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Evaluation of the Urgency of Unrealized Infrastructure Development in the Mandalika Special Economic Zone Using Structural Equation Model (SEM) Analysis

Johan Jasmadi*, Jauhar Fajrin, Made Mahendra
Universitas Mataram, Indonesia
Email: johanjasmadi4@gmail.com*, jauhar.fajrin@unram.ac.id,
mahendramade@unram.ac.id

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ABSTRACT

The development of the Mandalika Special Economic Zone (SEZ) faces challenges related to infrastructure that has not been fully realized, which may affect the effectiveness of the area. Adequate infrastructure is essential to support the competitiveness and sustainability of the Mandalika SEZ as a leading tourism destination. This study aims to identify the factors that influence the urgency of infrastructure development, analyze the relationships among variables, and determine the infrastructure priorities that need to be addressed immediately. This study uses an explanatory quantitative approach through stakeholder surveys and Partial Least Squares Structural Equation Modeling (PLS-SEM) analysis. The exogenous variables include infrastructure-related factors, while the endogenous variables include socioeconomic benefits, sustainability, community welfare, and tourism attractiveness. The results of the analysis show that the priorities for infrastructure development are as follows: 1) regional supporting infrastructure, 2) electricity facilities, 3) SWTP, 4) infrastructure for surrounding communities, 5) clean water and irrigation systems, and 6) WWTP. Regional supporting infrastructure has the greatest influence on socioeconomic benefits and destination attractiveness. Infrastructure development in the Mandalika SEZ needs to prioritize a value-creating infrastructure approach to improve the competitiveness and sustainability of the region. These findings provide a scientific basis for more strategic and sustainable infrastructure development planning.

INTRODUCTION

Infrastructure development is one of the key elements in enhancing regional competitiveness, driving economic growth, and ensuring a more equitable distribution of national development outcomes. In Indonesia, the development of Special Economic Zones (SEZs) is a strategic approach to attract investment and generate employment opportunities, particularly in regions with strong geographical and economic potential.

One of the national priority SEZs is the Mandalika SEZ, located in Pujut District, Central Lombok Regency, West Nusa Tenggara Province. This area was officially established through Government Regulation Number 52 of 2014, with tourism designated as its primary development focus. Geographically, Mandalika is strategically positioned in the southern part of Lombok Island, featuring a coastline of more than 16 kilometers directly facing the Indian Ocean. The region also holds significant advantages in terms of natural landscape and accessibility, as it is located near Zainuddin Abdul Madjid International Airport and supported by an increasingly developed transportation network.

To accelerate regional development, ITDC as the area manager secured a loan of USD 248.4 million (approximately IDR 3.6 trillion) from the Asian Infrastructure Investment Bank (AIIB). These funds are allocated to finance the Mandalika Urban and Tourism Infrastructure Project (MUTIP), which includes the development of essential infrastructure and public facilities. However, the realization of fund utilization has only reached approximately 51.38%. ITDC's limited financial capacity has been identified as one of the main factors contributing to the slow pace of development (Haerul & Nur Yamin, 2024; Najib Ali, 2022). There has even been discussion regarding the discontinuation of external loans and a shift toward internal financing, although this alternative is considered to carry high financial risk.

Development delays have broad impacts, ranging from disruption of local community activities to a decline in investment attractiveness. In addition, local communities have expressed dissatisfaction as several planned programs have not been fully realized, including the buffer village development initiative. This situation indicates that successful regional development depends not only on funding availability but also on precise, needs-based planning and implementation.

The novelty of this study lies in its integrated approach, combining stakeholder perceptions with Partial Least Squares Structural Equation Modeling (PLS-SEM) to evaluate the urgency of six types of unrealized infrastructure: WWTP (X1), electricity facilities (X2), SWTP (X3), infrastructure for surrounding communities (X4), clean water and irrigation systems (X5), and regional supporting infrastructure (X6). Unlike previous studies that focused on individual infrastructure components or applied different analytical techniques, this research provides a comprehensive prioritization framework based on the causal impacts of infrastructure on four development outcome dimensions. The use of PLS-Predict further strengthens the model's predictive relevance, which is rarely applied in prior studies on Mandalika infrastructure.

