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Perceptions of data governance: identifying critical success factors in a university system's implementation effort

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Abstract

This paper seeks to empirically validate a sector agonistic instrument that measures the perceived critical success factors in data governance. Twelve constructs (Leadership and Management Commitment; Leadership and Management Alignment; Executive Sponsorship; Robust Data Governance Strategy; Change Management; Training and Education; Governance Organizational Structure; Communication and Collaboration; Stakeholder Engagement and Support; Skills, knowledge, and expertise; Use of data governance tools; and Measurements to track progress) and their associated items were evaluated using data collected from 121 respondents representing a variety of stakeholders from a southeastern United States university system. All institutions had recently participated in a system-wide mandated data governance initiative. The data were analyzed using exploratory factor analysis. The instrument tested, comprised of forty-seven items, was found to be reliable to measure critical success factors of data governance consistent with those found in the literature and eleven of the twelve identified by Mahanti (2018).

Keywords: **data** governance; critical success factors; implementation; management; higher education

Introduction

Data Governance (DG) is an evolving field in the information technology, information management, and information systems disciplines, whose knowledge base, application, and popularity have grown tremendously among researchers, academics, and practitioners over the past few decades. (Al-Badi et al., 2018; Khatri & Brown, 2010; Weber et al., 2009). Begg & Caira (2012) suggest that "data governance formed from a convergence of several well-established areas concerned with data - such as data quality management, data management systems, data security, and data administration" (p.4). While a number of DG definitions exist, a simple characterization of the domain can be summarized as the "exercise of authority and control over the management of data resources" (Brackett et al., 2017, p. 19)

Over the past several decades, as the volume of data has increased and the regulatory environment has matured, institutions of higher education (IHE) have seen a rapid escalation in and attentiveness to institutionalizing data governance (DG). Driven by a number of factors from normative forces by sector peers, coercive forces defining compliance obligations, and market forces requiring fiscal stewardship and adaptability; data governance frameworks offer colleges and universities a structure to address data availability, usability, integrity, quality, and security – long adopted by similarly situated data intensive sectors like manufacturing, banking, aviation, telecommunications, and healthcare (Abraham et al., 2019; Brackett et al., 2017; Deloitte, 2023; DGI, 2022; Eckerson Group, 2019; McKinsey, 2022; Price Waterhouse Coopers, 2019). Both commentary and research have reinforced the notion that higher education institutions that "adapt to the ever-increasing demands for quality data and utilize effective master data management (MDM) and data governance (DG) practices" are not only "positioned to gain a strategic advantage over their peers", but "maximize student and institutional outcomes" (Hubbard et al., 2020, pp 51-52). This has driven the adoption of data governance initiatives at IHEs globally, providing opportunities for researchers to investigate the phenomenon.

The general need for formal data governance adoption has been well established in both the academic and practitioner literature (Young & McConkey, 2012; Daniel, 2015; Mahanti, 2018; Ladley, 2019; Hubbard et al., 2020; J. S. Gagliardi, 2022) Moreover, data governance consistently ranks high among the top issues facing higher education administrators who must balance organization needs, consumer expectations, compliance duties, and resource availability(Childers & Walz, 2018; HEDW, 2017).

Today, colleges and universities operate in a complex and competitive environment. The supply of data and demand for information intersect with the responsibility to collect, secure, and utilize faculty, staff, and student data in a meaningful way. When adding the demands for accountability, transparency, and efficacy, institutions of higher education have found themselves in a perfect storm in the timely implementation of data governance. Accordingly, because of their stewardship responsibility to educate, the sensitive nature of data maintained, and the diverse volume of data collected; colleges and universities are unique stakeholders in the space and should be leaders in the field of data governance design and implementation (Chapple, 2013). Despite consistent calls to action, adoption and implementation varies across IHE's. With data governance implementation come a number of challenges, from the social and political to the technological and financial; as such, the outcomes of implementation may directly be related to the presence of critical success factors (CSFs) within the organization. CSFs represent the "key elements without which the data governance initiative flounders" (Mahanti, 2018, p.8). Since a number of broadly defined and sector agnostic CSFs have been identified in the literature and a growing number of institutions of higher education are engaged in adoption and implementation of data governance, an opportunity presents itself to explore perceptions of these factors and see to what extent they have influenced data governance maturity. Based on the limited amount of research on data governance at institutions of higher education, there is both a need and opportunity to explore the intersection between the topic and sector further. (Nielsen, 2017; Jim & Chang, 2018).

The primary purpose of this study is to validate the identification and classification of critical success factors of data governance proposed by Mahanti (2018) within the sector of higher education. These CFSs include Leadership and Management Commitment; Leadership and Management Alignment; Executive Sponsorship; Robust Data Governance Strategy; Change Management; Training and Education; Governance Organizational Structure; Communication and Collaboration; Stakeholder Engagement and Support; Skills, knowledge, and expertise; Use of data governance tools; and Measurements to track progress. Secondarily, this research sets up a future research stream that would be used to explore the influence of these critical success factors to the data governance maturity. Consistent with the purpose, the researcher proposes the following research question.

RQ1: *Are the 12 CFS constructs/components reliable and interpretable among their associated items within the sector of higher education?*

This research will contribute to the data governance knowledgebase by exploring the presence of critical success factors in a data intensive sector – higher education. The results will provide insight into existing implementation efforts, and it has the potential to generate recommendations for higher education administrators beginning or struggling with implementation.

Review of the Literature

Pierce and colleagues (2008) concisely outlined data governance as a "collective set of decision-making processes for the use and value-maximization of an organization's data assets" (p.7). A leader in the data industry, the company Oracle (2011), noted in a white paper that data governance "is the specification of decision rights and an accountability framework to encourage desirable behavior in the valuation, creation, storage, use, archival and deletion of data and information" (p. 3). Abraham and associates (2019) extended their definition with qualifying actions, whereby data governance "formalizes data policies, standards, procedures, and monitors compliance" (p. 426). Nevertheless, the dynamics of external and internal forces, sector uniqueness, and applications contribute to a construct identity that is continually being analyzed, yet is still considered an under-researched topic (Otto, 2011; Lis & Otto, 2021; Abraham et al., 2019). Therefore, organizations – including those in higher education, often find the need to define what data governance means to them and their rational for pursing it (University of Colorado, 2013; University of Michigan, 2023; University of Rochester, 2022; USG, 2021) .

