IMPACT OF DATA CULTURAL ASPECT TO DATA GOVERNANCE PROGRAM IN HIGHER EDUCATION

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Abstract

Higher education is currently facing a data revolution. Universities are flooded with ever-increasing data, but the information tends to be poor. Some universities implement data governance programs (DGPs) by first assessing the level of data governance maturity. From these results, it was concluded that the gap was a problem. The gaps that occur in several frameworks are related to processes, technology, and people. In principle, when improving data governance, the process and technology parts can be improved relatively easily because there are clear indicators that need attention. The problem that still occurs is related to the involvement of users or people or actors in the data governance process. The university also needs a mechanism that can resolve problems in implementing data governance. The reason is the concept of data culture. This paper proposes a measurement mechanism to determine which aspects of data culture will influence the implementation of data governance. The research was conducted using the multiple linear regression (MLR) method to look at the domain of data culture aspects that influence the implementation of the DGP. The research results show that of the three research variables, namely domain importance, planning and context (*IPC*), domain perception, usability and communication (*PUC*), and domain people, leadership, and relationship (*PLR*), the *PLR* variable is the variable that has the greatest influence on DGP compared to the other two variables. Further research opportunities to assess the maturity of data culture program implementation in universities and other organizations can be made possible by this study.

Keywords: Data Cultural, Data Governance Program, Higher Education, Multiple Linear Regression, DAMA International, Recommendation

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1. INTRODUCTION

Currently, transactions that use information technology (IT) cause data volumes to continue to grow. The need for knowledge that organizations derive from data continues to grow. Even from the data, entire business processes are being improved, and organizations around the world are facing similar challenges in an ever-changing competitive landscape. However, surprisingly, some research results show that few companies have matured in data management or, for that matter, made the transition to a level where data analysis is a very potential tool (Sivarajah et al., 2017). This includes higher education institutions.

Universities are increasingly competing for students, academic staff, and research funds from both the private and international sectors. In conditions of rapid change like this, universities are required to have responsive management. Responsive management can, of course, consider several aspects of running higher education (Erickson et al., 2021), such as universities having freedom to run business, the extent to which universities depend on government funding or can utilize other sources, and so on. The explanation above concludes that these various factors have a tremendous impact on higher education. Problems between one university and another are certainly different, including data and information management issues. Until now, there are still many universities that do not realize that the data produced during their processes and activities is an extraordinary data asset because it is considered an intangible asset, namely an identifiable non-monetary asset without physical form. As a result, solving various problems in terms of data management is partial. Apart from that, in terms of organizational development, universities should be supported by optimal performance. Optimal performance will be realized if supported by valid data and information (Xu & Al-Hakim, 2005). It can be interpreted that higher education institutions currently have very large data growth but are poor in information, they are flooded with data but do not yet have a process to convert this data into actionable knowledge (Prasetyo & Surendro, 2015). This causes decision-makers in higher education, who do not have time to uncover data networks, to make choices based on data sets drawn from existing data. In short, institutions without a data culture make decisions without knowing the reality (Powers & Henderson, 2018). Decisions like this have the potential to have a big impact on students, lecturers, staff, alumni, and prospective students.

Several universities have conducted assessments related to the maturity level of data management in universities. Research that has been done shows that data management in universities is still far from the expected minimum standard (Davenport & Bean, 2018). Many factors cause this gap to occur. In principle, processes and technology can be built, but what about the people involved? How ready are they to face a data culture? When a university wants to build a data management program, are people ready to undergo the program? Of course, universities have an interest in aspects of data culture that are understood by organizations in general (Vicente, 2020). Which aspects of culture must be known by higher education organizations?

Based on the explanation above, the research carried out aims to find out which aspects of data culture have the most influence in implementing data governance in higher education. The research method used in this research is multiple linear regression (MLR). The research locations are five universities that have measured the maturity level of data governance and are preparing a data governance program (DGP). The research results show that the data culture domains that influence the implementation of data governance in higher education are the people, leadership, and relationship (PLR) domains. The results obtained from this research can be a recommendation for universities to respond to a data culture that is capable of binding DGPs in higher education.

