Classification Analysis of the Assessment of the Community Satisfaction Index for Public Service Mall Services Based on Education Using Decision Tree

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ABSTRACT

This study aims to analyze the classification of the Community Satisfaction Index (CSI) assessment of Public Service Mall (PSM) services based on the level of education using the Decision Tree algorithm. Assessment of public satisfaction with public services is very important to improve the quality of services, and educational factors can affect the perspective and assessment of the services received. The data used in this study is secondary data on Medan City SMEs collected from January to September 2023. The research process includes data collection, preprocessing, and modeling using the Decision Tree algorithm with the help of RapidMiner software. The results of the analysis showed that respondents with higher education levels, such as D3, S1/D-IV, S2, and S3, tended to give better assessments of PSM services, with most of them giving Excellent (4) and Good (3) scores. In contrast, respondents with lower education, such as high school and junior high school, gave more varied assessments, although the score of Very Good (4) was still dominant in most respondents. This study suggests that PSM managers consider educational factors in designing and improving the quality of public services to meet the diverse expectations of society. Further research can explore other factors that affect community satisfaction, such as age or user experience.

Keyword : Community Satisfaction Index, Public Service Mall, Decision Tree

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1. INTRODUCTION

The development of information technology today has affected almost all aspects of life, including the delivery of public services. Technology makes it easier for the public to access fast, accurate, and up-to-date information, and allows the government to improve the quality of public services. In response to this need, many local and central governments have begun to develop various innovations in public services, one of which is the Public Service Mall (PSM), which aims to make it easier for the public to access public services in an integrated and efficient manner (Septhya et al., 2023).

To measure the effectiveness of PSM in providing services to the community, evaluation of the Community Satisfaction Index (CSI) is very important. CSI is a method used to assess the level of community satisfaction with the services provided by the government. Measuring community satisfaction is crucial to improve the performance of government agencies and ensure that the services provided are in line with community expectations (Hendra & Abdul Rozak, 2024) One way to measure this satisfaction is to use data analysis tools that can identify patterns of community assessment of public services.

In this case, data mining can be used as an effective approach to analyze community satisfaction data. By utilizing machine learning techniques, data mining allows the processing and extraction of knowledge from large and complex data to gain deeper insights (Priscila Simanjuntak, 2024). One of the methods in data mining that can be used is the Decision Tree algorithm. This algorithm builds a decision tree-shaped model that predicts outcomes based on existing input variables (Mardiani et al., 2023). Using this algorithm, we can classify the level of public satisfaction with PSM services based on factors that affect their assessment, one of which is the level of education.

Education plays an important role in shaping a person's perspective and assessment of the quality of services received. Education not only provides knowledge, but also shapes a person's ethical, cultural, and social values, which in turn affects their expectations of public services (Hidayat & Ghofur, 2024). Community satisfaction itself can be interpreted as a feeling that arises when a person compares the real performance of a service with the expectations he has. If the service received is better than expected, then the satisfaction level will be high. Conversely, if the service is worse than expected, then satisfaction will be low (Fahlevi et al., 2024) These assessments can be categorized at various levels, such as not good, not good, good, or very good, each of which has a certain range of values to facilitate decision-making (Asman Abnur, 2017).

2. RESEARCH METHOD

a. Data Collection, at this stage the data is collected based on secondary data that is already available, namely the 2023 Medan City Community Satisfaction Index data from January to September 2023. Secondary data is data that has been previously collected by other people or certain institutions and can be accessed by researchers for specific research purposes (Hambali et al., 2024)

b. Preprocessing, The data mining process often involves data that is not in the best condition to be processed. Sometimes, the data contains various problems that can affect the outcome of the mining process itself, such as missing values, redundant data, outliers, or data formats that do not fit the system. Therefore, to overcome these problems, it is necessary to carry out a preprocessing stage. Preprocessing is an important step to eliminate problems that can interfere with the results of the data classification process (Purbolaksono et al., 2021)

c. Modeling and analysis, after the data is preprocessed, a decision tree model is created using a rapid miner, RapidMiner is a data processing software that can perform text analysis, predictive analysis, and data mining analysis (Zulfiana et al., 2024). Then an analysis of the resulting model is carried out