Critical Success Factors of Data Governance

The following section provides literature highlights for each of the associated data governance critical success factors (CSF). The term critical success factor was introduced and popularized by John F. Rockart as "the limited number of areas in which results, if they are satisfactory, will ensure successful competitive performance for the organization" (Bullen & Rockart, 1981, p. 7; Rockart, 1979, p. 81). Mahanti's (2018) research would conclude that 12 such sector agnostic CSF's were identifiable and relevant to data governance as "key elements without which the data governance initiative flounders" (p.8).

Leadership and Management Commitment - The academic and practitioner literature has resolved that data governance requires not only the involvement and commitment of all organizational staff but the full sponsorship and endorsement of operational management and senior-level executives (Fleissner et al., 2014; Ladley, 2019; Thomas, 2009). Bhansali (2013) notes that regardless of maturity level within an organization "data governance requires commitment at all levels" and one that "embrace(s) people, processes, software, and executive buy-in and support" (p.24). Furthermore, they note that for the "success of a data governance program and to provide strategic resources" it is essential that leadership be "inspired, committed, and visionary (p. 30).

Leadership and Management Alignment- Mahanti (2018) relays that "for data governance to be implemented successfully in an organization, the leaders and management, at all levels, need to be aligned with regard to solidarity in support and agreement on the definition of data governance success" (p. 8). Prainsack (2017, p.91) suggests that the "concept of solidarity provides a fruitful and timely framework to strengthen collective control, ownership and oversight of data use" – critical in framing data governance. (Brous et al., 2016) would identify in their literature review that alignment is one of the key principles of data governance. Whereas, "data governance should ensure that data meets the needs of the (entire) business and must be able to demonstrate business value" (p. 120). Rifaie et al. (2009) noted that "alignment also deals with balance between investments that run the current business, grow existing businesses, and have the potential to transform the business" (p. 589).

Executive Sponsorship - Identified and stable key executive sponsorship (often manifested as a board, cabinet, or core business and/or IT leader) is crucial to a successful data governance program (Plotkin, 2020; Poor, 2011). The literature has consistently established that the value proposition need not only to be understood, but communicated by executives for DG to be successful (Ladley, 2019). IBM lists obtaining executive sponsorship among its fourteen steps for a unified data governance process (Soares, 2010).

Bhansali, (2013) reports that executive sponsorship, along with a defined business case, are instrumental to the successful launch of enterprise-wide data governance program. Smith (2021) stresses that that the lack of sustained sponsorship is one of the main reasons data governance efforts fail, specifically during management and role changes.

Robust Data Governance Strategy - According to Powers (2019), a sound data strategy "should be synonymous with reliable data sources and effective data governance" (p. 109.) Broad data strategy and nuanced data governance strategy, establishes not only a roadmap to pursue alignment with business level strategy, but lays the foundation for cultural impact like enhanced data literacy or data quality (Gupta & Cannon, 2020; Powers, 2019). Mahanti, (2018) references that "data governance strategy provides the foundation for building the data governance program implementation plan"; asserting that "a robust data governance strategy is critical to the successful implementation in an organization" (p.9). Alhassan et al., (2019) further suggests that instituting DG strategy is more than a mission and vision statement and "requires certain top managers to have certain competencies" and "treat data as a strategic asset" (p.104).

Change Management - Given the complexity of the work and transformation required, data governance initiatives are known to require a not only a significant, but sustained change management effort (Harris, 2011; Ladley, 2019). Consequently, organizations must be capable of managing substantial change to successfully implement data governance (Hovenga & Grain, 2013). Gartner (2018) characterizes data governance as a normative force in their reference to "the rules of the game" allowing for organizations to both support business objectives while enabling them to "balance out the opportunities and risks in the digital environment" (p.1). Consequently, it lists the implementation of data governance among its four steps that data and analytics leaders should purse if they wish to "evolve their organizations' capabilities for greater business impact." Panian (2010) affirms that addressing change management issues is critical for the successful implementation of data governance.

Training and Education - Training and education efforts are established critical success factors integral to data governance implementation (Ahmadi et al., 2021; Mahanti, 2014, 2021a). Abraham et al., (2019) contends that "training programs ensure that stakeholders have the necessary knowledge and qualifications to support the implementation of data governance" (p. 430). Alhassan (2018) states that training is most important action/interaction item to ensure data competencies in data governance implementation. Fundamentally, training and education is critical to formalize accountability **(**Seiner, 2014)**.** Despite that, training and education efforts are described as one of the "most abused deliverables" of data governance implementation (Ladley, 2019, p. 225).

Governance Organizational Structure - Seiner (2014) characterizes the challenge of governance organizational structure well in the statement "a data governance program will not run itself" (p. 102). It is well documented successful data governance is reliant on sound structural investments (Gupta & Cannon, 2020; Ladley, 2019; Mahanti, 2018; Powers, 2019). This includes and is not limited to the establishment of a data ownership hierarchy, specific authorities, defined roles, responsibilities, committees, workgroups, and dedicated staff with and appropriate segregation of duties. Siloed organizations overcome this challenge by identifying cross functional oversight that creates "well-defined, trusted, well-understood data, leading to clarity and transparency" (Webber & Zheng, 2020, p. 133).

Communication and Collaboration - Communication is key to data governance, with some quantifying the burden in excess of 80% of the work (Hopwood, 2008). Benfeldt and colleagues (2020) characterize data governance as a collective action problem "rather than an exercise in assigning accountabilities" (p. 20). From this perspective, both communication and collaboration are instrumental in driving adoption and building culture. Along with training, purposeful communication is key to relaying a united and shared purpose, conveying necessity, and building a shared language, thereby fostering a culture of collaboration (Gupta & Cannon, 2020). Harris (2011) contends "that organizations that successfully implement data governance view collaboration not just as a guiding principle, but also as a call to action in their daily practices" (p.3). Harris concludes that "data governance not only reveals the business value of the organization's data but also reveals the communication and collaboration necessary to materialize that value as positive business impacts" (p. 2).

