadrants, we may assume that the respective companies have spent enough time evaluating their internal data management mechanisms and building a support structure that serves the needs of the stakeholders.

It is worth mentioning that the positive associations between these measures of maturity and the internally-focused quadrants are aligned in their purpose and use. Collaborative information cultures use data to "promote collaboration, cooperation, and the willingness to take the initiative to contribute and act on information" (Choo, 2013). Respondents in this quadrant were most enthusiastic about Scope; that is, how well the current data offerings serve the needs of all stakeholders. Controlling information cultures use data to "control internal operations" and "emphasize control and integrity" (Choo, 2013); respondents in this quadrant were most enthusiastic about Data Management and less likely to cite Access or Governance as a challenge.

Theme Four

Most of the maturity measures were significantly associated with the Competitive quadrant, externally-focused and valuing stability. This quadrant was more likely to cite Access as a priority, and more likely to rate analytics maturity the worst. In fact, this is the only quadrant that had significant relationships with more than one maturity subscale (Overall, Access, and Scope). Although it is on the externally-focused side of the matrix, it still values internal assessment. Competitive cultures "[seek] information about customers, competitors, markets, as well as data to assess its own performance" (Choo, 2013).

The Competitive quadrant is also known as the Rational Goal quadrant. Organizational effectiveness is measured by goal achievement, and these are met by having the right direction and guidance for maximum productivity. Access to data is important for everyone here, and any shortcoming in a company's data products will be hyper-visible to respondents in this quadrant. Given the limitations of this study, it would be helpful to examine the Competitive quadrant's relationships with the other variables in a study with a larger sample size. Power (2016) warned about the potentially overbearing "Competitor Information Culture" and viewed through that lens, this result is worth additional study.

Practice Implications of Study Findings

As data analytics competencies become a requirement at organizations worldwide, differentiators must emerge. Organizations will seek what can give them an edge. The literature has shown that culture is a significant impact to analytics maturity, and these results demonstrate the significance of occupational cultures. Enough significant relationships were found within this small sample of companies (N=4) to suggest that differences within occupational groups play a significant difference in how data analytics maturity is perceived, as well as how data is used to advance the company's common goals. Simply declaring a company's overall culture is not sufficient. Companies do not have monolithic cultures, and any assessment of analytics maturity must take these differences into account.

Such an action can take many forms. Companies and organizations may implement internal training and competency development based on the findings in this study, identifying various data subcultures across the organization and encouraging a more responsive form of data literacy. They may also choose to include this assessment in an annual or quarterly review process. Such a routine would set baselines and trackable goals for improvement in a company's overall data literacy. A company or organization may also run this assessment process to understand what features and benefits are the most critical when choosing an enterprise analytics tool rather than risking a bad rollout to winging it.

Analytics software vendors and data consulting firms may use this research to identify the most pressing needs for a client. It is presumptuous to recommend a solution without a solid understanding of the presenting needs, and the instrumentation used in this study yields a very granular view of those needs. Beyond that, it helps to understand how messaging and deployment should be tailored to each data subculture.

Mobilizing this framework to an industry audience is critical to its adoption, and for that reason it has been trademarked as the LDIS+ Analytics Impact Framework.[i] The CVF quadrants, in this context, are APTitudes[ii] (Analytics Personality Types). These trade names make the framework much easier to communicate to stakeholders and summarize the core elements in an industry-relevant way.

Recommendations for Further Research

The body of research in this specific problem is thin. This study stands as an early exploration of the subject. Because the sample size and number of participating companies were small, repeating this study with significantly more participants would benefit the strength of detected relationships and the generalizability of the results. The significant findings in this study should be compared to those found in further studies with greater statistical power. In addition, a balance of gender and age ranges would help determine whether attitudes are affected by these variables. As COVID-19 becomes less of a threat and businesses return to normal operation, organizations with 50 or more employees should be recruited (from a variety of industries) to participate.

Using the participants from that study and collecting qualitative data through a series of structured interview questions would help to both validate the quantitative results and yield a deeper understanding of them. Insights from both quantitative and qualitative methods can produce a "more workable solution" and "superior product" (Johnson & Onwuegbuzie, 2004). A within-stage mixed-model design suggested by Johnson and Onwuegbuzie (2004) would be the most appropriate, as the two different models should be utilized in the same interview process rather than separated in phases.

A focused study on the Competitive quadrant's relationship with the other measures of maturity would be helpful, as this particular quadrant yielded the most significant relationships. It would be helpful to understand whether these relationships persisted over various industries, company sizes, and relative strength with other quadrants in a larger sample. Conversely, other quadrants might show similar clusters of significant relationships with a larger sample.

Despite the small sample, significant relationships emerged between the measures of information culture and maturity. These relationships coalesced under four themes: data governance, scope, internal focus, and competitive culture. It is clear that companies are not monolithic cultures, and the unique relationships between occupational cultures and maturity measures suggest that the plurality of cultures within a single company should not be ignored when considering analytics maturity. Further research is recommended, specifically with more participating companies and with mixed methods.

6. ENDNOTES

i Leveraging Data Individual Strengths
ii The author is grateful to Marc Marta for his creativity and collaboration.

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APPENDIX A
TABLES AND FIGURES

	Collaborative	Creative	Competitive	Controlling
(P) Access			.48**	
(C) Access				-.35*
(C) Data Management				-.33*
(M) Overall			-.31*	
(M) Scope	.33*		-.30*	
(M) Data Management		.37*		.30*
(M) User Engagement			-.32*	

Table 2: Significant Correlations

Quadrant and Dimension	Chose Dimension		Did Not Choose			
	M	*SD*	*M*	*SD*	*t*(42)	*p*
Creative						
(C) Data Management	28.07	9.59	20.69	7.48	136.5	0.015
Controlling						
(C) Access	18.69	8.71	24.33	7.61	339.5	0.023
(C) Data Management	19.22	7.07	23.42	9.36	333.0	0.029

Table 3: Significant Quadrant Score Differences

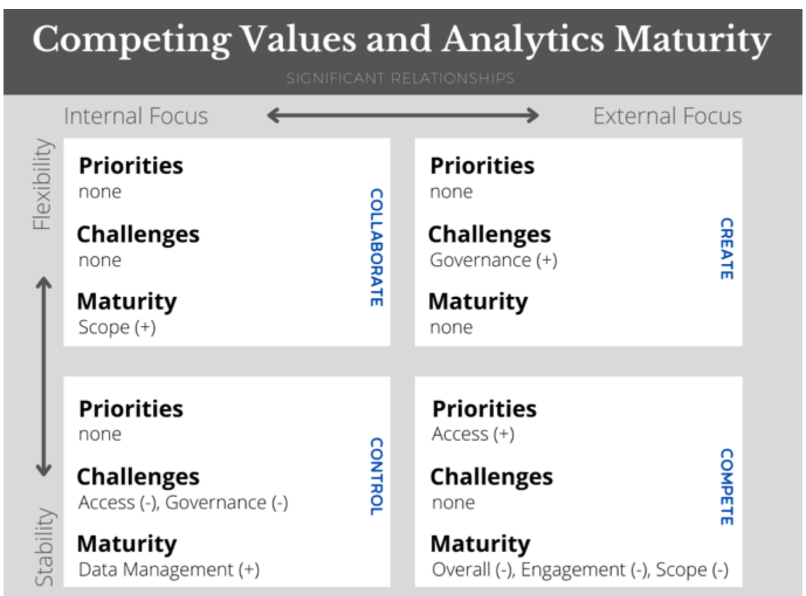

Figure 3: Combined Findings

How Firms Can Impact IT Project Continuation Intentions: A Human Capital Perspective

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Abstract

The failure rate of information technology (IT) projects is alarming, significantly costing organizations who find it hard even to justify the return on their investment. While Forbes suggests that the only way to reduce the likelihood of such failure is by looking closely at the project definition, scope, and management problems, we take a different lens, a human capital one. We propose that having certain individual characteristics for those involved in IT projects may lead to outcomes that will determine the success of a project. This study investigates the impact of locus of control, preference for consistency, and personal investment on mastery goal orientation. We postulate that learning and mastering skills during the IT project life cycle are key precursors to the intention to continue working on the IT project. We surveyed 232 professionals working on IT projects from Fortune 500 companies in the southern United States. We found that these individual characteristics influence mastery goal orientation. Also, mastery goal orientation and locus of control are determinants of intention to continue. Interestingly, mastery goal orientation fully mediates the impact of personal investment on the intention to continue. Theoretical and practical implications are discussed.

Keywords: mastery goal orientation, intention to continue, individual characteristics, IT project management.

1. INTRODUCTION

While project failure plagues firms across industries and functional areas, it is especially prominent among IT projects (e.g., Benschop, Nuijten, Keil, Rohde, Lee, & Commandeur, 2021). For example, Gartner reports that 75 percent of ERP projects fail (Andriole, 2021). In a study by the Consortium for Information and Software Quality, Krasner (2021), in conjunction with the University of Oxford, finds that "the CPSQ [cost of poor software quality] due to unsuccessful projects in the US in 2020 is $260 billion (up from $177.5 billion in 2018)" (p. 15). Despite the failure rate of IT projects and the associated costs, IT projects are especially subject to IT project escalation—the investment of additional resources in a project even when evidence suggests the project may fail (Lee, Keil, & Wong, 2021).

