Driving Digital Transformation: The Dynamic Interplay Between University Governance Capability , Emerging Technologies, and the Moderating Power of Government Regulation and University Rankings

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Abstract
Research on digital transformation strategies in higher education performance, which emerged in the second decade of the 21st century, explores the competitive dynamics and complex relationships among stakeholders through the lenses of technology, organization, and social. The aim of this research is to find the moderating impact of government regulation and university ranking on university governance capability and emerging technology in the digital transformation of private higher education institutions. This study uses two independent variables, namely *university governance capability* (X1) and *emerging technology* (X2), with digital transformation (Y1) as the dependent variable. In addition, there are two moderating variables, namely *university ranking requirement* (Z1) and *GR* (Z2). The unit of analysis in this study is the leadership of private universities under LLDIKTI IV. This research uses probability sampling technique with simple random sampling method, which ensures each element is selected independently and the sample is taken randomly from the sampling frame. Based on the analytical technique applied, namely Structural Equation Modelling (SEM), a minimum sample of 200 respondents from 325 accredited private HEI using SmartPLS 4.0. The study reveals that GRs and university rankings do not significantly influence the relationship between university governance and digital transformation. It suggests that other factors, beyond these, may be more influential. The findings suggest that further research is needed to understand the full impact of governance and new technologies on digital transformation in private universities.
Keywords: Digital transformation, government regulation, university ranking

1. Introduction

Indonesia's higher education sector faces several complex challenges that require urgent attention. These include low institutional productivity, which hampers global competitiveness [1], an organizational culture that lacks support for innovation and collaboration [2], and the need to enhance service quality, technology use, and human resource skills in alignment with Industry 4.0 demands [3]. Additionally, lecturer competence is critical for improving teaching and research quality to prepare graduates for global competition [4]. Furthermore, student stress negatively impacts mental health and academic performance [5]. The performance of higher education in Indonesia is indicated by a rapid increase in scientific publications, making it the highest in ASEAN since 2018; however, this growth is primarily in quantity rather than quality and innovation (scimagojr.com, 2024). Additionally, there is a

V. Mardiansyah and R. A. E. V. Targa Sapanji (eds.), *Proceedings of the 1st Widyatama International Conference on Management, Social Science and Humanities (ICMSSH 2024)*, Advances in Social Science, Education and Humanities Research 886,
https://doi.org/10.2991/978-94-6463-608-6_11

concerning downward trend in international collaboration between Indonesian and foreign researchers (scimagojr.com, 2024; jpnn.com, 2020).The Directorate General of Higher Education (Ditjen Dikti) categorizes higher education institutions (HEIs) based on their research and community service performance as measured by the Science and Technology Index (SINTA). Digital transformation has become one of the top priorities in the development of higher education institutions worldwide [6]. This process includes not only the adoption of the latest technologies, but also a thorough transformation in the university's governance and management strategies to face the challenges of the digital age [7]. Therefore, companies are competing to adapt their structures and governance in response to new social, environmental and economic challenges [8].

Based on this phenomenon, this research will focus in-depth and comprehensively on digital transformation in Indonesia's higher education sector, especially in private universities (PTS), which until now have received minimal attention in academic studies. In this context, the novelty of the research lies in the application of *Dynamic Capability* theory as the main analytical framework to explore and test various factors that can influence the digital transformation process in private universities. The focus of this research is on HEI institutions located in the LLDIKTI IV region, with the aim of identifying the extent to which these factors play a role in encouraging or hindering the implementation of digital transformation. Through this approach, it is hoped that a deeper insight into the dynamics, challenges, and opportunities faced by private universities in an effort to adapt to the demands of the digital era can be obtained