Stakeholder Engagement and Support - DG research consistently references importance of stakeholder engagement and support (Seiner, 2014; Simon et al., 2018; Mahanti, 2018). Speare (2017) submits that "for a governance program to succeed, stakeholders from all those areas should be involved and convinced of the value that data governance can provide" (p.1). Harris (2011) contends that while the sustained success of DG efforts requires executive sponsorship, it's the "grassroots advocates acting as bottom-up peer level influencers (who) make more effective change agents" (p. 3). Intentional stakeholder analysis is critical to ensuring adequate representation, minimizing resistance, and identifying expectations that will be managed during the course of DG implementation (Ladley, 2019). Gupta & Cannon (2020) note that one of the principle goals of DG is to "instill a sense of collective ownership" (p. 160). It's this ownership that is categorized in an institution level of DG maturity reflecting how varying stakeholders understand, value, and implement the DG plan plan/program.

Skills, knowledge, and expertise - Aiken & Harbour (2017) submit that the data science movement has increased organizational awareness to workforce data skills and the need to capitalize on them. Wang & Jiang (2022) additionally suggest that in this new era of big data, organizations must be attentive to not only professional ability but the quality of talents available to meet organizational objectives. They further comment that that it's not enough to secure external talent, but it's necessary to cultivate and motivate existing personnel. The literature also affirms that successful data governance implementation not only requires technical knowledge, but exceptional people skills – in order to execute the relationship dependent aspects of a DG plan (Gupta & Cannon, 2020; Mahanti, 2018).

Use of data governance tools- Mahanti (2021a) references that both governance tools and technologies "can form an important part of an overall data governance strategy and implementation…as they can automate repetitive activities and processes, enhance productivity, and reduce operational costs" (p. 145). Data Governance tools, like the assessment tools proposed by Marchildon and his collegues (2018), are imperative for data governance implementation as they allow for organizations to evaluate their current level of data governance maturity in order to "better define and prioritize the goals, content, and activities of their data governance initiatives" (p. 4). Seiner (2014) would note that the use of assessment tools, and other functional tools like a common data, activity/process, or communication matrices are instrumental in implementation and maturation progression of data governance. Consequently, the success of higher-level organizations "typically depends on the interaction between data governance and project management functions and the proper use of tools" (p. 41).

Measurements to track progress - Data governance consults, academics, and researchers often reference the accountability challenges associated with data governance planning and implementation (Infosys, 2018; Ladley, 2019; Mahanti, 2021b; Powers, 2019). Metrics ranging from implementation progress, return on investment, and utilization to data quality, data timeliness/availability, risk mitigation/cost avoidance, and implementation/effectiveness – inform stakeholders to the progress and the likelihood of data governance sustainability. Smith (2016), notes that "without identifying criteria for measuring the results of the data governance program and the activities of the data stewards and data management professionals, an organization cannot feel confident that the program is achieving its business goals or contributing quantifiable business value"(p.1). Ladley (2019) stresses that data governance "will not succeed if it cannot be measured, and the success measures must come from a set of business-oriented metrics" (p. 52).

Research Methodology

The instrument for this study is a modification of a survey designed by Mahanti (2018) that identified critical success factors in the implementation of data governance, broadly across several business sectors. This researcher used the 12 critical constructs, comprised of 47 items identified by Mahanti (2018) for the present study, customized for institutions of higher education. The referenced 12 critical success factors are not only derived from the literature, but affirmed through discussions with information technology, data governance, and information management professionals. The constructs and the associated item count are listed below in parenthesis () and detailed in Appendix A.

1. Leadership & Management Commitment (3)
2. Leadership and Management Alignment (2)
3. Executive Sponsorship (5)
4. Robust Data Governance Strategy (4)
5. Change Management (4)
6. Training and Education (6)
7. Governance Organizational Structure (6)
8. Communication and Collaboration (3)
9. Stakeholder Engagement and Support (4)
10. Skills, knowledge, and expertise (3)
11. Use of data governance tools (3)
12. Measurements to track progress (4)

Participants were required to answer two distinct question sets related to the 12 critical success factors. The first set (a) asks participants to identify the importance of the critical success factor; while the second set (b) asks the participants to evaluate the probability of the critical success factors occurrence within their organization. The questions related to the importance of the critical success factor (set a) uses a 5-point Likert-type scale as follows – Crucial (5); Very important (4); Important (3); Less important (2); and Not important (1). The questions related to the probability of the critical success factor occurrence (set b) uses a 5-point Likert-type scale as follows – Very Probable (5); Somewhat Probable (4); Neutral (3); Somewhat Improbable (2); and Not Probable (1). Respondents were also asked a series of basic background and demographic questions to contextualize the survey results.

Global data governance implementation and maturity was measured using the Oracle Data Governance Maturity Scale 0-6 scale. (0=None; 1=Initial; 2=Managed; 3=Standardized; 4=Advanced; 5=Optimized) The survey also inquired about the respondent's perception of data governance implementation at their institution by evaluating data governance maturity across several relevant components. The 22 components evaluated in the initial survey are based on the studied university system's data governance framework and include the following:

1. Governance and Organizational Structure
2. Policies and Procedures
3. Data Systems Documentation
4. Data Elements
5. Data Definitions
6. Data Quality Control
7. Data Availability
8. Data Lifecycle
9. Safeguards
10. Classification
11. Access Procedures
12. Segregation and Separation of Duties
13. Regulatory Compliance
14. Training
15. Monitor
16. Audit
17. Data Inventory
18. Data Risk Management
19. Data Processing Documentation
20. Disassociation and Deidentification
21. Data Process Awareness
22. Communication

Procedure and Sample

Following approval from the principal researcher's institutional review board, the survey was administered electronically through Qualtrics, an internet-based survey software, and disseminated across a number of faculty, staff, advisory, and data governance listservs, directories, and other avenues publicly available for member institutions of a university system located in the Southeastern United States. Each institution within the system had recently engaged in a guided data governance initiative. In addition to direct solicitation for participation, snowball sampling techniques were employed to ensure that the survey would reach and petition those familiar with data governance or participated in its implementation at their institution. All participates of the survey were assured both confidentiality and anonymity in their responses, agreed to the informed consent disclosure, were 18 years or older, and were familiar with or participated in data governance implementation at their institution.