Given the limitations of existing resources, infrastructure development priorities must be determined objectively and systematically. Therefore, an evaluation is required to identify which projects are most urgent to be implemented, both in terms of their impact on regional development and their benefits for local communities. One of the analytical approaches applied in this study is Structural Equation Modeling (SEM). This method enables a more comprehensive examination of relationships among variables influencing infrastructure urgency. Through SEM, this study aims to identify the main determinants of urgency levels and formulate the most strategic development priorities. The findings are expected to provide evidence-based recommendations for ITDC and relevant stakeholders, ensuring that infrastructure development in the Mandalika SEZ can be carried out more effectively, efficiently, and sustainably.

METHOD

Quantitative Research Approach

This research adopted a quantitative approach involving numerical data collection through surveys using valid and reliable instruments (Candra Susanto et al., 2024; Zulfikar et al., 2024). Statistical analysis and hypothesis testing were applied to examine relationships among variables. This approach enabled the quantification of phenomena, identification of relationships between variables, and generalization of findings to a broader population. The study focused on measuring relevant variables, analyzing interrelationships, and testing the hypotheses proposed by Zulfikar (2024).

Type of Research (Explanatory/Causal with a Survey Approach)

This research is explanatory or causal, with the aim of explaining the cause-and-effect relationship between variables that affect the urgency of infrastructure development in the Mandalika SEZ (Sadenova, 2025). The survey method was used to collect data from many respondents, especially related to the perceptions and opinions of various stakeholders. The analysis was carried out using the Structural Equation Model (SEM), which is able to test and validate the relationships between variables, including latent variables such as economic impacts, social needs, and environmental aspects (Sarwono, 2010). The combination of survey and SEM approaches allows this study to not only describe, but also explain the factors driving the urgency of development, thus providing a solid scientific basis for the prioritization process (Hair et al., 2019; Sadenova et al., 2025).

Population and sample

The research population includes all individuals or groups that have a direct relationship with infrastructure development in the Mandalika SEZ, such as the surrounding community, tourism business actors, local government representatives, and academics who understand regional development (Candra Susanto et al., 2024). Determination of demographic characteristics (age, education, role) and geography is essential so that the data obtained can accurately represent the target group. Given that the focus of the research is on the urgency of infrastructure development that has not yet been realized, the population must reflect the affected and interested parties. The proper definition of population is key in ensuring that the results of SEM analysis are relevant, generalizable, and useful for decision-making in the Mandalika SEZ (Nusrang et al., 2024; Sarwono, 2010).

The research sample is a subdivision of the population selected for observation or research purposes. Sample utilization allows researchers to make more efficient and cost-effective generalizations from sample to population. Careful sample selection is essential to provide an accurate picture of the entire population (Candra Susanto et al., 2024).

Data Analysis Techniques

The analysis was carried out using the Partial Least Squares SEM (PLS-SEM) approach. This method was chosen because it is able to process complex conceptual models, measure latent variables, and is suitable for quantitative data with a relatively limited number of respondents and data distribution that does not have to be normal (Kumar, 2025; Pham et al., 2024). PLS-SEM is used to analyze the causal relationship between variables X (various types of infrastructure that have not yet been realized) and variable Y (expected impacts, such as socio-economic benefits, environmental sustainability, community welfare, and tourism attraction). Each variable was measured through indicators based on Likert scale questionnaires.

The analysis process begins with building a measurement model (outer model) to test the validity and reliability of each indicator, then continues with a structural model (inner model) to see the strength and significance of the relationship between latent variables.

The main outputs of PLS-SEM include outer loading values, AVE, composite reliability, as well as path coefficient and R^2 values, all of which are used to assess how strong and valid the relationships between constructs in the model are. The results of this analysis will show which infrastructure contributes the most to the development goals of the Mandalika SEZ, so that it can be the basis for more objective and directed development priorities.

RESULT AND DISCUSSION

Structural Equation Modeling (SEM) Model Development

The SEM model image shown illustrates the causal relationship between exogenous variables (X1–X6) and endogenous variables (Y1–Y4) in this study. The model is built on a conceptual framework that places unrealized types of infrastructure as determining factors for development urgency, which are then measured through four impact dimensions.

