JTBC: Jurnal Teknologi dan Bisnis Cerdas
Volume 2 Nomor 2, Juni 2026
e-ISSN : 3109-8924
DOI: 10.64476/jtbc.v2i2.78

GREEN DIGITAL TRANSFORMATION CAPABILITY AND SUSTAINABLE ORGANIZATIONAL PERFORMANCE IN HIGHER EDUCATION: THE MEDIATING ROLE OF GREEN DIGITAL INNOVATION AND THE MODERATING ROLE OF DATA-DRIVEN CULTURE

GREEN DIGITAL TRANSFORMATION CAPABILITY DAN *SUSTAINABLE ORGANIZATIONAL PERFORMANCE* PADA PERGURUAN TINGGI DI KOTA MAKASSAR*:* PERAN MEDIASI *GREEN DIGITAL INNOVATION* DAN MODERASI *DATA-DRIVEN CULTURE*

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ABSTRACT
This study examines the effects of Green Digital Transformation Capability (GDTC) on Sustainable Organizational Performance (SOP) in higher education through Green Digital Innovation (GDI), while assessing Data-Driven Culture (DDC) as a moderating condition. A quantitative cross-sectional survey was conducted among 200 lecturers and educational staff at higher education institutions in Makassar City, Indonesia, from 1 to 14 April 2026. Data were analyzed using partial least squares structural equation modeling (PLS-SEM) with SmartPLS 4 and 5,000 bootstrap subsamples. The measurement model demonstrated satisfactory reliability and validity (outer loadings = 0.738-0.868; composite reliability = 0.923-0.938; AVE = 0.624-0.689; HTMT = 0.182-0.659). GDTC positively affected GDI (beta = 0.443; p < 0.001) and SOP (beta = 0.302; p < 0.001), while GDI positively affected SOP (beta = 0.372; p < 0.001). DDC positively affected GDI (beta = 0.234; p < 0.001) and SOP (beta = 0.274; p < 0.001). GDI partially mediated the GDTC-SOP relationship (beta = 0.165; p < 0.001), and DDC strengthened the GDTC-GDI relationship (beta = 0.388; p < 0.001). The model explained 42.7% of GDI and 50.4% of SOP variance. The findings extend digital sustainability research by demonstrating a capability-innovation-performance mechanism and identifying data-driven culture as a boundary condition in higher education.

Keywords: *Green Digital Transformation Capability; Green Digital Innovation; Data-Driven Culture; Sustainable Organizational Performance; Higher Education.*

ABSTRAK
Penelitian ini menganalisis pengaruh *Green Digital Transformation Capability* (GDTC) terhadap *Sustainable Organizational Performance* (SOP) pada perguruan tinggi melalui *Green Digital Innovation* (GDI), serta menguji *Data-Driven Culture* (DDC) sebagai kondisi moderasi. Penelitian menggunakan survei kuantitatif potong lintang terhadap 200 dosen dan tenaga kependidikan pada perguruan tinggi di Kota Makassar, Indonesia, yang dilaksanakan pada 1-14 April 2026. Data dianalisis menggunakan *partial least squares structural equation modeling* (PLS-SEM) melalui SmartPLS 4 dengan 5.000 subsampel *bootstrap*. Model pengukuran menunjukkan reliabilitas dan validitas yang memadai (*outer loading* = 0,738-0,868; *composite reliability* = 0,923-0,938; AVE = 0,624-0,689; HTMT = 0,182-0,659). GDTC berpengaruh positif terhadap GDI (beta = 0,443; p < 0,001) dan SOP (beta = 0,302; p < 0,001), sedangkan GDI berpengaruh positif terhadap SOP (beta = 0,372; p < 0,001). DDC berpengaruh positif terhadap GDI (beta = 0,234; p < 0,001) dan SOP (beta = 0,274; p < 0,001). GDI memediasi secara parsial hubungan GDTC-SOP (beta = 0,165; p < 0,001), sedangkan DDC memperkuat hubungan GDTC-GDI (beta = 0,388; p < 0,001). Model menjelaskan 42,7% variasi GDI dan 50,4% variasi SOP. Temuan memperluas riset *digital sustainability* dengan menunjukkan mekanisme *capability-innovation-performance* serta menempatkan budaya berbasis data sebagai *boundary condition* dalam pendidikan tinggi.

Kata Kunci: *Green Digital Transformation Capability; Green Digital Innovation; Data-Driven Culture; Sustainable Organizational Performance;* Perguruan Tinggi.

INTRODUCTION

Digital transformation has moved beyond administrative automation toward a strategic change process that reshapes organizational structures, processes, decision making, innovation, and value creation. Vial (2019) conceptualizes digital transformation as a process in which combinations of information, computing, communication, and connectivity technologies trigger significant organizational changes. Verhoef et al. (2021) further argue that such transformation requires appropriate assets, capabilities, structures, and performance metrics, while Warner and Wäger (2019) describe digital transformation as an ongoing process of strategic renewal that depends on sensing, seizing, and transforming capabilities. Accordingly, successful digital transformation is not determined by technology ownership alone, but by the organization's ability to configure technology, data, competencies, and processes into an integrated capability.

The sustainability agenda broadens these requirements. Digitalization can improve efficiency, transparency, decision quality, and resource monitoring, yet sustainability value does not emerge automatically from technology investment. Green Information Systems research has long emphasized that information systems can enable environmental change through process redesign, information provision, coordination, and decision support (Melville, 2010; Watson et al., 2010; Elliot, 2011; Jenkin et al., 2011). A meta-analysis by Bindeeba et al. (2025), synthesizing 44 studies and 17,284 observations, confirms a positive relationship between digital transformation and sustainable business performance across economic, environmental, and social dimensions. The heterogeneity reported across settings, however, suggests that organizations need capabilities and mechanisms that deliberately direct digitalization toward sustainability outcomes.

More recently, Green Digital Transformation Capability (GDTC) has emerged as a construct linking the digital and green transitions. Huang and Huang (2024) position GDTC as an organizational capability that integrates digital transformation with a green orientation and show its relationship with green learning and sustainability performance. Huang et al. (2026) extend this argument by demonstrating that GDTC enhances ambidextrous green innovation and, subsequently, corporate sustainability performance. Wu et al. (2026) likewise show that green digital transformation capabilities can foster sustainable innovation performance. Conceptually, GDTC can therefore be understood as an organization's ability to use digital technologies and information to sense sustainability opportunities, seize them through digital solutions, and transform operations through the reconfiguration of processes and resources.

