Business Management
Vol. 5 No 4 November 2026
p-ISSN:2828-7606, e-ISSN:2828-8203
Link: https://ejournal.mandalanursa.org/index.php/Bisnis

Digital Popularity and Tourist Arrivals in Labuan Bajo and Raja Ampat: Evaluating Indonesia's Super Priority Destination Policy

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Article Info
Article history:
Accepted: 3 November 2026
Publish: 11 November 2026

Keywords:
Difference-in-Differences (DiD); Digital Popularity; Google Trends; Super Priority Destinations; Tourist Arrivals.

Abstract
This study examines the relationship between digital popularity and tourist arrivals in Labuan Bajo and Raja Ampat, focusing on differences between Indonesia's Super Priority Destination (DSP) and non-priority destination policies. Monthly Google Trends data and annual tourist arrival statistics covering 2015–2025 were analyzed using geographic distribution analysis, Pearson correlation, and a multilevel modeling approach to compare tourism growth before and after DSP implementation. The results reveal different relationships between digital popularity and tourist arrivals across the two destinations. Labuan Bajo showed strong positive correlations between tourist arrivals and global ($r = 0.8712$) and domestic digital popularity ($r = 0.8912$), whereas Raja Ampat showed moderate correlations of 0.6543 and 0.5210, respectively. Tourist arrivals increased by 425.9% in Labuan Bajo and 75.8% in Raja Ampat over the study period. The multilevel model identified a positive and statistically significant interaction between DSP status and the post-policy period ($\gamma_{21} = 12.800$; $p < 0.05$), indicating different post-policy growth patterns between the destinations. However, the significant pre-policy growth difference suggests that their tourism trajectories were already unequal before DSP implementation. The findings highlight the importance of integrating digital indicators and official tourism statistics in evaluating destination performance. They also suggest that tourism policies should consider destination readiness, accessibility, and balanced development to strengthen the conversion of digital interest into actual tourist visits.

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1. INTRODUCTION

Digital technology has transformed how tourists search for information, evaluate destinations, and make travel decisions. Google Trends has become an important source of digital data for examining tourism interest and forecasting demand. Previous studies have demonstrated significant relationships between online search activity and tourist arrivals, as well as improvements in tourism demand forecasting (Camacho & Pacce, 2018; Li et al., 2017; Bokelmann & Lessmann, 2019; Havranek & Zeynalov, 2021). Its applications have also expanded to tourism demand forecasting, tourist behavior, and destination marketing (Dinis et al., 2019).

However, digital popularity does not necessarily translate into actual tourist arrivals. Google Trends measures relative search interest rather than physical visits, reflecting an early stage of travel decision-making. This relationship is consistent with the Theory of Planned Behavior, which identifies behavioral intention as an important predictor of actual behavior (Ajzen, 1991). Nevertheless, the conversion of online interest into actual visits depends on accessibility, infrastructure, facilities, and destination readiness (Starosta et al., 2019; Bhattacharjee et al., 2024). The 4A framework, comprising Attraction, Accessibility, Amenities, and Ancillary Services, emphasizes that destination attractiveness must be supported by adequate facilities and services (Goeldner & Ritchie, 2011; Wulandari et al., 2024). Visitor perceptions also provide an important dimension for evaluating Indonesia's super-priority destinations (Kusumawardani et al., 2024). These factors explain the potential digital-physical gap, in which high online popularity does not automatically generate corresponding tourist arrivals.

This issue is particularly relevant following Indonesia's introduction of the Super Priority Destination (DSP) policy in 2019. The government designated five destinations—Lake Toba, Borobudur, Mandalika, Labuan Bajo, and Likupang—for accelerated development through infrastructure investment, accessibility improvements, and integrated promotion (Kemenparekraf, 2020). In Labuan Bajo, this strategy has involved tourism infrastructure development, connectivity improvements, and destination management. Its development as a super-premium tourism destination and the formulation of marine tourism policy pathways have been discussed in previous studies (Andjelicus, 2021; Suharyanto et al., 2024). Research has also examined tourist destination preferences across the five priority destinations and sustainable tourism management strategies (Utari et al., 2024; Redha et al., 2025). These studies demonstrate that DSP development involves not only promotion but also infrastructure, governance, and sustainability.

Nevertheless, concentrating development support on selected destinations raises questions about tourism growth and destination competitiveness. Tourism policy implementation may involve governance challenges and unintended outcomes, while tourism development also has wider economic implications, particularly for island destinations (Hall, 2011; Pratt, 2015). This issue can be examined by comparing Labuan Bajo with Raja Ampat, a non-DSP destination internationally recognized for marine biodiversity and conservation-based tourism. The importance of institutional arrangements and entrance-fee governance in financing marine conservation tourism has been demonstrated in Raja Ampat, alongside broader considerations of governance, development prospects, and business models for marine tourism destinations (Atmodjo et al., 2017; Teguh, 2020). Despite their different development approaches, both destinations possess significant tourism potential, providing an opportunity to examine differences in digital popularity and tourist arrivals under different levels of government support.