Structurally, exogenous variables consist of:

1) X1 = WWTP (Wastewater Treatment Plant)
2) X2 = Electrical Facilities and Their Supports
3) X3 = SWTP (Solid Waste Treatment Plant)
4) X4 = Infrastructure for the Surrounding Community
5) X5 = Clean Water and Irrigation System
6) X6 = Area Supporting Infrastructure

The six variables are directed towards four endogenous constructs, namely:

1) Y1 = Social and Economic Benefits
2) Y2 = Environmental Sustainability
3) Y3 = Community Well-being and Participation
4) Y4 = Tourism Attraction and Satisfaction

The one-way arrow from X to Y in figure 4.1 shows the direct effect hypothesis, where each type of infrastructure is assumed to affect the perception of regional development impacts. The line thickness and path coefficient values shown in the figure represent the magnitude of the influence between variables, while the R^2 value in each endogenous construct shows the proportion of variation that the exogenous variables in the model can explain.

Thus, the image not only shows the structure of the theoretical relationship, but also visualizes the empirical strength of the relationship between constructs based on the results of the SEM-PLS estimation. The relatively small path coefficient values in most variables indicate that the influence of infrastructure on the impact of the area is limited, while the R^2 value in the weak–medium category indicates that there are still other factors outside the model that also affect the urgency of development in the Mandalika SEZ.

Methodologically, this model includes a reflective structural model with a variance-based SEM (PLS-SEM) approach, which is oriented towards the ability to predict and explore relationships between latent constructs. Therefore, model interpretation emphasizes more on the direction and strength of relationships, rather than solely on the suitability of the global model as in covariance-based SEM. This explanation emphasizes that the SEM model image is not just a conceptual illustration, but a mathematical representation of the relationship between variables that has been empirically tested and becomes the basis for drawing research conclusions.

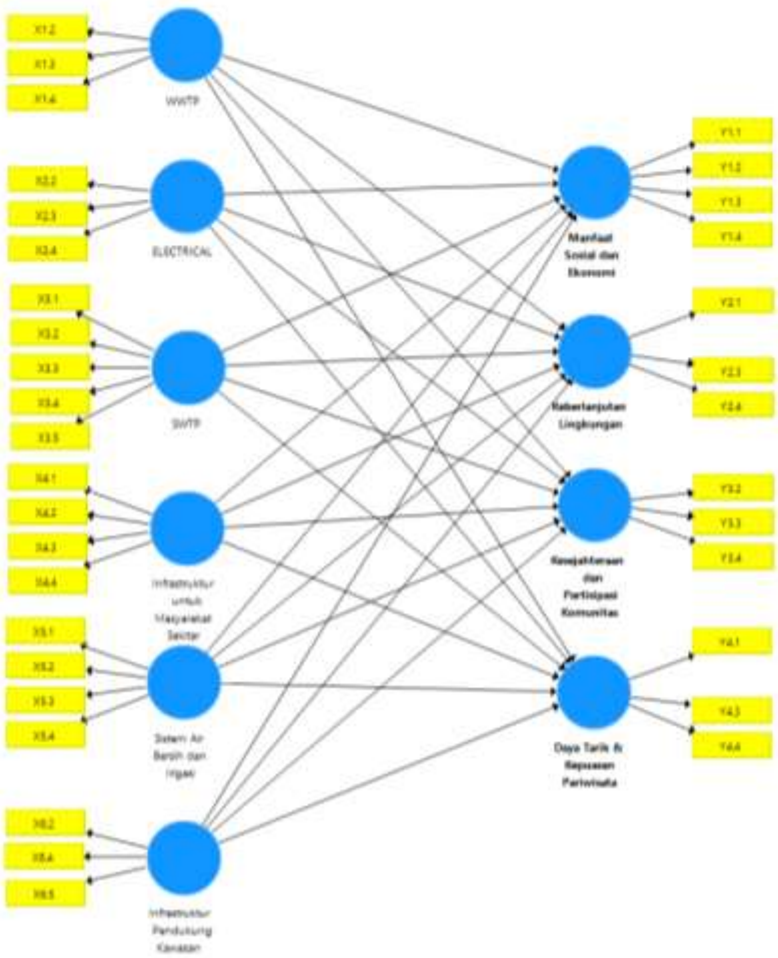

Figure 1 Uji Model SEM

Evaluation of Measurement Models *(Outert Model)*

In the evaluation of the measurement model on the SEM-PLS approach, Chin (1998) made an important contribution by recommending an outer loading threshold value of 0.70. The determination of this value is based on the consideration that an indicator with a load of ≥ 0.70 is able to explain at least 50% of the variance of the latent construct it measures. Therefore, indicators that meet these criteria are considered to have adequate indicator reliability and are worthy of maintaining in the model.