Higher education provides an important setting in which digital transformation and sustainability intersect. Higher education institutions manage academic, administrative, human resource, financial, facility, research, and student-service processes; consequently, digitalization can influence energy and paper consumption, space utilization, service time, accessibility, and governance quality. Zou et al. (2024) demonstrate that digitalization can strengthen green university initiatives across green education, green research, green campus, and green life domains. Carmo et al. (2025) further show that digital transformation in higher education management involves technologies, process change, governance, and managerial capabilities. Recent twin-transition research also indicates that the convergence of digital and green agendas is becoming strategically important in higher education (Bulut & Oğuz Haçat, 2026; Spilotro et al., 2026). Universities are therefore not merely technology users; they are knowledge-intensive organizations in which the conversion of digital capability into sustainability value can be examined directly.

One mechanism through which this conversion may occur is Green Digital Innovation (GDI). Nambisan et al. (2017) emphasize that digital technologies alter the logic of innovation by making the boundaries among innovation processes, outcomes, and actors more fluid. When this digital logic is combined with environmental goals, innovation may take the form of paperless process redesign, digital services that reduce travel or material use, intelligent resource monitoring, data integration for efficiency, or platforms that expand service access. Xu et al. (2023) find that digital strategy and digital capability enhance eco-process, eco-product, and eco-management innovation, which subsequently improve sustainable performance. Lu et al. (2023) also show that digital capabilities and sustainability innovation contribute to sustainability performance. In higher education, Shen et al. (2025) provide direct evidence that dynamic capabilities and organizational factors can promote green digital innovation. These findings provide a strong rationale for positioning GDI as a mechanism that translates GDTC into Sustainable Organizational Performance (SOP).

Technology and innovation, however, do not develop in a culturally neutral environment. Data-Driven Culture (DDC) represents organizational norms that encourage the use of data, evidence, and analytics in decision making. Gupta and George (2016) identify data-driven culture as an important organizational resource underpinning big data analytics capability. Chaudhuri et al. (2024) show that data-driven culture positively influences innovation capabilities and sustainability performance. In universities, DDC is reflected when leaders and work units use dashboards, indicators, and cross-functional data to identify inefficiencies, prioritize digital initiatives, evaluate service quality, and assess environmental and social impacts. DDC may therefore function both as an antecedent of innovation and as a contextual condition determining whether GDTC is actually converted into green digital solutions.

Three research gaps emerge from this literature. First, recent empirical work on GDTC remains concentrated in manufacturing and corporate settings (Huang & Huang, 2024; Huang et al., 2026; Wu et al., 2026), while evidence from higher education is still limited despite growing twin-transition research calling for the integration of digital and green governance in universities. Second, digital transformation-sustainability studies frequently employ eco-innovation or sustainable innovation as mediators, but Green Digital Innovation, which explicitly combines digital affordances with environmental objectives, has rarely been examined in university management. Third, DDC has generally been modeled as an antecedent or mediator of analytics and innovation capability, whereas its role as a boundary condition that strengthens the conversion of GDTC into GDI remains underexplored. This study integrates these three issues in a single model involving employees of higher education institutions in Makassar City, Indonesia.

The study is primarily grounded in the Dynamic Capabilities View (Teece et al., 1997; Teece, 2007). Within this framework, GDTC represents sensing, seizing, and transforming capabilities that direct digital assets toward sustainability opportunities; GDI represents the reconfiguration outcome through which capability is materialized into new processes and services; and DDC provides an information context that strengthens sensing quality and evidence-based reconfiguration. The Resource-Based View (Barney, 1991) is used as a complementary perspective to explain why data, system integration, competencies, and culture become valuable resources when orchestrated as organizational capabilities. Accordingly, this study examines the effects of GDTC on GDI and SOP, the effect of GDI on SOP, the mediating role of GDI, the effects of DDC on GDI and SOP, and the moderating role of DDC in the GDTC-GDI relationship.

Hypothesis Development

GDTC combines technological resources with an organization's capacity for strategic renewal toward sustainability objectives. When a university can integrate systems, data, automation, cloud technologies, and process redesign with environmental goals, it has a stronger foundation for identifying and implementing green digital solutions. Huang and Huang (2024) link GDTC with green learning processes, while Huang et al. (2026) show that GDTC enhances both exploitative and exploratory green innovation. Xu et al. (2023) likewise demonstrate that digital capability promotes multiple forms of eco-innovation. Following dynamic capability logic, stronger GDTC should therefore increase an institution's ability to generate GDI.

H1: Green Digital Transformation Capability positively affects Green Digital Innovation.

GDTC can also improve SOP directly. Integrating technology with sustainability objectives can shorten process time, reduce material consumption and coordination costs, limit data duplication, and improve transparency and service access. Lu et al. (2023) identify digital capabilities as important predictors of sustainability performance, while Bindeeba et al. (2025) confirm a positive relationship between digital transformation and economic, environmental, and social performance. Wang and Zhang (2025) similarly show that digital transformation improves Sustainable Organizational Performance. Accordingly, stronger green digital transformation capability is expected to generate more sustainable organizational performance.

H2: Green Digital Transformation Capability positively affects Sustainable Organizational Performance.

GDI represents the tangible creation of value from digital technologies directed toward green objectives. Digital process redesign can reduce waste, data-based monitoring can improve resource utilization, and digital services can broaden access while reducing material requirements. Xu et al. (2023) show that eco-innovation improves sustainable performance, while Huang et al. (2026) identify green innovation as a driver of corporate sustainability performance. GDI is therefore expected to enhance economic/operational, environmental, and social performance.

H3: Green Digital Innovation positively affects Sustainable Organizational Performance.

Dynamic capabilities generate performance when they are translated into process reconfiguration and innovation. GDTC is therefore expected to affect SOP not only directly but also indirectly through GDI. Evidence on the mediating role of eco-innovation (Xu et al., 2023) and green innovation (Huang et al., 2026) supports this mechanism. In higher education, digital-green capability must be translated into new services, processes, and systems before it can produce resource savings, transparency, and improved access.