Andriole (2021) notes in a Forbes article, "Big technology projects fail most of the time. Is there any way to reduce the likelihood of failure? Yes: look at definition, scope and management problems, but don't look too closely at problems with talent, executive support and corporate culture. They're nearly impossible to solve." (para. 1)

However, prior literature indicates that the project decision makers' (e.g., project managers) and IT project professionals' traits and perceptions may impact project outcomes such as IT project escalation (e.g., Benschop et al., 2021; Korzaan & Brooks, 2015). The talent—IT project professionals—are especially salient to both IT project outcomes and escalation because they have a great deal of influence on projects (e.g., via the project's functional and social aspects; Bond-Barnard, Fletcher, & Steyn, 2018). Further, IT project professionals take the knowledge learned from the project after completing it (e.g., Karagoz, Whiteside, & Korthaus, 2020). With the difficulty of retaining IT professionals (e.g., Zaza, Armstrong, & Riemenschneider, 2022), firms must better understand how IT project professionals impact project outcomes. Thus, we try to understand the human capital element of the project by using a goal orientation theoretical lens and the personality and escalation literature to investigate the impact of IT project professionals' characteristics on the intention to continue an IT project.

Thus, we examine the following research questions:

RQ1: What is the impact of IT project professionals' mastery goal orientation on their intention to continue?

RQ2: What are the impacts of IT project professionals' locus of control, preference for consistency, and personal investment on their mastery goal orientation?

By tackling these questions, organizations can plan on attracting IT project professionals who have these individual characteristics to offset the IT project failure rate. IT project managers can lean on the human capital side of the IT project to retain the workforce behind the project and sustain the intention to continue the IT project by offering learning opportunities for IT project professionals. In addition, while monetary value has historically been the driver to keeping IT talent (Joseph, Ng, Koh, & Ang, 2007), there is a silver lining. We postulate that building the skills needed on the job will derive IT project professionals' intention to continue working on the IT project. Our work highlights the need to consider the context when theorizing about the IT workforce.

We organize this paper as follows. We review relevant literature and develop our hypotheses in Section 2. We describe the research methodology and data collection, validate the measurement model, and present our findings in Section 3. We discuss the study's key findings, theoretical and practical implications, future research, and limitations in Section 4. We conclude the paper in Section 5.

2. THEORETICAL DEVELOPMENT AND HYPOTHESES

Based on the previous background, we present our proposed research model in Figure 1.

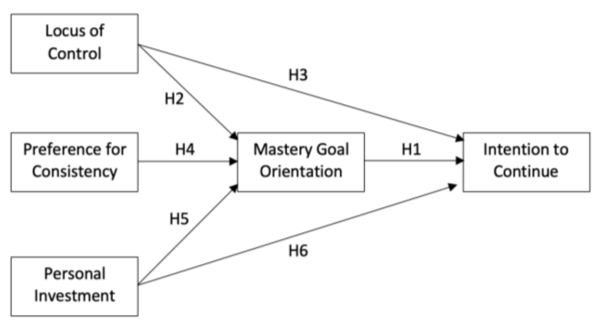

Figure 4: Proposed Model

Intention to Continue an IT Project

Intention to continue an IT project is the "behavioral tendency to continue investing time, money, and resources into an IT project" (Korzaan & Brooks, 2015). The operationalization of intention to continue in this study is a behavioral determination to continue or persist with an existing IT project. From a psychological perspective, it is the commitment to and persistence in goal-directed behavior. If the project is performing well, according to the project plan, then persistence and continuation with the project may lead to positive outcomes. Zhu, Wang, Wayng, and Yu (2021) found commitment to an IT project to be significantly related to project success. From an escalation perspective, if the project is performing poorly, experiencing problems with quality, missing deadlines, and running over budget, then the inclination to continue with a project may lead to the escalating commitment to a failing course of action and put the project at risk of failure (Brooks, Korzaan, & Brooks, 2021; Keil, 1995). Consequently, the intention to continue a project provides unique insight into individual contributors' impact on project outcomes. Intention to continue has also been used as a dependent variable in prior studies (Brooks et al., 2021; Keil, 1995); therefore, we also include it as the dependent variable for this research.

Mastery Goal Orientation

Mastery (learning) goal orientation is the degree to which individuals desire to advance their skills and knowledge (Phillips & Gully, 1997). Mastery goal orientation can be conceptualized as either a trait—" a propensity to engage in consistent behaviors across situations" (Vandewalle, Nerstad, & Dysvik, 2019, p. 119)—or a state condition—for which behavior depends on the circumstances of the situation (Vandewalle et al., 2019). For this research, we envision mastery goal orientation as a state condition that can be affected by personal characteristics and perceptions.

Individuals with a mastery goal orientation may intend to continue an IT project because they may anticipate being able to learn more while completing the remaining aspects of the project. Projects provide many opportunities for learning in organizations (Damm & Schindler, 2002). When a project ends, IT project professionals return to their normal functions (Schindler & Eppler, 2003), where fewer learning opportunities are available. Further, individuals with a learning goal orientation tend to be more focused on self-improvement and progress toward a goal (e.g., Ross, Pirraglia, Aquilina, and Zulla, 2022). These outlooks of mastery-oriented individuals may drive them to continue a project because they perceive an opportunity for self-improvement by completing the remaining work partly because of the opportunity to learn while completing the remaining work and because of the progress already made toward the project, respectively.

Hypothesis 1: IT project professionals' mastery goal orientation is positively related to their intention to continue an IT project.

Locus of Control

Locus of control is the degree to which an individual attribute the cause of life events to outside forces or the individual's behavior and actions (Rotter, 1966). Individuals who perceive they have great control over events have an internal locus of control. Conversely, when an individual perceives events are mostly the result of forces beyond their control, the individual has an external locus of control. For the remainder of this paper, we use locus of control to refer to an internal locus of control.

Individuals with a higher locus of control would have a greater mastery goal orientation because they believe their actions influence their life (Nunn & Nunn, 1993). Therefore, these individuals would be more motivated to learn during an IT project because they could use these skills in the future and further influence their lives and careers. Locus of control has been shown to correlate with mastery goal orientation in other academic contexts positively (e.g., Albert & Dahling, 2016). Therefore, we expect that locus of control will positively affect mastery goal orientation.

Hypothesis 2: IT project professionals' locus of control is positively related to their mastery goal orientation.

In addition, locus of control has been shown to positively impact intention to continue (Korzaan and Morris, 2009); therefore, we confirm that relationship and posit:

Hypothesis 3: IT project professionals' locus of control is positively related to their intention to continue an IT project.

Preference for Consistency

Preference for consistency is a desire to conform to the past (Cialdini, Trost, & Newsom, 1995). Preference for consistency includes three dimensions: internal consistency, consistency with one's previous behaviors and actions; public consistency, an outward appearance of consistency to others; and others' consistency, wanting others to behave and act consistently. Individuals with a high preference for consistency may have a unique vantage point with their motivation to learn because those with a high preference for consistency experience cognitive dissonance more intensely and are more susceptible to dissonance effects (Nolan and Nail, 2014). It is natural within the context of working in IT to constantly be learning and keeping one's skills up-to-date due to the rapidly changing nature of technology. Therefore, individuals may be motivated to learn to consistently appear competent and up-to-date on their skills as professionals working on IT projects.

Furthermore, as previously mentioned, projects in and of themselves provide opportunities for learning (Damm & Schindler, 2002). Individuals with a high preference for consistency may also be inclined to indicate that they are motivated to learn because it is consistent with the learning opportunities inherent in working in a project environment. Therefore, we believe that a preference for consistency will positively affect mastery goal orientation.

Previous research has evaluated the relationship between preference for consistency and intention to continue and found no significant relationship (Korzaan and Morris, 2009); therefore, we confirm that relationship and posit.

Hypothesis 4: IT project professionals' preference for consistency is positively related to their mastery goal orientation.

Personal Investment

Personal investment is the perceived amount of time, effort, and energy an individual spends on an IT project (Korzaan, 2009). Personal investment is a type of psychological "sunk cost" that aligns closely with the concept of an "emotional sunk cost" (Keil, Mann, & Rai, 2000). It represents a resource already invested in a project that cannot be recouped or regained. However, instead of the investment being an organizational resource, it is a personal resource of one's time, talents, energy, and effort. It is an investment of oneself into the project. Embedded within the nature of the sunk cost effect is the hope of realizing some return on the investment. Therefore, learning new skills and abilities may be perceived as a way to gain something back from this investment of personal resources (time, effort, energy). The time, effort, and energy may not be able to be recouped; however, one may be able to gain new knowledge, skills, and abilities from the experience of working on the project. In essence, learning something new is a return on one's personal investment in the project. Additionally, a perception of a higher amount of time, effort, and energy spent on an IT project may result from new or more complex project tasks requiring learning in the project. Experiencing the benefits of learning inherent in the work already invested in the project may motivate the individual to continue the project because there is more to learn.

Further, work engagement—"a positive, fulfilling work related state of mind that is characterized by vigor, dedication and absorption" (Schaufeli, Salanova, González-Romá, & Bakker, 2002, p. 74)—is positively associated with mastery goal orientation (Chughtai & Buckley, 2011). The dedication facet of work engagement—defined as "an intense work involvement and encompasses feelings of inspiration, pride, enthusiasm, significance and challenge" (Chughtai & Buckley, 2011, p. 684)—relates most closely to personal investment because personal investment indicates the amount of work invested in the project.

Personal investment has been found to be positively related to outcome variables similar to intention to continue an IT project, including normative commitment (Brooks et al., 2021) and commitment to IT project objectives (Korzaan, 2009). Additionally, Sleesman, Conlon, McNamara, and Miles (2012) found in a meta-analysis of escalation of commitment literature that sunk costs and time investment have a positive relationship with escalation. While this paper focuses on decision-makers, we expect the same relationship for IT project professionals for the same reasons: they do not want others to perceive them as wasting organizational resources or time.

Hypothesis 5: IT project professionals' personal investment is positively related to their mastery goal orientation.

Hypothesis 6: IT project professionals' personal investment is positively related to their intention to continue an IT project.

