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A NOVEL DEMAND FORECASTING METHOD USING LOGISTIC REGRESSION AND CONJOINT ANALYSIS FOR PREDICTING THE VOLUME OF NEW TRANSPORTATION ACTIVITIES

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Abstract

In developing new transportation projects, the common approach is to prioritize infrastructure first, with the expectation that demand will follow. This is particularly true for public sector logistics activities, such as seaports, airports, and logistics zones. Unlike the private sector, predicting future demand for public transportation is more challenging due to its complexity. Incorrect demand forecasting can result in improperly sized infrastructure and inefficient human resource allocation. This paper introduces a novel method for forecasting demand in public sector transportation projects. It integrates historical data with the perceptions of transportation stakeholders, improving forecasting accuracy. The method combines conjoint analysis with disaggregated forecasting for each product group. It was applied to a real case namely the Indonesian Ministry of Transportation's plan to develop a cargo transshipment terminal at Denpasar Airport in Bali. A survey of 233 logistics professionals in Jakarta, Bandung, and Denpasar was conducted, and the forecasts were verified through interviews. The results showed that the forecasts for each product category were accurate. This method's reliability suggests its potential for use in other transportation development projects.

Keywords: *Forecasting; Demand; Conjoint; Transportation*

1. Introduction

Logistics and transportation activities have grown exponentially in the last three decades and their rapid growth has pushed many significant advances all over the world (Wang et al., 2023). As a critical sub-system, logistics serves as a connective medium among various entities in business operations (Smirnova et al., 2024). This growing importance has spurred extensive research, primarily at the micro (corporate) level. However, studies focusing on logistics within the public sector remain limited (Barros & Hilmola, 2007).

The lack of attention to macro logistics is more salient when one focuses on demand management. Logistics is a series of activities designed to meet consumer needs, starting from production and even raw material supply. (Smirnova et al., 2024). Since demand is the primary driver of logistics systems, accurate forecasting is essential. Despite its importance, demand forecasting is often overlooked in public sector logistics, where decision-makers tend to prioritize infrastructure development (Grzybowska et al., 2022)(Croxton et al., 2002). Meanwhile, recent advancements in artificial intelligence and big data have significantly enhanced forecasting capabilities (Toorajipour et al., 2021).

The infrastructure-based development of logistics is an old paradigm which has basic drawbacks. Almost all elements in logistics and transportation systems are derived from the demand(Aytekin et al., 2024) (Croxton et al., 2002). Customer service levels, inventory levels and transportation plans are all figured out by the forecasted demand. Those three things later dictate infrastructure size and capacity of logistics systems, i.e., warehousing, production, and transportation. We can conclude that errors in predicting demand for new logistics activities have significant consequences in deciding the proper infrastructure size. In addition to infrastructure, demand forecasting is closely tied to human resource allocation. These errors not only lead to budget inefficiencies but can also result in sunk costs in the future.

Forecasting methods generally fall into two categories: quantitative approaches, which rely on

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numerical data and statistical models, and qualitative approaches, which draw on expert judgment and interpretive analysis. While quantitative models such as time-series forecasting are effective in established markets with consistent historical data, they are less applicable to public sector logistics, which often involves new initiatives lacking historical demand patterns. In such cases, qualitative methods like expert interviews and focus group discussions (FGDs) offer valuable insights but lack replicability and systematic validation.

In terms of developing new logistics activities at the corporate level, demand forecasting has been thoroughly investigated (Sultanbek et al., 2024). Starting new activities in a business does not always mean beginning from scratch. New business activities often build upon existing market trends, making time-series models applicable. However, public sector logistics often involves entirely new initiatives, such as the development of Special Economic Zones (SEZs), where no prior market behavior exists. These initiatives are influenced by macroeconomic conditions, policy shifts, and regulatory changes, rendering traditional data-driven models insufficient. Consequently, alternative approaches—incorporating expert judgment, scenario analysis, and machine learning—are needed to generate reliable forecasts.

The development of entirely new public logistics initiatives, such as some of which are caused by complexity of the macro logistics structure, Quantitative forecasting methods are widely used in corporate logistics, particularly time-series models, which analyze historical trends and extrapolate future demand(Stylos et al., 2021). These models assume that past consumption patterns will continue, making them effective for industries with established market behaviors and incremental technological advancements.