H4: Green Digital Innovation mediates the effect of Green Digital Transformation Capability on Sustainable Organizational Performance.

DDC encourages the use of evidence to identify problems and evaluate alternatives. When data are accessible, shared, and routinely used in decisions, organizations are better able to identify inefficiencies and innovation opportunities. Gupta and George (2016) position data-driven culture as a central resource for analytics capability, while Chaudhuri et al. (2024) show that DDC positively influences innovation capabilities. DDC is therefore expected to enhance GDI in higher education institutions.

H5: Data-Driven Culture positively affects Green Digital Innovation.

DDC can also contribute to performance through more accurate decisions, more efficient resource allocation, greater transparency, and better monitoring. Chaudhuri et al. (2024) report a positive relationship between DDC and sustainability performance. In a university setting, data use can improve administrative efficiency, space and energy utilization, student services, and organizational responsiveness. DDC is therefore expected to contribute directly to SOP.

H6: Data-Driven Culture positively affects Sustainable Organizational Performance.

Finally, DDC is positioned as a moderator. GDTC provides digital capacity and reconfiguration capability, but GDI requires evidence to select problems, test solutions, and evaluate impact. Under a strong data-driven culture, signals generated by information systems enter sensing and learning processes more quickly, making it easier to convert GDTC into innovation. Under a weak data culture, an institution may own advanced technologies while continuing to make fragmented and intuition-based decisions. Thus, the positive effect of GDTC on GDI is expected to become stronger when DDC is high.

H7: Data-Driven Culture strengthens the positive effect of Green Digital Transformation Capability on Green Digital Innovation.

RESEARCH METHOD

This study used a quantitative explanatory approach with a cross-sectional survey design. The unit of observation was the individual employee, including lecturers and educational staff, while the organizational constructs were measured through respondents' perceptions of their institution's green digital transformation capability, green digital innovation, data-driven culture, and sustainable organizational performance. Data were collected from higher education institutions in Makassar City between 1 and 14 April 2026. A total of 200 complete questionnaires were included in the analysis. This sample also exceeded the largest post-hoc minimum sample size reported by SmartPLS for the model paths at a 5% alpha level and 80% statistical power, which was 113 cases.

GDTC was measured using eight indicators developed through contextual adaptation of the GDTC domain reported by Huang and Huang (2024) and Huang et al. (2026), with conceptual support from Vial (2019), Warner and Wäger (2019), and Xu et al. (2023). The indicators capture the integration of sustainability objectives into digital strategy, replacement of manual processes, redesign and reconfiguration capability, resource monitoring, digital-green strategic alignment, use of cloud/automation/data systems, support for technology adoption, and responsiveness to changing sustainability needs. Because the eight-item measure represents a contextual adaptation for higher education rather than a verbatim reproduction of a single scale, revalidation through the measurement model was treated as an essential analytical step.

GDI was measured with six indicators integrating the logic of digital innovation (Nambisan et al., 2017) with green innovation and digital sustainability (Xu et al., 2023; Shen et al., 2025; Huang et al., 2026). The indicators reflect the development of digital services that reduce material use, process redesign for energy and time efficiency, use of data for environmental solutions, sustainability-oriented digital experimentation, platform integration, and the use of technology to create new sustainability practices. DDC was measured with six indicators based on the data-driven culture domain proposed by Gupta and George (2016) and the empirical evidence of Chaudhuri et al. (2024), including reliance on data rather than intuition, access to decision-relevant data, evidence requirements, data sharing, use of dashboards/analytics, and treatment of data as a strategic asset.

SOP was measured using nine indicators covering economic/operational, environmental, and social performance, consistent with the triple-bottom-line logic (Elkington, 1997) and sustainable performance measures used by Xu et al. (2023), Lu et al. (2023), Wang and Zhang (2025), and Bindeeba et al. (2025). In the SmartPLS model, the nine indicators were specified as a global reflective construct. This specification was retained because all indicators achieved satisfactory loadings, although future research may compare this approach with a higher-order specification explicitly modeling the three performance dimensions. All items were assessed using a seven-point Likert scale.

The analysis was conducted using SmartPLS 4 (Ringle et al., 2024). The measurement model was evaluated using outer loadings, Cronbach's alpha, rho_A, composite reliability (rho_C), average variance extracted (AVE), HTMT, and outer VIF. The structural model was evaluated using inner VIF, path coefficients, R-squared, adjusted R-squared, effect size f-squared, and Q-squared predictive relevance obtained through blindfolding. The significance of direct, specific indirect, and interaction effects was assessed using 5,000 bootstrap subsamples with a two-tailed test at a 5% significance level. General assessment criteria followed Hair et al. (2019, 2022), while discriminant validity was assessed using the conservative HTMT threshold of 0.85 recommended by Henseler et al. (2015). As an additional check of common method bias in this single-source design, full-collinearity VIFs were calculated from the PLS construct scores; values below 3.3 were interpreted as indicating that common method bias was unlikely to be a serious concern (Kock, 2015).

RESULTS AND DISCUSSION

Respondent Characteristics

The study involved 200 employees of higher education institutions in Makassar City, representing public and private institutions, lecturers and educational staff, and varying educational backgrounds, ages, and lengths of service. All data were collected between 1 and 14 April 2026. Detailed respondent characteristics are presented in Table 1.

Table 1. Respondent Characteristics

Characteristic	Category	Number	Percentage
Type of Higher Education Institution	Private	108	54.0%
	Public	92	46.0%
Gender	Male	105	52.5%
	Female	95	47.5%
Employment Status	Lecturer	108	54.0%
	Educational Staff	92	46.0%
Education	SMA/Diploma	12	6.0%
	S1	67	33.5%
	S2	95	47.5%
	S3	26	13.0%
Age	20-30 years	39	19.5%
	31-45 years	113	56.5%
	46-55 years	45	22.5%
	>55 years	3	1.5%
Length of Service	1-5 years	37	18.5%
	6-10 years	39	19.5%

Characteristic	Category	Number	Percentage
	11-20 years	80	40.0%
	>20 years	44	22.0%
Total		200	100.0%

Source: survey data processed by the authors, 2026

Of the respondents, 54.0% were employed by private higher education institutions and 46.0% by public institutions. Gender composition was relatively balanced, with 52.5% men and 47.5% women, while 54.0% of respondents were lecturers and 46.0% were educational staff. Master's degree holders represented the largest educational group (47.5%), respondents aged 31-45 years formed the largest age category (56.5%), and employees with 11-20 years of service were the largest tenure group (40.0%). This profile indicates representation from the two major employee groups and a substantial proportion of respondents with sufficient organizational experience to assess digital processes and institutional governance.