3. RESEARCH METHODOLOGY AND RESULTS

A field study was conducted that included professional stakeholders involved with IT projects from Fortune 500 companies in the southern United States. IT project professionals were identified by a member of upper management in each company and selected as participants based on their current involvement in working on IT projects in progress at various stages throughout the development life cycle. IT project professionals, instead of project managers or primary decision-makers, were chosen to complete the survey in order to expand our knowledge in the literature on the dispositions, interests, beliefs, and perceptions of individuals closest to the project. In addition, IT project professionals have been shown to influence the course of action for a project, perform key roles in project success (Hans & Mnkandla, 2019; Valerdi & Majchrzak, 2003), and bring awareness to the overall team dynamics, operations, and status of the project. Furthermore, their needs and interests are often neglected (Hans & Mnkandla, 2019).

Construct	Item	Factor Loading	Average Variance Extracted	Composite Reliability
Intention to Continue (IC)	IC1	.93	.79	.94
	IC2	.95		
	IC3	.87		
	IC4	.81		
Mastery Goal Orientation (MGO)	MGO1	.79	.64	.84
	MGO2	.90		
	MGO4	.69		
Preference for Consistency (PFC)	PFC1	.73	.50	.80
	PFC2	.80		
	PFC3	.74		
	PFC4	.56		
Personal Investment (PI)	PI1	.80	.96	.86
	PI2	.98		
	PI3	.99		
	PI4	.94		
Locus of Control (LOC)	LOC2	.79	.56	.79
	LOC3	.90		
	LOC4	.69		

Table 2: Confirmatory Factor Analysis and Convergent Validity

Surveying IT project professionals currently working on an IT project will help identify these individuals' important interests, needs, and dispositions and provide valuable insight into how human capital can influence project outcomes. Therefore, a survey was developed, adapting items from existing measures (Appendix A), and administered online to IT project professionals. Survey questions were measured on a 7-point Likert scale. All construct items, except for intention to continue, are anchored by strongly disagree and strongly agree. The anchors for each of the items for intention to continue are provided in Appendix A.

The data were analyzed using structural equation modeling with AMOS 25. The two-step modeling approach was used to confirm the measures' validity, followed by testing the hypotheses and assessing model fit.

Data Analysis

Information is provided in Table 1 for participant demographics. There were 232 survey responses. The sample comprised approximately 60% men, 38% women, and 2% who did not indicate gender. Thirty percent of the participants were between 30 and 39 years old, 44% between 40 and 49 years, 14% between 50 and 59 years, 11% between 20 and 29 years, less than 1% were over 60, and less than 1% did not indicate their age. On average, participants had an average of 9.9 years of IT work experience, and 60% had a 4-year college degree.

Demographic Variable	Count	Percent
Age		
Between 20 and 29	25	11
Between 30 and 39	70	30
Between 40 and 49	103	44
Between 50 and 59	32	14
60 and above	1	<1
Did not respond	1	<1
Gender		
Women	88	38
Men	139	60
Did not respond	5	2
Education		
High school graduate	12	5
Some college	19	8
2-year degree	13	6
4-year degree	139	60
Master's Degree	43	19
Doctorate	3	1
Did not respond	3	1

Table 1: Demographics

Measurement Model Validity

Results from the convergent and discriminant validity analysis are provided in Table 2 and Table 3.

We removed LOC1 because the average variance extracted for LOC was less than .5 and because LOC1 had the lowest factor loading. We removed MGO3 and MGO5 because the correlation between PI and MGO was .57 and because MGO3 and MGO5 factor loadings were lowest.

	IC	MGO	PC	PI	LoC
IC	**.89**				
MGO	.44	**.80**			
PC	.15	.40	**.71**		
PI	.27	.55	.17	**.93**	
LoC	.29	.37	.23	.16	**.75**

Notes: The numbers in bold shown on the diagonal are the square root values of the average variance extracted. The numbers below the diagonal are correlation coefficients. IC = intent to continue, MGO = mastery goal orientation, PC = preference for consistency, PI = personal investment, LoC = locus of control

Table 3: Discriminant Validity

In the final measurement model, convergent validity was confirmed with all construct items loading at .50 or higher and significant at p < .001 (Hair, Black, Babin, & Anderson, 2019; Fornell & Larker, 1981; Fang & Li, 2022; Hanaysha, 2022). Composite reliabilities for all constructs were above .70. All of the average variance extracted values were .50 or greater. All thresholds were met to confirm discriminant validity, demonstrated by the correlations between constructs being less than the square root values of the average variance extracted. VIF values were evaluated to test for multicollinearity. The VIF values range from 1.09 to 1.32, which are below the threshold of 3 indicating that multicollinearity is not an issue (Hair, Risher, Sarstedt, & Ringle, 2019).

Hypotheses Testing and Structural Model

The model fit assessment and hypothesis testing results are provided in Table 4 and Table 5. All hypotheses were supported except H6; personal investment was not found to significantly influence intention to continue. The model explains 17% of the variance in intention to continue and 27% of the variance in mastery goal orientation. The final model is shown in Figure 2. We ran the model with control variables for gender (**β**=.06; p=.363), education (**β**=.07; p=.243), and age (**β**=-.02; p=.703). The results indicated that none of the control variables were significant at the p=.05 level.

Fit Measures	Thresholds	Structural Model
Chi-square		.139
p-value	>= .10	.709
AGFI	>= .95	.996
NFI	>= .95	.999
Evaluation		Good Model Fit

Table 4: Model Fit Evaluation

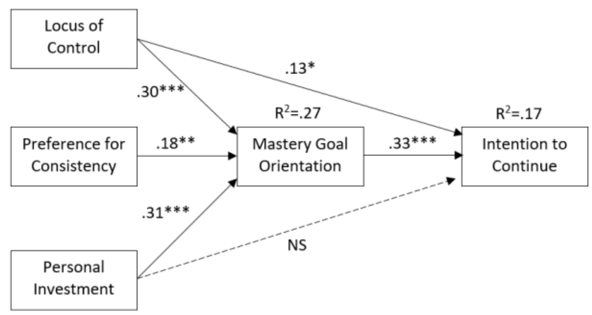

Figure 2: Final Model

In the next section, we discuss an additional analysis performed to evaluate the possibility of a full mediation through mastery goal orientation, explaining the non-significant relationship between personal investment and intention to continue.

Post-hoc Analysis for Full Mediation

In considering why we did not find a significant relationship between personal investment and intention to continue, we performed a post hoc analysis to see if the relationship between personal investment and intention to continue is fully mediated by mastery goal orientation. When mastery goal orientation is removed from the model, the relationship between personal investment and intention to continue is significant

Hypothesis	β	S.E.	*p*	Result
Mastery Goal Orientation -> Intention to Continue	.33	.105	< .001	Supported
Locus of Control -> Mastery Goal Orientation	.30	.051	< .001	Supported
Locus of Control -> Intention to Continue	.13	.087	.046	Supported at the .05 level
Preference for Consistency -> Mastery Goal Orientation	.18	.050	.002	Supported at the .001 level
Personal Investment -> Mastery Goal Orientation	.31	.063	< .001	Supported
Personal Investment -> Intention to Continue	.07	.107	.278	**Not Supported**

Table 5: Hypothesis Testing

and positive at the .01 level. When mastery goal orientation is included in the model, the relationship between personal investment and intention to continue becomes non-significant, indicating full mediation by mastery goal orientation, according to the Baron and Kenny (1986) method for testing full mediation. An analysis was also conducted using the Hayes SPSS Process Macro (Abu-Bader & Jones, 2021), which further supported this finding showing a significant indirect effect of personal investment on intention to continue of .24 and a non-significant direct effect of personal investment on intention to continue when controlling for mastery goal orientation (the mediator). Therefore, the result of these analyses confirms that mastery goal orientation does, in fact, fully mediate between personal investment and intention to continue. The total effect on the dependent variable (intention to continue) that is accounted for through the mastery goal orientation mediator is approximately 73%. The details of this analysis are provided in Figure 3.

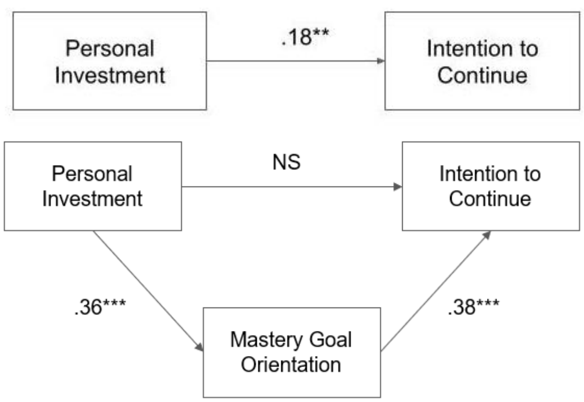

Figure 3: Test for Full-Mediation - Mastery Goal Orientation

4. DISCUSSION

This research contributes to the literature by testing a model that furthers our understanding of how goal orientation theory, personal investment, and individual characteristics play a role in IT project continuation intentions. The model explains 27% of the variance in mastery goal orientation and 17% of the variance in intention to continue. The central theoretical construct, mastery goal orientation, was found to positively influence the intention to continue an IT project. Locus of control, which was previously shown to positively impact the intention to continue (Korzaan & Morris, 2009), was also found to indirectly affect the intention to continue through mastery goal orientation. Personal investment significantly influenced mastery goal orientation; however, the relationship between personal investment and intention to continue was not non-significant. A post hoc analysis revealed an unexpected theoretical contribution finding that this non-significant relationship is explained by being fully mediated through mastery goal orientation. This study also contributes to the literature by expanding our understanding of the psychological factors at work in IT projects. While there is more to be learned about the composition of the project team, psychological factors, and the management of the human element in IT projects, this study takes a step in advancing our understanding in this area by applying goal theory, escalation theory, and personality traits to predict mastery goal orientation and in turn, its impact on intention to continue an IT project. This study confirms the importance of paying attention to the needs and interests of the professionals working on the IT project (Hans & Mnkandla, 2019)—especially for those with high motivations for mastery goal orientation, who need to have the opportunities to learn and develop new skills and abilities. This interest in learning is especially attenuated when the IT project professionals are working on projects where they feel they have already invested significant time, energy, and effort on the project, for individuals with a high preference for consistency and an internal locus of control.