The study adopted the *Dynamic Capability theory* introduced by David J. Teece in 1997 [9]–[11]. This theory states that to achieve competitive advantage, companies do not only need to rely on internal resources as suggested by the *Resource Based View* (RBV) theory, but must also integrate and utilize knowledge to configure internal and external competencies to adapt to rapid environmental changes [12]. In the *Dynamic Capability* theory approach, there are several factors that can affect the performance of HEI institutions, both from the internal and external environment. These factors include the emergence of new technologies (*emerging technology*) ET, *University governance capability* (UGC), international recognition such as *University ranking requirement* (URR), government regulations (GR) that can support digital transformation in HEI. The purpose of this study was to obtain the following findings: 1) An overview of *UGC* and its impact on *digital transformation* of HEIs in LLDIKTI IV moderated by *GR*, 2) *ET* and its impact on *digital transformation* of HEI in LLDIKTI IV, which is moderated by GR, 3) *UGC* and its impact on *digital transformation* of HEI in LLDIKTI IV which is moderated by *URR* and 4) *ET* and its impact on *digital transformation* of HEI in LLDIKTI IV which is moderated by *URR*.

2. Hypothesis Building

This research uses a *dynamic capability* theory approach that emphasizes the importance of an organizations ability to adapt and innovate, rather than relying solely on its static advantages. This theory is very relevant in the midst of technological disruption, where companies must continue to transform to maintain competitiveness. According to the *dynamic capability* theory approach, digital transformation in higher education is influenced by various factors from the internal and external environment.

Internal factors include *ET* and *UGC*, while external factors include *URR* and *GR*. Based on the theoretical approach, the research hypothesis can be formulated as follows:

1.1 *GR* moderates the relationship between *UGC* and digital transformation.

GR in higher education ensure that institutions follow standards covering quality, data privacy and accessibility [13]. GR also play a crucial role in influencing the adoption of digital transformation in higher education institutions [14]–[16]. These regulations can affect important aspects such as resource availability, funding, and policies related to digitalization [17]. By following GR and adopting digital transformation, educational institutions can be more effective in preparing students with the skills needed to succeed in the technological era [18].

H_1: GR moderates the relationship between *UGC* and digital transformation, thereby strengthening the positive impact of UGC on digital transformation.

1.2 GR moderates the relationship between ET and digital transformation

ET is a new innovation or technology that is developing rapidly. It includes new inventions or significant developments of existing technologies and has the potential to have a major impact on society, business, and higher education institutions [19]. The integration of emerging technologies into digital transformation strategies enables universities to optimize operations, take advantage of market opportunities [20], and support higher education institutions in their digital transformation journey [21]. In this context, GR plays an important role as a moderator in the relationship between ET and digital transformation. GR can strengthen or hinder the adoption of new technologies by creating a framework that supports innovation, while ensuring that technology implementation is in line with standards and public interest.

H2: *Governance regulation* moderates the relationship between ET and digital transformation, thereby strengthening the positive impact of ET on digital transformation.

1.3 *University ranking* moderates the relationship between *UGC* and digital transformation

University ranking has a correlation with global and digital competitiveness, making modern universities a centre of innovation and knowledge, which plays an important role in influencing the adoption of digital transformation in higher education institutions [22]. In line with that, research [23] revealed that university rankings have the potential to influence institutional strategies in implementing digital transformation strategies. The ranking can significantly encourage the adoption of digital transformation in higher education, as it triggers competition and efforts to achieve prestige. This may trigger strategic initiatives that include digital transformation to improve educational quality [24], and institutional reputation [25]. Overall, the ranking reflects the university's potential to drive successful digital transformation strategies in the institution [22].

H_3: *University ranking* moderates the relationship between *UGC* and digital transformation, thus strengthening the positive impact of *UGC* on digital transformation.

3.4 *University ranking* moderates the relationship between *ET* and digital transformation

University rankings can motivate institutions to invest in innovation and emerging technologies to improve their position in global rankings. High rankings are also often accompanied by higher standards and benchmarks, which encourage more effective development and integration of new technologies. As a result, policy decisions regarding funding allocation and technology prioritization at universities with high rankings may support the adoption of new technologies and accelerate the digital transformation process [26].

