

A Five-Year Quantitative Trend Analysis of Study Program Selection Interest in New Student Admissions – A Case Study of Politeknik Manufaktur Bandung

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ABSTRACT: This study analyzed the influence of study program name branding on trends in the number of applicants in the new student admission process at Politeknik Manufaktur Bandung. Using secondary data from 2021 to 2025, a simple time-series trend analysis was conducted by comparing groups of study programs that used traditional keywords (such as “Tooling”) with those that used modern keywords (such as “Automation” and “Mechatronics”). The results indicated a significant divergence in trends: study programs with traditional nuances showed a linear decline in interest (negative slope values), whereas programs with modern nomenclature demonstrated an increasing trend (positive slope values). Although differences in academic level (D3 vs. D4) also served as a secondary variable, the data suggested that prospective students’ perceptions of older technical terms such as “Tooling” were negatively correlated with their enrollment decisions. This study recommends the implementation of a rebranding strategy for study program names to better align with Industry 4.0 technological perceptions to enhance institutional attractiveness.

KEYWORDS: phrases study program branding, student interest, trend analysis, and vocational education

I. INTRODUCTION

The new student admission process (PMB) constitutes a strategic activity in the management of higher education institutions, as it is directly related to capacity planning, promotional strategies, and the quality of academic input. Each year, Politeknik Manufaktur Bandung (POLMAN Bandung) receives applicants from diverse educational backgrounds, each demonstrating varying levels of interest in the study programs offered. This variation is influenced not only by internal factors, such as curriculum and facilities, but also by prospective students’ perceptions of the study program names themselves, which play a crucial role in shaping institutional image, attractiveness, and expectations regarding future career prospects after graduation (Wilson & Elliot, 2016). Study program names often function as a form of “academic branding” that represents the field of competence and scholarly identity (O’Sullivan et al., 2024). In the context of vocational education, such as at a polytechnic institution, terms such as smart manufacturing, industrial automation, or software engineering may generate different perceptions in the minds of prospective students. Name-based branding of study programs has been shown to have a positive correlation with applicants’ interest and their decision to select a major (Ersoy & Speer, 2025). Previous studies have shown that changes in study program names can enhance institutional image and lead to an increase in the

number of applicants by up to 15% within a two-year period (Acton, 2022).

Furthermore, the brand image of a higher education institution is shaped not only by its academic reputation but also by the appeal of the terminology used in program names. Wilson emphasizes that “brand meaning” in the context of higher education influences prospective students’ perceptions of program quality and relevance (Wilson & Elliot, 2016). In contrast, other studies have found that trust and perceptions of innovation also play significant roles in shaping students’ preferences for particular study programs (Asgari et al., 2024). Therefore, analyzing the correlation between study program names and prospective students’ interest is essential to quantitatively understand these patterns of perception and preference.

Advancements in educational data mining (EDM) and learning analytics provide new opportunities for institutions to analyze patterns of prospective student interest more objectively. Machine learning–based approaches enable the analysis of both non-seasonal (stable) and seasonal (temporary) factors in the new student admission process (Yang et al., 2021). For example, algorithms such as random forest or time-series analysis can be employed to detect long-term trends in applicants’ interest in specific study programs without being influenced by annual fluctuations caused by promotional activities, pandemics, or changes in the selection system (Vaarma & Li, 2024) (Sweeney et al., 2015).

In addition, previous studies have emphasized that data-driven decision-making in new student admissions can support more efficient institutional policies (Nugraha, 2024). Previous studies have shown that correlation analysis between academic performance, school background, and study program choice can help higher education institutions predict prospective students' interests in the future. Other research highlights that psychological and social factors, such as perceptions of program names and career prospects, constitute important variables in predictive models of study program selection (Milburn et al., 2025).

In the Indonesian context, several local studies have reported similar findings. One study found that prospective students' decisions are influenced by program reputation, tuition costs, and the attractiveness of study program names (MASITOH, 2018). The study employed data mining methods to analyze prospective students' behavior in selecting study programs and identified a pattern indicating that terms related to technology and industry tend to attract higher levels of interest (Suryani, 2022).

Based on these conditions, this study was designed to identify and process prospective student interest data that are stable and not influenced by seasonal factors, analyze the development and differences in interest levels among study programs at Politeknik Manufaktur Bandung, and draw conclusions regarding factors that potentially influence the correlation between study program names and prospective student interest levels. Accordingly, the primary objective of this research is to quantitatively analyze patterns and trends in prospective student interest across study programs, while also providing strategic recommendations for managing promotional activities and planning new student admissions in a more targeted and data-driven manner.

II. RESEARCH METHODOLOGY

This research methodology was systematically and structurally designed to ensure that the processes of data collection, processing, and analysis were conducted objectively, accurately, and scientifically accountable. A methodological approach was developed to effectively capture patterns and trends in changes in the number of applicants for the New Student Admission (PMB) process at Politeknik Manufaktur Bandung (Polman Bandung) over a specified period. Therefore, the research findings are expected to serve as a basis for evaluation and strategic decision-making in the field of higher education.