The next sections of this paper are arranged in sequence: Section 2 analyses relevant literature. The literature review contains related previous research as well as the position of the research being carried out. Section 3 describes the materials and methods used. This section explains the material and points related to research and the research methods used in this research. Section 4 outlines the results. This section presents the calculation results obtained from the method used. Section 5 discusses the results, and provides recommendations for research results. Section 6 contains conclusions and future research opportunities.

2. LITERATURE REVIEW

There have been several studies that have tried to link data culture and data governance in the last five years. Research related to data culture partially only focuses on aspects of data culture at the school level, as carried out by Lasater et al. (2020). Apart from that, there is research related to data culture in dealing with big data, such as that carried out by Nguyen (2019). There is also other research conducted by Onwujekwe et al. (2019) which highlights the importance of data security culture in data governance. Then, in the aspect of data governance, research that reviews culture is still small and not specific, such as research conducted by Duvier et al. (2018), Jim and Chang (2018), Paskaleva et al. (2017), and Janssen et al. (2020) where the fourth study only states that culture is an important aspect of data governance. Research that tries to link data governance and culture has been carried out by previous studies, such as previous research conducted by Gupta and Cannon (2020) which repeated similar research conducted by Prasetyo (2013). Both studies tested organizational culture and governance data using the organizational culture assessment instrument (OCAI). The research was carried out to identify organizational forms that are ready to implement data governance.

Other research conducted by Delaney and Kitchin (2023) revealed how embedded institutional culture, structures, and work practices, which are relatively resistant to change, have thwarted data sharing, data-based analysis and decision-making within the scope of data governance. Another, almost the same research was conducted by Koltay (2020). The research conducted was to examine companies' interest in data quality and this is clearly visible in several thoughts and issues reported in business-related publications, although there are real differences between values and approaches to data quality data in corporate and academic (research) culture. Meanwhile, research by Liakh (2021) places culture as an important part of data governance in evaluating how to further increase corporate accountability (at strategic and operational levels) by taking advantage of the digitalization changes that companies are forced to experience and applying them to the sustainability evaluation process, including reporting as the foundation. At the same time, Nisar et al. (2021) conducted related research and found that data governance challenges (leadership focus, talent management, technology, and organizational culture for big data) are a significant precursor to big data decision-making capabilities in government and private hospitals. Lis et al. (2022) conducted research by proposing new approaches that develop from inter-organizational cultural dynamics such as data collaboration in each ecosystem. Based on this, there has been no research that has looked at the extent to which aspects of data culture influence DGPs. Thus, there is an opportunity to conduct research that links the influence of data culture on the implementation of DGPs, as has also been stated in the literature review by (Abraham et al., 2019).