Although Google Trends has been widely applied in tourism demand forecasting, previous studies have identified limitations related to data inconsistencies, search biases, and the need for validation against official tourism statistics (Dergiades et al., 2018; Behnen et al., 2020; Höpken et al., 2019; Rovetta, 2021). Research on Indonesian tourism has increasingly explored big data applications for tourism marketing and destination development (Istanto et al., 2023; Kartiasih et al., 2025). However, the integration of digital popularity, geographical search distribution, tourist arrivals, and tourism policy evaluation remains relatively limited. Existing research on DSP destinations has primarily examined destination preferences, development, and governance (Utari et al., 2024; Suharyanto et al., 2024), leaving limited comparative evidence on tourism performance between priority and non-priority destinations.

To address this gap, this study compares Labuan Bajo as a DSP destination and Raja Ampat as a non-DSP destination during 2015–2025. It integrates Google Trends indicators, official tourist arrival statistics, and geographical search distributions to examine whether differences in policy support are associated with different patterns of digital popularity and tourism growth. The conceptual argument is that digital popularity may generate different tourism outcomes depending on destination readiness, particularly accessibility, infrastructure, tourism facilities, and integrated promotion. Consequently, government support may strengthen the conversion of online interest into actual tourist visits.

The novelty of this study lies in integrating digital popularity analysis with a Multilevel Difference-in-Differences (MLM-DiD) framework to evaluate differences in tourist arrival growth before and after the DSP policy. By comparing the Pre-DSP period (2015–2018) and Post-DSP period (2019–2025), the study examines policy-associated differences in tourism performance and the potential relationship between digital attention toward priority and non-priority destinations.

Accordingly, this study aims to: (1) examine temporal changes in digital popularity and tourist arrivals in Labuan Bajo and Raja Ampat during 2015–2025; (2) analyze the geographical distribution of global and domestic search interest; (3) measure the relationship between digital popularity and tourist arrivals; and (4) evaluate differences in tourist arrival growth between the two destinations before and after the DSP policy using a Multilevel Difference-in-Differences framework. The findings are expected to contribute to evidence-based tourism policy evaluation and support more balanced tourism development in Indonesia.

2. METHOD

2.1 Research Design and Approach

This study employed a quantitative longitudinal comparative design to examine the relationship between digital popularity and tourist arrivals in Labuan Bajo and Raja Ampat during 2015–2025. The analysis combined Google Trends data and official tourism statistics using three approaches: geographic distribution analysis, Pearson correlation, and a Multilevel Difference-in-Differences (MLM-DiD) model. The longitudinal design enabled comparisons of tourism dynamics before and after the implementation of Indonesia's Super Priority Destination (DSP) policy (Menard, 2002).

2.2 Research Locations and Data Sources

The study focused on two destinations with different policy classifications. Labuan Bajo, located in West Manggarai Regency, East Nusa Tenggara, was designated as a DSP in 2019 and served as the treatment destination. Raja Ampat, located in Southwest Papua Province, was selected as the comparison destination because it was not included in the DSP program. Its tourism development is primarily associated with marine conservation and community-based management (Atmodjo et al., 2017).

The study used secondary data from three principal sources:

1. Google Trends: Monthly search interest for "Labuan Bajo," "Raja Ampat," and "Destinasi Super Prioritas," covering Worldwide and Indonesia geographical scopes from January 2015 to December 2025. The data were obtained as relative search volume indices ranging from 0 to 100 (Google, 2025; Nuti et al., 2014).
2. Statistics Indonesia (BPS): Annual tourist arrival statistics from West Manggarai and Raja Ampat regencies (BPS-Statistics of West Manggarai Regency, 2025; BPS-Statistics of Raja Ampat Regency, 2025).

3. Regional tourism authorities: Supporting information from the Raja Ampat Tourism Information System (SIPARI) and the Department of Tourism, Creative Economy, and Culture of West Manggarai Regency.

The observation period was divided into Pre-DSP (2015–2018) and Post-DSP (2019–2025), with 2019 representing the beginning of the policy period.

2.3 Data Processing

Outlier Detection

Google Trends observations were examined for irregular values using the Z-score and Interquartile Range (IQR) methods to minimize the influence of anomalous search activity (Dergiades et al., 2018; Bokelmann & Lessmann, 2019; Behnen et al., 2020).

The Z-score was calculated as:

$$Z = (X - \mu) / \sigma$$

Observations with $|Z| > 3$ were classified as potential outliers (Hair et al., 2019). The IQR method identified values outside the boundaries of $Q1 - 1.5 \times IQR$ and $Q3 + 1.5 \times IQR$. Identified outliers were replaced with the average of the preceding and following monthly observations.

Data Aggregation and Normalization

Monthly Google Trends observations were aggregated into annual averages to ensure consistency with annual tourist arrival statistics (Höpken et al., 2019). Maximum-based normalization was subsequently applied:

$$Normalized\ Value = (Actual\ Value / Maximum\ Value) \times 100$$

Normalization was conducted separately for global digital popularity, domestic digital popularity, and tourist arrivals to facilitate comparisons across variables (Balderas, 2022; Sousa et al., 2021).

2.4 Data Analysis

Geographic Distribution Analysis

Google Trends geographical data were analyzed to identify countries and Indonesian provinces with the highest search interest for each destination. The findings were presented through geographical rankings and map visualizations to compare international and domestic search distributions (Nuti et al., 2014).