This study offers several practical implications. First, human capital may play a role in the success of IT projects far beyond the project definition, scope, and management problems. We recommend hiring managers choose those who exhibit locus of control, preference for consistency, and personal investment. These individual characteristics make IT project professionals eager to learn and master the skills needed to get the job done. Future research can investigate other personality traits or states that can also lead to favorable outcomes, such as the personality big five constructs.

Second, IT project managers can motivate IT project professionals to continue working on the IT project by providing opportunities to learn the skills needed to get the job done. Periodic professional development workshops can be scheduled for every deliverable milestone. We advise that this schedule be shared detailing the outcome and skills learned from the workshops early on. Future research can look at what skills to be offered based on IT project professionals' tenure, job type, and generational differences to help organizations tailor specific workshops based on the needs of their employees.

Third, organizations are well-advised to acknowledge that even though IT project professionals are getting paid to do the job, IT project professionals perceive that they are personally invested in the IT project beyond the salary they get. While the escalation of commitment is the perspective of the organization that invests a lot in the project, a parallel of that kind of commitment can be derived from IT project professionals by offsetting their sunk cost. It may be good to have dedicated employees who spend effort and time on the job, but this alone will not guarantee that they will continue working on the project. One way to alleviate that is by signaling them how much they can learn on the job and fulfill their mastery goal orientation needs. Acknowledging that the influence of personal investment will only impact the intention to continue through mastery goal orientation, IT project managers are well-advised to communicate to their teams about the trajectory path of skill development from the start of the project and reinforce it during their routine meetings. Future research is urged to look at contextual factors that may strengthen the relationship between personal investment and mastery goal orientation, such as age and gender.

Fourth, IT project professionals who are high on preference for consistency can succeed in IT projects. Specifically, neurodivergent professionals who might feel distressed if change happens can be accommodated by providing them with workshops to learn the skills needed on the job. This study starts the conversation about hiring a neurodivergent workforce in the IT project context, contributing to other streams of research about the inclusion and contribution of neurodivergent IT professionals in the software development context (Annabi, Sundaresan, Zolyomi, 2017).

A limitation with field study data is the inability to verify causality in the model. Future research can address this limitation by conducting controlled experiments on the constructs of interest. Also, because projects (especially larger ones) may be ongoing for a significant time, it would be beneficial to see if the influence of the individual characteristics investigated in this study change over the project's life. Therefore, longitudinal research is another recommendation for future study. A limitation in the data collection is that objective project performance information was not attainable. Actual project status information would provide greater insight into the degree to which the project is experiencing or at risk of experiencing the escalation of commitment to a failing course of action. Escalation of commitment in IT projects is where the decision to commit additional resources to the project is increased when the project is troubled. Therefore, greater insight into this phenomenon could be gained if objective project status information (on time, within budget, meeting requirements) was available.

This study raises an intriguing scenario for future research to partial out when mastery goal orientation and intention to continue a project have positive effects on project outcomes and when it has negative connotations on the project by contributing to project escalation. In the context of a troubled project, a mastery goal might be detrimental because it could lead to team members influencing decision-makers on a course of action of the project towards escalation. Future research could look more specifically at the influence of IT project professionals on the decisions made in IT projects.

In addition, there is an opportunity for future research to investigate the impact of psychological constructs, including individual needs and interests, on the actual turnover of IT project professionals. For projects not escalating out of control, a mastery goal orientation appears to fuel the motivation for professionals to be committed to persist and continue with the project; thereby, making them less likely to quit or leave the project. Neglected needs and interests of IT project workers can lead to project challenges such as turnover (Hans & Mnkandla, 2019). Turnover on IT projects is a significant risk to the success of projects gaining more attention in recent literature (Hans & Mnkandla, 2019; Etemandi, Bushehrian, & Robles, 2022). Although we did not measure an intention to leave the project team specifically, it is reasonable to conclude that if an individual intends to continue with a project, then they are not going to be inclined to quit or leave it. Future research is called for to more clearly delineate when a mastery goal orientation lowers actual turnover on the project and results in a project environment that leads to motivated, committed professionals who are dedicated to working toward the successful completion of a project.

There is also a need for future research to provide a deeper understanding of the role of preference for consistency in IT projects. Future research could investigate potential contextual moderating factors on the relationship between preference for consistency and mastery goal orientation. According to Bator and Cialdini (2006, p. 229), “the role of consistency motivation can only be fully understood when factors of the person and the situation are considered conjointly.” Therefore, an opportunity for future studies is to investigate the interaction of the preference for consistency with contextual factors such as project characteristics, project status, team norms and values, and organizational factors.

5. CONCLUSION

IT project success is crucial for organizations that can lean on their human capital to thrive and preserve their competitive advantage. Having IT project professionals with high levels of locus of control, preference for consistency, and personal investment in projects can ultimately lead to their intention to continue working on the IT project. IT project managers can help build their commitment to continue working by providing opportunities to develop their skills on the job. While it is the norm for IT professionals to switch jobs frequently due to salary reasons, our work offers hiring managers another avenue to attract and keep their IT project professionals through fulfilling their mastery goal orientation needs.

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APPENDIX A
Measurement Items

Behavioral Intention to Continue (Korzaan & Brooks, 2015; Bhattacherjee, 2001)

Given the choice of whether or not to continue this project, how likely is it that you personally would:

1. Continue with the project. (anchored by "would not continue" and "would continue")
2. Persist until the project is completed. (anchored by "would not persist" and "would persist")
3. Continue with the project as planned. (anchored by "would not continue" and "would continue")
4. Keep investing resources in the project. (anchored by "would not keep investing" and "would keep investing")

Mastery Goal Orientation (Elliot & Church, 1997)

Consider your personal beliefs and feelings related to the project you are currently working on:

1. I want to learn as much as possible from working on this project.
2. It is important for me to understand this project as thoroughly as possible.
3. I hope to have gained a broader and deeper knowledge of systems development when I am done with this project.
4. I desire to completely master the tasks I am working on for this project.
5. On a project like this, I prefer to work on tasks that really challenge me so I can learn new things.

Locus of Control (Lee & Tsang, 2001; Levenson, 1974)

To what extent do you agree or disagree with the following statements about yourself in general:

1. When I get what I want, it is usually because I worked hard for it.
2. My life is determined by my own actions.
3. When I make plans, I am almost certain to make them work.
4. I determine what will happen in my life.

Preference for Consistency (Cialdini et al., 1995)

To what extent do you agree or disagree with the following statements about yourself in general:

1. It is important to me that those who know me can predict what I will do.
2. I want to be described by others as a stable, predictable person.
3. The appearance of consistency is an important part of the image I present to the world.
4. An important requirement for any friend of mine is personal consistency.

Personal Investment (Keil, 1995; Dholakia & Bagozzi, 2002; Taylor & Pierce, 1999)

Consider your personal beliefs and feelings related to the project you are currently working on.

1. I have worked particularly hard at doing a good job on this project.
2. I have already spent a great deal of energy on this project.
3. I have invested a considerable amount of effort on this project.
4. I have put in a great deal of time on this project.

A Comparative Analysis of Web Application Vulnerability Tools

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Abstract

Considering the perpetual need for security in network platforms, this study investigates various penetration testing tools in the abundance of options when it comes to network security. This study presents the experimental run results of select penetration testing tools on deliberately vulnerable network traffic, as well as the comparison of those tools. We test three vulnerability assessment tools: ZAP, Vega and Arachni as part of this research in the hope to provide current and practical data for the research community in the network security field. Our choice of vulnerability testing tools is based on the following criteria: being current, usability, reliability (stability), and performance w.r.t speed. Our results demonstrate that each vulnerability assessment tool depicts its own advantages and disadvantages by being better at one or more criteria than the others, but not prevailing in all. This, in turn, suggests that choosing a penetration tool to employ for testing the vulnerability web applications is a challenging decision that should consider multiple parameters, rather than being merely straightforward.

Keywords: Vulnerability Assessment, Penetration Testing, Web Applications, SQL Injection, Cross-Site Scripting (XSS).

1. INTRODUCTION

In today's society, many companies are faced with security threats, particularly through the use of third-party web-applications. As a result, it is imperative for them to find the security vulnerabilities in their systems that can be exploited by black-hat hackers in order to determine whether such applications can be used by their employees. We propose the use of security penetration tools, specifically open-source security testing tools for web applications.

There is a wide array of tools available on the market. Ultimately, we selected tools that were ubiquitous, free, open-source, and easy to use as this can be particularly beneficial for smaller companies, which are quite abundant. So, we ultimately decided to analyze and compare the tools ZAP (Owasp Zap"), Vega (Vega Vulnerability Scanner), and Arachni (Web application security scanner framework).

Our goal is to contribute to the field of data security and privacy with an in-depth analysis and comparison of free, open-source security testing tools that can aid a company in making the decision for the tool that would work best for their specific cybersecurity needs. With ever-increasing interconnectivity through third-party web applications, this research provides the means to fill the gap of a need for companies to instill tougher security guidelines since those web applications can so easily be exploited by attackers.

