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Powering BI Dashboard for Admission Roadshow Prioritization Using CRISP-DM

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ABSTRACT

Institut Teknologi Garut (ITG) determines the target schools for the New Student Admissions (PMB) roadshow based on team experience, without using historical data. PMB data for the 2018–2025 period covers 3,816 applicants and 3,374 accepted students that have not yet been processed into measurable indicators, such as conversion rates, school rankings, regional rankings, geographic distribution maps, and school-type distribution. This study processes that data within a Business Intelligence (BI) framework, in which the Decision Support System (DSS) component is applied as a rule-based calculation that converts two quantitative indicators, weighted 60% and 40%, into a single priority score per school and region, following the CRISP-DM methodology within a mixed-methods approach. Quantitative data were sourced from PMB historical records, while qualitative data were obtained through semi-structured interviews to determine indicator weights via expert judgment. A weighted scoring model was developed, assigning 60% weight to the number of accepted students and 40% to the conversion rate, producing rankings for 937 schools. The Power BI dashboard covers seven outputs: annual PMB trends, school rankings, regional rankings, a geographic distribution map based on Microsoft Azure Maps, study program distribution, school type distribution, and a yearly recapitulation table. Garut Regency recorded 3,637 applicants (95.31% of the total 3,816 applicants) with a conversion rate of 87.21%. Tarogong Kidul District recorded the highest number of applicants (412 students), while Garut Kota District recorded the highest number of accepted students (460 students, CR 121.69%), and SMAS recorded the highest conversion rate (97.73%). All rankings were deemed suitable for the ITG PMB team's roadshow priority determination needs.

1. INTRODUCTION

New Student Admissions (PMB) is an annual process at higher education institutions that determines the number of students admitted for each academic period [1]. One of the activities in the PMB process is a roadshow that involves direct visits to high schools to introduce academic programs to students [2]. The number of students admitted is not always proportional to the number of applicants from the schools visited [3]. This situation highlights the need for indicators that can measure the relationship between the number of applicants and the number of admitted students at the school or regional level [4]. In this study, an applicant record refers to one registration for one study program, while an admitted-student record refers to one acceptance into one study program; an individual accepted into more than one study program within the same admission period is

therefore counted as multiple admitted-student records. Under this counting basis, the number of admitted-student records for a school can exceed its number of applicants, which produces a conversion rate above 100%.

The Garut Institute of Technology (ITG) conducts roadshows to high schools every year. Based on interviews with the PMB team, the selection of target schools is carried out through an evaluation of previous PMB results and internal discussions, taking into account the number of applicants, admitted students, school type, and region of origin, without producing quantitative priority rankings based on historical data. ITG's historical PMB data for the 2018-2025 period consists of 3,816 registration records and 3,374 admitted student records, containing information on regency/city, subdistrict, school of origin, study program, and school type. The contribution of each school is uneven: some schools have many applicants, but few admitted students, indicating differences in conversion rates between schools and regions that have not yet been analyzed into priority ranking indicators. Current historical ITG PMB data is presented in a Microsoft Excel-based dashboard that summarizes applicant numbers and regional distribution. This dashboard is descriptive and lacks conversion rate indicators, school or regional rankings, regional distribution maps, annual summary tables, or segmentation by school type. Consequently, the data cannot yet be used to quantitatively establish priority rankings for schools and regions as a reference for roadshow implementation [5].