During the data collection period, 177 respondent results were collected, 56 were eliminated due to incomplete data – yielding a final functional response count of 121 used for data analysis and interpretation. Table 1 shows the demographic statistics where the largest respondent groups independently were age 50-59; female; and had worked in higher education between 21-25 years. Most respondents (88.4%) indicated that their institutions were beyond the initial stages of data governance implementation and is shown in Table 2. Table 3 shows the largest respondent groups independently held the role of data user; identified as director; worked at a state university

Table 1: Demographics (N=121)

Age	Gender	Years of Experience in Higher Education
18 – 20 = 0 (0%)	Male = 62 (51.2%)	1-5 = 8 (6.6%)
21 – 29 = 2 (1.7%)	Female = 55 (45.50%)	6-10 = 13 (10.7%)
30 – 39 = 17 (14.0%)	Non-binary / third gender = 0	11-15 = 22 (18.2%)
40-49 = 33 (27.3%)	Prefer not to say = 4 (3.3%)	16-20 = 21 (17.4%)
50-59 = 48 (39.7%)		21-25 = 24 (19.8)
60+ = 21 (17.4%)		26-30 = 15 (12.4%)
		30+ = 18 (14.9 %)

Table 2: Global Data Governance Implementation (N=121)

Implementation Milestone
0 – None = 3 (2.5%)
1 – Initial = 11 (9.1%)
2 – Managed = 41 (33.9%)
3 – Standardized = 50 (41.3%)
4 – Advanced = 12 (9.9%)
5 – Optimized = 4 (3.3%)

Table 3: Data Governance Roles, Participant Titles, and Institutional Classification N=121

Role:	Title:	Institutional Classification
Data Manager = 16 (13.2%)	Chief Technology Officer = 1 (.8%)	Comprehensive University = 11 (9.1%)
Data Owner = 10 (8.3%)	Provost = 1 (.8%)	Research University = 14 (11.6%)
Data Steward = 33 (27.3%)	Chief Data Officer = 1 (.8%)	State College = 21 (17.4%)
Data Trustee = 12 (9.9%)	Assistant Director = 3 (2.5%)	State University = 75 (62.0%)

Role:	Title:	Institutional Classification
Data User = 38 (31.4%)	Chief Information Security Officer = 2 (1.7%)	
None or N/A = 4 (3.3%)	Other Staff Member (Non-Disclosed) = 5 (4.1%)	
Other = 8 (6.6%)	Chair = 3 (2.5%)	
	Associate/Assistant Provost = 4 (3.51%)	
	Vice President = 6 (5.0%)	
	Faculty Member = 7 (5.8%)	
	Chief Information Officer = 7 (5.8%)	
	Executive Director = 9 (7.4%)	
	Dean = 11 (9.1%)	
	Associate/Assistant Vice President = 14 (11.6%)	
	Director = 22 (18.2%)	
	Other Staff Member =22 (18.2%)	

Important Data Governance Components

Respondent's perception of data governance implementation at their institution was evaluated by identifying importance assigned by their institution across 22 components within their data governance framework. The top five priorities identified by mean score included 1) data safeguards, 2) regulatory compliance, 3) policies and procedures, 4) data governance and organizational structure and 5) data access procedures. While the five lowest priorities recognized were 1) data processing documentation, 2) training, 3) data process awareness, 4) data disassociation and deidentification, and 5) communication.

Table 4: Important Data Governance Components

Data Safeguards	4.35
Data Governance Regulatory Compliance	4.22
Data Governance Policies and Procedures	4.21
Data Governance and Organizational Structure	4.15
Data Access Procedures	4.04
Data Systems Documentation	3.97
Data Related Segregation and Separation of Duties	3.95
Data Risk Management	3.87
Data Quality Control	3.84
Data Definitions	3.84
Data Elements	3.82
Data Classification	3.81
Data Availability	3.78
Data Inventory	3.64
Data Governance Monitoring	3.52
Data Lifecycle	3.51
Data Governance Auditing	3.50
Data Processing Documentation	3.50
Data Governance Training	3.43
Data Process Awareness	3.39
Data Disassociation and Deidentification	3.36
Data Governance Communication	3.35

Important Critical Success Factor

The means and associated standard deviations for each baseline critical success factors of data governance implementation are presented in Table 5. The highest mean identified is Leadership and Management Commitment (LMC)(=4.33) referencing high importance among higher education respondents, while Measurements to Track Progress (MTP)(=3.78) was rated among the lowest factors, indicating only slight above average agreement in its importance of this factor in data governance implementation.

Table 5: Means and SDs Baseline Critical Success Factor of Data Governance Implementation

Critical Success Factor	Mean	SD
Leadership and Management Alignment	4.33	.60
Executive Sponsorship	4.14	.73
Robust Data Governance Strategy	4.05	.71
Change Management	3.89	.74
Training and Education	3.88	.77
Leadership and Management Commitment	4.33	.60
Communication and Collaboration	4.07	.71
Stakeholder Engagement and Support	3.90	.78
Skills, knowledge, and expertise	4.02	.75
Use of data governance tools	3.85	.81
Measurements to track progress	3.78	.83
Governance Organizational Structure	4.09	.70

The means and associated standard deviations for each baseline critical success factor of data governance implementation are presented in Table 5. The highest mean identified is Leadership and Management Alignment (LMA)(=4.20) referencing the probability of the critical success factors occurrence within respondents, while Measurements to Track Progress (MTP)(=3.14) was rated among the lowest factors, indicating only slight above average probability of the critical success factors occurrence in data governance implementation within respondents organizations.