Pearson Correlation Analysis

Pearson correlation was used to examine the strength and direction of relationships between digital popularity and tourist arrivals, as well as between DSP popularity and destination-specific search interest (Hair et al., 2019). The Pearson correlation coefficient was calculated as:

$$r = \Sigma[(Xi - \bar{X})(Yi - \bar{Y})] / \sqrt{\{\Sigma(Xi - \bar{X})^2 \Sigma(Yi - \bar{Y})^2\}}$$

Correlation strength was classified as strong ($r > 0.70$), moderate ($0.40 < r \leq 0.70$), and weak ($r \leq 0.40$), following Neuman (2014).

Multilevel Difference-in-Differences Model

The MLM-DiD model was employed to examine differences in tourist arrival growth between Labuan Bajo (treatment) and Raja Ampat (comparison) before and after the DSP policy. The model accommodates repeated annual observations nested within destinations and estimates fixed and random effects (Raudenbush & Bryk, 2002; Heck et al., 2013; Snijders & Bosker, 2012).

The model was estimated using Linear Mixed Models in IBM SPSS Statistics Version 26.0, with Restricted Maximum Likelihood (REML) estimation and an Unstructured covariance matrix (IBM Corp., 2019; West et al., 2022).
The model specification consisted of two levels:

Level 1 (Annual Observations):

$$Y_{it} = \pi_{0i} + \pi_{1i}(PreDSP_t) + \pi_{2i}(PostDSP_t) + e_{it}$$

Level 2 (Destination):

$$\pi_{0i} = \gamma_{00} + \gamma_{01}(DSP_i) + u_{0i}$$
$$\pi_{1i} = \gamma_{10} + \gamma_{11}(DSP_i) + u_{1i}$$
$$\pi_{2i} = \gamma_{20} + \gamma_{21}(DSP_i) + u_{2i}$$

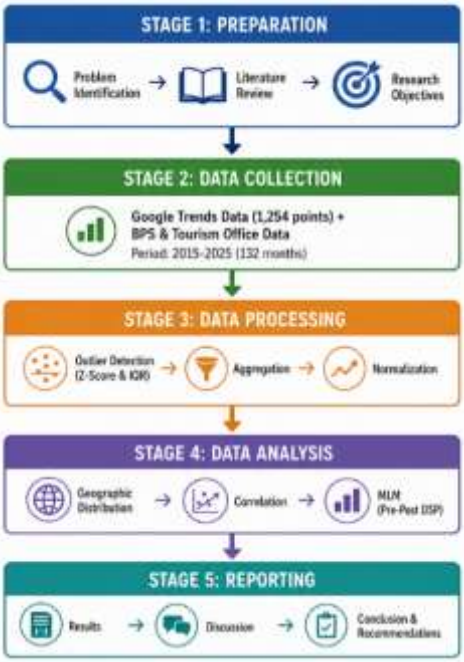
where Y_{it} represents annual tourist arrivals; PreDSP and PostDSP represent the respective time variables; DSP_i indicates destination status (1 = Labuan Bajo; 0 = Raja Ampat); γ represents fixed effects; u represents random effects; and e represents the residual error.
The principal parameter was γ_{21}, representing the difference in post-DSP growth between the two destinations. The destination-specific growth coefficients were calculated as follows:

Pre-DSP Raja Ampat: γ_{10}
Pre-DSP Labuan Bajo: $\gamma_{10} + \gamma_{11}$
Post-DSP Raja Ampat: γ_{20}
Post-DSP Labuan Bajo: $\gamma_{20} + \gamma_{21}$

A positive and statistically significant γ_{21} ($p < 0.05$) indicates higher post-DSP tourist arrival growth in Labuan Bajo relative to Raja Ampat, conditional on the specified model.

3.7 Research Flow Diagram

The research was conducted through several interconnected stages, from preparation to reporting. Figure 1 presents the research flow diagram.



Source: Processed by researchers (2026)

Figure 1. Research Flow Diagram

3. RESULTS AND DISCUSSION

3.1 Overview of Research Data

This study examines the relationship between digital popularity and tourist arrivals in Labuan Bajo and Raja Ampat over the period January 2015–December 2025. The analysis combines monthly Google Trends data with annual tourist-arrival statistics obtained from Statistics Indonesia (BPS), regional tourism offices, and destination-level tourism information systems. The Google Trends dataset contains six search series: global and domestic searches for Labuan Bajo, Raja Ampat, and the Super Priority Destinations (DSP) policy. Each series contains 132 monthly observations, producing 792 monthly observations in total. An additional 462 observations represent the geographic distribution of search interest.

The six search series cover the same observation period and provide a basis for comparing digital popularity across destinations and markets. Tourist-arrival statistics are available annually for both destinations. Labuan Bajo's arrivals are represented by statistics for West Manggarai Regency, while Raja Ampat's arrivals are represented by statistics for Raja Ampat Regency and the relevant local tourism information sources. The analysis distinguishes the Pre-DSP period (2015–2018) from the Post-DSP period (2019–2025). Summary of Google Trends Dataset can be seen in Table 1.

