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The Influence of Artificial Intelligence Literacy and Digital Transformation on Sustainable Organization Performance and Digital Leadership as Mediating Factors

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KEYWORDS

AI literacy; digital transformation; digital leadership; sustainable organization performance; resource-based view; dynamic capabilities..

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ABSTRACT

The rapid growth of Indonesia's e-commerce industry in the era of Industry 4.0 and Society 5.0 requires companies to be not only competitive but also able to achieve long-term sustainability. Despite the widespread adoption of digital technologies and artificial intelligence (AI), many e-commerce companies still face profitability and sustainability challenges. This study aims to analyze the influence of AI Literacy (AIL) and Digital Transformation (DT) on Sustainable Organizational Performance (SOP), with Digital Leadership (DL) as a mediating variable. The research approach used is quantitative with the Structural Equation Modeling–Partial Least Squares (SEM-PLS) technique. Data was collected through an online questionnaire from 273 marketing division employees from the five largest e-commerce companies in Indonesia (Shopee, Tokopedia, Lazada, Blibli, and Bukalapak) who were selected by purposive sampling. The results show that AI Literacy and Digital Transformation have a direct negative influence on sustainability performance, showing the paradox that technological readiness does not automatically produce sustainable performance. On the contrary, Digital Leadership plays a significant role as a mediator, which transforms these negative effects into positive indirect influences through adaptive and strategic leadership. The implications of this study show that digital literacy and transformation do not automatically improve organizational sustainability without adaptive and value-oriented leadership. For practitioners, these results emphasize the importance of investing in the development of digital leadership and organizational culture that aligns with ethics and sustainability goals. For academics, this research enriches the RBV theory by integrating the dimension of Dynamic Capabilities in the context of digitalization. Further research is suggested to expand the model by adding contextual variables such as organizational culture, AI governance, or green innovation to make the understanding of the relationship between technology and sustainability more comprehensive.

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1. INTRODUCTION

The development of digital technology is a major driver of business transformation in various sectors, including the e-commerce industry (Tran & Khoa, 2025). E-commerce has experienced rapid growth globally in recent decades. This transformation fundamentally changes the way consumers and business actors interact in buying and selling activities, from conventional systems to more efficient and integrated online platforms (Costa & Rodrigues, 2024). Advances in information technology, increased internet access, and changes in consumer behavior that increasingly rely on digital channels have accelerated the growth of e-commerce globally (Ahi et al., 2023). By 2024, the value of the global e-commerce market is estimated to reach USD 18.77 trillion, with projected growth to reach USD 75.12 trillion by 2034, reflecting a compound annual growth rate (CAGR) of 14.9% (Globe News Wire, 2025). This figure confirms the major shift from traditional trade patterns towards a digital system, while showing that technology adoption is now a major foundation in global economic development (Paun et al., 2024).

In the next few years, e-commerce is projected to continue to show rapid growth in various regions, especially in developing countries with high digital market potential (F. Li & Gan, 2025). This difference in growth rates illustrates the diversity of infrastructure readiness, technology adoption, and consumer behavior in utilizing digital platforms (Roszko-Wójtowicz et al., 2024). .

In Indonesia, the development of e-commerce shows very rapid growth and contributes greatly to the national digital economy. The value of Indonesia's e-commerce transactions in 2024 is estimated to reach USD 75 billion, with a projected CAGR of 19% until 2027 (Morgan, 2024). This growth is driven by several key factors, such as increased mobile connectivity, widespread adoption of digital payment systems, and the development of social commerce that combines social activities and online transactions. Figure 1 describes the trend of increasing the value of the Indonesian e-commerce market from 2019 to 2028, which shows consistent growth, although the annual growth rate tends to decline gradually. This phenomenon indicates that the national digital market is starting to move towards a maturity phase, where innovation-based competition and service quality will be the main differentiating factors between industry players

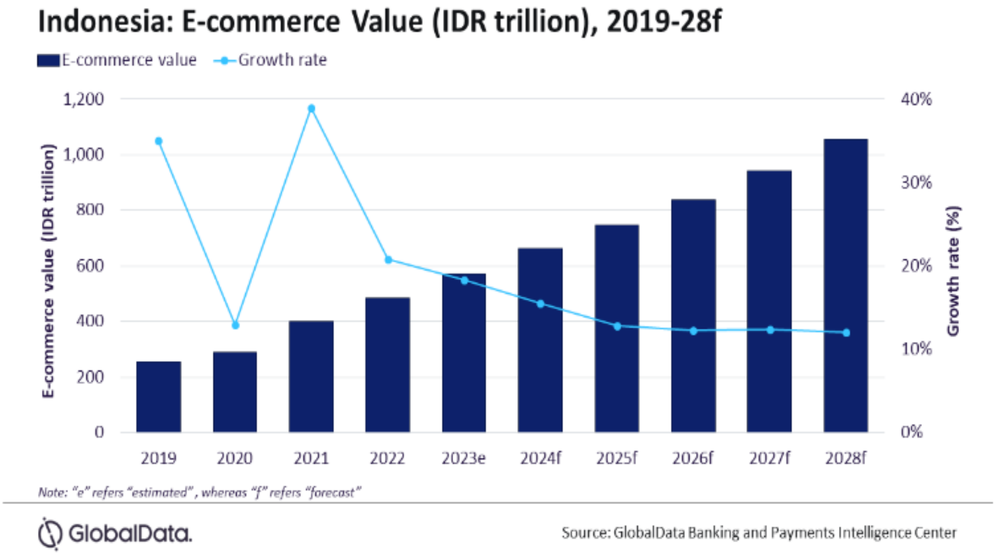

Figure 1

Projected Value of Indonesian E-commerce (2019–2028)

Source: (Kalodata, 2024)

The growth of the e-commerce market is also supported by an increase in people's digital literacy and increasingly equal access to technology. Internet penetration and smartphone use allow more consumers to connect with online shopping platforms, creating a great opportunity for digital business actors to expand market share (Bening et al., 2023; Nuralam et al., 2024). In addition, the Indonesian government plays an active role in encouraging digital transformation through policies, regulations, and strategic programs that support the strengthening of the e-commerce ecosystem (Ariansyah et al., 2021). The combination of these factors strengthens Indonesia's position as one of the fastest-growing e-commerce markets in Southeast Asia and opens up wide opportunities for improving the Sustainable Organizational Performance (SOP) of national digital industry players. In this context, the sustainability of organizational performance is not only measured by the volume of transactions, but also by the company's ability to maintain operational efficiency, social responsibility, and environmental sustainability simultaneously.