Despite the progress in AI and big data applications for private sector forecasting, their use in public logistics remains underexplored. Existing research predominantly addresses micro-level supply chain management, while replicable quantitative models for public sector logistics are still lacking. Current public sector forecasting relies heavily on qualitative methods, which, although rich in contextual insights, do not yield generalizable models. Therefore, there is an urgent need to develop objective, data-driven, and replicable forecasting models to enhance public logistics planning.

The complexity of logistics issues in the public sector has led to demand forecasting relying heavily on qualitative methods, such as focus group discussions (FGD) and in-depth interviews (Stylos et al., 2021). Additionally, governments often engage in direct consultations with prospective users, as seen in Frankfurt Airport's cargo hub development (Faraport, 2019). While these traditional approaches offer valuable insights, they lack systematic structure and replicability, not leveraging recent advancements in data availability and AI/ML -based forecasting techniques. Existing models, such as time-series forecasting, have been widely applied in corporate logistics due to their reliance on historical demand patterns.

These methods are not only non-systematic but are not necessarily repeatable for the case of developing other new logistics activities. Whereas in fact, demand analysis is an important thing to do in predicting logistics performance in the public sector. According to (Feizabadi, 2022) demand analysis is important because it can predict uncertainty, risk, and dynamic conditions in the business environment, so that business decisions to be taken will be much better because it has reduced or eliminated uncertainty (Feizabadi, 2022b).

However, these methods are insufficient for new public logistics activities, where no historical demand exists, and decisions are shaped by macroeconomic policies and business regulations. This gap underscores the need for a structured, AI/ML-driven demand forecasting model that integrates quantitative data analytics with expert-driven insights, ensuring higher accuracy and applicability across various public logistics scenarios. Inaccurate demand predictions have already led to costly miscalculations, such as the development of Kertajati Airport (Hudalah et al., 2021). Showing the pressing need for more robust forecasting models.

In this study, although the approach employed is qualitative, we deliberately adopt principles from the qualitative-positivist tradition, as outlined by Yin. (Yin, 2013) and Eisenhardt. (Eisenhardt, 1989).This approach allows qualitative research to keep replicability and generalizability through a rigorous methodological structure, including the use of consistent interview protocols, data triangulation, and theory-driven analysis. This framework enables qualitative research to achieve replicability and generalizability through rigorous methodological design, including standardized interview protocols, data triangulation, and theory-driven analysis. While FGDs and in-depth interviews are inherently contextual, their integration within a structured framework allows findings to be systematically linked to prior research. Thus, this study not only acknowledges existing literature but also contributes to the development of generalized conceptual models applicable across diverse contexts.

This research aims to develop methods and models for predicting demand in the development of new logistics activities, particularly in the public sector. The research makes three key contributions. First, it introduces demand prediction models for entirely new logistics activities, a type of quantitative model that is not widely found in current studies. These models ensure accuracy and can be applied to other cases. Second, the demand prediction model integrates multivariate analysis techniques with insights from logistics business professionals, allowing the development of new logistics businesses to align with expert knowledge. Third, the model has been tested in a real case in Indonesia, where the Ministry of Transportation is planning the development of a cargo transshipment airport in Denpasar, Bali.

This study aims to bridge the gap between traditional qualitative approaches and AI/ML-driven

Table 1. Research Approach

Research	Object	Forecasting Models	Notes
(Lee et al., 2006)	Sales of wide screen TV	Conjoint-diffusion model	• Consider the heterogeneity of consumers. • Forecast new product demand
(Bass, 1969)	Sales of durable products	Conjoint model	• Predict product requests using similar product demand data. • Does not account for repeat purchases (only for first purchases)

forecasting for new public logistics activities. The research key contributions:

1. Introducing structured, quantitative forecasting models for entirely new logistics activities, ensuring replicability and accuracy.
2. Integrating multivariate AI/ML-based demand prediction with expert knowledge, combining data-driven methods with insights from logistics professionals.
3. Validating the model with a real-world case study, applying the method to Indonesia's Ministry of Transportation's plan for developing a cargo transshipment airport in Denpasar, Bali.

This paper is presented as follows. The first part discusses the background of the problem, research position, and contributions. The developed model is presented in the second part. In the third part, real case studies are presented to implement the models that have been developed. Finally, in chapter four, the main findings are presented as well as a discussion of research deficiencies to be developed in further efforts.