Measurement Model Assessment

The PLS Algorithm results show that all indicators achieved outer loadings between 0.738 and 0.868, with no loading below 0.70. Internal consistency was also strong: Cronbach's alpha ranged from 0.900 to 0.925, rho_A from 0.902 to 0.932, and composite reliability from 0.923 to 0.938. AVE values ranged from 0.624 to 0.689 and therefore exceeded the 0.50 criterion. These results support convergent validity and internal consistency reliability for all constructs.

Table 2. Reliability and Convergent Validity

Construct	Item	Loading	Alpha	rho_A	rho_C	AVE
DDC	6	0.791-0.868	0.909	0.912	0.930	0.689
GDI	6	0.778-0.850	0.900	0.902	0.923	0.666
GDTC	8	0.750-0.861	0.924	0.931	0.938	0.653
SOP	9	0.738-0.844	0.925	0.926	0.937	0.624

Source: SmartPLS 4 PLS Algorithm output processed by the authors, 2026

Indicator-level outer VIF values ranged from approximately 1.86 to 3.01 and remained below levels generally considered problematic for measurement models. Inner VIF values were also low, ranging from 1.010 to 1.431, indicating no material collinearity problem in the structural model. In addition, full-collinearity VIF values based on construct scores ranged from 1.243 to 2.017, all below the 3.3 threshold, providing no indication of serious common method bias (Kock, 2015). Discriminant validity was subsequently assessed using HTMT.

Table 3. Heterotrait-Monotrait Ratio (HTMT)

Construct	DDC	GDI	GDTC	SOP
DDC	-			
GDI	0.319	-		
GDTC	0.182	0.547	-	
SOP	0.466	0.659	0.573	-

Source: SmartPLS 4 PLS Algorithm output processed by the authors, 2026

HTMT values ranged from 0.182 to 0.659, all below the conservative threshold of 0.85. DDC, GDI, GDTC, and SOP therefore demonstrated satisfactory discriminant validity. The Fornell-Larcker criterion supported the same conclusion because the square roots of AVE on the diagonal (DDC = 0.830; GDI = 0.816; GDTC = 0.808; SOP = 0.790) were higher than the corresponding inter-construct correlations.

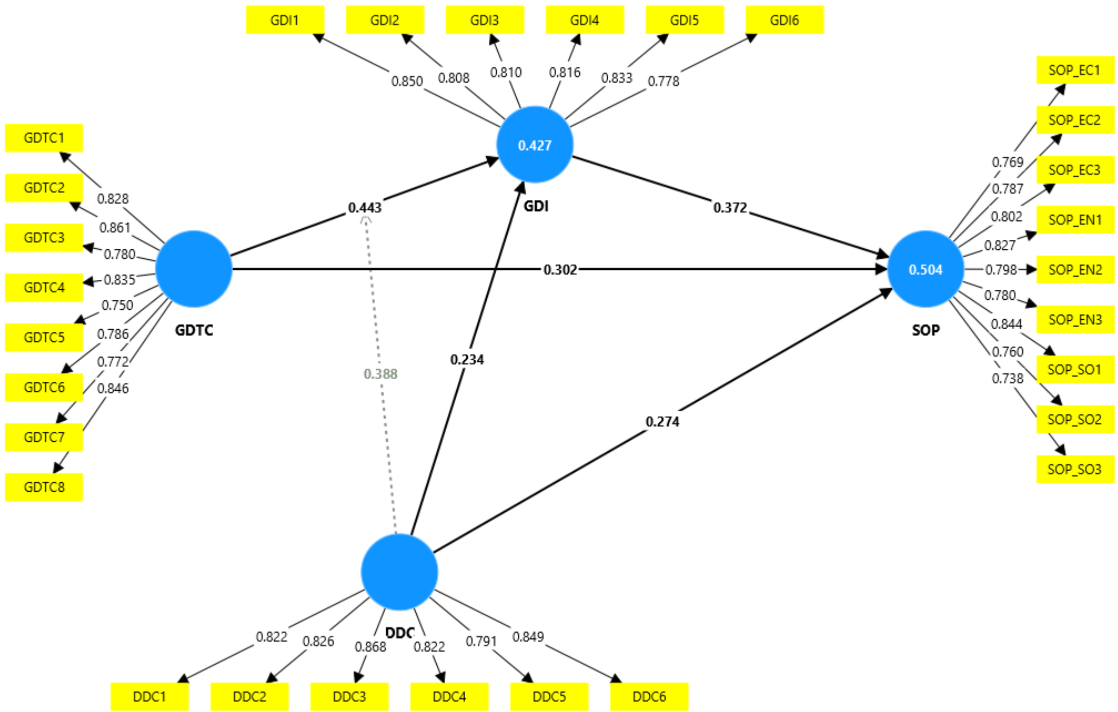

Figure 1. PLS Algorithm Model

Source: SmartPLS 4 output processed by the authors, 2026

Structural Model and Predictive Assessment

The model explained 42.7% of the variance in GDI (R-squared = 0.427; adjusted R-squared = 0.418) and 50.4% of the variance in SOP (R-squared = 0.504; adjusted R-squared = 0.497). Blindfolding yielded Q-squared values of 0.277 for GDI and 0.308 for SOP. Because both values were above zero, the model demonstrated predictive relevance for the endogenous constructs. The estimated-model SRMR was 0.054, indicating low residual discrepancy, while the NFI was 0.869. Since NFI was slightly below 0.90, global fit statistics were treated as supporting information rather than the primary decision criterion; evaluation focused on measurement quality, explanatory power, predictive relevance, and structural path significance.