This research presents novelty by exploring the relationship between digital leadership and Sustainable Organization Performance in the context of the e-commerce sector in Indonesia, a very dynamic sector that is still rarely studied empirically from the perspective of leadership and digital transformation. This study specifically addresses the limitations of the research of Asbeetah et al. (2025), which focuses on the manufacturing industry in Turkey with a cross-sectional approach and limited internal variables, by shifting the focus to a much more dynamic and technology-responsive digital services sector. This research expands the theoretical model by adding AI literacy as a new exogenous variable, as well as digital leadership as a mediator that connects digital transformation with Sustainable Organization Performance. In contrast to the research of Gao et al. (2023), which focuses on the adoption of technology in the form of operational platforms such as e-commerce and digital marketing, this study emphasizes the importance of AI literacy as a form of organizational strategic readiness in understanding and utilizing artificial intelligence in an integrated manner. The model developed in this study provides a new perspective that the success of Sustainable Organization Performance is also determined by digital leadership.

Based on the formulation of the problem that has been prepared, this study aims to test and analyze:

The effect of artificial intelligence literacy on Sustainable Organization Performance in e-commerce companies.

The Influence of Digital Transformation on Sustainable Organization Performance in E-Commerce Companies.

The effect of artificial intelligence literacy on digital leadership in e-commerce companies.

The influence of digital transformation on digital leadership in e-commerce companies.

The Influence of Digital Leadership on Sustainable Organization Performance in E-commerce Companies.

The role of digital leadership mediates the influence of artificial intelligence literacy on Sustainable Organization Performance in e-commerce companies.

The role of digital leadership mediates the influence of digital transformation on Sustainable Organization Performance in e-commerce companies.

2. RESEARCH METHODS

Approaches and Types of Research

The approach used in this study is quantitative. According to Malhotra & Birks (2007), quantitative research is a methodology that seeks to measure and quantify data in the form of numbers, so statistical analysis is needed in the process. Cooper & Schindler (2014) explain that quantitative research aims to measure something precisely. This study uses the concept of causality between variables, which is built in a conceptual framework. This type of causality research applies deductive reasoning, which systematically starts from the perspective of rationality and general theory, then narrows it down to specific hypotheses that can be tested empirically (Sekaran & Bougie, 2017).

This study examines the correlative relationship between several variables, namely AI Literacy (AIL), Digital Transformation (DT), Digital Leadership (DL), and Sustainability performance (SP). The approach used is quantitative, with the foundation of the philosophy of positivism, which focuses on testing the relationships between variables and their correlations in order to gain a deeper understanding of these relationships between these variables.

Research Strategy

This study applied a survey strategy using an online questionnaire distributed through Google Forms. The level of researcher involvement is minimal, which means that research is conducted in a natural environment without intervention. Data were collected from a sample of the population using questionnaires as the primary instruments. The survey method was chosen because it was considered appropriate and effective when the research variables had been identified and could be reliably measured, and the respondents' goals were also known (Sekaran & Bougie, 2017).

Research Variables

Variables are a key element in quantitative research and are defined in theory as characteristics that can differ between individuals or between objects (Sekaran & Bougie, 2017). In this study, the variables to be discussed include endogenous (bound), exogenous (free), and mediated variables, which are the basis for the research analysis.

Data Source

Data Primer

This study uses primary data, namely data obtained directly at the time of data collection and has never been analyzed by other parties, and was collected for specific research purposes (Sekaran & Bougie, 2017). In this study, primary data were obtained through questionnaires. To ensure the validity and reliability of the data, the questionnaire was distributed in two stages. The first stage is pilot testing or pre-testing, which involves a total of 30 respondents. According to Perneger et al. (2015), the pilot sample size should ideally be no less than 30 participants. Pre-testing serves to detect questions that are not clear or difficult for respondents to understand. In the second stage, after ensuring that all the questions in the questionnaire have been proven to be valid and reliable, the questionnaire is then distributed to the main respondents in the study.

Data Seconds

Data that is not obtained directly from the research collection process is called secondary data (Sekaran & Bougie, 2017). In this study, secondary data is used as an additional reference to explain the rejected hypothesis, so that it can provide deeper insights related to the phenomenon being studied. Secondary data sources in this study refer to published scientific articles, official reports from survey institutions, and e-books relevant to the research topic.

Data Collection Techniques

Data collection was carried out through the distribution of questionnaires using Google Forms, which were sent electronically via email, WhatsApp, and Telegram. This method was chosen by researchers because it is considered the most efficient, fast, and able to reach more respondents. The questionnaire consisted of 58 questions representing each research variable, with measurements using a 4-point Likert scale. According to Joshi et al. (2015), the Likert Scale is an instrument commonly used in surveys to measure respondents' attitudes towards a statement or topic.

Respondents were asked to indicate their level of agreement with the statements presented in the form of an ordinal scale. The Likert scale offers clear and easy-to-understand options, allowing respondents to express the frequency or intensity of a behavior, activity, or feeling (Roy, 2020). The Likert scale makes it easier for researchers to quantitatively measure attitudes that are useful in the process of data analysis and decision-making (Awang et al., 2016).

Population and Research Sample

Population

Population is the whole (universum) of research objects, which can be in the form of humans, animals, plants, air, symptoms, values, events, attitudes of life, and so on (Sekaran & Bougie, 2017). The research population is the entire subject or individual who has certain characteristics that are set by the researcher as the object of study (Adu, 2023). The population is the group that is the source of data in the study and is used to draw conclusions based on the results of the analysis (Bhat et al., 2024). The population of this study is shown in Table 1 below.

Table 1 Total Population

No.	Company	Number of Employees Marketing Division
1	Shopee	350
2	Tokopedia	150
3	Loop	250
4	Blibli	120
5	Bukalapak	75
	Total	945

Sample

Samples are part of a population that is systematically selected to represent population characteristics in scientific research (Cheek & ØBy, 2023). The use of samples aims to obtain relevant and representative data in a time, effort, and cost-efficient manner, without compromising the validity of results that can be generalized to a wider population (Wu & Thompson, 2020).