Table 6: Probability of Critical Success Factor

Critical Success Factor	Mean	SD	Critical Success Factor	Mean	SD
Leadership and Management Alignment	4.20	.89	Communication and Collaboration	3.66	1.10
Executive Sponsorship	3.67	.99	Stakeholder Engagement and Support	3.55	1.03
Robust Data Governance Strategy	3.36	1.07	Skills, knowledge, and expertise	3.83	1.01
Change Management	3.65	1.06	Use of data governance tools	3.32	1.09
Training and Education	3.39	1.13	Measurements to track progress	3.14	1.19
Leadership and Management Commitment	3.37	1.14	Governance Organizational Structure	3.71	1.18

Data Analysis

The researcher used SPSS™ version 28 to conduct an exploratory factor analysis (EFA) of the collected data. EFA is used to determine the underlying constructs for a specified set of measured variables and identify inappropriate items that should be removed (Netemeyer et al., 2003). EFA is routinely performed either the revision of a current instrument or the development of a new instrument (Wetzel, 2011). This analysis was undertaken to validate, within the higher education sector, the 12 factors comprised on 47 items previously identified by Mahanti (2018). Analysis norms suggest that no single criteria should be utilized to govern factor extraction (Osborne & Costello, 2005; Williams et al., 2010). The EFA includes a number sub-procedures/tests that include the 1) Kaiser-Meyer-Olkin measure of sampling adequacy and Bartlett's test of sphericity, 2) Eigenvalues (Kaiser Criterion) test, 3) test of variance explained, and 4) the Scree plot test, before concluding with a principal component analysis to address the research questions (Mertler et al., 2021; Thompson, 2004). The index for Kaiser-Meyer-Olkin measure of sampling adequacy qualified results above .60 as acceptable for factor analysis and above .80 as very well suited (Hair et al., 2006; Kaiser, 1974). Bartlett's test of sphericity is used to determine if correlations between items are sufficiently large for EFA, the resulting p value should be less than .05. Eigenvalue analysis uses the Kaiser Criterion to retain factors when the is greater than 1 (Kaiser, 1960). While the Kaiser criterion is based on a sample size assumption of 150, current rules of thumb regarding sampling size for EFA have disappeared as long as the data is strong enough to support the analysis (MacCallum et al., 1999; Osborne & Costello, 2005; Preacher & MacCallum, 2002)

While there is not fixed threshold for cumulative variance explained, certain percentages are suggested for various disciplines (Williams et al., 2010). We will utilize a threshold of 70% of the total variability for all factors. The screen test popularized by Cattell (1966), is considered among the best tools available in instrumentation analysis as it plots the eigenvalues against factors to detect the bend or break point where the curve flattens out (Cattell, 1966; Netemeyer et al., 2003; Osborne & Costello, 2005). Mertler and colleagues (2021) suggests that screen plots are reliable when sample size is less than 250, and communalities for each item are greater than .30. Following satisfactory results for the sub-procedures/tests, principal components analysis (PCA) with varimax rotation is conducted to answer the principal research question. PCA with varimax rotation is intended to maximize the variance shared among the items retained (Dilbeck, 2017).The Cronbach's alpha reliability test will be utilized to appraise internal consistency among the factors/items retained in the instrument. A coefficient greater than .70 or higher is acceptable to establish reliability (Blunch, 2008; Mertler et al., 2021).

Results

An initial exploratory factor analysis was conducted to identify the baseline factors in the dataset, with a minimum factor loading set at .50 (Osborne & Costello, 2005; (Hair et al., 2006). The communality of the scale, which indicates the amount of variance in each dimension was also assessed to ensure acceptable levels of explanation. The results show that all communalities were over .50 (ranging from .6 to .846).

Table 7: Item Communalities

Item	Initial	Extraction	Item	Initial	Extraction
LMC1_1	1.000	0.795	*GOS7_1*	1.000	0.739
LMC1_2	1.000	0.738	*GOS7_2*	1.000	0.671
LMC1_3	1.000	0.600	*GOS7_3*	1.000	0.690
LMA2_1	1.000	0.753	*GOS7_4*	1.000	0.705
LMA2_2	1.000	0.661	*GOS7_5*	1.000	0.626
ES3_1	1.000	0.735	*GOS7_6*	1.000	0.635
ES3_2	1.000	0.817	*CC8_1*	1.000	0.799
ES3_3	1.000	0.766	*CC8_2*	1.000	0.793
ES3_4	1.000	0.684	*CC8_3*	1.000	0.685
ES3_5	1.000	0.729	*SES9_1*	1.000	0.760
RBD4_1	1.000	0.769	*SES9_2*	1.000	0.782
RBD4_2	1.000	0.645	*SES9_3*	1.000	0.846
RBD4_3	1.000	0.637	*SES9_4*	1.000	0.808
RBD4_4	1.000	0.742	*SKE10_1*	1.000	0.674
CM5_1	1.000	0.753	*SKE10_2*	1.000	0.714
CM5_2	1.000	0.710	*SKE10_3*	1.000	0.755

Item	Initial	Extraction	Item	Initial	Extraction
CM5_3	1.000	0.694	*UDGT11_1*	1.000	0.760
CM5_4	1.000	0.665	*UDGT11_2*	1.000	0.808
TE6_1	1.000	0.799	*UDGT11_3*	1.000	0.757
TE6_2	1.000	0.828	*MPT12_1*	1.000	0.685
TE6_3	1.000	0.764	*MPT 12_2*	1.000	0.745
TE6_4	1.000	0.822	*MPT 12_3*	1.000	0.751
TE6_5	1.000	0.846	*MPT 12_4*	1.000	0.801
TE6_6	1.000	0.736			

The resulting Kaiser-Meyer-Olkin Measure, KMO = .906, verified the sampling adequacy for the exploratory factor analysis, as the value was greater than .60 and within the marvelous range defined by Kaiser (1974). The weighing of the overall significance of the correlation matrix was undertaken through the Bartlett's Test of Sphericity, which provides a measure of the statistical probability that a correlation matrix has significance correlation among some of its components. The test (Table 8) indicates significance with a p-value at the .000 level (x^2 (n=121) = 5201.82, df =1081 (p<.000)) suggesting the collected data is suitable for factor analysis.

Table 8: KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure		.906
Bartlett's Test of Sphericity	**Approximate Chi-Square**	5201.82
	df	1081
	Sig.	.000

The initial factor solution derived from this analysis yielded nine factors across the 47 items for the scale, fewer than the 12 posited by Mahanti (2021). Table 9 shows that each factor, having an Eigenvalue greater than 1, accounted for 73.776% of the variation in the data.