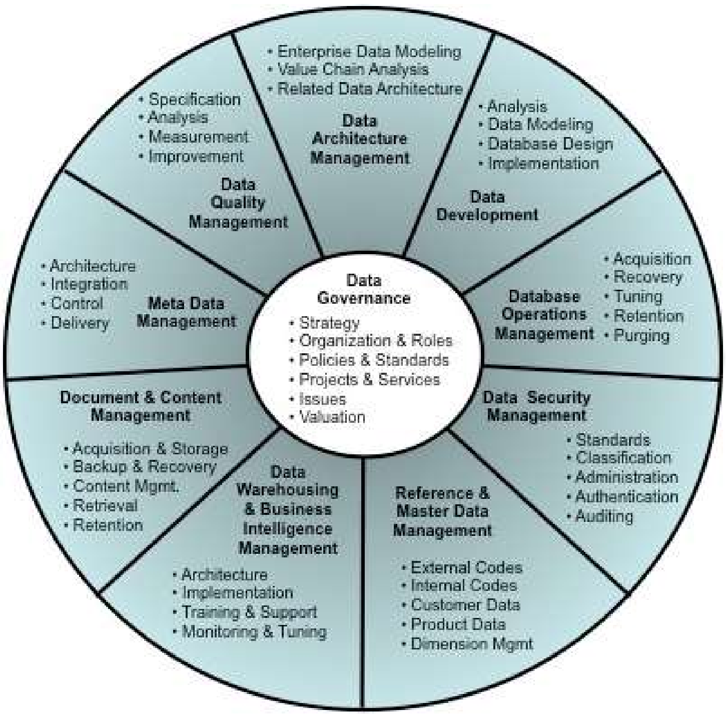
3. MATERIAL AND METHOD

3.1. Data governance framework

Departing from the basic concepts and problems of information management, there is an awareness of the importance of order and compliance in managing information resources. IT, as it is known today, is one of the fundamental factors in enterprise management, so the concept of IT governance emerged, which has now shifted to enterprise governance (de Haes & van Grembergen, 2004). This transition is an awareness that the management of business and IT is in the interests of the organization. However, awareness of the importance of managing an organization that is carried out properly and correctly both in terms of business and IT is felt to be insufficient because it does not really "touch" aspects of data and information as a whole. So, in early 2006, the concepts of data management and data strategy emerged. The need for data governance is felt to be very important, considering that business processes in large organizations ultimately produce big data (Morabito, 2015).

It can be seen how an organization must protect vulnerable customer information, such as credit card number facilities and personal data, as well as intellectual property, such as customer data to product design data, from both internal and external threats. So, in the end, organizations need to optimize related to the management of their data, initiatives such as controlling risk management properly. In this context, data may be the biggest source of an organization, and of course, it has a big risk. Insufficient data management often results in poor business decisions, large breaches of compliance, and data theft (Davenport et al., 2010). The balance between limited access and inappropriate use of data should be regulated by a data management program that contains regulations and policies so that organizations are able to make good use of reliable and quality data and information that can help organizations provide better services, be able to control customer loyalty, conduct reporting, improve innovation, and so on. In this study, the data governance framework used is the international data management (DAMA) approach. DAMA has ten main functions, as shown in Figure 1.

Figure 1. DAMA international framework



Source: Mosley (2010).

In Figure 1, the international DAMA framework shows that the data governance function is core. The data governance function interacts with and influences other functions that surround it. The ten data governance functions in DAMA International are as follows (Mosley, 2010):

1. Data governance, which includes planning, monitoring and controlling the management and use of data.

2. Data architecture management is an integrated part of enterprise architecture. In this case, what is done is to review, validate, approve, and re-filter

the data architecture. Defines the data specification requirements that the data architect organizes into the enterprise architecture. The process of integrating these specifications includes resolving differences in names and meanings.

3. Data development includes analysis, design, development and testing, distribution and maintenance. In this case, defining data requirements and specifications are organized by analysts and data architects into a logical data model. It also validates the physical data model and database design, participates in database testing and conversion, and ensures consistent use of terms in documentation and training.

4. Database operational management supports the physical structure of data assets, defines requirements for data recovery and performance, and helps level services in this area. This function also includes identifying, obtaining, and monitoring external data sources.

5. Data security management guarantees privacy, trust, and access rights. This provides security, trust and privacy needs, identifies data security issues, assists in data security audits, and classifies confidentiality in documents and other information products.

6. Reference and master data management. Manage master and replica versions of data, oversee the creation, modification, and deletion of code and other reference data, define master data management needs, and identify master data management issues.

7. Data warehouse and business intelligence (BI) management open access to provide data that supports decisions in terms of reporting and analysis. Provides BI requirements and management metrics, and identifies BI issues.

8. Document and content management, which includes storage, protection, indexing and access rights to discover unstructured data, create and manage business meta-data (names, meanings, and business rules), define meta-data access and integration needs, and use meta-data to make effective data stewardship and governance decisions. Defining and managing business meta-data is at the heart of data stewardship.