Table 4. Explanatory Power, Predictive Relevance, and Model Fit

Indicator	GDI	SOP
R-squared	0.427	0.504
Adjusted R-squared	0.418	0.497
Q-squared (blindfolding)	0.277	0.308
Estimated-model SRMR	0.054	-
Estimated-model NFI	0.869	-

Source: SmartPLS 4 PLS Algorithm and blindfolding output processed by the authors, 2026

Table 5. Effect Size (f-squared)

Relationship	f-squared	Relative interpretation
GDTC -> GDI	0.330	Largest contribution to GDI
DDC -> GDI	0.093	Small-to-moderate
DDC x GDTC -> GDI	0.219	Moderate
GDTC -> SOP	0.136	Small-to-moderate
GDI -> SOP	0.195	Moderate
DDC -> SOP	0.138	Small-to-moderate

Source: SmartPLS 4 PLS Algorithm output processed by the authors, 2026

Effect sizes indicate that GDTC made the largest contribution to GDI (f-squared = 0.330), followed by the DDC x GDTC interaction (0.219). For SOP, the largest contribution came from GDI (0.195), followed by DDC (0.138) and GDTC (0.136). This pattern suggests that green digital transformation generates value not only through a direct path but also through the innovation mechanism and its alignment with a data-driven decision culture.

Hypothesis Testing, Mediation, and Moderation

Table 6. Direct Effects and Moderation Effect

H	Path	Beta	STDEV	t	p	95% CI	Decision
H1	GDTC -> GDI	0.443	0.053	8.368	<0.001	0.338-0.545	Supported
H2	GDTC -> SOP	0.302	0.063	4.778	<0.001	0.176-0.425	Supported
H3	GDI -> SOP	0.372	0.055	6.784	<0.001	0.266-0.479	Supported

H	Path	Beta	STDEV	t	p	95% CI	Decision
H5	DDC -> GDI	0.234	0.063	3.697	<0.001	0.112-0.361	Supported
H6	DDC -> SOP	0.274	0.048	5.658	<0.001	0.177-0.369	Supported
H7	DDC x GDTC -> GDI	0.388	0.061	6.397	<0.001	0.260-0.500	Supported

Source: SmartPLS 4 bootstrapping with 5,000 subsamples, processed by the authors, 2026

All direct effects and the moderation effect were significant at the 5% level. GDTC positively affected GDI (beta = 0.443; t = 8.368; $p < 0.001$) and SOP (beta = 0.302; t = 4.778; $p < 0.001$). GDI positively affected SOP (beta = 0.372; t = 6.784; $p < 0.001$). DDC positively affected GDI (beta = 0.234; t = 3.697; $p < 0.001$) and SOP (beta = 0.274; t = 5.658; $p < 0.001$). The DDC x GDTC interaction positively and significantly affected GDI (beta = 0.388; t = 6.397; $p < 0.001$). Accordingly, H1, H2, H3, H5, H6, and H7 were supported.

Table 7. Specific Indirect Effects

Effect	Beta	STDEV	t	p	95% CI	Interpretation
GDTC -> GDI -> SOP	0.165	0.032	5.117	<0.001	0.107-0.233	Significant mediation
DDC -> GDI -> SOP	0.087	0.027	3.185	0.001	0.039-0.146	Effect tidak langsung
DDC x GDTC -> GDI -> SOP	0.144	0.028	5.158	<0.001	0.091-0.200	Conditional indirect effect

Source: SmartPLS 4 bootstrapping with 5,000 subsamples, processed by the authors, 2026

The specific indirect effect of GDTC on SOP through GDI was 0.165 and significant (t = 5.117; $p < 0.001$; 95% CI = 0.107-0.233). Because the direct effect of GDTC on SOP remained positive and significant, the pattern represents complementary partial mediation. The total effect of GDTC on SOP was 0.466, comprising a direct effect of 0.302 and an indirect effect of 0.165. H4 was therefore supported: GDI is an important mechanism through which GDTC contributes to sustainable organizational performance.

DDC also had a significant indirect effect on SOP through GDI (beta = 0.087; p = 0.001). In addition, the DDC x GDTC interaction generated a conditional indirect effect on SOP through GDI (beta = 0.144; $p < 0.001$). This additional result indicates that data-driven culture not only exerts direct and moderating effects; the strengthening of the GDTC-GDI relationship is also transmitted to SOP through innovation. The pattern provides evidence consistent with moderated mediation, although it is treated as an additional analysis to preserve parsimony in the hypothesized model.

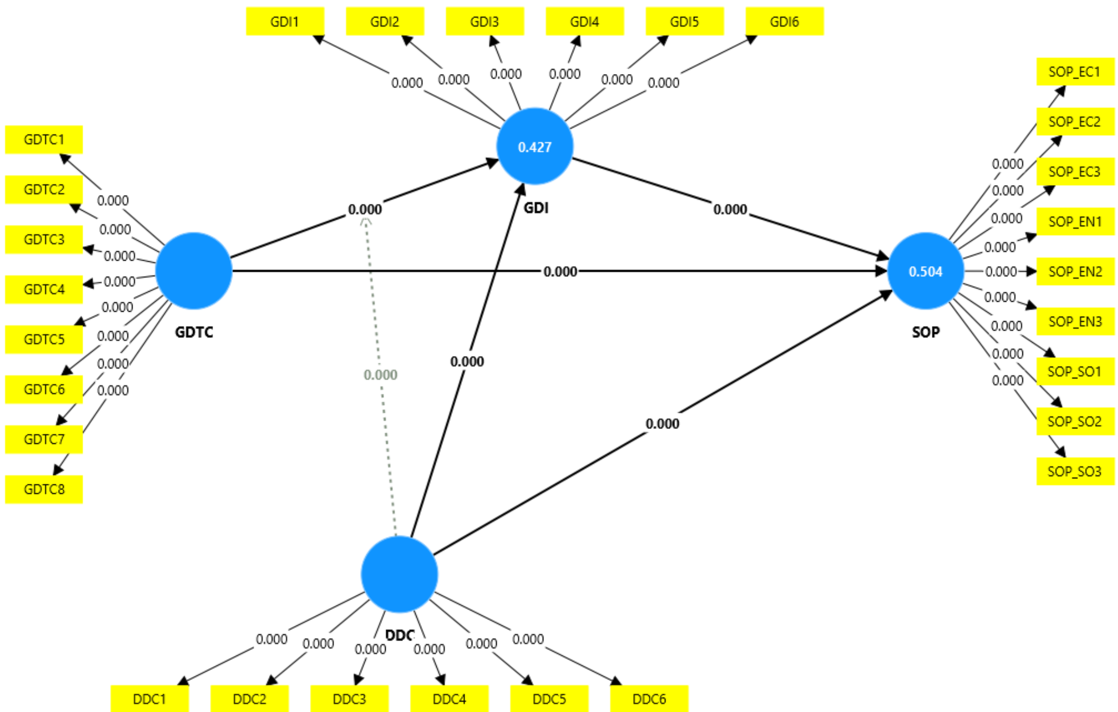

Figure 2. Structural Model Bootstrapping Results

Source: SmartPLS 4 bootstrapping output processed by the authors, 2026

Effect of GDTC on Green Digital Innovation (H1)