2. Method

The approach used in this study is derived from statistical techniques, i.e., a causal method, which is considered suitable for predicting demand for new logistical activities. A large demand historical data collected from the Ministry of Finance combined with large respondents' samples collected by the Ministry of Transportation are harnessed. This method does an analysis related to several independent variables (factors) to find the relationship in figuring out the number of requests in the future (dependent variables). In addition, this study also uses a forecasting approach using the conjoint model. This model is used to measure market share based on consumer preferences for products/ services. One of the reference models used in this study is the conjoined diffusion model (Lee et al., 2006) which is an improvement of the conjoint model by Bass (Bass, 1969). A more detailed explanation can be seen in **Table 1**.

The questionnaire was developed based on a thorough review of established literature relevant to the research domain. Items were adapted from validated instruments and carefully refined to ensure alignment with the study's objectives and contextual relevance. To ensure the inclusion of participants with right expertise, a purposive sampling technique was employed, targeting individuals with direct experience and knowledge in the subject area. The survey achieved a 90% response rate, reflecting strong participant engagement and enhancing the reliability of the collected data. Data collection was conducted over a two-week period, providing sufficient time for thoughtful responses and minimizing time-related bias.

The model for predicting demand for new logistics activities is a development of the Bass diffusion model (Bass, 1969). In the Bass diffusion model, to figure out the diffusion pattern of a product/service, we need sufficient historical data on the sale of the product. However, the Bass model cannot be used on new products/ services that have not been marketed before. In addition, the Bass model does not consider competition in the market. Based on these deficiencies, Lee developed a refinement model, namely the diffusion-conjoint model (Lee et al., 2006).

While logistic regression is a widely used and interpretable model for estimating choice probabilities and utility values, it is not without limitations. One notable concern is the potential for bias in coefficient estimates when predictor variables (utilities) are highly collinear. Multicollinearity can obscure the individual effect of each attribute, leading to unstable estimates and reduced model reliability. This issue is particularly relevant in conjoint analysis, where attributes may be conceptually or statistically related. Although diagnostic checks and variable selection techniques can mitigate this risk, it remains a methodological limitation that should be acknowledged when interpreting the results. Future studies may consider alternative modeling approaches or regularization techniques to address this challenge more robustly.

According to Lee (Lee et al., 2006), the steps to build a conjoint-diffusion model are as follows.

1) Estimating the value of static utilities to figure out consumer preferences.
2) Decide the level of factors that influence technological change and market demand for products/services.
3) Change the static utility value into a dynamic utility value by combining the results of the first and second steps.
4) Predict market share (market share) and volume of demand for each product based on the probability of individual choice.

The chosen dynamic factor is price (Lee et al., 2006) which follows the following equation (1)

$$p_{jt} = p_{j0}e^{-\theta_j t} \quad (1)$$

where,
p_{jt}: price of j-th product at the time t
p_{jo}: price of j-th product at the time of first launch
θ_j: degree of decrease in price of product j with respect to time.

Experts' opinions on the projected changes in the value of attributes in the future to determine dynamic factors follow the formulation of Lee's research (Lee et al., 2006).

Conjoint model development is done by determining the attributes that will be used. These attributes must be able to define the product/service to be tested and can assess consumer preferences for the product/ service. Attribute reduction needs to be done using the cut-off method to select the attributes that are judged to most influence the utility value given by the respondent, as explained in equation (2) extracted from (Tam & Tummala, 2001).

$$cut\ off\ point = \frac{a+b}{2} \tag{2}$$

where,
a = the highest average rating
b = the lowest average rating

The static attribute is then validated by comparing the results of the rating assessment with the ratings given by respondents which are processed using the weighted sum ranking method, which is the most famous multi-criteria decision making method and the easiest to compare and evaluate several alternative criteria in decision making (Roszkowska, 2013). The model was developed using the conjoint diffusion model. According to Lee (Lee et al., 2006), to build a diffused conjoint model, it is necessary to redefine the attributes so that they are dynamic (Lee et al., 2006). This research assumes that there is no interaction between attributes. The following is the equation of the traditional conjoint additive model in equation (3).

$$U_{hx} = \sum_{j=1}^{J} u_{ij}^{x} \tag{3}$$

where,
U_{hx} = total utility value of profile j according to respondent x.
u_{ij}^{x} = part worth value of attribute j at level i by respondent x.