The convergent validity in this study was evaluated through two main parameters, namely outer loading and Average Variance Extracted (AVE). The AVE value represents the proportion of the variance of the indicator that can be explained by its latent construct. Methodologically, the minimum acceptable AVE value is 0.50, which indicates that more than 50% of the variance of the indicator can be explained by the construct in question, thus meeting the criteria of convergent validity (Hair et al., 2019).

Meanwhile, discriminant validity was measured using the Heterotrait-Monotrait Ratio (HTMT) approach, which is considered more sensitive and accurate in detecting the problem of discriminant validity compared to the Fornell–Larcker criteria and cross-loading analysis.

Table 1 Measurement Test Criteria

Test Criteria	Parameter	Minimum Score	References
Validitas Convergence	*Average Variance Extracted*	0.5	Hair, dkk.
	Outer Loading	0.7	Chin
Discriminatory Validity	*Heterotrait-Monotrait Ratio*	0.9	Henseler, dkk.
Reliability	*Cronbach's Alpha*	0.7	Hair, dkk.
	Composite Reliability	0.7	Fornell & Larcker

Convergent Validity

Evaluation of convergent validity is carried out to measure the degree of correlation between indicators in one construct and ensure the internal consistency of the indicator in representing the estimated latent construct. In this study, the convergent validity test parameters were proxied through outer loading and Average Variance Extracted (AVE) values.

The outer loading value serves to identify the significance and relative contribution of each indicator to its latent construct. Meanwhile, the AVE value represents the proportion of variance of a set of indicators that can be explained by latent constructs simultaneously, which is also an indication of the construct's ability to explain the information contained in its indicators.

Construct Reliability

The reliability test is carried out to assess the level of internal consistency of the measurement instrument, namely the extent to which the indicators in a construct are able to provide stable and consistent results in measuring the same concept. In this study, the parameters used included Cronbach's Alpha, rho_A, and Composite Reliability (CR). Referring to Hair et al. (2019), the required value for the three reliability indicators is > 0.70, which indicates that the construct has a good level of internal consistency. Values above the threshold indicate that the indicators in a single construct are correlated with each other and together are able to reliably represent latent variables.

In addition to reliability, the evaluation of the measurement model also includes convergent validity testing using Average Variance Extracted (AVE). The minimum recommended AVE value is 0.50, which means that the latent construct is able to explain at least 50% of the variance of the indicators, while the rest is affected by measurement errors. If all criteria of convergent reliability and validity are met, then the constructs in the model can be declared feasible and accurate to proceed to the structural model analysis stage.

Table 2 SEM Model Construct Reliability Test

	Cronbach's Alpha	rho_A	Composite Reliability	Average Variance Extracted (AVE)
X1	**0.799**	**1.027**	**0.863**	**0.680**
X2	**0.722**	**0.771**	**0.838**	**0.635**
X3	**0.863**	**0.875**	**0.902**	**0.649**
X4	**0.703**	**0.723**	**0.815**	**0.526**
X5	**0.782**	**0.833**	**0.843**	**0.576**
X6	**0.655**	**0.658**	**0.814**	**0.594**
Y1	**0.724**	**0.728**	**0.825**	**0.542**
Y2	**0.722**	**0.724**	**0.844**	**0.644**
Y3	**0.889**	**0.918**	**0.931**	**0.817**
Y4	**0.895**	**0.901**	**0.934**	**0.826**

Based on the data in the table above, the results of the analysis can be described as follows:

Convergent Validity (AVE): The entire construct (X1 to Y4) has an AVE value that ranges from 0.526 to 0.826. Since all values have exceeded the standard of 0.50, all constructs are declared to have good convergent validity. Composite Reliability (CR): All constructs have a CR value above 0.814, which far exceeds the minimum requirement of 0.70. This shows that all indicators have a very strong internal consistency in measuring their latent variables.

Cronbach's Alpha and rho_A: The majority of constructs have values above 0.70. However, in the X6 variable, it was found that Cronbach's Alpha value was 0.655 and rho_A was 0.658. Although this value is below 0.70, the X6 construct is still declared reliable because its Composite Reliability value (0.814) has met the minimum requirements. According to Hair et al. (2019), in research that is developmental or exploratory, a reliability value between 0.60 – 0.70 is still acceptable, especially if the CR and AVE values of the construct meet the standards. Overall, the test results show that this research instrument has a level of reliability and validity that is eligible to proceed to the structural model testing stage (hypothesis test).