H1 was supported because GDTC positively affected GDI (beta = 0.443; $p < 0.001$) and produced an f-squared of 0.330, the largest contribution to GDI. This finding supports the Dynamic Capabilities View: technology generates innovation when organizations can sense sustainability needs, seize digital solutions, and transform processes. The result is consistent with Huang and Huang (2024), who conceptualize GDTC as an integrative digital-green capability, and Huang et al. (2026), who find that GDTC strengthens exploitative and exploratory green innovation. Xu et al.

(2023) likewise show that digital capability improves eco-innovation. In higher education, the result implies that investments in digital platforms become more productive when institutions can connect technology with material-reduction targets, process integration, resource monitoring, and service redesign.

The contextual contribution lies in extending the evidence beyond manufacturing-dominated settings to knowledge-intensive higher education organizations. Universities differ from manufacturing firms because value is created through academic services, administration, research, and facility management. Zou et al. (2024) show that green-university digitalization can occur across multiple campus domains, while Shen et al. (2025) confirm the relevance of dynamic capabilities for green digital innovation in higher education. The present findings therefore suggest that GDTC can serve as a linking capability between digital transformation and sustainability in knowledge-service organizations.

Effect of GDTC on Sustainable Organizational Performance (H2)

GDTC positively affected SOP (beta = 0.302; $p < 0.001$), supporting H2. This direct effect indicates that some sustainability value can arise from digital capability itself through coordination efficiency, reduction of manual processes, improved transparency, and better resource utilization. The result is consistent with Lu et al. (2023), who identify digital capabilities as important drivers of sustainability performance, and Wang and Zhang (2025), who show that digital transformation enhances Sustainable Organizational Performance. Bindeeba et al. (2025) provide additional cross-study evidence that digital transformation is associated with economic, environmental, and social performance.

In higher education, this direct effect may operate through digital workflows, e-office practices, integration of academic and HR data, facility monitoring, and online services that reduce paper use, waiting time, and mobility requirements. Nevertheless, the total effect of GDTC on SOP increased from a direct effect of 0.302 to 0.466 when the GDI pathway was included. This pattern indicates that capability matters, but innovation amplifies the value generated from that capability.

Effect of Green Digital Innovation on SOP and Its Mediating Role (H3-H4)

GDI positively affected SOP (beta = 0.372; $p < 0.001$; f-squared = 0.195), supporting H3. Green digital innovation translates technological potential into operational changes that can generate economic/operational, environmental, and social benefits. This finding is consistent with Xu et al. (2023), who show that eco-innovation improves sustainable performance, and Huang et al. (2026), who demonstrate that green innovation enhances corporate sustainability performance. In university settings, examples of GDI include paperless processes, intelligent energy monitoring, analytics for scheduling and space utilization, digital service integration, and access platforms that reduce friction for students and employees.

H4 was also supported because the indirect GDTC -> GDI -> SOP effect was significant (beta = 0.165; $p < 0.001$), while the direct effect remained significant. This complementary partial mediation indicates that GDI is not the only mechanism linking GDTC and SOP, but it is an important pathway through which green digital capability generates performance. The result extends evidence on eco-innovation mediation (Xu et al., 2023) and green innovation mediation (Huang et al., 2026) to the higher education context. Theoretically, the pattern is consistent with the Dynamic Capabilities View because a capability generates superior outcomes when it is materialized through reconfiguration and innovation.

Effects of Data-Driven Culture on GDI and SOP (H5-H6)

DDC positively affected GDI (beta = 0.234; $p < 0.001$) and SOP (beta = 0.274; $p < 0.001$), supporting H5 and H6. This result demonstrates that decision culture is an organizational resource with relevance beyond the technological domain. Gupta and George (2016) identify data-driven culture as an important component of analytics capability, while Chaudhuri et al. (2024) provide evidence that it improves innovation capabilities and sustainability performance. In this model, DDC operates through two routes: it helps the institution generate better innovation and it improves performance directly through decision quality, monitoring, and resource allocation.

In higher education, DDC can be operationalized through the use of dashboards and indicator systems in leadership meetings, cross-unit data integration, evidence-based service redesign, and systematic assessment of digitalization effects on service time, cost, paper use, energy, space, and accessibility. This interpretation is consistent with Spilotro et al. (2026), who emphasize the need for data and knowledge infrastructures and integrative governance in the university twin transition. Data culture should therefore be understood not merely as a technical analytics practice but as an institutional capability connecting digital transformation and sustainability.

Moderating Role of Data-Driven Culture (H7)

The DDC x GDTC interaction had a positive and significant effect on GDI (beta = 0.388; $p < 0.001$; f-squared = 0.219), supporting H7. This is a central contribution of the model because it demonstrates that GDTC effectiveness is contingent on organizational context. Based on the standardized coefficients, the illustrative simple slope is approximately 0.055 when DDC is low (-1 SD), 0.443 at the mean, and 0.831 when DDC is high (+1 SD). The pattern indicates that the effect of GDTC on innovation is weak when data culture is low but becomes very strong when data use is institutionalized. These simple-slope values are algebraic interpretations of the standardized main and interaction coefficients rather than a separate SmartPLS simple-slope output and are used only to clarify the direction of moderation.