Several previous studies have examined the use of Business Intelligence in the context of new student admissions. Aulia et al. dashboard was developed using Tableau to display the number of applicants, geographic distribution by province, and distribution by academic program; however, these studies did not calculate the conversion rate between applicants and admitted students, nor did they apply a weighted evaluation model to generate rankings of schools or regions [5]. Mohamed Isa generated student profile segmentation based on CRISP-DM, but it did not include conversion rates per school or region, a geographic map comparing applicants with admitted students, or an annual summary table [6]. Salman et al. built a Business Intelligence system using the Carlo Vercellis and Kimball model, displaying data on applicants, selection participants, successful candidates, and re-registrations per academic program; however, it lacks a weighted evaluation model based on conversion rates for regional rankings [7]. Thoib et al. also developed a dashboard to visualize trends and the distribution of applicants, but it does not categorize data by school type and cannot be used as a basis for setting PMB targets by school type [8]. Pratiwi et al. applied the SAW method in a decision-support system to rank prospective students based on five individual selection criteria, without considering conversion rates by school or region, the rankings of the top 10 schools, or geographic maps [9]. The five studies share a common limitation: they present descriptive visualizations of applicant data without calculating conversion rates or generating priority scores per school or region. None applied a weighted scoring model, geographic distribution mapping, annual summary tables, and school type segmentation as a unified output package. This study addresses that gap by developing a CRISP-DM-based Business Intelligence dashboard that integrates all seven of those elements into a single, validated tool for determining roadshow priorities at ITG.

This study employs Business Intelligence (BI), operationally defined as a series of processes for collecting, cleaning, transforming, and presenting historical data into quantitative indicators [10]. Decision Support Systems (DSS) are defined as rule-based calculation mechanisms using quantitative indicators and weights to generate scores and rankings [4]. This study also applies the CRISP-DM methodology, which encompasses six stages: Business Understanding, Data Understanding, Data Preparation, Modeling, Evaluation, and Deployment [11]. The output is a Power BI dashboard that processes historical ITG PMB data (2018-2025) into quantitative indicators: school rankings, Top 10 bar charts, regional rankings, distribution maps, annual summary tables, and school-type segmentation.

2. RESEARCH METHODOLOGY

This study employs a mixed-methods approach, combining quantitative and qualitative data within a single CRISP-DM methodology framework. The quantitative data consists of historical ITG New Student Admissions (PMB) data for the 2018-2025 period, encompassing 3,816 registration records and 3,374 admitted student

records. Qualitative data were obtained through semi-structured interviews with the ITG PMB team to inform the determination of indicator weights in the scoring model. The research framework follows the six stages of CRISP-DM: Business Understanding, Data Understanding, Data Preparation, Modeling, Evaluation, and Deployment [11]. The research framework is presented in Figure 1.

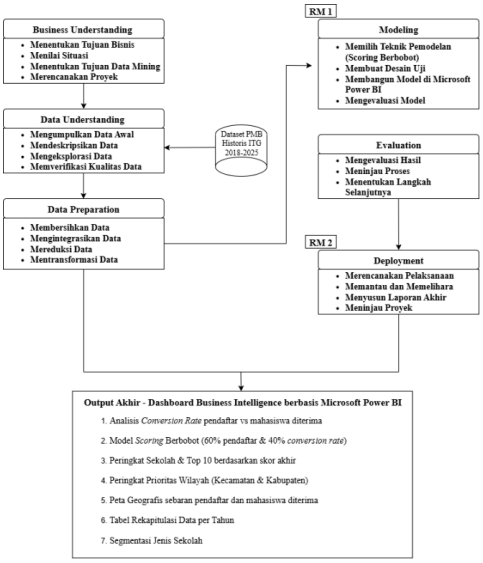

Figure 1. Research Framework (CRISP-DM)

Figure 1 shows the iterative CRISP-DM framework applied in this study, with each phase output feeding directly into the next.

2.1 Business Understanding

This stage aims to establish the direction of the analysis based on the needs of the ITG PMB team. Semi-structured interviews were conducted using 15 questions covering aspects of the roadshow process, data recording, challenges, and dashboard requirements. Three main issues were identified: target schools were determined without calculation based on historical data, quantitative indicators for comparing school contributions were not yet available, and applicant and recipient data had not been processed into a priority order. Through expert judgment, indicator weights were set at 60% for the number of admitted students and 40% for the conversion rate. This approach of combining weighted grade points for automated admission ranking aligns with automated decision support systems for admissions that use mathematical weighting methods to generate quantitative rankings [12].