The sampling technique in this study is purposive sampling, a non-probability sampling technique. The selection of this technique is based on the consideration that the study requires respondents with specific characteristics and expertise that are directly related to the research variable, namely marketing division employees at the five largest e-commerce companies who have direct experience in the use of AI technology and digital transformation processes (Sekaran & Bougie, 2017). The inclusion criteria set are: (1) have worked for more than one year, and (2) have a minimum of a Diploma education. These criteria are set to ensure that respondents have professional understanding and practical experience in digital marketing activities, so that they are able to provide relevant responses to research constructs such as AI Literacy, Digital Leadership, and Sustainable Organization Performance. Thus, the data obtained is expected to reflect the empirical reality in the field and support the external validity of the research.

3. RESULTS AND DISCUSSION

Descriptive Analysis of Variables

In this study, the measurement scale used is the ordinal scale, which was later developed into the Range Scale (RS). A scale range is used to classify respondents' response rates, ranging from very low to very high. According to the concept of scale range, the calculation is done with the following formula:

$$RS = \frac{\text{Highest Score - Lowest Score Number of}}{\text{Classes}}$$

The division of the scale range in this study was used to classify respondents' answer rates from very low to very high. Scores of 1.00 to 1.80 are categorized as Very Low, 1.81 to 2.60 as Low, 2.61 to 3.40 as Fair, 3.41 to 4.20 as High, and 4.21 to 5.00 as Very High. This information is a reference to interpret the distribution of respondents' answers to each research variable in the next descriptive analysis.

Descriptive statistical analysis was carried out to provide an overview of the characteristics of the research data, especially on the latent variables or constructs being studied. This method evaluates data based on mean values, standard deviations, and maximum and minimum values. (Purwanto & Sudargini, 2021). The mean value reflects the central or average tendency of the respondents' answers to each variable indicator, while the standard deviation indicates the extent to which the data is spread from the mean value, providing information regarding the variation or heterogeneity of the answers. The maximum and minimum values indicate the highest and lowest scores given by respondents, thus illustrating the range of assessments for each indicator item.

Thus, descriptive analysis provides a preliminary understanding of the homogeneity, diversity, and tendencies of respondents' answers. The variables analyzed in this study include *AI Literacy* (X1), *Digital Transformation* (X2), *Digital Leadership* (M), and *Sustainable Organization Performance* (Y), which are the basis for interpretation for further analysis stages in the research.

Analysis of *AI Literacy* Variable Descriptions (X1)

The AI Literacy (X1) variable was measured using 12 statement items grouped into four dimensions, namely *Awareness (AW), Understanding (US), Evaluation (EV),* and *Ethical Issues (ET).* The distribution of respondents' answers, frequency, percentage, and mean can be seen in **Table 2.**

Table 2 AI Literacy Variable Respondent Answers

Code	SS (4)		S (3)		TS (2)		STS (1)		*Mean*
	F	%	F	%	F	%	F	%	
AW1	125	45.79%	47	17.22%	63	23.08%	38	13.92%	2.95
AW2	70	25.64%	82	30.04%	68	24.91%	53	19.41%	2.62
AW3	109	39.93%	70	25.64%	61	22.34%	33	12.09%	2.93
US1	87	31.87%	95	34.80%	53	19.41%	38	13.92%	2.85
US2	114	41.76%	52	19.05%	71	26.01%	36	13.19%	2.89
US3	72	26.37%	95	34.80%	61	22.34%	45	16.48%	2.71
EV1	108	39.56%	68	24.91%	66	24.18%	31	11.36%	2.93
EV2	93	34.07%	87	31.87%	53	19.41%	40	14.65%	2.85
EV3	109	39.93%	56	20.51%	70	25.64%	38	13.92%	2.86
ET1	85	31.14%	83	30.40%	68	24.91%	37	13.55%	2.79
ET2	99	36.26%	79	28.94%	64	23.44%	31	11.36%	2.90
ET3	77	28.21%	101	37.00%	55	20.15%	40	14.65%	2.79
Average	95.67	35.04%	76.25	27.93%	62.75	22.99%	38.33	14.04%	2.84

The results showed that in the *Awareness* (AW) dimension, respondents had a relatively good awareness of artificial intelligence (AI) issues, with the highest score on the AW1 indicator (2.95). However, weaknesses are still visible in the AW2 indicator (2.62), which shows that some respondents do not fully understand certain aspects of AI. In the *Usage* (US) dimension, the level of AI utilization was in the moderate category with an average score of 2.71–2.89, where the US3 indicator (2.71) obtained the lowest score. This indicates that limitations in the practical application of AI are still an obstacle for most respondents.

Meanwhile, in the Evaluation (EV) dimension, respondents showed a fairly good ability to assess the benefits and risks of AI, shown by the highest score on EV1 (2.93). This condition reflects a critical awareness of the use of this technology. In the Ethical Issues (ET) dimension, attention to the ethical aspects of AI was also moderate, with the highest score at ET2 (2.90), although the ET3 indicator (2.79) showed the need for increased normative and ethical awareness. Overall, respondents' AI literacy is in the sufficient category, with strengths in the aspects of awareness and evaluation, but still needs to be strengthened in depth understanding and practical application. These findings have important implications for organizations to design training and education strategies that not only emphasize ethical aspects but also strengthen technical and conceptual competencies to support sustainable digital transformation.

Analysis of Digital *Transformation* (X2) Variable Description

The Digital Transformation (X2) variable is measured through 25 statement items that cover several dimensions, namely Business Strategy (BS), Data Analytics (DA), Innovation and Integration (II), Infrastructure and Digitalization (ID), Digital Culture (DC), and Environmental and Social Impact (EESI). The distribution of respondents' answers, frequency, percentage, and mean can be seen in Table 3.