After processing the data with the conjoint model to obtain individual and aggregate part-worth values, the results will be analyzed using a binary logistic regression model to determine the market share of the new logistics activities being studied. The binary logistic regression model will process the data based on two possible outcomes namely yes or no. The binary logistic regression model that is suitable for this study is the model described in (Hair et al., 2022), which can be seen mathematically in equation (4).

$$Prob\ P_{ij} = \frac{\exp\,(\beta_0+\beta_1 X_{ij})}{\exp(\beta_0+\beta_1 X_{ij})+1} \tag{4}$$

where,
P_{ij}: probability of using product/service profile j.
X_{ij}: value of consumer preferences for profiles j.
β_0, β_1: the coefficient of binary logistic regression results, with the value of the dependent variable 1 for the rating value ≥ 9 and the value of 0 for the rating value < 9 on a scale of 1-10.

In this study, ratings of 9 and 10 are categorized as a positive outcome ("yes") within the binary logistic regression framework. This high threshold was deliberately chosen to ensure that the classification reflects only the most favorable evaluations. By narrowing the definition of "yes" to the top-tier ratings, the model gains greater precision and interpretive clarity, as it focuses on outcomes that are unequivocally positive.

According to Wilson & Lorenz (2015), binary logistic regression is particularly effective when modeling dichotomous outcomes that are clearly defined and meaningful. The use of a stringent threshold aligns with their recommendation to ensure that the binary categories represent distinct and interpretable states. In this context, the higher the threshold, the more confident we can be that the predicted "yes" truly reflects a strong positive sentiment, thereby enhancing the reliability of the model's predictions.

Data processing with binary logistic regression requires an independent variable representing respondent preference values, obtained by summing individual part-worth/utility values based on the product/service level. The dependent variable is the prediction score given by the respondent. The validity of the binary logistic regression model was tested using two methods. The first method involves comparing the predicted values (Y predicted) with the observed values (Y observed) provided by the respondent. The second method uses bootstrapping to estimate the model by randomly selecting subsamples from the respondent group and comparing the average results of these subsamples with the estimated parameter values. (Hair et al., 2022). A model is said to have passed the validity test if it has a hit ratio value greater than proportional chance criterion, which is mathematically explained as follows in equation (5).

$$C_{pro} = p^2 + (1-p)^2 \tag{5}$$

where,
C_{pro} = Hit ratio proportion value.
p = Individual proportion in group 1.
$1\text{-}p$ = Individual proportion in group 2.

3. Results and Discussion

As a country with the largest economy in Southeast Asia, logistics performance in Indonesia is still not satisfactory. Based on the latest release from the World Bank (World Bank, 2023) , Indonesia's logistics performance index (LPI) ranks 61th, losing to Singapore (1), Thailand (34), Vietnam (43) and Malaysia (26). The logistics aspects that have not been worked out properly have made some business activities unable to run optimally, one of which is the cargo terminal. Until now, there is no world-class cargo air terminal (world-class) in the country.

One type of air cargo business is transshipment, or in customs terms known as 'angkut lanjut'. Unlike imports where cargo is subject to clearance for

Table 2. Determinants of Consumer Preferences in Using Air Cargo Transshipment Services

Factors	References
Airport connectivity	(Yeo et al., 2008), (Pels et al., 2009), (Larrodé et al., 2018), (Wong et al., 2023), (Balakrishnan & Karsten, 2017), (Ma et al., 2023)
Airplane cargo capacity	(Larrodé et al., 2018), (Ma et al., 2023)
The size of the transshipment cargo warehouse	(Larrodé et al., 2018), (Wong et al., 2023) , (Ma et al., 2023) , (Chao & Yu, 2013)
Speed of document transshipment services	(Yeo et al., 2008), (Larrodé et al., 2018), (Ma et al., 2023) , (Chao & Yu, 2013), (Prasetyo et al., 2015)
Cargo loading and unloading speed	(Yeo et al., 2008), (Larrodé et al., 2018), (Wong et al., 2023), (Chao & Yu, 2013), (Prasetyo et al., 2015), (Gardiner et al., 2005)
On time cargo delivery	(Larrodé et al., 2018), (Ma et al., 2023), (Prasetyo et al., 2015), (Hess & Polak, 2006), (Loo, 2008), (Jacquillat & Odoni, 2018), (Danielis & Lucia, 2002), (Kofteci & Ergun, 2010)
Cargo security	(Larrodé et al., 2018), (Wong et al., 2023) , (Prasetyo et al., 2015), (Danielis & Lucia, 2002), (Kofteci & Ergun, 2010)
Transshipment service fee	(Yeo et al., 2008), (Larrodé et al., 2018), (Zhang, 2003), (Ma et al., 2023), (Chao & Yu, 2013), (Gardiner et al., 2005), (Hess & Polak, 2006), (Loo, 2008), (Danielis & Lucia, 2002), (Kofteci & Ergun, 2010), (Institute of Transportation, 1999), (Y. Park & Y. Kim, 2003)
Human resources quality	(Larrodé et al., 2018), (Prasetyo et al., 2015)
Airport reputation	(Yeo et al., 2008), (Larrodé et al., 2018), (Chung et al., 2013)