2.2 Data Understanding

Historical ITG PMB data were obtained from the Academic and Student Affairs Bureau in the form of two Excel spreadsheets: 3,816 rows of registration data and 3,374 rows of admitted student data, covering the period 2018-2025. The dataset contains 12 original attributes and 4 derived attributes (Regency/City, Subdistrict, School Type, Year of Registration). Data quality verification is presented in Table 2; completeness is 100%, with no missing or duplicate values, but there are inconsistencies in school names across periods, which were addressed during the Data Preparation stage. Table 2 presents the results of the data quality verification conducted during the Data Understanding phase, confirming the completeness of the historical PMB dataset. The need for structured data preparation pipelines in prospective student data analysis has been highlighted in recent Indonesian higher education studies, which emphasize data cleaning, normalization, and integration as prerequisites for accurate BI outputs [13].

Table 2. Results of the Verification of the Quality of Historical PMB Data

Data Type	Rows	Columns	Empty	Duplicate	Completeness
Registration Data	3,816	16	0	0	100%
Admitted Student Data	3,374	16	0	0	100%

Table 2 confirms that both datasets achieved 100% completeness; spelling inconsistencies in school names were resolved in the subsequent Data Preparation phase.

2.3 Data Preparation

This stage produces a final dataset that is clean, consistent, and ready for use in modeling. Five activities were carried out sequentially: selecting data (7 attributes out of 16 available), cleaning data (standardising the spelling of school and region names using Find & Replace and the TRIM function), building the dataset (defining three derived attributes: number of applicants, number of admitted students, and conversion rate per school and region), integrating the data (combining eight admission periods into a single worksheet), and formatting the data (adjusting the format to .xlsx for import into Power BI). Unused attributes, namely NIK, Name, Phone Number, and Address, were excluded as they are not required for indicator calculations. A summary of the Data Preparation process is presented in Table 3.

Table 3. Summary of the Data Preparation Process

Process	Activity	Output
Data Selection	Specification of 7 attributes: Record Type, School of Origin, Regency/City, Subdistrict, School Type, Enrollment Year, Study Programme	List of attributes and coverage of eight data periods
Data Cleaning	Standardization of school and region names using Find & Replace and TRIM function	Dataset without duplicates and naming inconsistencies
Data Construction	Specification of three derived attributes: number of applicants, number of admitted students, and conversion rate per school and region	Derived attribute design as input for Modeling stage
Data Integration	Merging data from eight 2018–2025 admission periods into a single worksheet	Integrated dataset covering the entire 2018-2025 period
Data Formatting	Adjusting data types per column and .xlsx format for import into Power BI	Dataset ready for import into Microsoft Power BI

Table 3 shows that the five activities produced a unified, clean dataset covering 2018–2025 in .xlsx format, ready for Power BI.

2.4 Modelling

The technique used is a weighted scoring model that combines two indicators using weights that reflect their relative importance [11]. Weights were set based on expert judgment from the ITG PMB team: 60% for the number of admitted students and 40% for the conversion rate. All modeling activities were performed in Microsoft Power BI using the DAX language.

Model development was carried out in three steps. First, normalization of indicator values using max normalization according to Equation (1). Second, the calculation of the conversion rate according to Equation (2). Third, calculation of the final score according to Equation (3).

$$N^{\mathrm{I}} = \frac{X^{\mathrm{I}}}{X_{\max}} \quad (1)$$

$$CR = \left(\frac{Number\ of\ Admitted\ Students}{Number\ of\ Applicants}\right) \times 100\% \quad (2)$$

$$S = (N^{\mathrm{TP}} \times 0.6) + (N^{\mathrm{NO}} \times 0.4) \quad (3)$$

Notes: N^{I} = normalized value of indicator i; X^{I} = actual value; X_{max} = maximum value of all alternatives; CR = conversion rate (%); S = final score; N^{TP} = normalized value of admitted students; N^{NO} = normalized value of conversion rate. Rankings are determined using the RANKX function in DAX.

2.5 Evaluation

The Evaluation phase assesses whether the dashboard output aligns with the objectives set during the Business Understanding phase. Testing is conducted directly by the PMB team as end users. Validation interviews cover five aspects: the appropriateness of school rankings, the accuracy of indicator weights, the presence or absence of results differing from the team's estimates, the benefits of regional rankings, and the suitability of the dashboard as a reference for future PMB processes.