Multicollinearity Test (VIF)

After ensuring the validity and reliability of the construct are met, the next stage in model evaluation is to perform a multicollinearity test. This test aims to ensure that there is no very strong correlation between indicators or between independent variables in the research model, as these conditions can cause bias in the estimation of path coefficients and reduce the stability of the analysis results. High multicollinearity can magnify the error standard and make it difficult to interpret the influence of individual variables in a structural model.

The measuring tool used to detect symptoms of multicollinearity is the Variance Inflation Factor (VIF) value. According to Hair et al. (2019), a VIF value below 3.00 indicates ideal conditions and is free from collinearity problems. A VIF value below 5.00 is still acceptable and is considered to indicate a moderate level of collinearity. However, if the VIF value exceeds 5.00, it indicates a serious multicollinearity problem, so model evaluation, such as the removal of indicators or adjustment of variable specifications, is needed so that the estimation results remain valid and can be interpreted accurately.

Evaluation of Structural Models (Inner Model)

After the measurement model (outer model) is declared to meet the criteria of validity and reliability, the next stage in the SEM-PLS analysis is the evaluation of the structural model (inner model). The structural model represents the causal relationship between latent constructs that formulated within the conceptual framework and hypothesis of the research. The internal evaluation of the model aims to assess the predictive ability of the model and test the strength and significance of the influence between constructs (Hair et al., 2017).

According to Chin (1998) and Hair et al. (2017), structural model testing includes four main criteria, namely determination coefficient (R^2), effect size (f^2), predictive relevance (Q^2), and significance of path coefficients. The coefficient of determination (R^2) indicates the proportion of variance of endogenous constructs that can be explained by exogenous constructs. The effect size (f^2) is used to assess the relative contribution of each exogenous construct to the endogenous construct. Predictive relevance (Q^2), calculated through a blindfolding procedure, indicates the model's ability to predict endogenous construct indicators. Meanwhile, the significance of the relationship between constructs was tested using a bootstrapping procedure by looking at t-statistic and p-value.

R-Square

The R-Square value (R^2) is used to assess the predictive ability of the structural model (inner model), i.e. the extent to which exogenous variables are able to explain the variations that occur in endogenous variables. In the PLS-SEM approach, R^2 represents the proportion of endogenous latent construct variance that can be explained by independent constructs that affect it (Hair et al., 2019). In other words, the higher the R^2 value, the greater the model's ability to explain the phenomenon being studied.

Interpretively, the value of R^2 indicates the explanatory power of the model on the dependent construct. Hair et al. (2019) categorized the R^2 value as 0.75 as strong, 0.50 as moderate, and 0.25 as weak. However, in social and behavioral research, R^2 values that are in the weak to moderate category are still acceptable, given the complexity of the factors that influence a phenomenon and the presence of external variables outside the model that were not included in the analysis.

In the context of this study, the R^2 value provides an idea of how much variation in the impact of regional development can be explained by the types of infrastructure that have not yet been realized. If the R^2 value is at a low to medium level, then it shows that the infrastructure variable does have a contribution in explaining the urgency of development, but it is not fully able to explain the overall variation in the impact of the area. Thus, the interpretation of R^2 not only assesses the strength of the model, but also provides an indication of the presence of other factors outside the model that have the potential to influence endogenous variables and can be on the agenda for further research.

F-Square

The F-Square (f^2) test is used to assess the magnitude of the effect of each exogenous variable on the endogenous variable in a structural model. According to Hair et al., the f^2 value is interpreted as follows: 0.02 (small effect), 0.15 (medium effect), and 0.35 (large effect). A value below 0.02 indicates a very weak or negligible effect.

Goodness of fit & Predictive Accuracy

Model feasibility testing in PLS-SEM is not only evaluated through the global goodness of fit measure, but also through the model's predictive accuracy. This approach is in line with the characteristics of PLS-SEM which is oriented towards prediction and theory development. Therefore, in addition to looking at R^2 and other effect measures, the evaluation also needs to ensure that the model has the ability to accurately predict observational data.

One of the methods recommended by Hair et al. (2019) to test predictive ability is PLS Predict. This procedure works with a holdout sample or cross-validation technique, where some of the data is used to estimate the model and the other part is used to test the accuracy of the prediction. The predictive results of the PLS model were then compared with the linear regression-based comparative model (LM). The evaluation indicators used are generally Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) values.