9. Meta-data management integrates, controls, and distributes meta-data.

10. Data quality management defines, monitors, and improvises data quality. Define data quality requirements and business rules, edit and validate test applications, assist with analysis, certification, and data quality audits, lead data cleansing efforts, identify proactive ways to resolve root causes of low data quality, promote awareness about data quality, and ensure data quality requirements are found. Effectively display and analyze data quality in conjunction with data professionals.

3.2. Data governance in higher education

Data governance in higher education includes policies, procedures, and practices designed to manage data effectively and securely. Universities have many types of data, including student data, staff data, research data, and others. The following are several general principles of data governance in higher education, such as privacy policy and data security, student and staff data management, authentication and authorization processes, research data management, regulatory compliance, training and awareness, risk management and commitment to higher education leaders. By implementing good data governance, universities can ensure that their data is managed effectively, and safely, and this is in accordance with Omar and Almaghthawi (2020).

The implementation of a DGP in higher education involves a series of steps that include planning, policy development, implementation of procedures, and continuous monitoring (Smallwood, 2019). Implementing an effective DGP requires collaboration between various departments in higher education and commitment from the entire academic community. In this case, data culture is important in implementing DGPs in higher education.

3.3. Data governance program

A DGP is a set of policies, procedures, practices and organizational structures designed to manage and protect a company's data assets (Plotkin, 2021). The primary goal of a DGP is to ensure the reliability, quality, security, and compliance of data within an organization (Alhassan et al., 2018). With a good DGP in place, organizations can optimize the value of using their data and reduce the risks associated with data management.

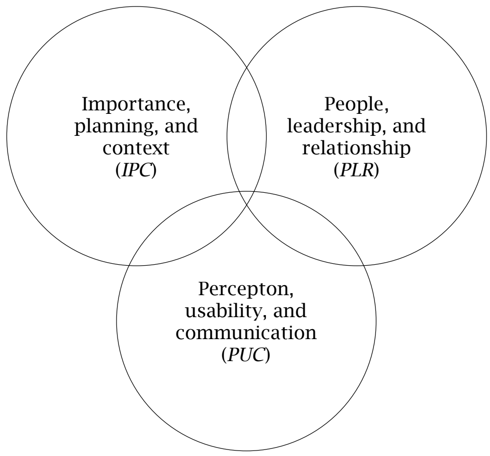
3.4. Data culture

Conceptually, data culture focuses on using information to make sound decisions that help institutions achieve a competitive advantage. In principle, it is not based on numerical data but rather on behavior that is understood by actors and process managers in responding to existing data (Simon et al., 2018). In general, the data culture used in this study is divided into three domains, namely (Powers & Henderson, 2018):

- The first domain is the *IPC* domain. The *IPC* domain is a dimension consisting of aspects of importance (I), planning (P), and context (C).
- The second domain is the *PUC* domain. The *PUC* domain is a dimension consisting of perceptions (P), usability (U), and communication (C).
- The third domain is the *PLR* domain. The *PLR* domain is a dimension consisting of people (P), leadership (L), and relationship (R).

The three domains in general can be shown in Figure 2.

Figure 2. Data culture components



Adopting analytics and creating a data culture go hand in hand, and both are often critical components of a company's digital transformation (Brunetti et al., 2020). Different organizations will define "data culture" in different ways. Organizational conventions and behavior are referred to as "data culture". This encourages a culture where data-driven decision-making is used routinely. The concept of data culture is relatively abstract. These are standards and behaviors that are acceptable, respected, and encouraged, as well as standards and behaviors that are unacceptable and rejected. In principle, workers in organizations at all levels are encouraged to generate and share actionable knowledge when there is a strong data culture. In essence, data culture status is the result of compliance (or non-compliance) with data governance rules as they are implemented (Mahanti, 2021).