2.6 Deployment

The Deployment phase is the final phase of CRISP-DM, presenting the analysis results as a Power BI dashboard. The dashboard consists of one Cover page and four analysis pages: Summary, Region, School, and Program, each equipped with year and region filters. The dashboard is published to the Power BI Service, allowing access through a browser without opening Power BI Desktop. Power BI is reported as a platform suited to building integrated dashboards with real-time indicator visualization, supporting decisions based on dashboard output rather than manual recapitulation [14].

3. RESULT AND DISCUSSION

3.1 Business Understanding

Based on expert judgment, the ITG PMB team assigned 60% weight to the number of admitted students and 40% to the conversion rate. This weighting approach is consistent with Multi-Attribute Decision Making (MADM) frameworks, in which indicator weights are determined based on the relative importance of each criterion as assessed by domain experts [4]. Admitted students carry a higher weight because this indicator directly reflects each school's absolute contribution to the total number of students enrolled at ITG, making it the primary criterion for roadshow prioritization. The conversion rate, weighted at 40%, serves as a complementary indicator that measures recruitment efficiency per school, capturing the ratio of admitted students to applicants. The combined use of both indicators ensures that priority rankings reflect both the volume of contribution and the quality of engagement from each school, rather than relying on a single metric that could be misleading in isolation [12]. The team also identified three additional information needs for the dashboard: a regional distribution map, an annual summary table, and school type segmentation.

3.2 Data Understanding

Historical ITG New Student Admissions (PMB) data were obtained from the Academic and Student Affairs Office in Microsoft Excel format. The data consists of two files: 3,816 rows of registration data and 3,374 rows of admitted student data, covering eight admission periods from 2018 to 2025. The dataset contains 12 original attributes and 4 derived attributes (Regency/City, Subdistrict, School Type, and Enrolment Year). Based on Table 2, both datasets have 100% completeness with no missing or duplicate values. However, during the

exploration phase, inconsistencies in school name spelling across periods were found, including variations such as “SMKN,” “SMK N,” and “Smkn” for the same school. These inconsistencies were addressed during the Data Preparation phase.

3.3 Data Preparation

As shown in Table 3, five Data Preparation activities were carried out sequentially, resulting in a clean, consistent, and ready-to-use PMB dataset as input for the Modeling stage. Of the 16 available attributes, seven were selected for use in the analysis. Standardization of school and region names was performed using Find & Replace and the TRIM function in Microsoft Excel. All data from the eight admission periods were combined into a single worksheet. The final dataset was saved in .xlsx format for import into Power BI.

3.4 Modelling

A weighted scoring model was built in Power BI using DAX formulas. Max normalization (Equation 1) produced a value range of 0–1. The final score was calculated using Equation (3). The DAX formulas for the final score and ranking, using RANKX(DESC), are presented in Figures 2 and 3, respectively.

```
Skor Akhir =
([Normalisasi Jumlah Penerima] * 0.6) + ([Normalisasi Conversion Rate] * 0.4)
```

Figure 2. DAX Formula for Final Scores in Power BI

Figure 2 shows the DAX formula that combines max normalization with 60%–40% weighting to automatically compute final scores for all 937 schools. Figure 3 presents the DAX formula used in Power BI to generate school rankings based on the final weighted scores calculated using the RANKX function

```
Ranking Sekolah =
IF(
    ISBLANK([Jumlah Penerima]) || [Jumlah Penerima] = 0,
    BLANK(),
    RANKX(
        FILTER(
            ALL('Lembar1'[Asal Sekolah]),
            [Jumlah Penerima] > 0
        ),
        [Skor Sekolah],
        ,
        DESC,
        DENSE
    )
)
```

Figure 3. DAX Formula for School Rankings in Power BI

Figure 3 shows the RANKX(DESC) formula generating an automatically updated school ranking table each time the dataset is refreshed. Table 4 presents the five schools with the highest scores under the applicant-based ranking.