expenses and checks for entry, transshipment cargoes only stop at the airport, then depart again. The most a common reason for transshipment is economies of scale. Until now, connoisseurs of the transshipment cargo business are Changi Airport, Singapore. With its strategic position, coupled with a variety of added value creation activities such as labeling, packaging and customization, Singapore has the largest air cargo market share in Southeast Asia.

In Indonesia, transshipment practices have yet to be established, despite the country's geographic advantages, which are comparable to Singapore. Specifically, at I Gusti Ngurah Rai Airport in Denpasar, there is already a captive supply of direct air transport from regions such as Oceania (south), Japan, South Korea, China (north), and the United Arab Emirates (Middle East), as reported by Air Cargo News (Air Cargo News, 2017). Analysis indicates that shipping cargo from Australia to Japan via Denpasar offers a time advantage over the Singapore route. The airport also has sufficient capacity. Although there are no freighter cargo flights in Bali at present, the bellyhold capacity at Ngurah Rai, which is 2,000 tons per day, is currently underutilized, with only 273 tons per day being used around 14% of its total capacity (Angkasa Pura Logistik News, 2025).

Analysis of cargo demand aims to accurately predict future cargo traffic, so that airports and cargo operators can anticipate consumer demand and to prepare for the optimal development of airport potential (Hong et al., 2023), (Yu & Zou, 2022), (Bunahri et al., 2023). The results of the demand analysis can be used to determine the size and layout of the warehouse, facilities and human resources needed, and to conduct an economic analysis of the costs involved and the benefits to be gained.

Logistic Regression combined with Conjoint Analysis is well-suited for in modeling individual-level choices and market simulations using interpretable, survey-based data (María et al., 2025). Time-Series Models, including ARIMA, are well-suited for forecasting trends in sequential data, capturing seasonality and autocorrelation, though they assume continuity and stationarity (Abdoli, 2020) AI models such as neural networks, random forests, and gradient boosting offer high accuracy and handle complex, high-dimensional data but often lack interpretability and require substantial computational resources (María et al., 2025).

Demand forecasting is divided into two types. The first type addresses entirely new demand, specifically the new logistics cargo transshipment activity in Denpasar. The second type focuses on existing demand at Ngurah Rai Airport, based on over 300 months of historical customs data from the Ministry of Finance, which will be forecasted using time-series models. For the first type of forecasting, the method developed in this study is used. The first step involves identifying the factors that influence consumer preferences when selecting transshipment services, as outlined in **Table 2**.

The distribution of the conjoint questionnaire obtained data from 233 respondents, which met the minimum number of samples as presented in **Table 3**. Based on the developed model, the part worth and importance for each attribute is presented in **Table 4** and **Table 5**.

The classification of importance value was selected based on a combination of historical cargo traffic data and expert judgment. Historical data on air cargo volumes across the evaluated routes were analyzed to identify patterns of utilization and frequency. Routes with consistently high cargo throughput and frequent flight schedules were categorized as having “high connectivity,” while those with lower volumes and less frequent service were classified as “low connectivity.” This classification was then validated through interviews with logistics

Table 3. The Respondents

Airports	Respondents	Number	Percentage (%)
Husein Sastranegara (Bandung)	Airlines	30	40.00
	Cargo forwarder	45	60.00
Soekarno Hatta (Jakarta)	Airlines	5	4.81
	Cargo forwarder	99	95.19
I Gusti Ngurah Rai (Denpasar)	Airlines	19	35.19
	Cargo forwarder	35	64.81