Table 3 Digital Transformation Variable Respondent Answers

Code	SS (4)		S (3)		TS (2)		STS (1)		*Mean*
	F	%	F	%	F	%	F	%	
BS1	77	28.21%	101	37.00%	55	20.15%	40	14.65%	2.79
BS2	66	24.18%	112	41.03%	51	18.68%	44	16.12%	2.73
BS3	64	23.44%	113	41.39%	63	23.08%	33	12.09%	2.76
BS4	74	27.11%	105	38.46%	60	21.98%	34	12.45%	2.80
BS5	63	23.08%	112	41.03%	60	21.98%	38	13.92%	2.73
BS6	72	26.37%	104	38.10%	58	21.25%	39	14.29%	2.77
BS7	54	19.78%	123	45.05%	64	23.44%	32	11.72%	2.73
DA1	86	31.50%	91	33.33%	56	20.51%	40	14.65%	2.82
DA2	70	25.64%	108	39.56%	58	21.25%	37	13.55%	2.77
DA3	70	25.64%	107	39.19%	58	21.25%	38	13.92%	2.77
DA4	65	23.81%	115	42.12%	69	25.27%	24	8.79%	2.81
DA5	74	27.11%	104	38.10%	56	20.51%	39	14.29%	2.78
II1	61	22.34%	115	42.12%	57	20.88%	40	14.65%	2.72
II2	75	27.47%	102	37.36%	57	20.88%	39	14.29%	2.78
II3	57	20.88%	120	43.96%	61	22.34%	35	12.82%	2.73
ID1	91	33.33%	86	31.50%	60	21.98%	36	13.19%	2.85
ID2	59	21.61%	118	43.22%	64	23.44%	32	11.72%	2.75
ID3	78	28.57%	97	35.53%	69	25.27%	29	10.62%	2.82
DC1	59	21.61%	120	43.96%	51	18.68%	43	15.75%	2.71
DC2	82	30.04%	96	35.16%	56	20.51%	39	14.29%	2.81
DC3	78	28.57%	98	35.90%	61	22.34%	36	13.19%	2.80
DC4	69	25.27%	108	39.56%	64	23.44%	32	11.72%	2.78
EESI1	61	22.34%	116	42.49%	60	21.98%	36	13.19%	2.74
EESI2	79	28.94%	100	36.63%	59	21.61%	35	12.82%	2.82
EESI3	69	25.27%	106	38.83%	62	22.71%	36	13.19%	2.76
Average	70.12	0.26	107.08	0.39	59.56	0.22	36.24	0.13	2.77

Based on the calculation results, the *Digital Transformation* variable has an overall average **of 2.77**, including a *sufficient* category according to scale criteria, indicating that digital transformation in the organization is at a medium level and has shown a positive development direction. The analysis by dimension shows variations: *the Business Strategy* (BS) dimension averages 2.73–2.80, indicating that digital-based business strategies are starting to be implemented, although not evenly. The *Data Analytics* (DA) dimension was stable at 2.77–2.82, reflecting the use of data analytics that is sufficient to support decision-making.

The *Innovation and Integration* (II) dimension averaged 2.72–2.78, indicating inconsistent efforts at digital innovation and integration. *Infrastructure and Digitalization* (ID) is relatively superior (ID1 = 2.85), indicating a fairly good readiness of digital infrastructure. The *Digital Culture* (DC) and *Environmental and Social Impact* (EESI) dimensions averaged 2.71–2.81 and 2.82, respectively, indicating the formation of digital culture and moderate attention to sustainability. Overall, digital transformation is at an intermediate stage, with strength in infrastructure and data analytics, while digital culture, innovation, and business strategies still need to be strengthened to support more effective and sustainable transformation.

Analysis of *Digital Leadership* Variable Description (Z)

The Digital Leadership (Z) variable was measured using five statement items, which included the dimensions *of technology adoption* (TA), *empowerment & support* (ES), *risk-taking & innovation* (RI), and *collaborative vision* (CV). The distribution of respondents' answers and average scores can be seen in Table 4.

Table 4 Answers of Digital Leadership Variable Respondents

Code	SS (4)		S (3)		TS (2)		STS (1)		*Mean*
	F	%	F	%	F	%	F	%	
TA1	74	27.11%	74	27.11%	81	29.67%	44	16.12%	2.65
TA2	66	24.18%	81	29.67%	65	23.81%	61	22.34%	2.56
ES1	60	21.98%	87	31.87%	77	28.21%	49	17.95%	2.58
RI1	79	28.94%	69	25.27%	75	27.47%	50	18.32%	2.65
CV1	62	22.71%	86	31.50%	79	28.94%	46	16.85%	2.60
Average	68.20	0.25	79.40	0.29	75.40	0.28	50.00	0.18	2.61

Based on Table 4, the Digital Leadership (Z) variable measured through five indicators in the dimensions of technology adoption (TA), empowerment & support (ES), risk-taking & innovation (RI), and collaborative vision (CV) obtained an overall average **score of 2.61**, including the *category of sufficient* by the scale range. These results show that respondents' perceptions of digital leadership are at a moderate level. The TA and RI dimensions have a relatively higher score (2.65), indicating that technology adoption and innovation encouragement have begun to be implemented, although not evenly.

The ES and CV dimensions obtained an average score of 2.58–2.60, which reflects the empowerment of the team and the collaborative vision is beginning to be implemented, but the implementation still needs consistency and improvement. Overall, digital leadership is at a medium stage, with the potential to strengthen the consistency of empowerment, develop collaborative visions, and optimize technology adoption to support the organization's digital transformation in a sustainable manner.

Measurement Model Analysis (Outer Model)

The Outer Model is one of the important stages in the Partial Least Squares Structural Equation Modeling (PLS-SEM) approach, which is used to evaluate the relationship between indicators (question items) and latent constructs (variables that cannot be measured directly). At this stage, testing is carried out on the validity and reliability of the latent constructs or variables used in the research. Outer models focus on measurement models, which assess how well indicators reflect the construct in question.