Table 1. Summary of Google Trends Dataset

Code	Keyword	Geographic scope	Period	Data points
GT-LB-G	Labuan Bajo	Worldwide	2015-2025	132 months
GT-LB-I	Labuan Bajo	Indonesia	2015-2025	132 months
GT-RA-G	Raja Ampat	Worldwide	2015-2025	132 months
GT-RA-I	Raja Ampat	Indonesia	2015-2025	132 months
GT-DSP-G	Destinasi Super Prioritas	Worldwide	2015-2025	132 months

GT-DSP-I	Destinasi Super Prioritas	Indonesia	2015-2025	132 months

Source: Google Trends, processed by the researchers (2026).

3.2 Outlier Identification and Data Revision

Potential outliers in the monthly Google Trends series were examined using the Z-score and Interquartile Range (IQR) procedures. Two unusually high observations were identified in the worldwide search series for Raja Ampat. The first occurred in April 2020, when the index reached 100, compared with 13 in March and 12 in May. This observation exceeded the Z-score threshold (Z = 3.27) and the IQR upper bound (47.75). For the revised series, the April value was replaced by the mean of the adjacent months, producing a value of 12.5.

The second observation occurred in June 2025, when the index also reached 100, compared with 17 in May and 24 in July. This value exceeded the IQR upper bound (47.75), although its Z-score (2.80) did not exceed the threshold of 3.0. It was therefore identified as an outlying observation by the IQR procedure only. The value was replaced by the mean of the adjacent months, resulting in 20.5. No observations in the DSP search series were revised. Outlier Detection and Revision in Raja Ampat Worldwide Google Trends Series can be seen at Table 2.

Table 2. Outlier Detection and Revision in Raja Ampat Worldwide Google Trends Series

Month	Original index	Z-score result	IQR result	Revised index
April 2020	100	Outlier (3.27)	Outlier (>47.75)	12.5
June 2025	100	Not outlier (2.80)	Outlier (>47.75)	20.5

Source: Google Trends, processed by the researchers (2026).

The revisions were intended to reduce the influence of isolated extreme observations on subsequent comparisons. However, an unusually high search index may also represent a genuine increase in public attention rather than a data error. Accordingly, the revised values should be interpreted as an analytical adjustment, not as proof that the original observations were invalid. The sensitivity of the correlation results to the original and revised values should be checked where possible, particularly because Google Trends reports normalized relative search interest and may exhibit sampling and scaling variation (Bokelmann & Lessmann, 2019; Behnen et al., 2020).

3.3 Digital Popularity and Tourist Arrival Trends

The monthly Google Trends series indicates that searches for Destinasi Super Prioritas began to rise after the policy was introduced in 2019 and reached their highest annual average in 2022 (global index = 52.00; domestic index = 48.58). The highest monthly index in the DSP series was recorded in August 2021 (index = 100). Labuan Bajo's annual average global search index increased from 6.33 in 2015 to 30.10 in 2025, while its domestic index increased from 8.67 to 22.36. By comparison, Raja Ampat's domestic index declined from 25.17 in 2015 to 13.09 in 2025, although its global index fluctuated and reached 23.38 in 2025.

Tourist arrivals followed different trajectories. Labuan Bajo recorded an increase from 95,075 visits in 2015 to 500,008 in 2025, equivalent to an overall increase of 425.9%. A particularly strong annual increase occurred in 2019, when arrivals rose by

56.65%. Raja Ampat recorded an increase from 22,262 visits in 2015 to 39,145 in 2025, equivalent to 75.8%. Both destinations experienced substantial declines during the COVID-19 disruption in 2020–2021, followed by recovery from 2022 onward. The magnitude and timing of recovery differed between the destinations.

Table 3. Annual Average Google Trends Digital Popularity Index, 2015–2025

Year	LB global	RA global	LB domestic	RA domestic	DSP global	DSP domestic
2015	6.33	19.33	8.67	25.17	0.00	0.00
2016	9.42	20.17	11.92	20.58	0.00	0.00
2017	13.92	22.50	17.08	22.75	0.00	0.00
2018	17.75	19.75	21.25	18.08	0.00	0.00
2019	20.50	18.00	24.33	13.42	4.58	5.33
2020	18.33	14.58*	22.17	15.25	14.92	15.67
2021	18.75	11.25	22.67	9.83	36.83	37.58
2022	26.33	13.58	27.42	9.42	52.00	48.58
2023	31.83	16.67	29.33	9.08	45.92	42.33
2024	28.08	19.08	24.83	9.33	33.25	31.33
2025	30.10	23.38*	22.36	13.09	18.50	12.75

*Source: Google Trends, processed by the researchers (2026). Note: *Raja Ampat values for 2020 and 2025 reflect the revised observations described in Section 3.2.*

Table 4. Tourist Arrivals and Annual Growth, 2015–2025

Year	Labuan Bajo	Raja Ampat	LB growth (%)	RA growth (%)
2015	95,075	22,262	–	–
2016	83,621	26,088	−12.05	17.19
2017	116,975	36,091	39.89	38.34
2018	163,807	43,910	40.04	21.67
2019	256,609	46,375	56.65	5.61
2020	44,543	8,253	−82.64	−82.20
2021	41,340	2,230	−7.19	−72.98
2022	170,352	5,725	312.08	156.73
2023	423,847	19,839	148.81	246.53
2024	411,349	33,277	−2.95	67.74
2025	500,008	39,145	21.55	17.63

Source: Statistics Indonesia (BPS) of West Manggarai Regency; Department of Tourism, Creative Economy, and Culture of West Manggarai Regency; Statistics Indonesia (BPS) of Raja Ampat Regency; Tourism Information System of Raja Ampat (SIPARI); and Marine Conservation Area Management Unit of Raja Ampat (processed by the researchers, 2026).