Table 4. Aggregate Part Worth

Level At The Attributes		Part Worth Values
Airport connectivity	63 routes	0.235
	147 routes	0.470
	275 routes	0.056
Speed of document transshipment services	5 minutes	-0.029
	30 minutes	-0.058
	60 minutes	-0.087
Cargo loading and unloading speed	< 45 minutes	-0.196
	45-60 minutes	-0.391
	> 60 minutes	-0.587
On time cargo delivery	Delay risk is 1 day.	-0.841
	Delay risk is 4 day.	-1.682
	Delay risk is 5 days	-2.523
Cargo security	Full compensation from cargo values, but due to payment of Rp 100.000/kg	-0.256
	Compensation of Rp 100.000/kg	0.091
	Compensastion of Rp 50.000/kg	0.165
Constant		5.599

Table 5. Important Value

Attribute	Importance Value
Airport connectivity	23.198
Speed of document transshipment services	13.657
Cargo loading and unloading speed	13.983
On time cargo delivery	13.258
Cargo security	35.904

Table 6. Transshipment Cargo Market Share

Stage	Time	Part Worth	Utility	Market Share (%)
1	60.00	-0.087	-0.920	10.74
2	30.00	0.783	-0.050	15.20
3	5.00	1.508	0.675	19.99
4	4.00	1.537	0.704	20.21
5	2.00	1.595	0.762	20.64
6	1.67	1.605	0.772	20.71
7	1.10	1.621	0.789	20.84
8	0.52	1.638	0.805	20.96
9	0.34	1.643	0.811	21.00
10	0.09	1.650	0.818	21.06

professionals and air cargo operators who confirmed the practical relevance of these distinctions in operational decision-making. Based on the importance value, it can be projected a market share for new logistics activities at Ngurah Rai Airport, namely cargo transshipment, as presented in **Table 6**.

The second type of projection focuses on existing demand that existed prior to the introduction of new logistics activities. This projection is carried out using time-series methods, based on extensive historical demand data. Data on existing cargo demand for advanced/continuous transport is collected through a questionnaire distributed to Customs and Excise, Ministry of Finance. An example of the forecasting results for food commodities and live animals is shown in **Figure 1**, while the total forecasting results for both the causal method and time-series approach are presented in **Figure 2**.

4. Conclusions

This research develops a demand forecasting model for new logistics activities in the public sector.

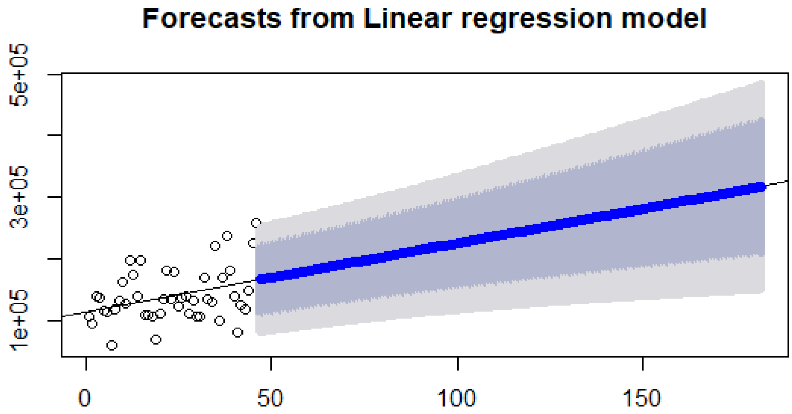

Figure 1. Example of Forecasting Results of Time Series of Food Commodities and Live Animals