According to Ghozali (2021), the outer model test aims to ensure that the instrument or questionnaire used in the study is able to measure constructs accurately (validly) and consistently (reliably). Testing the outer model involves several statistical indicators, such as outer loading, average variance extracted (AVE), composite reliability (CR), and Cronbach's alpha. The following graphical output of the measurement model test:

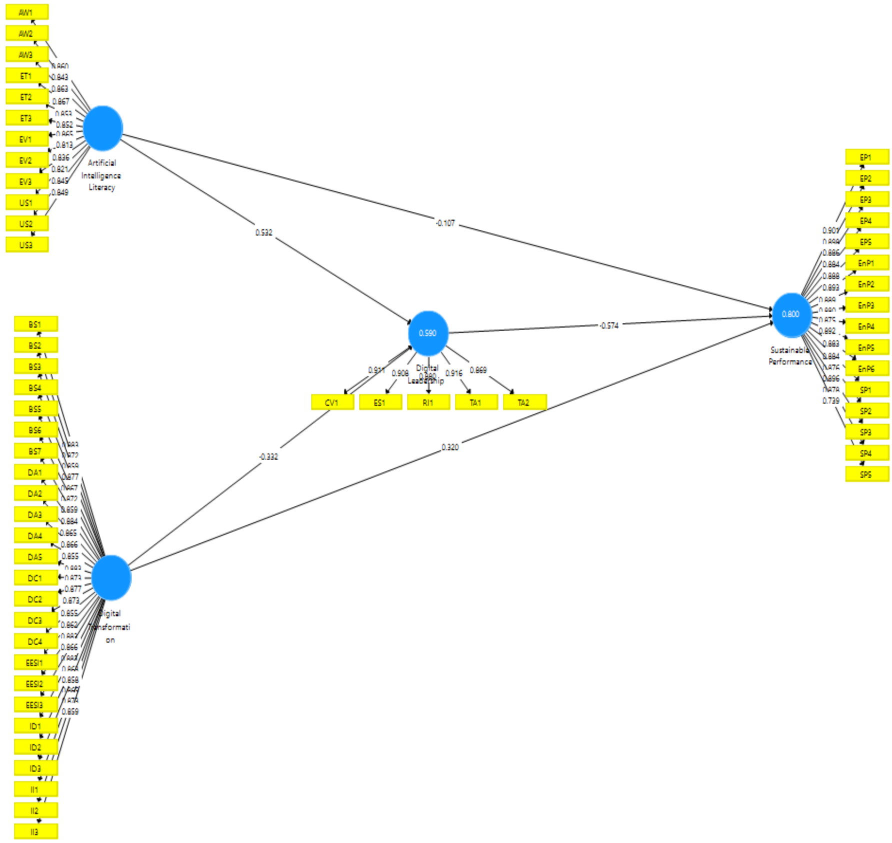

Figure 2 Outer Model Results

Based on Figure 2, the results of structural model analysis using the PLS-SEM approach show that Artificial Intelligence Literacy (AIL) has a fairly strong positive influence on Digital Leadership (DL), with a path coefficient value of 0.532. On the contrary, AIL has a negative effect on Sustainable Organizational Performance (SOP) with a coefficient of -0.413, which indicates that AI literacy without the right strategic support can pose challenges for organizational sustainability. Furthermore, Digital Transformation (DT) has a negative effect on Digital Leadership (DL) with a coefficient of -0.332, but has a direct positive effect on SOPs of 0.511. Another interesting finding is that Digital Leadership (DL) has a negative effect on SOPs with a coefficient of -0.574, a result that shows a potential mismatch between the digital leadership style applied and the needs of the organization's sustainability strategy.

The value of the determination coefficient (R^2) in the Digital Leadership and Sustainable Organizational Performance constructs is not shown in the table, but in general, these results confirm that the relationship between AI literacy, digital leadership, and digital transformation is complex. While AI literacy and digital transformation play an important role in shaping digital leadership, their impact on an organization's sustainability performance can be paradoxical, thus demanding a more adaptive managerial strategy in integrating digital technology into organizational sustainability practices.

Convergent Validity

Convergent validity *testing* is one of the stages of external model evaluation in PLS-SEM analysis, which aims to ensure that the indicators used truly represent the same construct. Convergent validity assesses the extent to which indicators in a construct have high internal consistency and accurately measure the same concept. Thus, convergent validity confirms that all indicators in a single construct have a strong correlation and lead to the same latent dimensions.

According to Hair et al. (2014), the indicator is declared to meet the requirements for convergent validity if the outer loading value is greater than 0.70. The higher the loading factor value, the greater the contribution of the indicator in explaining the latent construct being measured. In addition, the convergent validity test is also supported by *the Average Variance Extracted* (AVE) value, which reflects the average variance of the indicator that can be explained by the construct. An AVE value above 0.50 indicates that more than half of the indicator's variance can be explained by latent constructs.

Table 5 Values c

Item	AIL	DL	DT	SOP
AW1	0.860			
AW2	0.843			
AW3	0.863			
BS1			0.883	
BS2			0.872	
BS3			0.859	
BS4			0.877	
BS5			0.867	
BS6			0.872	
BS7			0.859	
CV1		0.911		
DA1			0.884	
DA2			0.865	
DA3			0.866	
DA4			0.855	
DA5			0.883	
DC1			0.873	
DC2			0.877	
DC3			0.873	
DC4			0.855	
EESI1			0.862	
EESI2			0.883	
EESI3			0.866	
EP1				0.901
EP2				0.898
EP3				0.886
EP4				0.884
EP5				0.888
ES1		0.908		
ET1	0.867			
ET2	0.853			
ET3	0.852			

Item	AIL	DL	DT	SOP
EV1	0.865			
EV2	0.813			
EV3	0.836			
EnP1				0.893
EnP2				0.889
EnP3				0.880
EnP4				0.875
EnP5				0.892
EnP6				0.883
ID1			0.883	
ID2			0.863	
ID3			0.858	
II1			0.865	
II2			0.873	
II3			0.859	
RI1		0.880		
SP1				0.884
SP2				0.876
SP3				0.896
SP4				0.878
SP5				0.739
TA1		0.916		
TA2		0.869		
US1	0.821			
US2	0.845			
US3	0.849			

Based on the table above, all indicators have an outer loading value above 0.70, except for the SP5 (0.739) and EV2 (0.813) indicators, which, although lower than other indicators, still meet the minimum threshold. This indicates that each indicator has an adequate contribution in explaining its own latent constructs. Thus, all constructs in this study have met the criteria of convergent validity, so it can be concluded that the measurement model used is convergently valid and feasible to continue at the next stage of analysis.