The descriptive trends show that Labuan Bajo's tourism growth was already substantial before the DSP period, particularly in 2017–2019. This pre-policy trajectory is important when interpreting the subsequent comparison because post-2019 growth cannot be attributed to the DSP policy solely on the basis of a before-and-after increase.

The pandemic also represents a major external disruption within the Post-DSP period and should be considered when interpreting annual changes.

3.4 Geographic Distribution Analysis

The geographic distribution of Google Trends interest reveals different market profiles for the two destinations. In the worldwide comparison, Labuan Bajo recorded relatively high search-interest proportions in Indonesia (63%), Malaysia (66%), and Singapore (54%). Raja Ampat recorded higher relative proportions in several European countries, including Hungary (88%), France (85%), Sweden (85%), the Czech Republic (85%), and Italy (83%). These figures indicate that the relative distribution of search interest differs across countries, with Labuan Bajo more prominent in selected Southeast Asian markets and Raja Ampat more prominent in the selected European markets.

Table 5. Comparative Search-Interest Distribution by Country, 2015–2025

Country	Raja Ampat	Labuan Bajo	Country	Raja Ampat	Labuan Bajo
Indonesia	37%	63%	Hungary	88%	12%
Malaysia	34%	66%	France	85%	15%
Singapore	46%	54%	Sweden	85%	15%
India	78%	22%	Czech Republic	85%	15%
Maldives	83%	17%	Italy	83%	17%

Source: Google Trends, regional distribution processed by the researchers (2026).



Figure 2. Map of Search Interest by Country for Labuan Bajo and Raja Ampat

At the domestic level, Labuan Bajo recorded its highest relative search-interest proportion in East Nusa Tenggara (99%), followed by West Nusa Tenggara (85%), Bali (79%), and DKI Jakarta (61%). Raja Ampat was more prominent in West Papua (97%), Papua (72%), North Maluku (59%), and Maluku (57%). The pattern suggests that Labuan Bajo's domestic search interest is concentrated in eastern Indonesia and major tourism or population centers, while Raja Ampat's domestic search interest is more concentrated in provinces geographically closer to the destination.

Table 6. Comparative Domestic Search-Interest Distribution by Province

Province	Raja Ampat	Labuan Bajo	Province	Raja Ampat	Labuan Bajo
West Papua	97%	3%	East Nusa Tenggara	1%	99%
Papua	72%	28%	Bali	21%	79%
North Maluku	59%	41%	West Nusa Tenggara	15%	85%
Maluku	57%	43%	DKI Jakarta	39%	61%

Source: Google Trends, regional distribution processed by the researchers (2026).