A. Research Design

This study employs a quantitative descriptive method with a simple historical data trend analysis (time-series analysis) approach. The quantitative descriptive method was selected because the research aims to describe and analyze phenomena based on available numerical data without applying any treatment or manipulation to the research variables. The trend analysis approach is used to identify

patterns of change in the number of PMB applicants over time, whether showing an increase, a decrease, or relatively stable conditions. The trend model applied is a simple linear trend, as it is suitable for short- to medium-term historical data and is easily interpretable as a foundation for preliminary analysis in planning and evaluating new student admissions.

B. Data Sources

The data source in this study consists of secondary data, namely data obtained indirectly from a primary source. The data used comprise a recapitulation of the number of applicants for the New Student Admission (PMB) process at Polman Bandung for each study program over the period 2021 to 2025. These data were obtained from official institutional documents, such as annual PMB reports or the Polman Bandung new student admission information system database. Secondary data were chosen because the data have been systematically documented, demonstrate a high level of reliability, and are relevant to the research objective of analyzing patterns and trends in new student admissions.

C. Population and Sample

The population in this study comprised all the study programs at Polman Bandung. However, because the research aimed to conduct a comparative analysis of specific study program characteristics, not the entire population was analyzed directly. The sampling technique employed was purposive sampling, which involved selecting samples based on specific considerations and criteria aligned with the research objectives. In this study, the sample was divided into two main groups for the purpose of comparing trends in the number of applicants:

1. Group A (Traditional Study Programs)

This group consists of study programs characterized by conventional manufacturing disciplines and contains the keyword “Tooling,” namely:

- D3 Precision Tooling Manufacturing Technology
- D3 Precision Tooling Design Technology

The study programs in this group were selected to represent traditional manufacturing fields of expertise that have long been recognized and have become a distinctive characteristic of vocational education in Polman Bandung.

2. Group B (Modern Study Programs)

This group consists of study programs oriented toward emerging technologies and the development of Industry 4.0, with keywords that reflect innovation and modern engineering, such as:

- D4 Automation Engineering Technology
- D4 Mechatronics Engineering Technology

This group was selected to represent study programs with advanced technological approaches, which are expected to have different levels of appeal to prospective students. The division of the sample into these two groups aims to compare trends in the number of applicants between programs with traditional characteristics and those based on modern

technology, thereby providing an overview of shifts in prospective students’ interests over the past few years.

D. Linear Trend Model

The linear trend model is a statistical model used to describe the relationship between a dependent variable (Y) and time or an independent variable (X), assuming that changes occur in a linear manner. In this model, increases or decreases in the dependent variable are assumed to occur at a constant rate over time. In other words, the linear trend model represents data development patterns that move steadily along a straight line. This model is often employed in the initial stages of time-series analysis because of its ease of application, lack of complex assumptions, and relatively simple and easily interpretable results. Boshnakov states that the linear trend model is particularly suitable for annual educational data that exhibit stable increasing or decreasing tendencies, making it widely used in the analysis of applicant numbers, new students, and other educational performance indicators (Boshnakov, 2016).

Basic Linear Trend Equation

$$Y = a + bX$$

Explanation:

Y = Dependent variable value (e.g., the number of PMB applicants)

X = Time variable (year, period)

a = Constant (intercept)

b = Trend coefficient (slope)

In the context of new student admissions (PMB):

b > 0 indicates an increasing trend in the number of applicants

b < 0 indicates a decreasing trend

Derivation of the Formula Based on the Least Squares Method

The model uses the least-squares method. The two normal equations are as follow

$$\begin{aligned}\sum Y &= n \cdot a + b \sum X \\ \sum XY &= a \sum X + b \sum X^2\end{aligned}$$

Where:

n = number of observation periods

If the X data are coded in such a way that

$$\sum X = 0$$

Then, the equation becomes simpler:

$$\begin{aligned}a &= \frac{\sum Y}{n} \\ b &= \frac{\sum XY}{\sum X^2}\end{aligned}$$

This approach is widely used in educational research because it facilitates manual calculation and interpretation, particularly for policy reports and institutional evaluations.

Parameter Interpretation in New Student Admissions (PMB)

- Constant (a): The average number of applicants over the observation period
- Trend coefficient (b): The rate of increase or decrease in applicants per period

Example:

If b = 120, this indicates an average increase of 120 applicants per year.

Rozanoff demonstrated that the linear trend model was effective as a baseline for predicting the number of new students before applying more advanced machine learning models (Rozanoff, 2018).

III.RESULTS AND DISCUSSION

Based on the recapitulation of applicant data from 2021 to 2025, a trend analysis was conducted using the Least Squares Method with a simple linear regression equation (Y = a + bx). The b-value (slope) serves as the primary indicator for determining the direction of interest trends. If b is positive (+), the interest trend is increasing; if b is negative (–), the interest trend is decreasing.