Table 6 AVE Value of Research Variables

Variabel	Average Variance Extracted (AVE)
Artificial Intelligence Literacy	0.718
Digital Leadership	0.804
Digital Transformation	0.756
Sustainable Organization Performance	0.772

Based on the results of the Average Variance Extracted (AVE) test, a score of 0.718 was obtained for the Artificial Intelligence Literacy construct, 0.804 for Digital Leadership, 0.756 for Digital Transformation, and 0.772 for Sustainable Organization Performance. AVE is a measure used to assess convergent validity, i.e., the extent to which a set of indicators can represent a consistently measured latent construct and explain the variance of the indicators.

Referring to the criteria put forward by Hair et al. (2014), a construct is declared to meet convergent validity if the AVE value exceeds the minimum threshold of 0.50. Thus, all constructs in this study can be categorized as convergently valid. In more detail, the AVE value of 0.718 in the Artificial Intelligence Literacy construct shows that 71.8% of the variance of the indicator can be explained by the construct. Furthermore, Digital Leadership with AVE 0.804 was able to explain 80.4% of the variance of indicators, Digital Transformation with AVE 0.756 explained 75.6%, and Sustainable Organization Performance with AVE 0.772 explained 77.2% of the variance of indicators attached to it.

These findings confirm that the four study constructs not only meet the minimum requirements of convergent validity but also demonstrate a high level of indicator consistency in reflecting the latent constructs they represent. In other words, the measurement model used has a solid basis for further analysis at the structural model evaluation stage.

Discriminant Validity

Discriminant validity is an important aspect in testing the measurement model (outer model) in *Partial Least Squares Structural Equation Modeling* (PLS-SEM). The goal is to ensure that each construct in the research model is completely distinct from the other, so that the indicators of one construct do not mismeasure other constructs. With good discriminant validity, it can be ensured that each construct is unique and empirically separate.

One of the most commonly used methods is the *Fornell-Larcker* criterion. According to Fornell & Larcker (1981), discriminant validity is achieved when the square root value of *the Average Variance Extracted* (√AVE) on the diagonal is greater than the correlation value of the construct to other constructs.

Reliability Test

Instrument reliability testing aims to ensure that the instrument used in the study is able to produce accurate, consistent, and stable measurements in measuring the construct being studied. Reliability shows the extent to which an instrument is reliable and free from systematic measurement errors. Instruments are said to be reliable if respondents provide consistent answers even though they are measured at different times or conditions (Ghozali, 2021). Thus, reliable instruments guarantee that the results of the research can be replicated under similar conditions without producing significant differences.

To test reliability, this study uses two main indicators, namely Cronbach's Alpha and Composite Reliability. According to Hair et al. (2014) and Ghozali & Latan (2015), a construct is declared reliable when Cronbach's Alpha and Composite Reliability values exceed 0.70. Values above the threshold confirm the existence of good internal consistency between indicators in measuring the same construct. The results of the reliability test in this study are presented in the following table:

Table 7 Cronbach's Alpha and Composite Reliability Values

	Cronbach's Alpha	Composite Reliability
Artificial Intelligence Literacy	0.964	0.968
Digital Leadership	0.939	0.954
Digital Transformation	0.987	0.987

Sustainable Organization Performance	0.980	0.982

Based on the results of the reliability test, all constructs in this study show *Cronbach's Alpha* and *Composite Reliability* values that are well above the minimum threshold of 0.70 as recommended by Hair et al. (2014). Construct Artificial Intelligence Literacy obtained *a Cronbach's Alpha* value of 0.964 and a Composite Reliability of 0.968, indicating an excellent level of internal consistency. Konstruk *Digital Leadership* also showed strong reliability, with a *Cronbach's Alpha* value of 0.939 and a *Composite Reliability* of 0.954.

Furthermore, the Digital Transformation construct recorded the highest score with *Cronbach's Alpha* of 0.987 and Composite Reliability of 0.987, which confirms the indicator's very high level of consistency. The Sustainable Organization Performance construct also showed excellent reliability with a *Cronbach's Alpha* value of 0.980 and a *Composite Reliability* of 0.982. Overall, these results confirm that the entire construct has a very adequate internal consistency, so that the indicators used in the study are able to consistently reflect the latent variables measured. Thus, research instruments can be declared **reliable**, which means that the quality of measurements is guaranteed, and the results of the analysis obtained can be trusted and scientifically accounted for.

Structural Model Analysis (*Inner Model*)

An inner model or structural model is a model that describes the cause-and-effect relationship (causality) between latent variables, which are variables that cannot be measured directly in research. This model is used to test and predict the influence of one latent variable on another latent variable within a pre-formulated relationship framework. Inner models focus on relationships between latent constructs that interact with each other and can describe the mechanisms underlying the phenomenon being studied.