Theoretically, this finding extends the Dynamic Capabilities View by showing that green digital transformation capability requires a supportive decision context. DDC strengthens sensing because relevant information becomes more accessible and credible, strengthens seizing because solution priorities can be selected on the basis of evidence, and strengthens transforming because outcomes of change can be monitored. This result complements Chaudhuri et al. (2024), who treat DDC as an antecedent of innovation capability, by demonstrating its role as a boundary condition. In higher education, the implication is clear: platform development without data governance and a culture of data use may produce administrative digitalization rather than genuine transformation.

Theoretical Implications

The study offers four theoretical implications. First, it extends GDTC to higher education, a sector increasingly exposed to the twin transition but still less frequently examined quantitatively than manufacturing. Second, the results support a capability-innovation-performance mechanism: GDTC directly improves SOP, yet part of its influence operates through GDI. Third, DDC functions not only as an antecedent but also as a boundary condition that determines the strength with which GDTC is converted into innovation. Fourth, the significant conditional indirect effect indicates that alignment between digital-green capability and an evidence-oriented culture can extend to sustainability performance through innovation. The contribution is therefore not limited to showing that digitalization affects sustainability; it clarifies how and under what organizational condition the relationship becomes stronger.

Practical Implications and SDG Relevance

For higher education managers in Makassar City, the findings imply that digital transformation should be managed as a capability portfolio rather than as a collection of applications. First, digital strategy should be integrated with sustainability objectives, with each digital initiative accompanied by indicators of its effects on process time, paper use, energy, space, cost, accessibility, or service quality. Second, universities should establish an innovation pipeline through which work units can propose, test, measure, and scale green digital solutions. Third, data governance should be strengthened through clear data ownership, interoperability, data quality, relevant dashboards, data literacy, and mechanisms that embed evidence in managerial decisions. Cybersecurity, privacy, and ethical data use should also be treated as prerequisites so that digital sustainability does not introduce new institutional risks.

These implications are relevant to SDG 9 through infrastructure, innovation, and technological capability; SDG 12 through resource efficiency and waste reduction; and SDG 13 through monitoring and decision capabilities that support climate action (United Nations, 2015). In higher education, digital-green integration is also consistent with the development of smart universities and sustainable digital university ecosystems discussed in recent research (Zou et al., 2024; Bulut & Oğuz Haçat, 2026). The present study does not operationalize SDG achievement as a statistical construct; SDG linkages are therefore interpreted as organizational and policy implications of the empirical findings.

Limitations and Future Research

Several limitations should be acknowledged. First, all constructs were measured through individual respondents' perceptions during a single data-collection period. As an additional statistical check, full-collinearity VIFs ranged from 1.243 to 2.017, below Kock's (2015) threshold of 3.3, suggesting that serious common method bias was unlikely. Nevertheless, future studies should use multi-source or time-lagged designs where possible. Second, the cross-sectional design limits causal inference; longitudinal or multi-wave data could test the temporal ordering among GDTC, innovation, and performance. Third, SOP was modeled as a global reflective construct even though its indicators span economic/operational, environmental, and social performance; future work may compare this specification with a hierarchical component model. Fourth, geographical generalizability is limited to Makassar City, and replication across multiple cities or provinces is needed to assess the stability of the model in broader contexts.

CONCLUSION

The results are consistent with the Dynamic Capabilities View. GDTC positively affects both GDI and SOP; GDI improves SOP and partially mediates the GDTC-SOP relationship; and DDC improves GDI and SOP while strengthening the effect of GDTC on GDI. R-squared values of 0.427 for GDI and 0.504 for SOP, together with positive Q-squared values, indicate satisfactory explanatory power and predictive relevance. The positive DDC x GDTC interaction is particularly important because it shows that green digital transformation capability generates innovation more effectively when an institution has a data-driven decision culture.

Conceptually, the findings position successful sustainable digital transformation as the alignment of three elements: digital-green capability, innovation that materializes capability into solutions, and a data culture that directs sensing and decision making. For universities, simply adding applications is insufficient. Institutions need to integrate systems, data, sustainability targets, innovation governance, and evidence-based decision making so that technology can generate sustained efficiency, environmental benefits, and social value.

Overall, the study demonstrates that digital transformation oriented toward sustainability creates stronger organizational value when capability is translated into green digital innovation and supported by a data-driven decision culture. For higher education, the findings imply that successful digital-green transformation requires integration among technology, data governance, process innovation, and sustainability orientation rather than merely adding applications or digitizing existing procedures.

ACKNOWLEDGMENTS

The authors thank all lecturers and educational staff at higher education institutions in Makassar City who participated in the data collection conducted from 1 to 14 April 2026, as well as all parties who supported the implementation of this study.

REFERENCES

Barney, J. (1991). Firm resources and sustained competitive advantage. Journal of Management, 17(1), 99-120. https://doi.org/10.1177/014920639101700108

Bindeeba, D. S., Tukamushaba, E. K., & Bakashaba, R. (2025). Digital transformation and its multidimensional impact on sustainable business performance: Evidence from a meta-analytic review. Future Business Journal, 11, 90. https://doi.org/10.1186/s43093-025-00511-z

Bulut, A., & Oğuz Haçat, S. (2026). The twin transition in higher education: Bibliometric insights into digital and green convergence. European Journal of Education, 61(1), e70526. https://doi.org/10.1111/ejed.70526

Carmo, J. E. S., Lacerda, D. P., Klingenberg, C. O., & Piran, F. A. S. (2025). Digital transformation in the management of higher education institutions. Sustainable Futures, 9, 100692. https://doi.org/10.1016/j.sftr.2025.100692

Chaudhuri, R., Chatterjee, S., Mariani, M. M., & Wamba, S. F. (2024). Assessing the influence of emerging technologies on organizational data driven culture and innovation capabilities: A sustainability performance perspective. Technological Forecasting and Social Change, 200, 123165. https://doi.org/10.1016/j.techfore.2023.123165

Chen, Y. S., Lai, S. B., & Wen, C. T. (2006). The influence of green innovation performance on corporate advantage in Taiwan. Journal of Business Ethics, 67, 331-339. https://doi.org/10.1007/s10551-006-9025-5

Elkington, J. (1997). Cannibals with Forks: The Triple Bottom Line of 21st Century Business. Capstone.