3.5. Method

This study uses a quantitative approach through a survey using a Likert scale-based data collection instrument. The method used is MLR, which is used to explore the analysis carried out on the research object. MLR is used because it is suitable to see the effect of two or more independent variables that affect the dependent variable (Grégoire, 2014). The research methodology carried out is shown in Figure 3.

Figure 3. Research flow

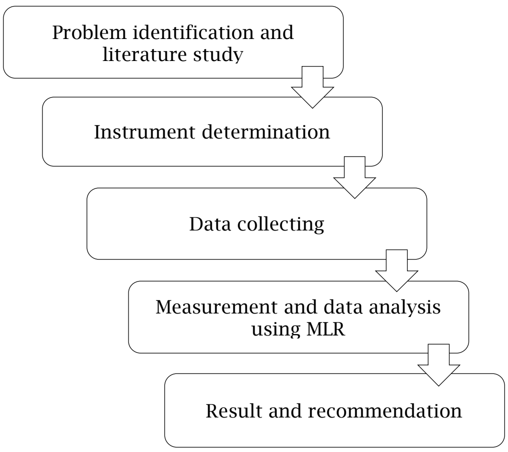


Figure 3 is a research flow with the following explanation:

1. *Problem identification and literature study.* Problem identification is defined as an attempt to explain the problem and make the explanation measurable. This identification was carried out as an initial step of research by Brown (2008). So, in summary, identification is defining the research problem. Then, to strengthen the identification process, a literature study is carried out related to studies related to the research problem.

2. *Instrument determination.* The determination of research instruments is to determine a test tool that has the characteristics of being able to measure informants through a number of research questions (Onwuegbuzie et al., 2010). The dimensions used in the instrument include three dimensions of data culture and one dimension related to DGPs.

3. *Data collecting.* Data collection is a research process in which the researcher applies scientific methods to collect data systematically for analysis.

4. *Measurement and data analysis using MLR.* At this stage, the assessment and measurement process, as well as data analysis using the MLR method, are carried out. MLR is a statistical technique that simultaneously develops a mathematical relationship between two or more independent variables and a dependent variable. The purpose of MLR analysis is to find out how much influence several independent variables have on the dependent variable and also to be able to predict the value of the dependent variable if the value of all independent variables is known (Uyanık & Güler, 2013). To carry out MLR testing, classical assumption tests are required, such as the data normality test, heteroscedasticity test, and multicollinearity test (Hanley, 2016). Other research methods, such as a qualitative approach, can also be an alternative to this research, but in this context, a quantitative approach will be more appropriate and effective.

5. *Result and recommendation.* In this section, the results of data analysis and research recommendations are obtained.

3.6. Research subject

In this study, the subjects were people who were involved in the data management process at universities, such as lecturers, education staff, and organizational officials drawn from five universities with a total of 25 respondents.

3.7. Multiple linear regression analysis

MLR discusses the relationship between several independent variables and one dependent variable using a regression equation. The multiple regression model can be shown using the following formula (Schmidheiny, 2013):

$$Y = \beta_0 + \beta_1 x_1 - \beta_2 x_2 + \beta_3 x_3 +_{\dots} + \varepsilon \qquad (1)$$

where, β_0 is an intercept, which is a constant indicating the magnitude of the value of Y when $x_i = 0$; β_1 is the slope for the independent variable x which shows the magnitude of the influence of the independent variable x on the dependent variable Y (i = 1, 2, 3, ...).

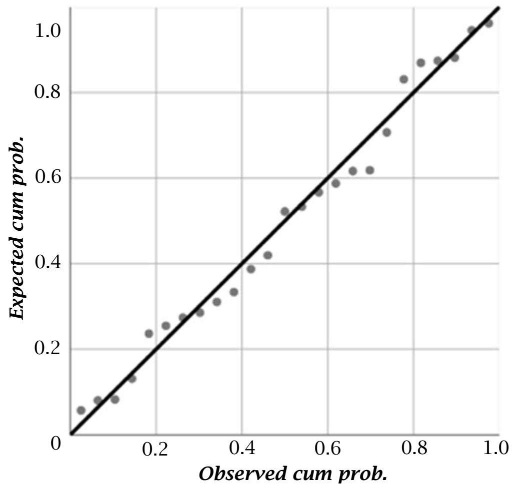
4. RESEARCH RESULTS

4.1. Normality test

The following discussion is an assumption of compliance with multiple regression analysis.