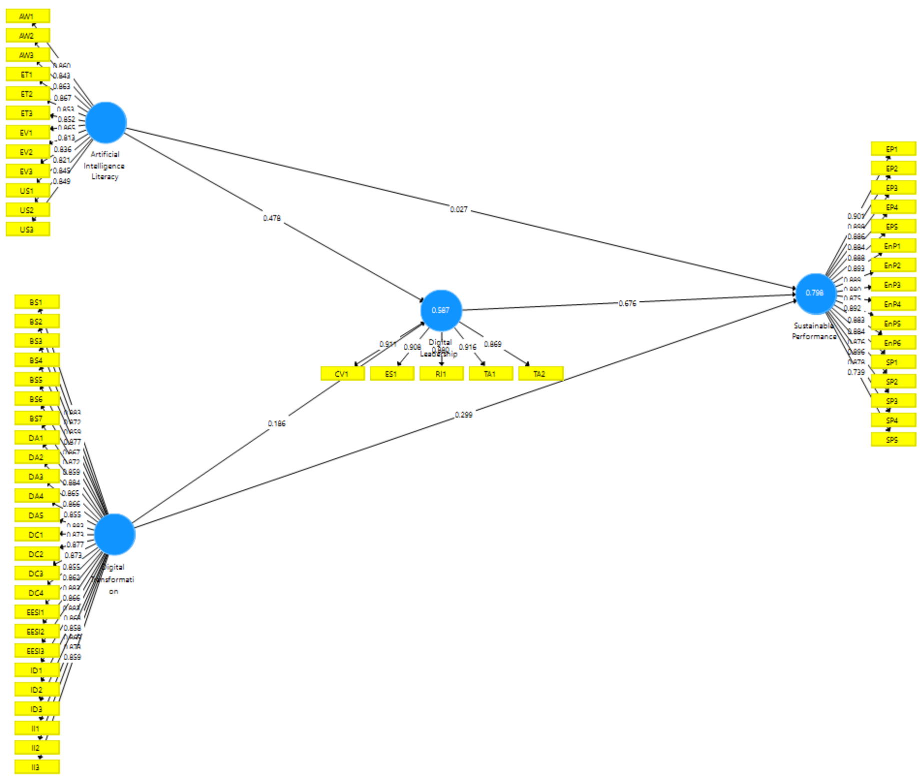

Figure 3 Inner Model Test Results

The structural model developed in this study represents the relationship between latent constructs, especially between Artificial Intelligence Literacy, Digital Transformation, Digital Leadership, and Sustainable Organization Performance. The results of the pathway analysis showed that Artificial Intelligence Literacy had a positive effect on Digital Leadership ($\beta = 0.478$), but not significantly on Sustainable Organization Performance ($\beta = 0.027$). Furthermore, Digital Transformation has a positive influence on Digital Leadership ($\beta = 0.186$) and on Sustainable Organization Performance ($\beta = 0.299$). Digital Leadership has been proven to make a substantial contribution to Sustainable Organization Performance with a path coefficient of $\beta = 0.676$, making it a key variable in the research model.

Based on the results of the estimated determination coefficient, the R-square value in the dependent construct shows a high level of model explanation. Digital Leadership has an R-square of 0.590 with an adjusted R-square value of 0.587, which means that about 58.7% of the Digital Leadership variance can be explained by Artificial Intelligence Literacy and Digital Transformation. Meanwhile, Sustainable Organization Performance obtained an R-square value of 0.800 with an adjusted R-square of 0.798, indicating that approximately 79.8% of the variance of Sustainable Organization Performance can be explained by the three predictor constructs in the model.

These findings reinforce the evidence that Digital Leadership plays a significant mediating role in linking artificial intelligence literacy and digital transformation with sustainable performance. The high R-square value and the consistency between the R-square and R-square adjusted values confirm that this research model has good structural validity and is able to provide a strong explanation of the phenomenon being studied. Thus, the results of this study not only support the proposed conceptual framework but also make an empirical contribution in understanding the strategic role of digital leadership in the era of technological transformation towards sustainable performance.

Uji Hypothesis

Direct Effect

The influence of external factors on endogenous variables directly, without involving intermediate variables, is called the direct effect. In the SEM-PLS analysis, the *path coefficient*, t-statistic value, and p-value indicate the direction and level of significance of the influence. If the t-statistic value is greater than 1.96 (double-sided test, α = 5%) or greater than 1.65 (single-sided test), and the p-value is less than 0.05, then the relationship is considered significant (Hair et al., 2022).

Table 8 Direct Test Results

Hubungan	**Original Sample (O)**	**P Values**
Artificial Intelligence Literacy → Digital Leadership	0.532	0.000
Artificial Intelligence Literacy → Sustainable Organization Performance	-0.107	0.039
Digital Leadership → Sustainable Organization Performance	-0.574	0.000
Digital Transformation → Digital Leadership	-0.332	0.000
Digital Transformation → Sustainable Organization Performance	0.320	0.000

The results of the *direct effect* analysis showed that *Artificial Intelligence Literacy* had a significant positive effect on *Digital Leadership* ($\beta = 0.532$, $t = 8.922$, $p < 0.05$). These findings indicate that the higher the artificial intelligence literacy that an organization has, the stronger the digital leadership capacity that can be developed. In other words, understanding and skills in utilizing AI technology contribute significantly to strengthening the role of digital leaders.

Furthermore, *Artificial Intelligence Literacy* had a significant negative effect on *Sustainable Organization Performance* ($\beta = -0.107$, $t = 2.074$, $p = 0.039$). These results show that increasing AI literacy does not necessarily improve the sustainable performance of organizations; in fact tends to have the opposite effect. It can be interpreted that the use of AI literacy requires the right adaptation and integration mechanisms, so that without the support of an implementation strategy that is aligned with sustainability goals, AI has the potential to reduce the effectiveness of sustainable performance.

Furthermore, *Digital Leadership* had a significant negative effect on *Sustainable Organization Performance* ($\beta = -0.574$, $t = 7.609$, $p < 0.05$). This means that the high role of digital leadership does not automatically encourage increased organizational sustainability. This negative effect hints at a possible trade-off, where the focus on technology-oriented digital leadership has not been fully integrated with the organization's sustainability agenda.

Digital *Transformation* had a significant negative effect on *Digital Leadership* ($\beta = -0.332$, $t = 6.297$, $p < 0.05$). These findings indicate that the ongoing digital transformation process is not always accompanied by an improvement in the quality of digital leadership. Conversely, transformations that are not managed strategically can give rise to resistance, adaptation challenges, or an imbalance of leadership competencies in the face of technology-based change.

Finally, *Digital Transformation* had a significant positive effect on *Sustainable Organization Performance* ($\beta = 0.320$, $t = 4.832$, $p < 0.05$). This confirms that digital transformation is directly able to improve the sustainable performance of the organization. With the right implementation of digital transformation, organizations can increase efficiency, innovation, and competitiveness, ultimately strengthening operational and strategic sustainability.

Indirect Effect

Indirect effect testing was carried out to evaluate the role of mediation variables, in this case *Digital Leadership*, in mediating the relationship between independent variables (*Artificial Intelligence Literacy* and *Digital Transformation*) and dependent variables (*Sustainable Organization Performance*). The significance of the mediation effect was determined through the criteria of *T-statistical* value (> 1.96) and *P-value* (< 0.05) according to the reference of Hair et al. (2022). This analysis allows for a more comprehensive understanding of the mechanisms of interdependency in the research model, particularly related to how digital leadership capabilities reinforce the influence of artificial intelligence literacy and digital transformation on sustainable performance.