Table 9: Eigenvalues Test and Variance Explained

	Initial Eigenvalues		
Component/Factor	Total	% of Variance	Cumulative %
1	23.212	49.386	49.386
2	2.209	4.700	54.086
3	1.847	3.929	58.015
4	1.623	3.453	61.468
5	1.501	3.194	64.662
6	1.166	2.480	67.143
7	1.088	2.315	69.457
8	1.025	2.180	71.637
9	1.005	2.139	73.776
	Rotation Sums of Squares		
Component/Factor	Total	% of Variance	Cumulative %
1	5.749	12.232	12.232
2	5.592	11.897	24.129
3	5.229	11.126	35.256
4	4.122	8.77	44.026
5	3.722	7.919	51.945
6	3.551	7.555	59.500
7	2.971	6.321	65.821
8	2.111	4.491	70.312
9	1.628	3.464	73.776
Extraction Method: Principal Component Analysis			

Principle Components Analysis and Final Six Factor Solution

Based on the outcomes of the initial exploratory factor analysis, where 10 items either didn't adequately load onto a factor, loaded onto a conflicting factor, or cross-loaded onto a factor, therefore additional EFA and PCA with varimax rotations were conducted. The final six factor solution (Table 10) produced a Kaiser-Meyer-Olkin Measure, KMO = .905, verifying the sampling adequacy for the exploratory factor analysis. The Bartlett's Test of Sphericity was significant with a p-value at the .000 level (x^2 (n=121) = 3963.14, df = 666) affirming the collected data is suitable for factor analysis. The six factors were defined as Leadership Investment (1), = Data Governance Strategy and Organizational Structure (2) Change Management and Planning (3), Communication and Stakeholder Engagement (4) Workforce Competency and Use (5) and Measurements to Track Progress (6). The extraction method was Principal Component Analysis. Rotation Method: Varimax with Kaiser Normalization. The simpler and final 6 factor solution, with eigenvalues ranging from 1.085 to 18.771, would be comprised of 37 items representing the following factor constructs.

Factor 1 (Leadership Investment) manifested as a convergence of 2 previously identified success factor constructs (Leadership and Management Alignment; Executive Sponsorship) the new factor retained several items (LMA2_1, LMA2_2, ES3_1, ES3_2, ES3_3, ES3_4, and ES3_5) of the original ten. All three items, from the Leadership Management Commitment factor identified by Mahanti failed to find an assignment. LMC1_3 "Understanding the importance of data governance" failed to load on any factor and we deleted. Subsequently, LMC1_1 "Approval by top management to implement formal data governance" failed to load and was also deleted. The last item deleted, LMC1_2, "Top management involvement of data governance" similarly loaded independently (.806) as a single item on a single factor and was therefore deleted.

Factor 2 (Change Management and Planning) expresses as the union of 2 previously identified success factor constructs (Change Management; Training and Education). Eight Items of the original ten were retained (CM5_2, CM5_3, CM5_4, TE6_1, TE6_2, TE6_4, TE6_5, TE6_6). CM5_1 "Stakeholder analysis to identify different user groups" was removed as it cross loaded (.517 and .551) onto 2 factors. TE6_3 "Training for policies, processes, roles, and responsibilities" was also removed as it failed to load onto any item. Factor 3 (Data Governance Strategy and Organizational Structure) appears as a convergence of 2 previously identified success factor constructs (Robust Data Governance Strategy; Governance Organizational Structure). Seven items were retained (RBD4_1, RBD4_2, RBD4_3, RBD4_4, GOS7_1, GOS7_2, GOS7_5) GOS7_6 "Dedicated data governance office/staff" failed to load an any factor and was summarily deleted. GOS7_3 "Establishing cross-functional data governance bodies" (.523) and GOS7_4 "Establishing critical data ownership" (.536), loaded on conflicting factors and was deleted.

Factor 4 (Communication and Stakeholder Engagement) emerges as a combination of 2 previously identified success factor constructs (Communication and Collaboration; Stakeholder Engagement and Support). Six items were retained (CC8_1, CC8_2, SES9_1, SES9_2, SES9_3, SES9_4. Item CC8_3 "Clear processes for resolving data governance disputes" failed to load on the relevant factor or any factor and was deleted. Factor 5 (Competencies and Use) appears as a grouping of 2 previously identified success factor constructs (Skills, knowledge, and expertise; Use of data governance tools) and would be comprised of five items (SKE10_1, SKE10_2, UDGT11_1, UDGT11_2, UDGT11_3). SKE10_3 "Soft skills (communication, writing, interpersonal skills)" uncharacteristically loaded (.533) on a factor outside the construct and was therefore deleted.

Factor 6 (Measurements to Track Progress) appears to be the only factor that retained all original items mirroring a singular success factor construct (Measurements to Track Progress).

Table 10: Final Six Factor Solution

			Factor					
Factor	**Sub-Group**	**Item**	**1**	**2**	**3**	**4**	**5**	**6**
1	Leadership Management Alignment	LMA2_1	**0.589**					
	Leadership Management Alignment	LMA2_2	**0.568**					
	Executive Sponsorship	ES3_1	**0.592**					
	Executive Sponsorship	ES3_2	**0.782**					
	Executive Sponsorship	ES3_3	**0.780**					
	Executive Sponsorship	ES3_4	**0.727**					
	Executive Sponsorship	ES3_5	**0.677**					
2	Robust Data Governance Strategy	RBD4_1			**0.669**			
	Robust Data Governance Strategy	RBD4_2			**0.577**			
	Robust Data Governance Strategy	RBD4_3			**0.558**			
	Robust Data Governance Strategy	RBD4_4			**0.617**			
	Governance Organizational Structure	GOS7_1			**0.620**			
	Governance Organizational Structure	GOS7_2			**0.625**			
	Governance Organizational Structure	GOS7_5			**0.538**			
3	Change Management	CM5_2		**0.601**				
	Change Management	CM5_3		**0.685**				
	Change Management	CM5_4		**0.581**				
	Training and Education	TE6_1		**0.587**				
	Training and Education	TE6_2		**0.536**				
	Training and Education	TE6_4		**0.678**				
	Training and Education	TE6_5		**0.729**				
	Training and Education	TE6_6		**0.645**				
4	Communication and Collaboration	CC8_1				**0.710**		
	Communication and Collaboration	CC8_2				**0.751**		
	Stakeholder Engagement and Support	SES9_1				**0.662**		
	Stakeholder Engagement and Support	SES9_2				**0.660**		
	Stakeholder Engagement and Support	SES9_3				**0.528**		
	Stakeholder Engagement and Support	SES9_4				**0.568**		
5	Skills, knowledge, and expertise	SKE10_1					**0.522**	
	Skills, knowledge, and expertise	SKE10_2					**0.607**	
	Use of data governance tools	UDGT11_1					**0.729**	
	Use of data governance tools	UDGT11_2					**0.798**	
	Use of data governance tools	UDGT11_3					**0.661**	
6	Measurements to track progress	MPT12_1						**0.661**
	Measurements to track progress	MPT 12_2						**0.554**
	Measurements to track progress	MPT 12_3						**0.746**
	Measurements to track progress	MPT 12_4						**0.696**