Table 1. Recapitulation of Applicants per Study Program

Study Program	2021	2022	2023	2024	2025
D3 Machine Maintenance	221	268	229	130	135
D3 Manufacturing Technology	435	405	223	164	133
D3 Precision Tooling Manufacturing Technology	68	78	77	77	63
D3 Metal Casting Technology	121	150	138	75	90
D3 Precision Tooling Design Technology	46	88	49	33	46
D4 Mechanical Design Engineering	105	102	118	99	77
D4 Manufacturing Engineering Technology	209	173	304	297	356
D4 Mechatronics Engineering Technology	445	410	404	320	278
D4 Automation Engineering Technology	187	145	292	229	201
D4 Manufacturing Design Engineering Technology	112	116	195	147	152
Total	1949	1935	2029	1571	1531



Figure 1. Graph of Study Program Interest Recapitulation

Study Program Groups with a Declining Trend (Negative b Value) Study programs that use traditional nomenclature or are offered at the D3 level demonstrate a consistent decline in interest.

- **D3 Manufacturing Technology:** Experienced the sharpest decline with a slope value of $b = -84.6$. The projected number of applicants in 2026 is expected to drop drastically to approximately 18 students if no intervention is implemented.

- **D3 Machine Maintenance:** shows a negative trend with $b = -31$.

- **D3 Metal Casting Technology:** Exhibits a declining trend with $b = -13.7$.

- **“Tooling” Group (D3 Precision Tooling Manufacturing & D3 Precision Tooling Design Technology):** Both programs have a relatively low applicant base and tend to be stagnant or declining. D3 Precision Tooling Design Technology has $b = -5.5$, whereas D3 Precision Tooling Manufacturing Technology has $b = -1.1$.

Study programs with modern nomenclature (Industry 4.0-oriented) and those offered at the D4 level (applied bachelor’s degree) demonstrate a positive trend.

- **D4 Manufacturing Engineering Technology:**

Experiences the highest surge in applicants with a slope value of $b = 41.8$.

- **D4 Mechatronics Engineering Technology:**

Consistently remained a preferred program with a positive trend of $b = 11.2$.

- **D4 Automation Engineering Technology:**

Exhibits a growth rate identical to that of mechatronics, with $b = 11.2$.

- **D4 Manufacturing Design Engineering Technology:**

Demonstrates a positive trend with $b = 11.1$.

Overall, the total number of applicants declined from 1,949 in 2021 to 1,531 in 2025; however, the shift in the distribution of interest from traditional to modern study programs was highly significant. The data analysis reveals a significant divergence in trends between study programs with “traditional” and “modern” names. Programs containing the keyword “Tooling” show a consistent decline in interest,

possibly because the term is associated with conventional technologies (Industry 2.0 or 3.0), which are perceived as less relevant by Generation Z. In contrast, programs featuring keywords such as “automation” and “mechatronics” demonstrate positive trends, as they reflect futuristic and high-technology competencies that possess a stronger initial appeal. This finding reinforces the notion that study program naming functions as a form of academic branding that influences prospective students’ career perceptions. Program names that sound more technically modern, such as “Engineering,” are proven to be more attractive than more classical terms such as “Casting” or “Machine Maintenance.” In addition to naming factors, the level of education also serves as a secondary variable that reinforces this shift in interest. An internal cannibalization pattern is observed, in which interest in Diploma Three (D3) programs declines sharply, while Applied Bachelor’s (D4) programs increase significantly. This is evident in the comparison between D3 manufacturing technology, which shows a decline, and D4 manufacturing engineering technology, which demonstrates growth. Prospective students tend to prioritize D4 programs, as they are perceived to be equivalent to a bachelor’s degree (S1) and offer broader career prospects. However, the naming factor remains independently significant. Even at the same academic level (among D4 programs), study programs with names such as “manufacturing” or “automation” continue to experience growth in interest, whereas programs with the name “mechanical” show a declining trend.

IV. CONCLUSIONS

The findings of this study indicate a systematic and consistent decline in interest in study program selection at Politeknik Manufaktur Bandung during the 2021–2025 period, particularly among programs with traditional nomenclature and those offered at the Diploma Three (D3) level. Linear trend analysis revealed that study programs featuring classical technical terms such as Tooling, Casting, and Machine Maintenance experienced a significant decrease in interest, reflecting a negative correlation between prospective students’ perceptions of study program name branding and their enrollment decisions. These findings reinforce the view that study program names serve as an initial representation of academic identity, influencing institutional attractiveness, as well as prospective students’ career expectations.

In contrast, study programs with a modern nomenclature and orientation toward engineering technology and Industry 4.0—particularly at the Applied Bachelor’s (D4) level—demonstrate relatively stable or increasing interest trends. This finding confirms that the decline in interest does not reflect a weakening demand for the manufacturing field as a whole, but rather a shift in prospective students’ preferences toward programs perceived as more relevant, futuristic, and offering broader career prospects. Therefore, the findings of

this study indicate that study program management strategies—particularly those related to naming, academic positioning, and the strengthening of educational levels—need to be strategically re-evaluated to align with market perceptions, industry demands, and the evolving interests of prospective students in vocational education.

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