3. Methodology

This study uses two independent variables, namely *UGC* (X1) and *ET* (X2), with digital transformation (Y1) as the dependent variable. In addition, there are two moderating variables, namely *university ranking requirement* (Z1) and *GR* (Z2). The unit of analysis in this study is the leadership of private universities under the Higher Education Service Institution (LLDIKTI) Region IV. Based on the variables studied, the type of research applied is descriptive and verification research. Descriptive research aims to provide an overview of certain characteristics of relevant groups, such as consumers, salespeople, or organizations. In this study, which uses a descriptive and verification approach through field data collection, the method applied is an explanatory survey. This method involves collecting information using a questionnaire to gather opinions from a portion of the population under study. The research population includes leaders of private universities (PTS) in LLDIKTI Region IV West Java and Banten, which consists of 439 PTS, of which 325 have been accredited. This research uses probability sampling technique with simple random sampling method, which ensures each element is selected independently and the sample is taken randomly from the sampling frame. Based on the analytical technique applied, namely Structural Equation Modelling (SEM), a minimum sample of 200 respondents from 325 accredited private HEI using SmartPLS 4.0.

4. Result and Discussion

4.1. Convergent Validity

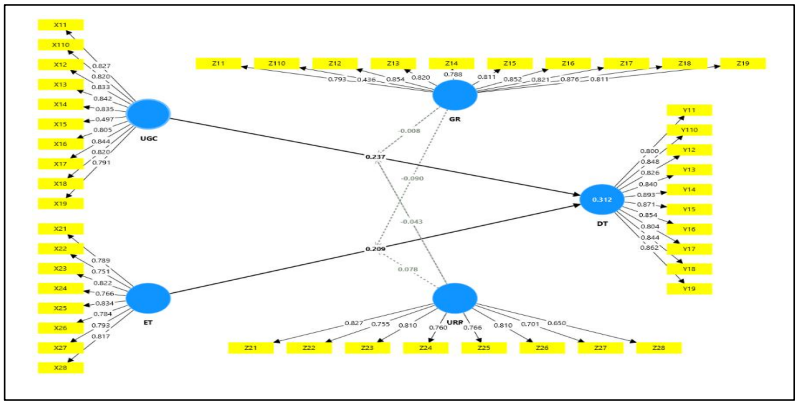

Figure 1 Outer Loading

Convergent validity assesses the extent to which two or more measuring instruments measuring the same concept have a high correlation, indicating measurement consistency and accuracy. Testing is done through statistical analysis, and this validity is important to ensure the measuring instrument accurately reflects the concept under

study. Based on the measurement results, that all loading factors > 0.70 except for items X15, X16, Z110, Z27, and Z28. In factor analysis, loading factors indicate the strength of the relationship between each item and the construct being measured. A loading factor value > 0.70 is generally considered strong enough to indicate convergent validity, which means that the item contributes significantly to the measured construct. Items with loading factors values <0.70, such as X15, X16, Z110, Z27, and Z28, are considered to have a weak contribution to the measured construct and do not meet the convergent validity criteria. This suggests that these items may not fully reflect the constructs they are supposed to measure, so they may need to be considered for removal or revision.

Meanwhile, other items that have loading factors > 0.50 are declared convergent valid, indicating that they have a strong enough correlation with the construct being measured, so they should be retained in the analysis. This convergent validity is important to ensure that the measured constructs are truly reflected by the items in the measurement instrument, thus increasing the accuracy and reliability of the research results.

Table 1. Loading Factor After Corrected

	DT	ET	GR	UGC	URR	GR x UGC	GR x ET	URR x ET	URR x UGC
X11				0.840					
X110				0.831					
X12				0.851					
X13				0.839					
X14				0.842					
X17				0.855					
X18				0.826					
X19				0.800					
X21		0.789							
X22		0.751							
X23		0.822							
X24		0.766							
X25		0.834							
X26		0.784							
X27		0.793							
X28		0.817							
Y11	0.801								
Y110	0.848								
Y12	0.826								
Y13	0.840								
Y14	0.893								
Y15	0.871								
Y16	0.854								
Y17	0.804								
Y18	0.844								
Y19	0.863								
Z11			0.791						
Z12			0.860						
Z13			0.831						
Z14			0.795						
Z15			0.820						
Z16			0.861						
Z17			0.839						
Z18			0.888						
Z19			0.803						
Z21					0.835				
Z22					0.757				
Z23					0.812				
Z24					0.768				
Z25					0.784				
Z26					0.805				
GR x ET							1.000		
URR x UGC									1.000
GR x UGC						1.000			
URR x ET								1.000	