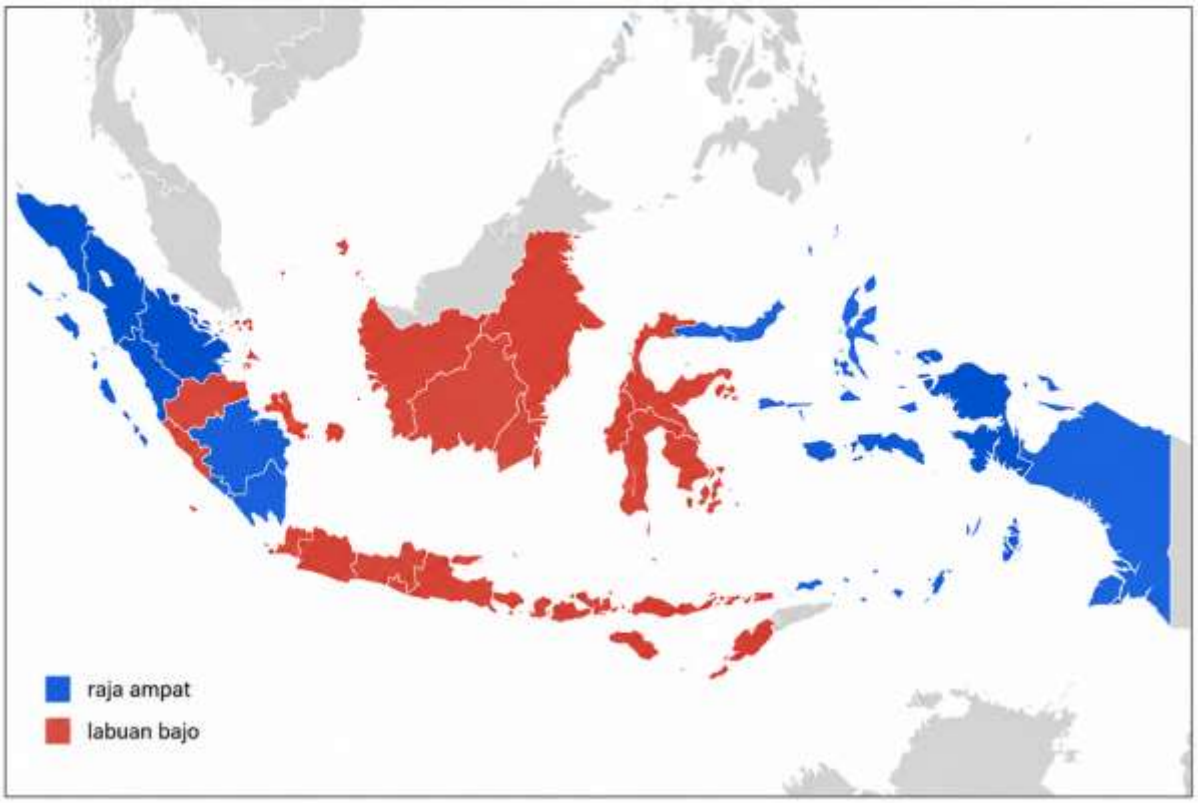


Figure 3. Map of Domestic Search Distribution for Labuan Bajo and Raja Ampat

The geographic patterns are consistent with the different destination profiles described in previous studies. Raja Ampat's international recognition is closely associated with its marine biodiversity and marine tourism resources, whereas Labuan

Bajo has received substantial policy attention and connectivity investment as a Super Priority Destination (Teguh, 2020; Andjelicus, 2021; Suharyanto et al., 2024). These results support the use of differentiated promotional strategies that reflect each destination's source markets and geographic characteristics.

Interpretation note: the percentages in Tables 6 and 7 should be understood according to the researchers' regional comparison procedure. They should not be described as absolute market shares or actual proportions of tourists unless the calculation method explicitly establishes those meanings. The manuscript should state how the paired destination percentages were derived from Google Trends regional data.

3.5 Correlation Analysis

Pearson correlation analysis was used to examine the association between digital popularity and tourist arrivals. Labuan Bajo showed strong positive correlations between tourist arrivals and global digital popularity (r = 0.8712) and domestic digital popularity (r = 0.8912). Raja Ampat showed moderate positive correlations for global popularity (r = 0.6543) and domestic popularity (r = 0.5210). The results indicate that the strength of the association between digital interest and tourist arrivals differed across destinations and market scopes.

DSP popularity was positively correlated with Labuan Bajo's tourist arrivals (r = 0.7336), global popularity (r = 0.7389), and domestic popularity (r = 0.8012). In contrast, DSP popularity was negatively correlated with Raja Ampat's tourist arrivals (r = −0.4114), global popularity (r = −0.7762), and domestic popularity (r = −0.8234). These coefficients indicate that DSP search interest moved in the same direction as Labuan Bajo's digital indicators and arrivals, while it moved in the opposite direction to Raja Ampat's corresponding indicators during the observation period.

Table 7. Pearson Correlation Matrix Between Variables

Variable	Visit LB	Visit RA	Global LB	Global RA	Domestic LB	Domestic RA	DSP
Visit LB	1.000						
Visit RA	0.8152	1.000					
Global LB	0.8712	0.5123	1.000				
Global RA	−0.2192	0.6543	−0.4757	1.000			
Domestic LB	0.8912	0.4012	0.9321	−0.5123	1.000		
Domestic RA	−0.3812	0.5210	−0.4012	0.8123	−0.4567	1.000	
DSP	0.7336	−0.4114	0.7389	−0.7762	0.8012	−0.8234	1.000

Source: Google Trends and BPS data, processed by the researchers (2026).

The Pre-DSP and Post-DSP comparison also reveals different patterns. In Labuan Bajo, the correlation between global popularity and tourist arrivals increased from 0.7123 in the Pre-DSP period to 0.9210 in the Post-DSP period. The domestic correlation increased from 0.7234 to 0.9345. In Raja Ampat, the global correlation increased from 0.5432 to 0.6891, whereas the domestic correlation declined from 0.6123 to 0.4512.

Table 8. Correlation Coefficients Before and After DSP Implementation

Relationship	LB Pre-DSP	LB Post-DSP	RA Pre-DSP	RA Post-DSP
Global popularity vs. visits	0.7123	0.9210	0.5432	0.6891
Domestic popularity vs. visits	0.7234	0.9345	0.6123	0.4512

Source: Google Trends and BPS data, processed by the researchers (2026).

The stronger correlations in Labuan Bajo suggest a closer association between digital interest and physical visitation, particularly in the Post-DSP period. Raja Ampat's results indicate a different pattern, with a weaker domestic association after 2019 despite a stronger global association. These findings provide a basis for examining differences in tourism growth across the two destinations. However, correlation does not establish causality. Because the data contain longitudinal trends, the coefficients may also be influenced by common time trends, serial correlation, and major shocks. The manuscript should report the observation frequency and sample size used for each correlation, as well as significance levels and, where feasible, robustness tests based on changes or detrended series.