Table 9 Indirect Test Results

Indirect Pathway	**T Statistics (|O/STDEV|)**	**P Values**
Artificial Intelligence Literacy → Digital Leadership → Sustainable Organization Performance	6.288	0.000
Digital Transformation → Digital Leadership → Sustainable Organization Performance	4.936	0.000

Based on the results of the specific *indirect effects test*, the following findings were obtained:

The Effect of Artificial Intelligence Literacy on Sustainable Organization Performance through Digital Leadership estimated results showed a T-statistic value of 6,288 and a P-value of 0,000. This value met the significance criteria (T > 1.96; P < 0.05), so it can be concluded that the indirect relationship between Artificial Intelligence Literacy and Sustainable Organization Performance through Digital Leadership is significant. Thus, Digital Leadership plays a role as a mediating variable that strengthens the contribution of artificial intelligence literacy in encouraging the sustainable performance of the organization.

The Effect of Digital Transformation on Sustainable Organization Performance through Digital Leadership mediation pathway test showed a T-statistic value of 4,936 with a P-value of 0.000. These results also met the significance criteria (T > 1.96; P < 0.05). Thus, Digital Leadership has proven to play a significant mediator role in the relationship between Digital Transformation and Sustainable Organization Performance. This indicates that the effectiveness of digital transformation in improving sustainable performance is greatly influenced by the extent to which digital leadership can direct, manage, and optimize the transformation process.

The Influence of AI Literacy on SOPs

The results of the analysis showed that AI Literacy had a significant negative effect on SOPs (β = -0.107; t = 2.074; p = 0.039). These findings indicate that improving AI literacy does not necessarily directly improve sustainable performance, especially when organizations do not have a robust structural readiness, innovative culture, and AI ethics policies.

From the perspective of the Resource-Based View (RBV), this result confirms that knowledge-based resources, such as AI literacy, are potential and have not become a valuable strategic resource if they have not been managed and strategically integrated into the organizational system. New technological knowledge will create sustainable value when supported by managerial capabilities and leadership direction that are able to convert it into a competitive advantage. In other words, AI literacy requires an internalization process in order to function as an organizational capability, not just an individual competence.

These findings are also in line with previous research that highlighted the importance of organizational context in the application of artificial intelligence. Dwivedi et al. (2021) and Nishant et al. (2020) found that AI adoption without governance and cultural readiness can lead to inefficiencies and socio-environmental risks, especially when data-driven decisions are not accompanied by the principles of transparency and accountability.

In practice, organizations need to ensure that increasing AI literacy is accompanied by the development of digital ethics, ongoing training programs, and the integration of AI in strategic decision-making processes so that its impact on sustainability is more positive.

Digital Leadership Mediation on Digital Transformation Relations and SOPs

The bootstrapping results also showed that Digital Leadership (DL) significantly mediated the relationship between Digital Transformation (DT) and Sustainable Organizational Performance (SOP) ($t = 7.004$; $p < 0.001$). These results show that digital transformation will only produce sustainable performance if accompanied by leadership that is able to steer these changes strategically. In the RBV framework, Digital Transformation represents organizational capability, while Digital Leadership is a managerial capability that ensures digital resources are effectively orchestrated towards sustainable excellence.

These findings expand the application of RBV by showing that Digital Leadership is a bridge that connects technological capabilities with the strategic value of the organization. The success of digital transformation depends on the ability of leaders to manage structural, cultural, and strategic changes so that synergy between technology and people produces a positive impact on the economic, social, and environmental dimensions. Thus, digital leadership acts as a catalyst that converts the potential of digitalization into real sustainability performance.

When viewed through the lens of Dynamic Capabilities (DC), the results of this mediation reflect the role of Digital Leadership as a dynamic capability that ensures that the reconfiguration and renewal process runs continuously. Digital leaders not only leverage existing resources but also develop the organization's ability to continuously adapt to technological advances and market changes. In this context, Digital Leadership acts as a microfoundation of the organization's dynamic capabilities, linking digital transformation investments to long-term sustainability outcomes. This confirms that the success of digitalization does not depend on technology alone, but on the ability of leaders to adjust, update, and align internal resources with external dynamics on an ongoing basis.

4. CONCLUSION

As the final part of the empirical analysis, this chapter summarizes the results of research that examines the influence of AI Literacy (AIL), Digital Transformation (DT), and Digital Leadership (DL) on Sustainable Organization Performance (SOP) in the e-commerce industry in Indonesia. Based on the results of the structural model analysis using PLS-SEM, several conclusions were obtained as follows.

First, Artificial Intelligence Literacy (AIL) had a significant negative effect on Sustainable Organizational Performance (SOP) ($\beta = -0.107$; $t = 2.074$; $p = 0.039$). These results show that increasing AI literacy has not directly improved the sustainability performance of organizations. Second, Digital Transformation (DT) had a significant positive effect on Sustainable Organizational Performance (SOP) ($\beta = 0.320$; $t = 4.832$; $p < 0.05$). These findings show that the higher the level of digitalization and technology integration in an organization, the better the sustainability performance achieved. Third, Digital Leadership (DL) has a significant negative effect on Sustainable Organizational Performance (SOP) ($\beta = -0.574$; $t = 7.609$; $p < 0.05$). These results indicate that digital leadership that is too focused on technological efficiency without paying attention to social and environmental dimensions can reduce sustainability performance. Fourth, AI Literacy has a significant positive effect on Digital Leadership ($\beta = 0.532$; $t = 8.922$; $p < 0.05$), showing that understanding and skills in managing AI strengthen the quality of digital leadership, especially in terms of data-driven decision-making, digital innovation, and strategic adaptation. Fifth, Digital Transformation had a significant negative effect on Digital Leadership ($\beta = -0.332$; $t = 6.297$; $p < 0.05$). These results suggest that accelerating digitalization without cultural readiness and organizational structure can put pressure on leaders, reducing their effectiveness in managing change. Sixth, Digital Leadership has been shown to significantly mediate the influence of AI Literacy on Sustainable Organizational Performance ($t = 6.288$; $p = 0.000$) and the influence of Digital Transformation on Sustainable Organizational Performance ($t = 7.004$; $p < 0.001$).

Overall, the results of this study show that the achievement of Sustainable Organizational Performance does not only depend on technology investment, but on the organization's ability to manage, direct, and balance digital resources through adaptive and sustainability-oriented leadership capabilities. This reinforces the relevance of the Resource-Based View as the primary framework for explaining sustainable excellence in the digital age, with the support of the Dynamic Capabilities perspective that explains the adaptive dimension of the management of such resources..

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