2. BACKGROUND AND RELATED WORK

Background

Penetration testing simulates an attack by an ethical hacker and is used for evaluating the security of a network or computer system. The ultimate goal of penetration testing is to increase the data security for a given party, whether that be an individual or a company. Penetration tests are typically done with a license and requires a signed contract with a company. The output of the penetration testing is provided as a report to disclose the weakness found in the system. It is very important for companies to have high data security since their data is one of their most valuable assets. In addition, with the rise of internet usage in various fields like medicine, finance, and the military, web security has become an increasing concern. As a result, penetration tools for web applications are especially critical when it comes to maintaining data security (Mirjalili, Nowroozi, & Alidoosti, 2013).

Penetration Tools

This study explores three free, open-source penetration tools named Zap, Vega, and Arachni for vulnerability assessment purposes. Zap is a free, open-source, GUI-based application that can be used on Windows, Linux, and Mac ("Owasp zap"). It is officially called the Owasp Zap. Zap can be used to test the security of web applications with penetration testing. It can also be used to find security vulnerabilities such as Cross-Site Scripting, SQL injections, and information leaks. Zap has an automated scanner and monitors the responses to requests it sends to the web application to find vulnerabilities. The application was programmed using a combination of Java, JavaScript, HTML, Python, and PHP. We ran Zap on a Windows OS computer and supplied it with the Spotify Web Player and a deliberately vulnerable target website with the URL http://testphp.vulnweb.com.

Vega is also a free, open-source, GUI-based web security scanner and testing platform that tests web application security ("Vega Vulnerability Scanner"). Vega can find vulnerabilities such as Cross-Site Scripting (XSS), SQL injection, and inadvertently disclosed information. Vega has an automated scanner for fast tests and an intercepting proxy to observe the interaction between clients and servers. The operating system that we ran Vega on is Windows, but it can be run on Linux and MAC OS as well.

The last tool we examined was Arachni ("Web application security scanner framework"). In regard to the Operating System, we present results for the Arachni tool running on the Windows platform, but it can be run on Linux and Mac OS X as well. Arachni is an open-source, modular web application security scanner framework. It focuses on identifying, classifying, and logging vulnerabilities in web applications. It is licensed under the Arachni Public Source License v1.0. It is important to note that for commercialization a non-free license is required. It also requires 2GB of memory and 10 GB of available disk space. Furthermore, the distributed architecture of Arachni allows remote control of the scan. This is done by deploying agents on remote servers.

Related Work

In Mirjalili et al. (2014), authors introduce various types of penetration tools based on the parameters as whether the tool is manual or automatic, and whether it offers black-box, white-box, or grey-box testing. Furthermore, this paper explains different web vulnerabilities like injection, broken authentication, session management, and cross-site scripting (XSS). The authors look specifically at black-box web vulnerability scanners, both open-source and commercial. Some of such tools are Websecurity, Wapiti, ZAP, and Acunetix. The paper compares whether those tools are GUI based or not, and rate how good their configuration, usability, stability, and performance are. Similar to this paper, we too compare different penetration tools for web applications. However, we focus more on comparing the results of three different tools: Vega, Arachni, and ZAP. Additionally, we analyze their vulnerability results and how they compare to one another.

In Fonseca, Vieira, & Madeira (2007), authors delineate how different penetration tools produce different results, which is also verified by our study. In addition, they also explain how several vulnerabilities were missed by some of the penetration tools they tested, and oftentimes they tended to have a significant rate of false positives.

Khera, Kumar, Sujay, & Garg (2019) discusses and analyzes the VAPT (vulnerability assessment and penetration tools) and life cycle. Some of the assessment tools that this paper explores for network security include Wire shark, Nmap, and Metasploit. A case study is shown where Nmap is used to target the Metasploitable virtual machine, which is a vulnerable version of Linux Ubuntu designed for testing purposes. In addition, Khera et al. discuss both the advantages and disadvantages of VAPT as a cyber defense technology. In our study, we also discuss different vulnerability assessment tools, but focus on those targeting web applications, as opposed to network security like Khera et al. In addition, we too have a case study where we use a vulnerable web application, but instead of testing it using a single tool such as Nmap, we test three tools Vega, ZAP, and Arachni and compare the results.

Zakaria, Phin, Mohmad, Ismail, Kama, & Yusop (2019) explains how there is no standardized format of penetration testing reports. As a result, they analyze eight different penetration testing reports found online in order to compare their similarities and patterns to aid them in creating a standardized format of the report. This format focuses on catering to both security personnel and upper management of the organization. This lack of standardization is important to note since in our case study we witness three very different reports from three different tools for a single web application.

In Abu-Dabaseh & Alshammari (2018), the authors discuss the standards for penetration testing tools. A detailed comparison of automated versus manual penetration testing techniques is provided in this paper. The paper compares the current methodologies used to build an automated penetration testing system. These methodologies target HTTP/TCP/IP and SIP attacks, all protocols and services, and databases. The different tools, phases, methods of implementation, and aim of the methodologies are considered. Tools such as ZAP and Metasploit are referenced in this paper as well. Lastly, the importance of automating the process of penetration testing is discussed. Those presented in Abu-Dabaseh & Alshammari (2018) all contribute as a basis framework for our paper.

Nagpure & Kurkure (2017) discusses the different vulnerabilities of web applications. The attacks discussed in this paper include SQL injection, Session Hijacking, Cross-Site Request Forgery, Security Misconfigurations, Buffer over Flows, Privilege Escalation, Cross-Site Scripting (and the different types), etc. The paper reviews and compares two testing methods: automated vs. manual testing. Lastly, a comparison of three penetration testing tools of web applications is presented. The paper compares the features of ZAP, Acunetix, and Burpsuit.

Kang, Lee, Kim, & Kim (2016) discusses how penetration testing can be implemented into businesses within the financial sector to make them more secure. The model put forth in this article gives practical steps companies can take to implement penetration testing tools into their security testing. It also gives the definitions of SQL Injections and Cross-Site Scripting. These are both vulnerabilities we focus on in our paper.

In Muñoz, Armas Vega, & Villalba (2016), the efficiency and false positive rates of multiple penetration testing tools are examined. This article examined both OWASP ZAP and Arachni, but it did not examine Vega. OWASP ZAP was found to be more time efficient than Arachni. However, Arachni generates more requests to the server. In this test OWASP ZAP had one vulnerability that was found by the application's requests but was not reported to the user. Arachni did not have any false positive reports during this experiment. We use those results for comparing with our results.

3. METHODOLOGY

ZAP

Upon opening the application, the Automated Scan button is pressed to start the scan. The URL to test must be given. Once the web application URL has been entered the attack button is pressed. The scan tests the website and any associated URL to find vulnerabilities. Once the scan is completed, the alerts section will be populated with any vulnerabilities found. By going to the alerts section, details about each vulnerability can be analyzed.

Vega

The first step for running a Vega Scan is clicking the "Scan" tab and creating a new scan. Then we select which modules to enable for this scan (we leave the default selections). We then press the "Finish" button so that the scan can start. Furthermore, each vulnerability of the web application can be clicked on for a further explanation of the vulnerability.

Arachni
In order to run Arachni, the folder \arachni-1.6.1-0.6.1-windows-x86_64\bin must be opened. Inside the folder, arachni_web.bat file must be run by double-clicking the file. The file will open the command line that displays the address it's listening on. The address can then be copied and pasted onto a web browser which will prompt the log-in screen. The default parameters can be found in the Arachni documentation. This then opens the Arachni web interface. A new scan can be started by clicking the Scans tab and then selecting New Scan. The URL for the web application can then be inserted. Clicking the Go button will then begin the scan. The vulnerabilities are then shown, where each one can be selected for further inspection.

4. EXPERIMENTAL WORK

In our study, we tested three vulnerability assessment tools: ZAP, Vega and Arachni. Specifically, each tool ran a vulnerability assessment of the same malicious test website called Acuart ("Acunetix Web Vulnerability Scanner - test websites") and we furthered compared the results of one another. It is important to note that Acuart is one of several vulnerable test websites provided by Acunetix. The results of this test are shown below.

ZAP Tool Results
As seen in Figure 1, Zap found three types of high-risk vulnerabilities. Two of these are different types of Cross-Site Scripting, DOM Based and Reflected. The other high-risk vulnerability found were SQL Injections. Further information can be found on each case by clicking on the requests in the drop-down menu for each category. There were four types of medium-risk vulnerabilities found. There were seven instances of .htaccess Information Leaks, 47 cases of CSP Headers not being set, 40 cases of an Absence of Anti-CSRF Tokens, and 44 cases of Missing Anti-Clickjacking Headers. In total 138 medium-risk vulnerabilities were found. Two different types of low-risk vulnerabilities were found by Zap. There were 62 cases of Server Leaks found and 67 X-Content-Type-Options. In total 129 different low-risk vulnerabilities were found. For each vulnerability found, information on the exact call that exposed the vulnerability can be found under the vulnerability for each one. The right side of the screen gives additional information on vulnerabilities.

Vega Tool Results
The results shown in Figure 2 for the test website display a total of 36 vulnerabilities. These vulnerabilities are categorized into high, medium, low, and info alerts. There was a total of 21 high alerts, 6 medium alerts, 2 low alerts, and 7 info alerts.