4.2. Validity Discriminant

Table 2 Discriminant Table

	DT	ET	GR	UGC	URR
DT	0.845				
ET	0.358	0.795			
GR	0.353	0.263	0.833		
UGC	0.404	0.292	0.313	0.836	
URR	0.390	0.414	0.293	0.309	0.794

Based on the analysis results in Table 2, it can be seen that the Average Variance Extracted (AVE) root value of each variable is > from the correlation between constructs. This indicates that each variable has good discriminant validity, where the construct is able to distinguish itself from other constructs in the model. The correlation matrix given shows the relationship between some of the variables in this study. The main diagonal values (0.845, 0.795, 0.833, 0.836, and 0.794) indicate that each variable is highly correlated with itself, which is as expected. The correlations between the other variables also show that there is a positive relationship, although not very high. For example, DT has a moderate correlation with ET (0.358), GR (0.353), UGC (0.404), and URR (0.390). ET, on the other hand, had a weaker correlation with GR (0.263) and UGC (0.292), but a stronger correlation with URR

(0.414). GR and UGC have a medium correlation (0.313), while GR and URR (0.293) and UGC and URR (0.309) show a medium relationship as well. The relatively low correlations between these variables suggest that each variable measures a different aspect. This supports determinant validity, which means that the variables measure different things well and do not overlap too much.

4.3. Reliability Test

Table 3 Realibility Test Result

	Cronbach's alpha	Composite reliability (rho_c)
DT	0.955	0.957
ET	0.917	0.924
GR	0.945	0.952
UGC	0.938	0.946
URR	0.883	0.889

Based on the analysis results, the Cronbach's alpha and composite reliability values on all variables are > 0.70, which indicates that the research instruments have good reliability. This value indicates that the indicators in each construct have high internal consistency, so they can be relied upon in measuring the concept they represent. Cronbach's alpha shows consistency between items in a construct, while composite reliability provides a more accurate measure of reliability by considering the weight of each indicator. Therefore, it can be concluded that all variables in this study are declared reliable.

For example, Cronbach's alpha values of 0.955 for DT and 0.917 for ET indicate that the items used to measure these two constructs are highly consistent with each other. This means that the instruments used can be relied upon to consistently measure the intended constructs. Meanwhile, one of the composite reliability values of 0.957 for DT and 0.924 for ET shows that these constructs have excellent reliability, given the weight of each indicator.

4.4. Result of Evaluation Equation Model (*Inner Model*)

4.4.1.R Square Test

Table 4 R Square Test Result

	R-square	R-square adjusted
DT	0.308	0.279

The R Square (R^2) value of 0.308 in the regression model indicates that 30.8% of the variation in the dependent variable, Digital Transformation (DT), can be explained by the independent variables in the model, namely UGC and ET. This result indicates that UGC and ET together have a significant contribution in influencing DT, implying that they play an important role in explaining changes in DT. However, the R^2 value of 0.308 also reveals that 69.2% of the variation in DT is still influenced by other factors outside this model. In other words, although UGC and ET play an important role, there are still additional factors that have not been accounted for in this model that affect DT. Therefore, while this model provides important insights into the influence of UGC and ET, there is a need for further research to explore additional factors that may contribute to digital transformation, to gain a more thorough and accurate understanding.

4.4.2.F Square Test

The f^2 value is used to measure the effect size or contribution of the independent variable to the dependent variable in the regression model. In this analysis, the f^2 value for UGC on DT is 0.062, which is less than 0.35. This indicates that the direct effect of UGC on DT is small, meaning that the contribution of UGC in explaining changes in DT is relatively low in the context of this model. In addition, the f^2 value for the effect of UGC on DT through GR is 0.000. This value indicates that GR has no significant moderating effect on the relationship between UGC and DT. In other words, GR does not influence or strengthen the relationship between UGC and DT. Overall, these results indicate that both the direct effect of UGC and its effect through GR on DT are relatively small. This suggests that although UGC contributes to DT, its contribution is not practically significant in this model. Therefore, other factors beyond UGC and GR likely play a more dominant role in explaining variations in DT. This underscores the need to consider additional factors that may have a greater influence in understanding and influencing digital transformation.