The model is declared to have good predictive ability if the value of the prediction error in the PLS model (both RMSE and MAE) is smaller than the LM model. If most of the indicators show a lower PLS error value, then the model has the relevant predictive power. Conversely, if the PLS prediction error is higher than that of the LM model, then the model's predictive ability is considered weak even though the model may have significant structural relationships. Thus, evaluation through PLS Predict provides an idea of whether the model is not only statistically significant, but also accurate in predicting empirical phenomena.

Table 3 Predict Analysis Results of PLS-SEM Model

	PLS		**LM**	
	RMSE	**MAE**	**RMSE**	**MAE**
Y1.2	**0.813**	**0.660**	0.945	0.760
Y1.4	**0.885**	**0.717**	1.120	0.876
Y1.1	**0.958**	**0.763**	1.083	0.852
Y1.3	**0.945**	**0.719**	1.352	0.965
Y2.4	**0.896**	**0.755**	1.075	0.883
Y2.3	**0.946**	**0.747**	1.227	0.977
Y2.1	**1.092**	**0.897**	1.342	1005
Y3.4	**1.067**	**0.941**	1.217	1008
Y3.2	**1.029**	**0.856**	1.253	1000
Y3.3	**0.972**	**0.775**	1.126	0.896
Y4.3	**0.691**	**0.524**	0.852	0.670
Y4.1	**0.726**	**0.519**	0.847	0.642
Y4.4	**0.774**	**0.609**	0.916	0.733

Based on the results of PLS Predict in Table 3, all endogenous construct indicators (Y1–Y4) show that the RMSE and MAE values in the PLS model are lower than those in the LM model. For example, the Y1.2 indicator has an RMSE of 0.813 in PLS and 0.945 in LM, and an MAE of 0.660 in PLS and 0.760 in LM. The same pattern is also seen in other indicators, such as Y4.3 (RMSE PLS = 0.691; RMSE LM = 0.852) and Y3.4 (RMSE PLS = 1.067; RMSE LM = 1.217).

According to Hair et al., if most or all indicators have PLS prediction errors that are smaller than the LM model, then the model can be categorized as having good predictive power (high predictive power). Thus, these results show that the structural model has adequate to good predictive accuracy in estimating the value of endogenous constructs (Benediktus Primus Gunteja et al., 2021).

Substantively, these findings indicate that the combination of infrastructure variables (X1–X6) is not only structurally relevant (as demonstrated by R-Square, F-Square, and Q-Square), but also effective in predicting patterns of socio-economic benefit value, environmental sustainability, community welfare, and tourism attractiveness and satisfaction in the Mandalika SEZ. Thus, the model developed in this study can be declared empirically feasible, both in terms of model suitability and in terms of prediction accuracy (Pasciucco et al., 2023; Putri et al., 2022).

CONCLUSION

The main factors influencing the urgency of unrealized infrastructure development in the Mandalika Special Economic Zone (SEZ) include socioeconomic benefits, environmental sustainability, community welfare and participation, and tourism attraction and satisfaction. These four dimensions served as the basis for assessing the importance of each type of infrastructure for regional development.

The results of the model evaluation using the Partial Least Squares Structural Equation Modeling (PLS-SEM) approach showed that the structural relationships among variables fell within the small to medium effect range, while the coefficient of determination (R^2) indicated a weak to moderate level of explanatory power. This suggests that the infrastructure variables examined influence regional development outcomes, but do not fully explain the overall variation in development urgency, indicating the possible presence of other external contributing factors.

Based on the analysis results, the priority order of infrastructure with the highest urgency is regional supporting infrastructure (X6), followed by electricity facilities (X2), SWTP (X3), infrastructure for surrounding communities (X4), clean water and irrigation systems (X5), and WWTP (X1). Regional supporting infrastructure was found to have the most significant positive impact on socioeconomic benefits and destination image strengthening, although the magnitude of its effect remains relatively limited.

Theoretically, basic infrastructure such as clean water, sanitation, and wastewater management systems is categorized as enabling infrastructure—serving as a prerequisite for development but not always generating direct socioeconomic impacts (World Bank; Aschauer). Therefore, it is reasonable that the infrastructure variables in this study do not fully explain the variation in regional development outcomes. Accordingly, infrastructure development in the Mandalika SEZ should be directed toward a value-creating infrastructure approach that emphasizes improving tourism experience, regional connectivity, and strengthening the local economic ecosystem. This aligns with Destination Competitiveness and Experience Economy theories to promote more significant, effective, and sustainable development outcomes.

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