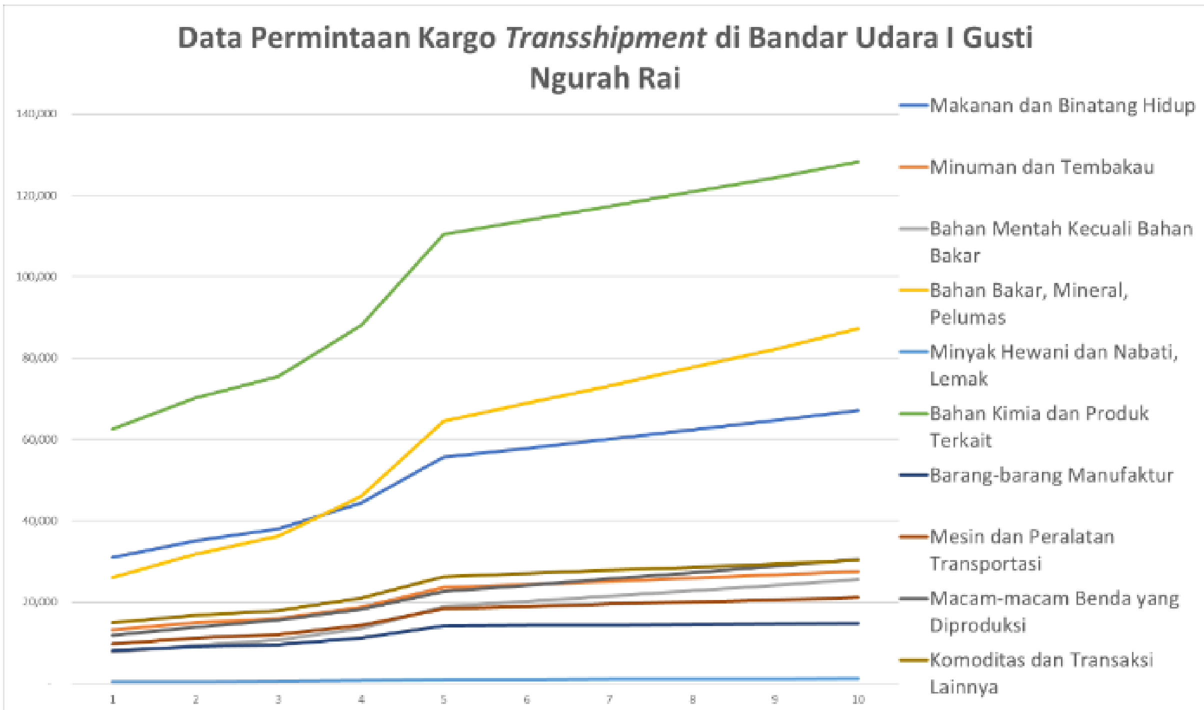

Figure 2. Example of Forecasting Results for New Logistics Activities at Ngurah Rai Airport

The conjoint model is used to capture consumer preferences for new logistics services, with the resulting preference values predicting market share. These values can also be decomposed to identify the key attributes influencing the choice of logistics services. The selection of attribute levels was based on a thorough review of literature, earlier research, and interviews. A key strength of the chosen levels is that they allow for comparison with similar logistics services that have shown robust performance.

Once the attributes and their levels were selected, an experimental profile was constructed using fractional factorial design. This approach helps generate a subset of all possible profile combinations, focusing on those that most influence the main effects in the conjoint analysis. The advantage of this design is that it simplifies the task for respondents, making it easier for them to provide assessments.

The model was evaluated with a case study on the development of a cargo transshipment airport in Denpasar. It was used to understand consumer preferences for cargo transshipment services and predict market share. By decomposing the preference values, the model identifies which attributes are most important when selecting cargo transshipment services. This offers valuable insights into the potential transshipment cargo market at I Gusti Ngurah Rai Airport, even though the service has not yet been implemented. The findings can inform policy recommendations and strategies for the government.

In the case study, five key attributes were identified through an analysis of large-scale historical and perception data from the Ministry of Finance and Ministry of Transportation. These attributes include airport connectivity, speed of transshipment document service, cargo loading and unloading speed, accuracy of cargo delivery duration, and cargo security. The identification of these attributes involved an exploratory process, including earlier studies, interviews with industry experts, and testing and validation with respondents. Five attributes were selected from an initial set of twelve to simplify the evaluation process while still allowing for meaningful trade-offs between distinct levels of each attribute.

While the conjoint model offers significant strengths, it also has limitations. One key assumption is that respondents evaluate alternative profiles solely based on the attributes presented, which may influence their decision-making trade-offs. On the practical side, the model holds promise for application in other new logistics development cases.

It is important to note that the scope of this study is limited to forecasting demand for a potential air cargo transshipment terminal. While the findings provide valuable insights for policy formulation and strategic planning, this research does not extend to the implementation phase, such as facility design, staffing requirements, or cost estimation. These aspects fall under different disciplinary domains. Therefore, this study should be viewed as a foundational step that informs and supports subsequent interdisciplinary efforts in terminal development and operational planning.

This research advances the field of demand forecasting and public logistics planning by introducing an innovative, replicable framework that harmonizes stakeholder preferences with diffusion dynamics. Move away from traditional infrastructure-focused strategies towards demand-oriented logistics in the public sector. This expansive policy and system-level perspective not only amplifies the study's academic robustness but also offers a concrete blueprint for policymakers and public administrators to rethink logistics planning amid shifting market trends.

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