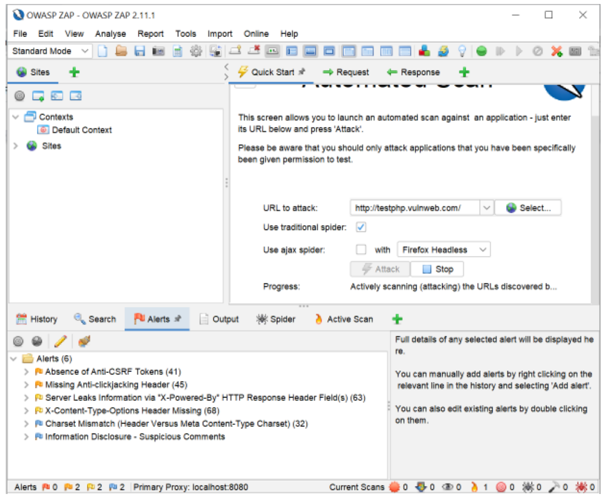

Figure 5: ZAP Interface with the Vulnerability Alerts for the Test Website Shown

For each alert, an explanation of what the vulnerability is, the request, resource content, a discussion, impact, and resources are available. The high-level alerts include 2 cleartext password over HTTP alerts, 10 Cross-Site Scripting alerts, 3 MySQL Error Detect- Possible SQL Injection, and 6 SQL Injection alerts. The medium-level alerts include 6 Local Filesystem Paths Found alerts. The low-level alerts include 2 Form Password Fields with Autocomplete Enabled alerts. The info-level alerts include 2 Possible AIAX Code detected, 4 Character Set Not Specified, and 1 Blank Body detected.

Arachni Tool Results
In the results shown in Figure 3, we see that it found a total of 69 alerts where 37 were of high risk, 7 medium risk, 10 low risk, and 24 that are informational. In regard to the high-risk alert, the largest number of alerts fall under the category of Cross-Site Scripting (XSS). XSS can make the system vulnerable where clients can inject scripts into a request and the server then returns in the response the script to the client. Another high-risk vulnerability found in this malicious web application by Arachni is SQL injection. Web applications use SQL queries to retrieve data from databases. SQL injections occur when a value from the client's request is used in the SQL query without sanitization. This makes it vulnerable to

attackers executing arbitrary SQL code to steal data or even take control of more server components by exploiting the additional functionalities of the database server. It is important to note that this is one of the most common web application vulnerabilities. This specific vulnerability was detected by Arachni by causing the server to respond to a request with a database-related error. Some of the medium risk alerts include common directory and unencrypted password form, while the low-level risks include common sensitive file and password fields with auto-complete.

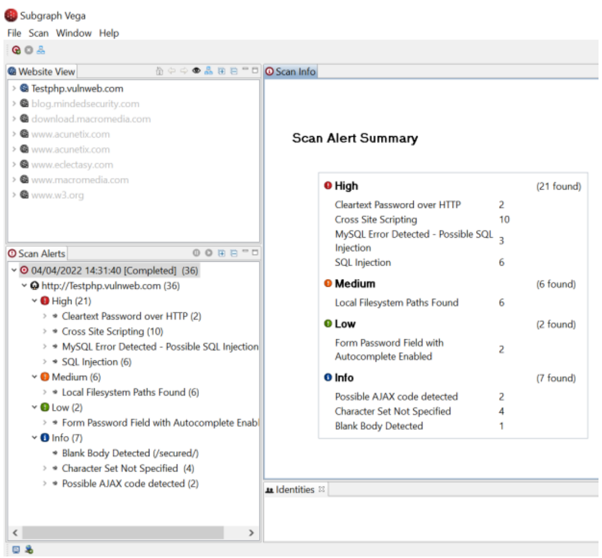

Figure 2: Vega Interface with the Vulnerability Alerts for the Test Website http://testphp.vulnweb.com

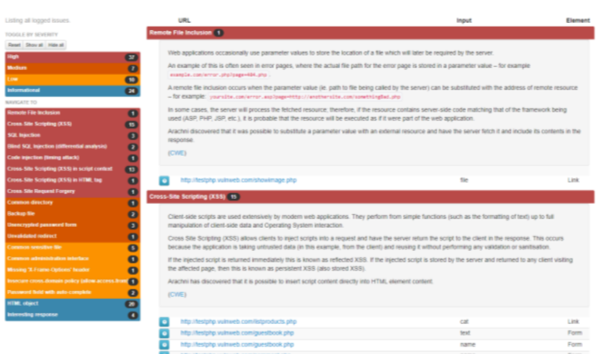
Figure 3: Arachni Interface with the Vulnerability Alerts for the Test Website http://testphp.vulnweb.com

Tool Comparison

We have constructed a table that compares the vulnerabilities of ZAP, Vega, and Arachni:

	ZAP	Vega	Arachni
Total Vulnerabilities	341	36	69
High Alerts	41	21	37
Medium Alerts	138	6	7
Low Alerts	129	2	10

Table 2: Comparison of the Total Vulnerabilities and Types of Vulnerabilities for the Test Website in Each of the Tools

From Table 1 above, we can see that ZAP has a total of 341 vulnerabilities that it detects. This is significantly higher than both Vega and Arachni, which have 36 and 69 vulnerabilities, respectively. Additionally, ZAP has a larger number of high, medium, low, and information alerts in comparison to the other tools. When comparing Vega and Arachni, Arachni detected more vulnerabilities in total and in each of the types of vulnerabilities.

	ZAP	Vega	Arachni
SQL Injection	7	6	5
XSS	34	10	29

Table 2: Comparison of the Two Different Vulnerabilities Present in the Test Website for Each of the Tools

Table 2 shows the comparison of the two different vulnerabilities present in each of the tools: SQL injection and Cross-Site Scripting (XSS). ZAP found the most SQL injections and Cross-Site Scripting vulnerabilities. ZAP found 7 SQL injections and 34 Cross-Site Scripting vulnerabilities, 18 of which were DOM-based and 16 that were reflections. In comparison, Arachni found 29 Cross-Site Scripting vulnerabilities and only 5 SQL injections, 2 of which were Blind SQL injections. Lastly, Vega found 10 Cross-Site Scripting vulnerabilities, which is considerably lower than its counterparts, and 6 SQL injections and 3 possible SQL injections. Altogether, ZAP showed the most proficiency in finding SQL injections and Cross-Site Scripting vulnerabilities.

	ZAP	Vega	Arachni
Interface Platform	Yes	Yes	For the most part
Ease of Use	Simple	Very Simple	Complex
Performance	Med (4-5 min)	High (2-3 min)	Low (8-9 min)
Stability	High	Low	Very Low

Table 3: Comparison of Penetration Tool Characteristics

Table 3 shows a comparison of the tool

characteristics such as the interface, ease of use, performance, and stability. ZAP and Vega had great interfaces, and Arachni has a good interface but involves additional work from the command line to start the application.

Vega was the easiest tool to use because it only involved downloading the software and inputting the URL of the application we needed to scan. ZAP was also simple to use as it also only involved downloading the software and inputting the URL of the application we needed to scan. However, ZAP was a little more difficult to use versus Vega in that assessing the results wasn't as simple. Arachni was the hardest to use because we needed to download the software, run a .bat file, which opened the command line, and had to copy a URL from the command line that is used in order to access Arachni's GUI. After the GUI was opened, a password and email were needed from Arachni's documentation that would allow us to use the tool. Then we could input the URL of the application we needed to scan and assess the vulnerabilities.

Furthermore, Vega's performance was the highest with the scan running in 2-3 minutes. ZAP had the next best performance, taking 3-4 minutes. Arachni had the lowest performance and took about 8-9 minutes to run. We also assess the tool's stability. ZAP was a very stable tool as it did not give us any problems when running. Vega, on the other hand, would not work on a public Wifi and affected our computer's internet access as well. Arachni had the worst stability as it also did not work on the university Wifi and crashed multiple times.

As a result, from this analysis, ZAP is the best penetration testing tool for web applications when compared to Vega and Arachni. This is the tool that we expected to be the best of the three tools based on our initial research. Other previous works compare ZAP to other tools, and these other tools may have a better implementation than ZAP and have the potential to find more vulnerabilities. However, ZAP does a decent job for a free, open-source tool available to everyone.

We show that ZAP is the best penetration testing tool for web applications when compared to Vega and Arachni. This can be seen in our results as ZAP found the most vulnerabilities, and specifically, more SQL injection and Cross-Site Scripting vulnerabilities when compared to its counterparts. ZAP was also simple to use, had a great interface, had a performance time of 3-4 minutes, and was a very stable tool as it did not give us any problems when running.

5. CONCLUSION AND FUTURE WORK

Considering the everlasting request for reliable, current, and fast network penetration testing tools in the hope to provide current and practical reference for researchers and practitioners, this work presents the results and comparison of test running three vulnerability assessment tools for web appications: ZAP, Vega and Arachni. While selecting those tools the criteria we considered were being current, usability, reliability (stability), and performance measured in speed. The comprehensive test run of these 3 tools yields the fact that each vulnerability testing tool possesses its own advantages and deficiencies, rendering each unique tool being better at one or more criteria than the others, but not prevailing in all parameters.

The span of network vulnerability tools is large and is expanding even more, thanks to constant developments in network and PC technologies. Hence, to be more inclusive, we plan to explore more penetration tools for testing purposes and provide a comparative study on a wider span of such tools as part of future work. In particular, we intend to include Vulcan (Vulcan), Invicti (Invicti), Intruder (Intruder), and BeyondTrust (BeyondTrust) as our next step of expanding this research for a more comprehensive analysis and comparison of network vulnerability assessment tools.

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Information Worth: Investigating the Differences in the Importance and Value of Personally Identifiable Information

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Abstract

People are faced with a variety of incentives to divulge personally identifiable information (PII) as online businesses aim to personalize consumer experiences. However, little is known about how people perceive the worth of their PII in relation to the benefits they receive. This brings to question the true worth of information specifically in terms of importance and value. Understanding how people perceive the worth of the PII allows online businesses to establish strategies to enhance the experiences offered to online consumers. In this study, we examine the question "what is the worth of PII?" by employing a survey instrument measuring perceptions across different groups of socioeconomic indicators: education, income, and age. Our findings suggest that the worth of PII is not equally perceived across all groups. More specifically, we find education to be a larger contributor to the perceived differences in information worth. We believe our findings can impact how researchers evaluate PII and how online businesses evaluate PII worth to improve the consumer experience.

Keywords: personally identifiable information (PII), PII importance, PII value, PII worth, privacy paradox.