Table 4. Top 5 Schools by Applicant Data

No	School of Origin	Number of Applicants	Applicant Final Score	Conversion Rate
	School A	441	4.09	79.82%
	School B	150	2.67	94.00%
	School C	147	2.54	78.91%
	School D	143	2.55	88.81%
	School E	125	2.29	80.00%

School A holds both the highest applicant count and the highest score. School D achieves a higher score than School C despite a lower applicant count because its conversion rate (88.81%) exceeds School C's (78.91%). Therefore, the ranking order depends on the two indicators combined, not on applicant count alone.
Table 5 presents the five schools with the highest scores under the admitted-student-based ranking.

Table 5. Top 5 Schools by Admitted Student Data

No	School of Origin	Number of Admitted Students	Admitted Final Score	Conversion Rate
1.	School A	352	3.73	79.82%
2.	School B	141	2.51	94.00%
3.	School D	127	2.33	88.81%
4.	School C	116	2.07	78.91%
5.	School F	107	2.94	93.04%

Table 5 shows that School A also leads this ranking by admitted-student count. School F, although outside the top three by admitted-student count, records the highest conversion rate (93.04%) among the five schools listed and therefore obtains a higher score than School D and School C. Table 6 presents the top five regencies/cities ranked by number of applicants.

Table 6. Top 5 Regions by Regency/City (Applicants)

No	Regency/City	Number of Applicants	Conversion Rate	Regency Applicant Score
	Garut	3,637	87.21%	0.69
	Bandung	46	113.04%	0.12
	Sumedang	29	55.17%	0.06
	Tasikmalaya	23	126.09%	0.13
	Bekasi	13	76.92%	0.08

Table 6 shows that Garut Regency accounts for 3,637 applicants, with a conversion rate of 87.21%, indicating that the applicant pool is concentrated in the area surrounding the institution. Table 7 presents the top five regencies/cities ranked by the number of admitted students.

Table 7. Top 5 Regions by Regency/City (Admitted Students)

No	Regency/City	Number of Admitted Students	Conversion Rate	Regency Admitted Score
1.	Garut	3,172	87.21%	0.69
2.	Bandung	52	113.04%	0.12
3.	Tasikmalaya	29	126.09%	0.13
4.	Sumedang	16	55.17%	0.06
5.	Bekasi	10	76.92%	0.08

Table 7 shows that Garut Regency leads in the number of admitted students (3,172) with a conversion rate of 87.21%, further reinforcing its position as the primary recruitment area for ITG. Table 8 presents the top five subdistricts ranked by the number of applicants.

Table 8. Top 5 Subdistricts by Number of Applicants

No	Subdistrict	Number of Applicants	Conversion Rate	Subdistrict Applicant Score
	Tarogong Kidul	412	86.41%	0.63
	Garut Kota	378	121.69%	0.59

No	Subdistrict	Number of Applicants	Conversion Rate	Subdistrict Applicant Score
	Karangpawitan	353	74.22%	0.54
	Tarogong Kaler	228	110.09%	0.37
	Cilawu	183	54.64%	0.28

Table 8 shows Tarogong Kidul records the highest applicant count (412) and the highest applicant score (0.63), ahead of Garut Kota despite the latter's higher conversion rate (121.69%). Table 9 presents the corresponding ranking by number of admitted students.

Table 9. Top 5 Subdistricts by Number of Admitted Students

No	Subdistrict	Number of Admitted Students	Conversion Rate	Subdistrict Admitted Score
	Garut Kota	460	121.69%	0.64
	Tarogong Kidul	356	86.41%	0.49
	Karangpawitan	262	74.22%	0.37
	Tarogong Kaler	251	110.09%	0.36
	Banyuresmi	145	81.46%	0.22

Tables 8 and 9 confirm that Garut Kota leads the admitted-student ranking (460 admitted students, score 0.64), while Tarogong Kidul, the leading subdistrict by applicant count, falls to second position here. The two tables identify different subdistricts as the leading contributors, depending on which indicator forms the base of the score.