In this section, SPSS v. 23 software is used, and the output is obtained as shown in Figure 4.

Figure 4. Fulfillment of normality assumptions based on the normal P-P plot (Dependent variable — *Y*)



Based on the calculation by looking at the P-P plot normal diagram in Figure 4, it is found that the diagram shows the plots follow a straight line, so it can be said to meet the normality assumption. The assumption of data normality in this section is fulfilled.

4.2. Heteroskedasticity test

In this section, SPSS v. 23 software is used, and the output is obtained as shown in Table 1.

Table 1. Coefficient for heteroskedasticity measurement

Model		Unstandardized coefficients		Sig.	p-value
		B	Std. error		
1	Constant	2.639243	0.894935	2.949089	0.007662
	x_1	0.127759	0.187989	0.679607	0.504176
	x_2	0.117211	0.302945	0.386906	0.702719
	x_3	0.092265	0.24724	0.373179	0.712756

Based on the output from Table 1, it can be shown that the p-value or Sig. of all independent variables is > 0.05, which means that it can be said that there is no heteroscedasticity problem in the regression model, so in this section, the assumptions are fulfilled.

4.3. Multicollinearity test

In this section, SPSS v. 25 software is used, and the output is obtained as shown in Table 2.

Table 2. Compilation of variance inflation factor score

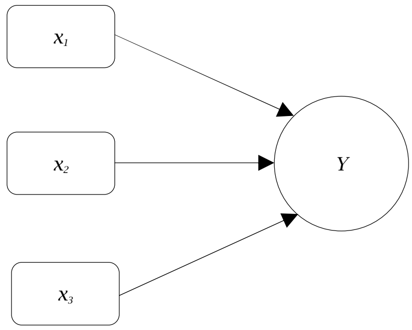
Model		Correlations part	Collinearity statistics	
			Tolerance	VIF
1	Constant			
	x_1	0.148	0.931	1.074
	x_2	0.084	0.389	2.570
	x_3	0.081	0.404	2.476

The output of SPSS v. 23 in Table 2, shows that the VIF value of all variables is < 10, which means that it can be concluded that there is no multicollinearity disorder, or in other words, that the multiple regression model tested is free from multicollinearity symptoms, so in this section the assumptions are fulfilled.

4.4. Calculation and analysis model

In this section, we see which variables in the data culture are dominant, and then MLR analysis will be used where the independent variables to be measured are three and the dependent variable is one. This is illustrated in the multiple regression model in Figure 5.

Figure 5. Multiple regression model on case study



Then, the next process is still using SPSS v. 25 software, the output of MLR is obtained in Table 3.

Table 3. Coefficients of multiple linear regression

Model		Unstandardized coefficients		Standardized coefficients
		B	Std. error	Beta
1	Constant	3.789	0.983	
	x_1	-0.014	0.126	-0.024
	x_2	-0.033	0.194	-0.037
	x_3	0.087	0.088	0.216

Based on Table 3, mathematically the model can be written as:

$$Y = 3{,}789 - 0{,}014x_1 - 0{,}033x_2 + 0{,}087x_3 + \varepsilon \quad (2)$$

where,
- β_0 = intercept;
- β_1 = coefficient of regression variable x_1 against *Y;*
- β_2 = coefficient of regression variable x_2 against *Y;*
- β_3 = coefficient of regression variable x_3 against *Y;*
- x_1 = *IPC* domain;
- x_2 = *PUC* domain;
- x_3 = *PLR* domain;
- *Y* = DGP;
- ε = term error or an error related to variables that are not researched.