1. INTRODUCTION

Today's online businesses aim to provide seamless and personalized customer experiences through digital channels such as social media, web, and mobile apps. To be successful in this endeavor, companies are moving toward making use of information about individuals on a personal level instead of generic socioeconomic indicators such as age, income, and education. To accomplish this, it requires the collection of personally identifiable information (PII) such as an individual's name, phone number, address, social media account, and their preference for various services and affiliations. In contrast, the same PII is also collected by nefarious actors that build doxing databases of individuals, relying mostly on stolen PII available on the dark web for a price. For hackers, a victim with a good credit score can fetch a premium price (Kan, 2017). For instance, a hacked Gmail account sold for $80 in 2021 (Sen, 2021) while for people with high credit scores, a Social Security number, birth date, and full name can sell for $60 to $80 on the digital black market. Some stolen identity information can go for as little as $1 per person, or even $0.10 when bought in bulk, according to a 2017 report from security firm Flashpoint. Such baseless and fluctuating valuations can make it difficult for online businesses to offer a suitable incentive to the consumer in exchange for their PII, leading to a negative experience.

Even though consumers have a protective attitude toward their PII, they have been known to reveal their PII in the presence of incentives and personalization, a phenomenon known as privacy paradox (Acquisti et al., 2015; Awad & Krishnan, 2006; Kokolakis, 2017; Martin, 2020; Norberg, Horne et al., 2007). Although a large amount of research exists regarding consumers' attitudes toward the collection of personally identifying data (Kolotylo-Kulkarni et al., 2021), there is little knowledge about the financial *value* that consumers assign to such data (Fehrenbach and Herrando, 2021) and whether the importance they attach to the data matches its monetary value. To our knowledge there are few examples where researchers have looked at the true value of PII as a financial transaction (e.g., Carrascal et al., 2013; Montes et al., 2019), but a gap still remains in the privacy literature from a socioeconomic perspective regarding the differences between information 'importance' versus its 'value', which we refer to as information 'worth'.

Thus, our research mainly aims to understand the nature of the incentives to be provided by 1) having customers assess information by importance and monetary value, 2) checking for consistency in correspondence between what customers consider as important information with its relative monetary value and 3) conducting a drill down to glean insights on how customers in different demographics -- such as education, income, and age -- ranks the worth of their PII. By considering the importance and value of the PII, companies can understand its worth and implement a strategy to provide incentives aligned with customer expectations, resulting in a higher likelihood of disclosure. Additionally, companies can directly incentivize customers in exchange for PII without having to involve third party providers.

Results of our study illustrate both the perceived importance and value of PII by an individual. We surveyed people asking them to rate the importance of keeping certain PII private, based on an adapted scale. Additionally, we asked the respondents to attach a monetary value to PII based on the relative cost of a meal. In addition, we subdivided the responses by education, income, and age to determine if there were significant differences between each group.

From here, our paper is organized as follows. First, we introduce our methodology of collecting data on people's perception of PII. We follow by summarizing our analysis and results. We then provide a discussion of our findings. Lastly, we conclude with implications and steps forward with this research.

2. METHODOLOGY

Aligned with our research goals, we developed a survey instrument aimed at collecting people's perceptions of importance and value toward personal identifying information (PII). With this goal in mind, we adapted an instrument used by Fehrenbach and Herrando (2021) that identified the types of PII people find vital. Our adaptation asked people how important each type of information was to keep private. Expanding on this scale, we constructed an instrument requesting a person's perceived value of each PII with respect to their average cost of lunch. There is some research that links the cost of lunch to a family's socioeconomic situation (e.g., Domina et al., 2018), thus we felt this offered a normalized monetary reference to people at all income levels. People's budgets for lunch offers a baseline for people to evaluate their perceived value of PII. The measurement items can be found in the Appendix.

To collect the data, we administered the survey to a sample group through Amazon's Mechanical Turk. All participants who fully completed the survey received monetary compensation.

Once the data was collected, incomplete and/or erroneous data was removed from the final dataset. The dataset consisted of 222 valid responses with 33.3 % Females and 66.7 % Males. There were predominantly 3 levels of education: High School (or equivalent) (11.7%), College Degree (undergraduate) (64.0%), and Master's Degree (24.3%). Using information found at Beresford Research, (Brunjes, n.d.) we transposed each year of birth to their respective generation. Lastly, the participants had a normal distribution of income levels with the mean occurring at $40 – $59.9k (33.3%). Table 1 below provides a summary of the sample statistics.

Table 1: Demographic Sample Statistics

Sample Size:	N = 222
Gender	*%*
Female	33.3
Male	66.7
No response or other	0
Level of Education	*%*
High School or Equivalent	11.7
College Degree	64.0
Master’s Degree	24.3
Generation (based on YOB)	*%*
Boomer I	3.6
Gen X	23.4
Gen Y	62.2
Gen Z	10.8
Income Level	*%*
< $20k	10.4
$20k – 39.9k	20.3
$40k – 59.9k	33.3
$60k – 79.9k	20.7
$80k – 99.9k	10.4
$100k +	5.0

3. ANALYSIS & RESULTS

We examined the data for each individual PII and their overall mean scores. Regarding information importance, the highest ranked PII was ‘Current Bank Account Balance, followed by ‘Social Media Account Access’. The lowest ranked PII was ‘Political Preference, closely followed by ‘First and Last Name. With regards to information value, the highest value PII was also ‘Current Bank Account Balance’, followed closely by ‘Social Media Account Access’. Like information importance, the least valued was ‘Political Preference’, and secondarily ‘First and Last Name’. All PII and respective values are summarized in Table 2.

Table 2. Descriptive Statistics

Personal Identifying Information	Importance *(1 to 5)*		Value *(-5 to +5)*	
	Mean	*Std Err*	*Mean*	*Std Err*
First and Last Name	3.33	1.22	1.75	2.52
Personal Phone Number	3.76	1.04	2.39	2.22
Personal Street Address	3.91	1.04	2.35	2.28
Mother's Maiden Name	3.66	1.24	1.99	2.51
Political Preference	3.23	1.30	1.18	2.71
Current Bank Account Balance	4.14	1.00	2.75	2.09
Browser History	3.92	1.01	2.49	2.20
Social Media Account Access	3.97	1.04	2.62	2.13

Note: N = 222

To evaluate the effect of education, income, and age, as potential socioeconomic indicators, we conducted a multivariate analysis of variance (MANOVA) with the information importance and value as dependent variables as it relates to each respective PII. Using Wilkes Lambda test for significance, the results showed that differences in education was significant on the dependent variables for all PIIs. Overall, this suggests that education level can impact different perceptions on the worth (importance and value) of PII.

With respect to income, there were no significant differences found. This suggests that regardless of income, people have an equal view of the worth of PII.

Lastly, in terms of generational (age) difference, significance was found based on ‘First and Last Name’ will all other PIIs showing no significance. This suggests there are generational gaps regarding perceptions of the worth of PII that is offered in online contexts. A complete breakdown of significant differences among all groups is offered in Table 3.

We also conducted a post hoc analysis of the results to see which dependent variable (information importance vs. information value) had significance among the different levels of education, income, and age. Interestingly, apart from the case of 'First and Last Name' where there was a significant difference for information importance with levels of education and information value for generation levels, no other differences were found in the areas of income or generation toward information value or importance. However, we found the majority of differences for the remaining PIIs to be based on education levels.

Table 3. Multivariate Analysis of Variance
Wilkes Lambda test for Significance
(post hoc summary noted)

Personal Identifying Information	***Educ***	***Income***	***Gen***
First and Last Name	<0.001*[i]	0.080	0.033*[v]
Personal Phone Number	0.001*[v]	0.187	0.322
Personal Street Address	<0.001*[v]	0.822	0.361
Mother's Maiden Name	0.019*[i]	0.515	0.146
Political Preference	0.004*[iv]	0.063	0.266
Current Bank Account Balance	0.006*[v]	0.720	0.478
Browser History	0.002*[v]	0.324	0.665
Social Media Account Access	0.022*[v]	0.925	0.296

note:
All PIIs satisfied assumptions test of normality
Dependent Variables: Information Importance and Information Value
*ρ values shown, * significant $\rho < .05$, N=222*
[i] post-hoc analysis (Tukey) indicates significance between groups for Information Importance
[v] post-hoc analysis (Tukey) indicates significance between groups for Information Value

Specifically, we found that there was significant difference in information importance across levels of education for First and Last Name, Mother's Maiden Name, and Political Preference. In the case of First and Last Name and Mother's Maiden Name, the differences were between Undergraduate college and Master's level college individuals. For Political Preference, differences were found across all education groups. Information value showed significant differences in Personal Phone Number, Personal Street Address, Political Preference, Current Bank Account Balance, Browser History, and Social Media Account Access. These differences were for the most part between High School and those with some college degree (Undergraduate and Masters). A summary of the post hoc analysis is show in Table 3., with a more detailed breakdown of education in the Appendix, Table 4.

4. DISCUSSION

The set of data items were chosen to reflect a holistic overview of the various data types that previous research has deemed as personally identifying and important to consumers (Carrascal et al., 2013; Huberman et al., 2005; Tsai et al., 2011). Table 2 shows that overall, consumers rank 'Current Bank Account Balance' and 'Social Media Account Access' as the most *important* and the most *valuable* PII. Also, our analysis shows that 'First and Last Name' and 'Political Preference' rank the least in terms of both information *importance* and *value*. We believe this suggests that consumers do have some consistency in the worth of PII. This finding suggests that individuals are aware that their financial wellbeing, as shown in their current bank account balances is important to maintain as private over other PIIs. Furthermore, we can see that there is high worth placed on a person's social media information, which can also indicate that people seek to maintain a degree of privacy as it pertains to their social lives when asked to divulge related information. This can lead to future research in these areas to determine as to the reasons people find high value in such types of PIIs.