3.6 MLM Results: Pre-DSP and Post-DSP Comparison

The multilevel model (MLM) estimates were obtained using restricted maximum likelihood (REML) and an unstructured covariance specification in SPSS version 26. Annual tourist-arrival data for 2015–2025 were used to compare the estimated growth patterns of Labuan Bajo and Raja Ampat across the Pre-DSP (2015–2018) and Post-DSP (2019–2025) periods. The reported fixed-effect estimates are presented in Table 9.

Table 9. MLM Estimation Results for Pre-DSP and Post-DSP Comparison

Parameter	Coefficient	Std. error	t-value	Significance
γ_{00} (Global intercept)	52.800	8.120	6.50	$p < 0.01$
γ_{01} (DSP intercept difference)	−30.500	10.340	−2.95	$p < 0.05$
γ_{10} (Pre-DSP slope for Raja Ampat)	2.100	1.234	1.70	$p > 0.05$
γ_{11} (Pre-DSP slope difference)	28.900	9.876	2.93	$p < 0.05$
γ_{20} (Post-DSP slope for Raja Ampat)	15.200	3.456	4.40	$p < 0.01$
γ_{21} (DSP × Post-DSP interaction)	12.800	4.567	2.80	$p < 0.05$

Source: Google Trends and BPS data, processed by the researchers (2026).

The interaction coefficient (γ_{21} = 12.800; $p < 0.05$) is positive and statistically significant, indicating that the estimated Post-DSP growth slope for Labuan Bajo was 12.800 units per year higher than the corresponding slope for Raja Ampat under the specified model. The significant Pre-DSP slope difference (γ_{11} = 28.900; $p < 0.05$) also indicates that the two destinations were already following different growth trajectories before DSP implementation. This pre-policy difference is important because it raises a

concern about the parallel-trends assumption commonly required for a causal Difference-in-Differences interpretation.

Table 10. Estimated Annual Tourist-Arrival Growth by Destination and Period

Destination	Period	Estimated growth/year	Calculation
Labuan Bajo	Pre-DSP (2015-2018)	+31,000	$\gamma_{10} + \gamma_{11} = 2{,}100 + 28{,}900$
Labuan Bajo	Post-DSP (2019-2025)	+28,000	$\gamma_{20} + \gamma_{21} = 15{,}200 + 12{,}800$
Raja Ampat	Pre-DSP (2015-2018)	+2,100	$\gamma_{10} = 2{,}100$
Raja Ampat	Post-DSP (2019-2025)	+15,200	$\gamma_{20} = 15{,}200$

Source: Researchers' calculations based on the fixed-effect estimates (2026).

The estimated slopes show that Labuan Bajo's annual growth rate was +31,000 visits during the Pre-DSP period and +28,000 during the Post-DSP period. Raja Ampat's corresponding estimates increased from +2,100 to +15,200 visits per year. Thus, although the interaction coefficient is positive and statistically significant, the estimated Labuan Bajo slope did not increase relative to its own Pre-DSP slope. Rather, the coefficient indicates that the Post-DSP growth slope in Labuan Bajo was higher than the Post-DSP slope in Raja Ampat by the estimated interaction amount. It does not, by itself, demonstrate that DSP caused additional growth beyond Labuan Bajo's pre-existing trend.

The Post-DSP period includes the COVID-19 shock in 2020–2021 and the subsequent recovery. Retaining these years preserves the observed longitudinal record, but the pandemic may have influenced the estimated period slopes. The MLM findings should therefore be interpreted as model-based differences in growth patterns associated with the two periods. A causal policy claim would require stronger identification, including an assessment of pre-policy trend comparability, additional comparison destinations or a more suitable counterfactual, and sensitivity analysis excluding or separately modelling the pandemic years.

Methodological qualification: the analysis contains only two destination-level units, one DSP destination and one comparison destination. If destination is specified as the higher-level grouping unit in a multilevel model, the small number of groups limits the reliability of estimates of between-destination variance and standard errors. The model specification, degrees of freedom, covariance structure, and coding of the time and interaction variables should therefore be verified against the original SPSS output before submission.

3.7 Discussion

The Digital-Physical Gap in Raja Ampat

The findings reveal a difference between digital visibility and physical visitation in Raja Ampat. Its global digital popularity was positively associated with tourist arrivals, but the relationship was weaker than that observed in Labuan Bajo. The moderate global and domestic correlations suggest that online interest may not translate proportionally into visits. Accessibility, tourism infrastructure, and supporting services may influence

the extent to which digital interest becomes actual travel demand (Atmodjo et al., 2017; Kusumawardani et al., 2024). This interpretation is consistent with research showing that online attention and physical visits do not always move together (Starosta et al., 2019; Bhattacharjee et al., 2024).

The Role of Domestic and Global Markets

The market comparison reveals different associations across destinations. In Labuan Bajo, the domestic correlation with tourist arrivals (r = 0.8912) was slightly higher than the global correlation (r = 0.8712), whereas Raja Ampat showed a stronger global association (r = 0.6543) than domestic association (r = 0.5210). These differences suggest that domestic digital interest is particularly relevant to Labuan Bajo, while global interest has a relatively stronger association with Raja Ampat's arrivals. The results support destination-specific marketing strategies rather than a uniform promotional approach (Utari et al., 2024). Accessibility improvements and flight connectivity may also have supported the relationship between digital interest and arrivals in Labuan Bajo (Suharyanto et al., 2024).