Elliot, S. (2011). Transdisciplinary perspectives on environmental sustainability: A resource base and framework for IT-enabled business transformation. MIS Quarterly, 35(1), 197-236. https://doi.org/10.2307/23043495

Gupta, M., & George, J. F. (2016). Toward the development of a big data analytics capability. Information & Management, 53(8), 1049-1064. https://doi.org/10.1016/j.im.2016.07.004

Hair, J. F., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2022). A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM) (3rd ed.). Sage.

Hair, J. F., Risher, J. J., Sarstedt, M., & Ringle, C. M. (2019). When to use and how to report the results of PLS-SEM. European Business Review, 31(1), 2-24. https://doi.org/10.1108/EBR-11-2018-0203

Hanelt, A., Bohnsack, R., Marz, D., & Antunes Marante, C. (2021). A systematic review of the literature on digital transformation: Insights and implications for strategy and organizational change. Journal of Management Studies, 58(5), 1159-1197. https://doi.org/10.1111/joms.12639

Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. Journal of the Academy of Marketing Science, 43, 115-135. https://doi.org/10.1007/s11747-014-0403-8

Huang, C.-H., & Huang, Y.-C. (2024). Exploring the linkages among green digital transformation capability, ambidextrous green learning and sustainability performance: A case study of manufacturing firms in Taiwan. Journal of Manufacturing Technology Management, 35(5), 1103-1123. https://doi.org/10.1108/JMTM-10-2023-0452

Huang, Y.-C., Huang, C.-H., & Lin, S.-Y. (2026). Leveraging green digital transformation capability for ambidextrous green innovation: A pathway to sustainability performance in Taiwan's manufacturing sectors. Sustainable Development, 1-21. https://doi.org/10.1002/sd.70934

Jenkin, T. A., Webster, J., & McShane, L. (2011). An agenda for green information technology and systems research. Information and Organization, 21(1), 17-40. https://doi.org/10.1016/j.infoandorg.2010.09.003

Kock, N. (2015). Common method bias in PLS-SEM: A full collinearity assessment approach. International Journal of e-Collaboration, 11(4), 1-10. https://doi.org/10.4018/ijec.2015100101

Lu, H. T., Li, X., & Yuen, K. F. (2023). Digital transformation as an enabler of sustainability innovation and performance - Information processing and innovation ambidexterity perspectives. Technological Forecasting and Social Change, 196, 122860. https://doi.org/10.1016/j.techfore.2023.122860

Melville, N. P. (2010). Information systems innovation for environmental sustainability. MIS Quarterly, 34(1), 1-21. https://doi.org/10.2307/20721412

Nambisan, S., Lyytinen, K., Majchrzak, A., & Song, M. (2017). Digital innovation management: Reinventing innovation management research in a digital world. MIS Quarterly, 41(1), 223-238. https://doi.org/10.25300/MISQ/2017/41:1.03

Ringle, C. M., Wende, S., & Becker, J.-M. (2024). SmartPLS 4. SmartPLS GmbH.

Shen, Y., Deng, Y., Xiao, Z., Zhang, Z., & Dai, R. (2025). Driving green digital innovation in higher education: The influence of leadership and dynamic capabilities on cultivating a green digital mindset and knowledge sharing for sustainable practices. BMC Psychology, 13, 288. https://doi.org/10.1186/s40359-025-02552-z

Spilotro, C., Posa, M., Secundo, G., & De Turi, I. (2026). Disclosing the twin transition: Digital and green transformation in Italian universities from an institutional perspective. Journal of Innovation & Knowledge, 14, 100964. https://doi.org/10.1016/j.jik.2026.100964

Teece, D. J. (2007). Explicating dynamic capabilities: The nature and microfoundations of (sustainable) enterprise performance. Strategic Management Journal, 28(13), 1319-1350. https://doi.org/10.1002/smj.640

Teece, D. J., Pisano, G., & Shuen, A. (1997). Dynamic capabilities and strategic management. Strategic Management Journal, 18(7), 509-533. https://doi.org/10.1002/(SICI)1097-0266(199708)18:7<509::AID-SMJ882>3.0.CO;2-Z

United Nations. (2015). Transforming our world: The 2030 Agenda for Sustainable Development. United Nations.

Verhoef, P. C., Broekhuizen, T., Bart, Y., Bhattacharya, A., Dong, J. Q., Fabian, N., & Haenlein, M. (2021). Digital transformation: A multidisciplinary reflection and research agenda. Journal of Business Research, 122, 889-901. https://doi.org/10.1016/j.jbusres.2019.09.022

Vial, G. (2019). Understanding digital transformation: A review and a research agenda. The Journal of Strategic Information Systems, 28(2), 118-144. https://doi.org/10.1016/j.jsis.2019.01.003

Wang, S., & Zhang, H. (2025). Enhancing SMEs sustainable innovation and performance through digital transformation: Insights from strategic technology, organizational dynamics, and environmental adaptation. Socio-Economic Planning Sciences, 98, 102124. https://doi.org/10.1016/j.seps.2024.102124

Warner, K. S. R., & Wäger, M. (2019). Building dynamic capabilities for digital transformation: An ongoing process of strategic renewal. Long Range Planning, 52(3), 326-349. https://doi.org/10.1016/j.lrp.2018.12.001

Watson, R. T., Boudreau, M.-C., & Chen, A. J. (2010). Information systems and environmentally sustainable development: Energy informatics and new directions for the IS community. MIS Quarterly, 34(1), 23-38. https://doi.org/10.2307/20721413

Wu, Y., Alsagr, N., Aman, A., & Suhail, A. (2026). Accelerating the green shift: How green digital transformation capabilities foster sustainable innovation performance through circular economy readiness and business innovation environment. Corporate Social Responsibility and Environmental Management, 33(3), 3543-3562. https://doi.org/10.1002/csr.70340

Xu, J., Yu, Y., Zhang, M., & Zhang, J. Z. (2023). Impacts of digital transformation on eco-innovation and sustainable performance: Evidence

from Chinese manufacturing companies. Journal of Cleaner Production, 393, 136278. https://doi.org/10.1016/j.jclepro.2023.136278
Zou, Y., Zhong, N., Chen, Z., & Zhao, W. (2024). Bridging digitalization and sustainability in universities: A Chinese green university initiative in the digital era. Journal of Cleaner Production, 469, 143181. https://doi.org/10.1016/j.jclepro.2024.143181