There are significant differences in the worth perceptions of PII with respect to their degree of importance and value based on the education level of the individual. Our findings show that differences exist in all PII variables as it relates to education. In the areas of education, we were able to see some differences in the importance of keeping PII private, however, the findings also start to identify where people may find some difference between what information is important to keep private (information importance) and what information can be used as means of trade (information value). More specifically, our findings suggest that differences in education appear to illuminate the true value of information and the benefits people expect to receive if divulged. Furthermore, education levels reveal the need for further research to understand incentive adjustments for PII requests, since a majority of the PII are significant for information value along those groups.

Examining differences in income on PII, we find that there was almost no difference in information importance or value. Overall, our findings suggest that regardless of income, the view of PII are equal between groups as identified in the MANOVA analysis in Table 3. This finding is important as it indicates that the same incentives can be given as income has minimal influence on PII worth.

Investigating generational (age) differences, the data suggests differences as it relates to the importance and value of PII. More specifically, some PII shows a significant difference based on its value but not importance as it comes to requests for 'First and Last Name'. However no other PII was found to show significance. When reviewing our sample demographics, there were fewer later generation participants (e.g., 3.6% of Boomer Generation), who had adapted using information technology later in life. Whereas the majority of other generations were born at time with information technology introduced earlier in their lifetime (e.g., Digital Natives). Although our findings may show minimal impact in this area, there is a need to explore this further to include a larger sampling of later generations.

Overall, our analysis shows that there is consistency in the ranking of PII in terms of information importance and value. The highest ranked PII was a person's 'Bank Account Balance' and 'Social Media Account Access'. However, upon deeper inspection, we find that differences of education have a larger impact on the worth of information with a greater degree of significance found in terms of information value.

5. IMPLICATIONS

Our analysis shows that consumers bestow different worth for the PII considered in this study. This may be a critical component for researchers that study the privacy paradox, the idea people believe it important to maintain information private yet offer it for a benefit. The findings in the paper suggest that people are willing to offer their PII for a price that is consistent with its perceived worth.

Our study also reveals that there is a consistency in information worth across income and generation since the valuation and importance of PII across income and generation do not have significant changes. However, from an education viewpoint, information worth is perceived differently since information value and importance are perceived differently as seen in how importance remains the same for most PII, but value differs significantly between education levels.

Additionally, our study offers a unique measurement of information value providing a standardized monetary basis to evaluate PII. This is directly usable for researchers that seek to explore not just the importance of PII, but what value people place on PII.

We believe this research offers companies a perspective that some PII's are worth more than others and that the worth of PII's differ across socioeconomic variables, especially when considering the education level of the consumer. Thus, companies should pay attention to each PII and carefully design their monetary incentive for each PII to increase the likelihood of its disclosure.

6. LIMITATIONS

As with all research, limitations are present, and we recognize that there are gaps in this study that may limit the suggested findings. For example, we recognize there is a smaller distribution of Boomer generations, which when applied to our analysis, may cause some concern due to its imbalance across the dataset. This can be easily remedied by collecting data targeting this age group to increase the sample size in this dimension.

Also, we recognize that a survey instrument alone has its limitation and can introduce some inconsistencies of people's true perceptions. To improve upon this, other studies may be able to add some qualitative analysis (e.g., via open ended questions) by targeting people's perceptions.

7. FUTURE WORK

With this study we can see there a need to look deeper into the educational and generational difference in the perceptions of the worth of PII. For example, our study illustrates there are some differences based on education, however, the question as to the degree of difference and cause of differences needs further investigation. This is also the same with differences found based on the different generations. Furthermore, it would be valuable to see what PII each individual group finds of highest worth. For example, what PII is of highest worth to Gen Z, or those with a High School level of education. There is need for future studies to understand these differences and create a ranking of PII worth between groups based on education and/or generation (age).

Future studies could consider other non-socioeconomic variables such as ethnicity and gender to understand the variation if any in the worth of different PII. Furthermore, since our study analyzed only a subset of consumer's PII, future studies can consider the worth of additional PII relative to modern consumers such as their health-related information.

Additionally, we can see the need for a information worth construct from a privacy paradox perspective since our results show that though importance and value are consistent over most of the PIIs considered, there are perceived differently in the case of education levels possibly across demographic variables that can be considered in future research. This may require the construction and validation of a formative construct with indicators given that will provide a single construct of information worth.

8. CONCLUSION

With the aim of smoothening the consumer experience, we investigated the perception of PII worth and whether the incentives offered can remain consistent across the demographic groups considered in this study. To this end, we conducted a survey of individuals asking questions regarding different types of PII and their importance and relative value. Our findings show that there are significant differences on the perceptions of PII worth based on an individual's education level and age. Also, we show that perceptions of PII worth are consistent across gender. This study opens new perspectives to both the research community examining the privacy paradox and businesses seeking to collect PII to benefit the consumer experience.

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APPENDIX A

Survey Instrument

Information Importance *(adapted from Fehrenbach and Herrando, 2021)*

Question 1: For the following personal information, what **degree of importance** do you feel it is to maintain as private? *5-point likert scale: Not important to keep private, Slightly important to keep private, Moderately important to keep private, Important to keep private, Very important to keep private.*

1. First and Last Name
2. Personal Phone Number
3. Personal Street Address
4. Mother's Maiden Name
5. Nationality
6. Political Preference
7. Current Bank Account Balance
8. Browser History
9. Social Media Account Access
10. Preferred Brand of Underwear

Information Value *(new)*

Question 2: For the following personal information, what **amount of value** would you expect to receive if shared? *11-point polar scale: -5 Less than the cost of lunch, 0 Average cost of lunch, +5 More than the cost of lunch*

1. First and Last Name
2. Personal Phone Number
3. Personal Street Address
4. Mother's Maiden Name
5. Nationality
6. Political Preference
7. Current Bank Account Balance
8. Browser History
9. Social Media Account Access
10. Preferred Brand of Underwear

Table 4: Post Hoc Analysis - Multiple Comparisons in Education - Tukey HSD

			Importance		Value	
Dependent Variable	**Education (I)**	**Education (J)**	**Mean Diff (I-J)**	**Sig.**	**Mean Diff (I-J)**	**Sig.**
First and Last Name	H.S. or equal	U.G. College	0.06	0.968	0.07	0.991
		Masters	-0.57	0.115	0.38	0.784
	U.G. College	H.S. or equal	-0.06	0.968	-0.07	0.991
		Masters	-0.63	**0.003***	0.32	0.693
	Masters	H.S. or equal	0.57	0.115	-0.38	0.784
		U.G. College	0.63	**0.003***	-0.32	0.693
Personal Phone Number	H.S. or equal	U.G. College	0.16	0.741	1.01	0.074
		Masters	-0.08	0.944	1.59	**0.007***
	U.G. College	H.S. or equal	-0.16	0.741	-1.01	0.074
		Masters	-0.24	0.309	0.58	0.223
	Masters	H.S. or equal	0.08	0.944	-1.59	**0.007***
		U.G. College	0.24	0.309	-0.58	0.223
Personal Street Address	H.S. or equal	U.G. College	0.22	0.575	1.76	**0.001****
		Masters	-0.07	0.953	2	**0.001****
	U.G. College	H.S. or equal	-0.22	0.575	-1.76	**0.001****
		Masters	-0.29	0.18	0.23	0.789
	Masters	H.S. or equal	0.07	0.953	-2	**0.001****
		U.G. College	0.29	0.18	-0.23	0.789
Mother's Maiden Name	H.S. or equal	U.G. College	-0.05	0.981	0.54	0.579
		Masters	-0.54	0.161	0.7	0.471
	U.G. College	H.S. or equal	0.05	0.981	-0.54	0.579
		Masters	-0.49	**0.036***	0.17	0.908
	Masters	H.S. or equal	0.54	0.161	-0.7	0.471
		U.G. College	0.49	**0.036***	-0.17	0.908
Political Preference	H.S. or equal	U.G. College	-0.8	**0.008***	-1.94	**0.002***
		Masters	-1.37	**0.000****	-1.98	**0.004***
	U.G. College	H.S. or equal	0.8	**0.008***	1.94	**0.002***
		Masters	-0.58	**0.011***	-0.04	0.994
	Masters	H.S. or equal	1.37	**0.000****	1.98	**0.004***
		U.G. College	0.58	**0.011***	0.04	0.994
Current Bank Account Balance	H.S. or equal	U.G. College	0.44	0.102	1.03	0.052
		Masters	0.33	0.342	1.66	**0.002***
	U.G. College	H.S. or equal	-0.44	0.102	-1.03	0.052
		Masters	-0.1	0.793	0.63	0.133
	Masters	H.S. or equal	-0.33	0.342	-1.66	**0.002***
		U.G. College	0.1	0.793	-0.63	0.133
Browser History	H.S. or equal	U.G. College	-0.02	0.995	1.11	**0.042***
		Masters	-0.25	0.571	1.71	**0.003***
	U.G. College	H.S. or equal	0.02	0.995	-1.11	**0.042***
		Masters	-0.23	0.35	0.6	0.187
	Masters	H.S. or equal	0.25	0.571	-1.71	**0.003***
		U.G. College	0.23	0.35	-0.6	0.187
Social Media Account Access	H.S. or equal	U.G. College	0.16	0.749	1.21	**0.020***
		Masters	0.02	0.996	1.7	**0.002***
	U.G. College	H.S. or equal	-0.16	0.749	-1.21	**0.020***
		Masters	-0.14	0.679	0.49	0.313
	Masters	H.S. or equal	-0.02	0.996	-1.7	**0.002***
		U.G. College	0.14	0.679	-0.49	0.313

Based on observed means.