3.5 Evaluation

The Evaluation phase compared dashboard rankings against the Business Understanding objectives through validation interviews with the ITG PMB team. One pattern emerges from this comparison: a higher admitted-student count does not, by itself, produce a higher final score. School A records 441 applicants and 352 admitted students (CR 79.82%) and obtains a final score of 3.73, while School B records 150 applicants and 141 admitted students (CR 94.00%) and obtains a final score of 2.51, as shown in Table 10.

Table 10. Comparison of Applicant Count, Admitted Student Count, and Final Score for School A and School B

No	School of Origin	Number of Applicants	Number of Admitted Students	Conversion Rate	Final Score
	School A	441	352	79.82%	3.73
	School B	150	141	94.00%	2.51

Two additional patterns were found. Several schools recorded conversion rates exceeding 100%, with extreme cases reaching up to 700%, because one applicant was accepted into more than one study program within the same admission period, causing the number of admitted student records to exceed the number of applicants for that school. ITG applicants were also concentrated in Garut Regency (3,637 of 3,816 total; 95.31%). Both patterns were verified through validation interviews covering five aspects, presented in Table 11.

Table 11. Results of the ITG Admissions Dashboard Validation Interviews

No.	Aspect	Question	Result
1	School ranking suitability	Based on the dashboard results, School A ranks first by applicant count and by admitted-student count (441 applicants, 352 admitted students), while a different school outside the five listed in Table 4 and Table 5 obtains the highest final score among the full set of 937 schools. Does this result match the PMB team's records?	Suitable
2	Accuracy of indicator weights	The weights applied are 60% for the number of admitted students and 40% for the conversion rate. Is this weight distribution appropriate?	Appropriate
3	Accuracy of analysis results	Are there any schools or regions whose results differ from the PMB team's estimates?	None
4	Benefits of regional rankings	Does the regional ranking by subdistrict and regency/city help in establishing priority areas for the roadshow?	Helpful
5	Dashboard feasibility	Is this dashboard valid and can it be used as a reference for the next PMB roadshow?	Valid

Based on the validation interviews, all five aspects met the stated requirements. Rankings matched PMB team records; the 60%-40% weight distribution was assessed as appropriate, no results differed from team estimates, regional rankings were rated as useful for roadshow planning, and the dashboard was declared valid for future PMB use.

3.6 Deployment Power BI Dashboard

The validated dashboard is published to the Power BI Service and accessed through a browser. It consists of one Cover page and four analysis pages: Summary, Region, School, and Program. Table 12 lists each page's visualization components and interaction features.

Table 12. Technical Design of the ITG PMB Dashboard

No.	Page	Visualization Components	Interaction Features
	Cover	ITG logo, dashboard title, and four navigation buttons to the Summary, Region, School, and Programme pages	Direct navigation to each analysis page
	Summary	Six summary cards (applicants, admitted students, conversion rate, schools, programmes); annual PMB trend chart, 2018–2025; annual summary table	Year and city filters; drill-down by period
	Region	Two-dimension tab buttons (regency/city and subdistrict); Top 10 region donut chart; Azure Map; regional ranking table	Year and city filters; region dimension selection via tab buttons; map exploration
	School	Top 10 school bar chart; table of 937 schools with scores and rankings; school search field	Year and city filters; school name search
	Programme	Bar and donut charts of applicants and admitted students per programme, with conversion rate; table of source-school distribution per programme	Year and city filters

Each page covers one analytical dimension, with year and city filters applied throughout. The Cover page links to the four analysis pages—Summary, Region, School, and Program which together present the seven analytical outputs noted in the Abstract: the Summary page holds the annual PMB trend chart and yearly recapitulation table; the Region page holds the regional ranking table and geographic distribution map; the School page holds the school ranking table; and the Program page holds the study-program and school-type distributions. The page count and output-type count are therefore separate figures, as shown in Figures 4 through 8. Figure 4 is a screenshot of the Power BI dashboard Cover page, which links to the system's four analysis pages.

Figure 4. Cover Page

Figure 4 shows the Cover page with four navigation buttons linking to each analytical view. Figure 5 presents a screenshot of the Summary page, which provides an overview of the total applicants, admitted students, overall conversion rate, and annual PMB trend from 2018 to 2025.