Ultimately, the resulting 37 items were found to explain 70.466% of the variance in the pattern of relationships among the items. The relative percentages explained by each factor were 50.72% (Leadership Investment), 5.09% (Change Management and Planning), 4.427% (Data Governance Strategy and Organizational Structure), 3.996% (Communication and Stakeholder Engagement), 3.285% (Workforce Competency and Use), and 2.934% (Measurements to Track Progress) respectively. An item analysis was conducted to test the reliability of each factor identified. Cronbach's Alpha higher than .70 are traditionally considered acceptable (Taber, 2018). The Cronbach's Alpha for the 6 factors ranged from .874-.933 as noted in Table 11.

Table 11: Cronbach's Alpha for Factors

Factor	Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	Number of items
Leadership Investment	.915	.915	7
Data Governance Strategy and Organizational Structure	.896	.989	7
Change Management and Planning	.933	.933	8
Communication and Stakeholder Engagement	.915	.915	6
Workforce Competency and Use	.874	.874	5
Measurements to Track Progress	.885	.888	4

Discussion of Findings

The principle purpose of this study was to validate the identification and classification of 12 critical success factors (CSF) of data governance proposed by Mahanti (2018) within the sector of higher education. The 12 instrument constructs were evaluated across 47 items from data collected from 121 respondents employed by institutions of higher education in a southeastern United States university system. The discussion of findings follows:

Factor 1 (Leadership Investment) manifested as a convergence of two previously identified success factor constructs (Leadership and Management Alignment; Executive Sponsorship) the new factor retained seven items (LMA2_1, LMA2_2, ES3_1, ES3_2, ES3_3, ES3_4, and ES3_5) referencing 1) Agreement on and unified support for the need for a formal data governance program, 2) Agreement about what defines success in a data governance implementation, 3) Ability to communicate the value proposition of data governance at different organizational levels, 4) Budget and resources allocated for training, 5) Budget and resources allocated for data governance, 6) Sustained data governance sponsorship, 7) Setting expectations for support and commitment from key stakeholders and senior management. These items find relevancy in higher education, where Hubbard et al., (2020) would that "an effective DG program is top-down driven and bottom-up executed. Senior leadership at the institution must be steadfast and visible in their commitment to the program by endorsing the activities and, where appropriate, actively participating" (p. 54). Furthermore, Elouazizi (2014) would emphasize that data governance in higher education requires "continuous alignment with the strategic, business, and educational goals of the institution" (p.220). Smith (2009, 2021) declares that "the key to [DG] success is the sustainment of the sponsorship, which gives the organization a chance to recognize the permanent nature of a program" (p.1).

Factor 2 (Change Management and Planning) was expressed as the combination of two previously identified success factor constructs (Change Management; Training and Education). Eight Items of the original ten were retained (CM5_2, CM5_3, CM5_4, TE6_1, TE6_2, TE6_4, TE6_5, TE6_6). Those items addressed 1) Demonstrating the benefits of data governance to user groups, 2) Tailoring communication and training plan and strategy in line with anticipated reaction of different user groups, 3) Broadcast/communicated successes throughout the process, 4) To identify the key role training for employees, 5) Training in the appropriate tools and technologies, 6) Frequency of training sessions organized, 7) Extent of training sessions organized, and 8) Implications of other methods and ideas that complement data governance. Researchers have noted that change management is not only an integral part of an organization thriving in digital-driven era, but that data governance is key to carrying out that transformation to capitalize on data as an asset (Krishnan et al., 2022; Zorrilla & Yebenes, 2022). Institutions of Higher Education, with their vast stakeholder groups, must be especially attentive to change management. As noted by Brown (2014), it's the "cultural change that underpins effective innovation" and warning that "cultural change is harder than technical innovation" (p.1).

Factor 3 (Data Governance Strategy and Organizational Structure) appears as a convergence of 2 previously identified success factor constructs (Robust Data Governance Strategy; Governance Organizational Structure). Seven items were retained (RBD4_1, RBD4_2, RBD4_3, RBD4_4, GOS7_1, GOS7_2, GOS7_5). Those items reflect the following elements: 1) Data governance mission and vision statement, 2) Alignment of data governance strategy and business level strategy, 3) Alignment of data governance strategy and other data initiatives, 4) Strategic roadmap for data governance, 5) Defining the data governance organizational structures, roles and associated responsibilities, authorities, fit for the organization, 6) Clear definitions of roles, responsibilities, and decision rights, and 7) Appropriate segregation of duties. As previously discussed, the need for both analytics and data-driven decision making has compelled colleges and universities to rapidly evaluate and respond to the intersection of IT and business strategy (Hosch, 2019). To effectively use big data in higher education, many IHEs have institutionalized formal DG committees, hired data architects and chief data officers, expanded or integrated institutional research and information technology operations, and redrafted policies and procedures to better support functional and technical oversight (Borgman & Bourne, 2022; Jim & Chang, 2018; Plaid Consulting, 2021).