4.4.3.Hipotesis Testing

Table 6 Hypothesis Table Result

	Path Koefisien	T Statistic	P Values	F Square
ET -> DT	0.213	2.465	0.007	0,041
GR x ET -> DT	-0.102	0.837	0.201	0,006
URR x ET -> DT	0.075	0.996	0.160	0,011
UGC -> DT	0.229	0.075	0.001	0,062
GR x UGC -> DT	0.010	0.095	0.462	0,000
URR x UGC -> DT	-0.044	0.585	0.279	0,004

Based on Table 6. can be explained as follows: 1) The GR x UGC interaction variable obtained a P value of 0.462>0.05, a negative coefficient value of 0.010 and an F Square value of 0.000 <0.062, then H1 is rejected, namely GR moderates the relationship between UGC and DT so as to strengthen the positive impact of UGC on DT. 2) The GR x ET interaction variable obtained a P value of 0.201>0.05, the coefficient value is negative, namely -0.102 and the F Square value is 0.006 <0.041, then H2 is rejected, namely GR moderates the relationship between ET and DT so as to strengthen the positive impact of ET on DT. 3) The URR x UGC interaction variable obtained a P value of 0.279>0.05, the coefficient value is positive, namely -0.044 and the F Square value is 0.004 <0.041, then H3 is rejected, namely URR moderates the relationship between UGC and DT so as to strengthen the positive impact of UGC on DT. The URR x ET Interaction variable obtained a P Value of 0.011>0.05, a positive coefficient value of 0.075 and an F Square value of 0.011 <0.041, then H4 is rejected, namely URR moderates the relationship between ET and DT so as to strengthen the positive impact of ET on DT.

4.4.4.Goodness of Fit

Table 7 Goodness of Fit Result

	Path Koefisien	T Statistic	P Values	F Square
ET -> DT	0.213	2.465	0.007	0,041
GR x ET -> DT	-0.102	0.837	0.201	0,006
URR x ET -> DT	0.075	0.996	0.160	0,011
UGC -> DT	0.229	0.075	0.001	0,062
GR x UGC -> DT	0.010	0.095	0.462	0,000
URR x UGC -> DT	-0.044	0.585	0.279	0,004

$$GOF = \sqrt{average\ of\ AVE\ x\ average\ of\ R\ Square}$$

$$GOF = \sqrt{0{,}6734\ x\ 0{,}308}$$

$$GOF = 0{,}45$$

Based on the calculation results, the Goodness of Fit (GOF) value of 0.45 indicates that the combined performance between the outer model and the inner model in this study can be classified into the small GOF category, because the value is less than 0.95. In the context of model evaluation, GOF is used to measure the extent to which the overall model, which includes the fit between indicators and constructs (outer model) and the relationship between constructs (inner model), can explain the variation in observed data. GOF values greater than 0.95 usually indicate an excellent model fit, while lower values indicate a lower level of fit. With a GOF value of 0.45, this model falls into the small GOF category, indicating that while the model has some fit, there is significant room for improvement in terms of how the model describes the data overall. This indicates that the model may need to be refined or further developed to improve the fit and relevance to the observed data.

5. Conclusion

Overall, the results of this study indicate that neither GR nor University Ranking Requirement has a significant moderating effect on the relationship between University Governance or Emerging Technology and Digital Transformation. This finding provides insight that other factors, besides GR and URR, may be more influential in moderating the relationship between the independent variables and Digital Transformation. Further research is needed to explore additional factors that may have a significant impact in this relationship.

Digital transformation in private universities is influenced by various internal and external factors, including GRs and university rankings. However, these elements alone may not adequately explain the impact of governance and new technologies on digital transformation. This highlights the necessity to explore additional relevant variables that can help private universities develop effective strategies for implementing digital transformation, optimizing governance, and leveraging technology to gain a competitive edge in the education market.

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