Figure 5. Summary Page

Figure 5 shows the Summary page KPIs, with the highest annual CR in 2025 (99.23%) and the lowest in 2019 (78.49%). Figure 6 presents a screenshot of the Region page, which offers two geographic dimensions of analysis, Regency/City and Subdistrict, along with an interactive Azure Map showing applicant distribution

Figure 6. Region Page

Figure 6 shows the Region page, which combines a donut chart, Azure Map, and a ranking table, confirming Garut Regency as the dominant applicant source.

Figure 7 presents a screenshot of the School page, which displays the complete ranking table of 937 schools, accompanied by bar charts of the top 10 schools by applicant and admitted student count

Figure 7. School Page

Figure 7 shows the School page, which ranks all 937 institutions and includes a search feature for targeted lookup by the PMB team. Figure 8 presents a screenshot of the Program page, which visualizes the distribution of applicants and admitted students across the five study programs offered at ITG.

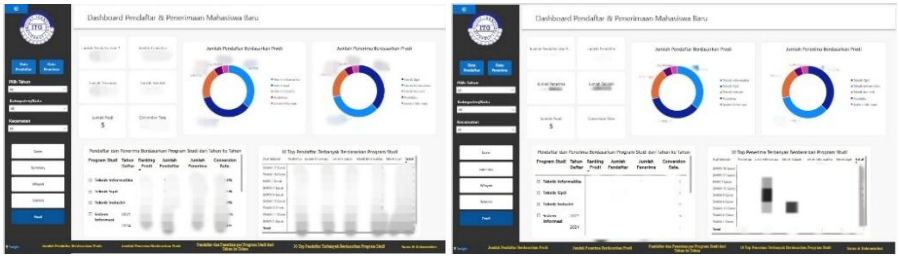

Figure 8. Study Program Page

Figures 4 through 8 collectively show the deployed dashboard, which covers all analytical dimensions validated in Section 3.5.

3.7 Discussion

The seven dashboard outputs stem directly from applying CRISP-DM to ITG's 2018-2025 PMB data, turning descriptive summaries into measurable indicators, conversion rates, and weighted priority scores [10]. This aligns with evidence that data visualization quality, data quality, and BI management drive the quality of strategic decision-making, reinforcing the value of well-structured BI systems [15]. and reflects the DSS concept of processing data into analytical information for semi-structured decisions [4]. The model generates rankings, not final decisions, leaving the PMB team free to weigh factors like travel distance, team size, and budget [7]. Methodologically, it extends prior CRISP-DM work toward weighted priority scores per school and region—rather than student segmentation —addressing a gap in earlier dashboards [5],[6],[7],[8], which lacked conversion rates, weighted scoring, or school-type segmentation. This study has three limitations: the 60%/40% weights were set via expert judgment rather than a formal method like AHP, suggesting future use of structured weighting for more verifiable results; the data covers only ITG over 2018-2025, with 95.31% of applicants from Garut Regency, limiting generalisability to other regions or applicant distributions; and the model excludes operational factors such as travel distance, team capacity, and budget. Future research should test the model's replicability at other institutions and incorporate these operational constraints.

4. CONCLUSION

This study used CRISP-DM on ITG's 2018-2025 PMB data (3,816 applicants; 3,374 admitted) to derive three indicators per school and region: applicant count, admitted count, and conversion rate. The six phases converted this descriptive data into weighted priority scores, allowing the PMB team to rank targets by evidence rather than experience. The resulting Power BI dashboard, validated by the PMB team, delivers seven outputs: annual trends, school and regional rankings, a geographic map, program distribution, school-type segmentation, and a summary table. This enables data-driven targeting: high-admission areas like Tarogong Kidul and Garut Kota become primary roadshow targets, while high-conversion, low-applicant areas signal expansion potential. Segmentation also guides tailored strategies; e.g., SMKN's steady upward trend in applicants across 2018-2025

suggests more frequent vocational-school visits. Institutionally, the dashboard offers a replicable, auditable tool for annual promotional planning and resource allocation. Future work should add real-time updates, operational constraints (distance, team capacity), and test replicability elsewhere.

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