Factor 4 (Communication and Stakeholder Engagement) materializes as a combination of 2 previously identified success factor constructs (Communication and Collaboration; Stakeholder Engagement and Support). Six items were retained (CC8_1, CC8_2, SES9_1, SES9_2, SES9_3, SES9_4). The items referenced include: 1) Core business and IT partnership and involvement, 2) Continual interaction among core business area and IT teams, 3) Appropriate stakeholder coverage, 4) Building stakeholder relationships, 5) Defining stakeholders' expectations, 6) Empowering key stakeholders. In higher education, units like institutional research, critical to the assurance of data quality and availability must routinely collaborate with members of the information technology unit, whose practical skills in cyber security, data storage, and enterprise management jointly inform data governance structure, process, and outcomes. Webber and Zheng *(*2020*)* note that adaptable data governance emphasizes frequent communication and collaboration among a breadth of stakeholders, critical to ensuring "good decision making" (p. 4). In higher education, these decisions can range from training expectations and operational definitions to permissioning and auditing timelines, all of which require engagement with and representation from stakeholders like legal affairs, fiscal affairs, enrollment management, and academic affairs. Using every communication avenue available from the invasive to non-invasive is critical in higher education to achieve not only compliance but DG buy-in (Seiner, 2014; Young & McConkey, 2012).

Factor 5 (Competencies and Use) emerges as a set of 2 previously identified success factor constructs (Skills, knowledge, and expertise; Use of data governance tools) and would be comprised of five items (SKE10_1, SKE10_2, UDGT11_1, UDGT11_2, UDGT11_3). These items cover the following elements: 1) Business understanding of the data, 2) Understanding of technologies relating to the data domain, 3) Extent of familiarity with data governance tools, 4) Ease of use of data governance tools, 5) Selection of data governance tool by mapping its capability to business requirements. Gagliardi (2022) notes that in today's data rich higher education environment - data literacy is a now a critical competency or essential skill. Concurring, Wang & Jiang (2022), proclaim that the investment in and enhancement of informatization personnel is imperative for the successful implementation of DG in higher education, as management reinforce the capacity of existing human resources, attach importance to training, and encourage collaboration.

Factor 6 (Measurements to Track Progress) is the only factor that retained all original items mirroring a singular success factor construct (Measurements to Track Progress). These items include 1) Measure impact to revenue and cost, 2) Measure use of data and data standards, 3) Dashboards to showcase progress, 4) Ability to track progress changes. Each of these elements are instrumental to promote implementation and sustained adoption. As suggested Dyche and Nevela (2017) "to be valuable…and propel the business forward" data governance "must be practiced… measured…demonstrate positive outcomes and hard payback" (p.14). Webber & Zheng, (2020) would suggest that "quick wins can provide not just their own accomplishments, but also provide evidence of how effective DG can be" (p. 109).

The results of this research have several implications. First it extends the field of data governance research, noted as an emerging and under researched area and contributes to an expanding knowledge base (Abraham et al., 2019). Second, it tests the sector agnostic critical success factors identified by Mahanti (2018) in higher education, broadening the relevance of the CSFs and instrument. Third it positions the launch of a research stream to provide insight into existing implementation and has the potential to generate recommendations for higher education administrators beginning or struggling with implementation efforts.

Conclusion

Higher education finds itself at the intersection of an accountability, analytics, and technical revolution – where institutions are leveraging data for a range of purposes for an array of stakeholders and data governance is at the center of institutional response. Data governance has slowly gained legitimacy and attention in higher education, where it's now considered a best practice among IHEs seeking to enhance the use of business intelligence in their operations (Perkins & Ariyachandra, 2021). SAS (2022) affirms that within higher education "a sound data governance strategy is the foundation that allows access to the data needed to make timely organizational decisions" (p. 1).

Gagliardi (2018) suggest that "absence of a strong and flexible data governance plan can stall the maturation of campus-wide analytics functions" (p. 192). Chester (2018) warns that "good data governance is not a one-off project, but a series of collaborations that recur over time" (p.63) – noting that "good data governance is difficult—it takes time and commitment, and it requires constant vigilance and collaboration" (p. 61). Ultimately, the implementation of data governance is exactly as Wang and Jiang (2022) characterize it, "complex, iterative and spiraling" (p. 239).

Findings from this initial analysis among institutions of higher education suggest that managers and stakeholders tasked with executing data governance plan must 1) secure leadership investment, 2) craft an appropriate data governance strategy and organizational structure, 3) exercise change management and plan to train and educate, 4) foster stakeholder engagement and communication, 5) develop workforce competency and usage practices, and 6) institute measurements to track progress to improve their chances of a successful implementation.

|This research aimed to provide insight into existing implementation efforts and the relevancy of data governance critical success factors to the sector of higher education. This research is the initial effort to empirically validate the identification and prevalence of critical success in the sector with the intention to generate future recommendations for higher education administrators beginning or struggling with implementation. The instrument tested, comprised of forty-seven items, was found to be reliable to measure critical success factors of data governance consistent to those found in the literature and eleven of the twelve identified by Mahanti (2018).

Limitations and Future Research

This study has recognizable limitations that should be taken into consideration when interpreting the results and their implications. First, the study was limited to institutions of public higher education in the southeastern United States, its generalizability to private sector IHEs and public or private institutions outside of the US are limited. Second, the study restricted respondents to employees of the individual institutions within the university system sampling frame, and excluded perceptions of system leadership and staff, whose inclusion may have yielded different outcomes with assumptions of criticality, compliance, and resource dependency. Third, data collection method, while appropriate, was dependent on both self-selection and penetration into a broad stakeholder group ranging from executives to front line faculty and staff. Fourth, the temporality of the system mandated data governance initiative may have influenced perception outcomes in respondents.

While the results of this study suggest that the twelve critical success factors of data governance resonate in higher education, the instrument should undergo additional testing and item analysis. New items should be examined to improve construct representation and further refinement might generate a shorter and manageable question set. As this research was limited to institutions of public higher education in the southeastern United States, future research should extend the investigation of critical success factors to a larger sampling frame, this would allow for the analysis by institution type (public and private) and respondent role or institutional position.

Future research might explore the nuances of leadership investment in data governance implementation to explore the falling out of the leadership and management commitment factor displayed in this research study. Forthcoming research will explore, differences in critical success factor perceptions by maturity level – exploring the staging of CSF during the implementation timeline. Last, confirmatory factor analysis might be considered to further test the theoretical foundations of the success factors critical to the implementation of data governance in higher education.

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