The DSP Policy and Differences in Tourism Growth

The positive and statistically significant interaction coefficient indicates a difference in estimated Post-DSP growth slopes between Labuan Bajo and Raja Ampat. However, Labuan Bajo's estimated annual growth slope was +31,000 visits before DSP and +28,000 after DSP, while Raja Ampat's slope increased from +2,100 to +15,200. In addition, the significant pre-policy slope difference indicates that the destinations were already on different growth trajectories before the policy period. These findings do not support an unqualified claim that DSP caused additional growth beyond Labuan Bajo's previous trend. They instead show that the destinations experienced different growth patterns during the policy period, against a background of unequal pre-policy trends and the COVID-19 disruption. The importance of integrated infrastructure, connectivity, marketing, and attractions in destination development remains consistent with previous research on Labuan Bajo (Andjelicus, 2021; Utari et al., 2024; Suharyanto et al., 2024).

Changes in Public Digital Attention

DSP popularity was negatively correlated with Raja Ampat's global and domestic digital popularity (r = −0.7762 and r = −0.8234, respectively), while it was positively correlated with Labuan Bajo's global and domestic popularity (r = 0.7389 and r = 0.8012). Raja Ampat's domestic index also declined from an average of approximately 21.65 in 2015–2018 to 11.35 in 2019–2025, a decrease of approximately 47.6% based on the annual values in Table 4. This contrasts with the increasing digital visibility of Labuan Bajo over much of the Post-DSP period. The pattern may reflect a concentration of public attention toward destinations receiving greater policy and promotional emphasis, but the correlations do not establish a direct transfer of attention from one destination to another. Concentrated tourism policies and investment may affect the relative visibility and competitiveness of destinations (Hall, 2011; Pratt, 2015). The integrated development approach applied in Labuan Bajo provides a relevant example of the relationship between policy priorities, infrastructure, connectivity, and destination visibility (Andjelicus, 2021).

4. CONCLUSION

This study demonstrates that digital popularity is positively associated with tourist arrivals, although the strength of this relationship differs between priority and non-priority destinations. Labuan Bajo exhibited a stronger relationship between digital interest and actual tourist arrivals than Raja Ampat, while Raja Ampat showed a gap between digital visibility and physical visitation. These findings indicate that high online popularity alone may be insufficient to increase tourist arrivals without adequate destination readiness, accessibility, and supporting infrastructure (Starosta et al., 2019; Bhattacharjee et al., 2024).

The findings also indicate that tourism growth in Labuan Bajo was stronger than in Raja Ampat during the implementation of the Super Priority Destination (DSP) policy. However, the updated data show that Labuan Bajo had already experienced substantial growth before the policy was implemented, suggesting that its selection as a priority destination may have reflected its existing performance and growth potential. Nevertheless, the significant interaction coefficient (γ_{21} = 12.800; $p < 0.05$) indicates an additional growth difference associated with the DSP period beyond the pre-existing trend. A shift in public digital attention was also observed, as increased interest in Labuan Bajo coincided with declining digital attention to Raja Ampat. These findings highlight the importance of integrating digital indicators, official tourism statistics, and multilevel analysis in evaluating destination performance and tourism policies (Utari et al., 2024).

From a policy perspective, tourism development should adopt a more balanced approach by strengthening support for both priority and non-priority destinations to reduce disparities in tourism development (Hall, 2011; Pratt, 2015). Google Trends can serve as a complementary indicator for monitoring destination popularity and supporting evidence-based tourism planning (Bokelmann & Lessmann, 2019; Havranek & Zeynalov, 2021). For destinations such as Raja Ampat, improving accessibility and tourism infrastructure should be prioritized to strengthen the conversion of digital interest into actual visits (Atmodjo et al., 2017; Kusumawardani et al., 2024).

Several limitations should be considered when interpreting these findings. First, Google Trends measures relative search interest rather than absolute search volume, limiting its direct quantitative interpretation (Google, 2025; Rovetta, 2021). Second, the COVID-19 pandemic during 2020–2021 may have affected tourism dynamics and the observed relationships. Third, tourist arrival data for Labuan Bajo were represented by aggregated statistics for West Manggarai Regency because more specific data were unavailable. Finally, the study focused on only two destinations and did not explicitly incorporate other factors that may influence destination performance, including tourist perceptions, service quality, and social media sentiment (Kusumawardani et al., 2024).

Future research should include a wider range of destinations, incorporate additional digital data sources, and examine the long-term relationship between tourism policies, digital popularity, and actual tourist arrivals. Further studies should also consider destination readiness and other socioeconomic factors to provide a more comprehensive assessment of tourism development outcomes (Kartiasih et al., 2025; Suharyanto et al., 2024).

5. ACKNOWLEDGMENTS

The authors would like to express their sincere gratitude to Universitas Sahid for providing financial support through its Internal Research Funding Program Batch XX (Even Semester 2025/2026).

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