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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.

Grubliešič 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" (Grubliešič & 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 (Grubliešič & 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

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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

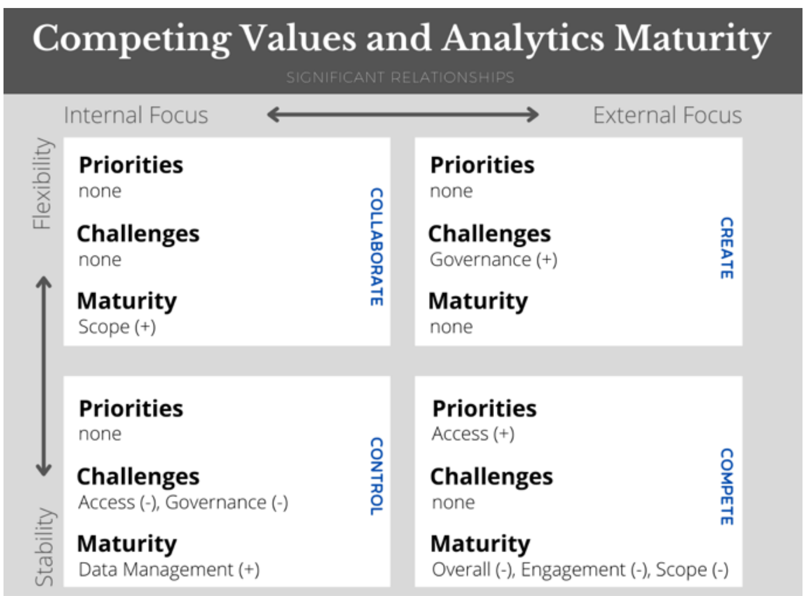

Figure 1: Combined Findings