The MLR model shows that there are two variables that have negative coefficients. This shows that two independent variables, namely *IPC* and *PUC*, have a negative effect on the DGP and one has an effect on the DGP, namely the *PLR* variable.

4.5. Model analysis

Based on the results of calculations using SPSS v. 23 software, the following results were obtained.

Table 4. Compilation of t-test value

Model		*Unstandardized coefficients*		*Standardized coefficients*	*t*	*Sig.*	*Correlations*	
		B	*Std. error*	*Beta*			*Zero-order*	*Partial*
1	Constant	3.789	0.983		3.855	0.001		
	x_1	-0.014	0.126	-0.024	-0.111	0.913	0.017	-0.024
	x_2	-0.033	0.194	-0.037	-0.170	0.867	-0.026	-0.037
	x_3	0.087	0.088	0.216	0.996	0.330	0.210	0.212

The three independent variables included in the model turned out to have a significant effect at $\alpha = 5\%$. This can be seen from the probability of the significance of all variables above 0.05. However, to see the order that has an effect, one can look through the t-test values. The three t-test values show that the *PLR* variable is positive, meaning that the *PLR* domain is the variable that has the most influence on variable *Y*, namely the data management program compared to the other two variables. This means that the *PLR* domain or people, leadership, and relationships should be of greater concern for universities in developing their DGPs.

5. DISCUSSION

The information age has a tremendous impact on organizations. In addition to supporting the performance of the organization, the data and information generated will be very influential on the decision-making process that occurs in various activities in organizations, particularly for higher education. However, most high-level organizations are faced with insufficient data and information, or so much data that it is often difficult to get reliable analysis results. Many organizations implement management strategies for both the management of organizations and the management of IT. However, in connection with data and information management, organizational governance and IT are perceived to be less adequate in the context of data management and information, given that the organization's governance focuses on stakeholders while IT governance is more focused on the implementation and investment of IT infrastructure. Therefore, data governance is an urgent matter for universities. The data governance model must be implemented in the form of a consistent and periodic program.

The results of this research showed that the *PLR* domain was the most influential variable in the DGP. This needs to be noted for universities. When developing the DGP, aspects of people, leadership, and relationships become important components. The things that need to be included in the program are:

1) Provide training to actors or users related to data culture that supports the DGP.

2) Provide leadership training for every user involved in the DGP.

3) Provide or make policies that regulate the relationship process in higher education organizations related to the implementation of the DGP in each enabler process. In this case, the data management framework approach is run by higher education (the use of the DAMA framework related to the determination of the international framework DAMA variable in the instrument measurements above).

The limitations of this research are the small number of respondents and the number of universities surveyed. We hope that in the future we can conduct research with a larger volume of respondents and a wider reach of universities.

6. CONCLUSION

Based on the discussion, it can be concluded that based on the analysis of the MLR model, there are three variables, namely *IPC*, *PUC*, and *PLR*, which have a positive influence on the DGP. The T-test results show that the *PLR* variable is the one that has the greatest influence on the DGP compared to the other two variables. This means that universities must pay attention to the priority scale for cultural aspects of data related to *PLR*. These results become recommendations for universities to provide strengthening in terms of data culture before and after implementing DGPs. The strengthening in question is that the data culture aspect, especially in the *PLR* aspects, is very important in implementing DGPs because it plays a key role in how data is valued, managed and used, reflects the attitudes, values and behavior of the organization related to data, in terms of awareness and understanding, trust and accountability, participation and engagement, change and innovation, data violations and ethics, collaboration and communication, and the importance of data in making decisions. The weakness of this research is the limited number of respondents used in the analysis. A better and larger number of respondents will produce more precise research in the future.

Based on the results of this research, there are great opportunities for further research related to data culture, the *IPC*, *PUC*, and *PLR* domains can be broken down into more detailed components to see the relationship between variables and their influence on the implementation of data culture DGP. Apart from that, it can also open up research opportunities to measure the level of maturity of data culture in organizations at universities and other organizations in general.

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