3. RESULTS AND DISCUSSION

A. Data Collection

NO	NAME	GENDER	EDUCATION	ASSESSMENT DATE	U1	U2	U3	U4	U5	U6	U7	U8	U9	AVERAGE INTERVAL VALUE	AVERAGE PERCEPTION VALUE	PERFORMANCE
1	ADE KURNIAWAN	Male	D3	01/01/2023	4	4	4	4	4	4	4	4	4	4,0000	4	VERY GOOD
2	dr. LILY SURANTA KETAREN	Female	S1/D-IV	01/01/2023	4	4	4	4	4	4	4	3	4	3,8889	4	VERY GOOD
3	APT. VIRGINIA LISTYANI, S.FARM.	Female	S1/D-IV	01/01/2023	4	3	3	4	3	3	3	3	4	3,3333	3	GOOD
4	KORLENTA PANJAITAN	Female	S1/D-IV	01/01/2023	3	3	2	4	3	3	3	3	4	3,1111	3	GOOD
5	dr. KALVIN RAVELI	Male	S1/D-IV	02/01/2023	4	4	4	4	4	4	4	4	4	4,0000	4	VERY GOOD
6	DEWITA BR SEMBIRING, AMK	Female	D3	02/01/2023	3	3	3	3	3	3	3	3	4	3,1111	3	GOOD
7	PUTRI PRISKA MANALU	Female	D3	02/01/2023	3	3	3	4	3	3	3	3	4	3,2222	3	GOOD
8	DEWI WARNI	Female	D3	02/01/2023	4	4	4	4	4	4	4	4	4	4,0000	4	VERY GOOD
9	RICCARD FERNANDO SITUMEANG	Male	S1/D-IV	02/01/2023	3	3	2	4	3	3	3	3	1	2,7778	2	LESS GOOD
10	WITRI NADILA FATHIA A.Md.Kes	Female	D3	02/01/2023	3	3	3	3	4	3	3	3	4	3,2222	3	GOOD
11	PUTRI EVELINE, A.Md.Keb	Female	D3	02/01/2023	4	4	4	4	4	4	4	4	4	4,0000	4	VERY GOOD
12	HERMANTO SIMANJUNTAK, A.MK	Male	D3	02/01/2023	4	4	4	4	4	4	4	4	4	4,0000	4	VERY GOOD
13	ELFRIDA SIJABAT	Female	D3	02/01/2023	4	4	4	4	4	4	4	4	4	4,0000	4	VERY GOOD
14	CHRISTIN NABABAN, A.Md.AK	Female	S1/D-IV	02/01/2023	4	4	4	4	4	4	4	4	4	4,0000	4	VERY GOOD
15	dr. INDRI YANI	Female	S1/D-IV	02/01/2023	4	4	4	4	4	4	4	4	4	4,0000	4	VERY GOOD
16	EMI NOVIYANTI, AM.Keb	Female	S1/D-IV	02/01/2023	4	4	4	4	4	4	4	4	4	4,0000	4	VERY GOOD
17	DITA MAGPRATIWI, S.Farm.Apt	Female	S1/D-IV	02/01/2023	4	4	4	4	4	4	4	4	4	4,0000	4	VERY GOOD
18	ROSA MUNKWAN SELIN,AMD.RAD	Female	D3	02/01/2023	3	3	3	4	3	3	3	3	3	3,1111	3	GOOD
19	L. Meri Diana Sirait, SST	Female	S1/D-IV	02/01/2023	4	4	4	4	3	4	4	4	4	3,8889	4	VERY GOOD
20	ARMELIA HAYATI, S.FARM., APT	Female	S1/D-IV	04/01/2023	3	3	3	4	3	3	3	3	4	3,2222	3	GOOD
21	apt. UMMI KALSUM ACEH, S.Farm.	Female	S1/D-IV	04/01/2023	4	4	4	4	4	4	4	4	4	4,0000	4	VERY GOOD
22	RANI DWITA, A.Md.Keb	Female	D3	04/01/2023	4	4	4	4	4	4	4	4	4	4,0000	4	VERY GOOD
23	TRIA ANGGREINI	Female	D3	04/01/2023	3	3	3	3	3	4	4	4	4	3,4444	3	GOOD
24	dr. ADI MURADI MUHAR, Sp.B	Male	S2	04/01/2023	3	3	3	4	3	3	4	3	4	3,3333	3	GOOD
25	dr. ADI MURADI MUHAR, Sp.B	Male	S2	04/01/2023	3	3	3	4	4	4	4	3	4	3,5556	4	VERY GOOD

Data Preprocessing

Average: 3744 Count: 7488 Sum: 28031328

Fig 1. Data Collection

In figure 1, data collected from January to September 2023 includes data on name, gender, education, assessment date, U1, U2, U3, U4, U5, U6, U6, U8, U9, average interval value, average perception value, performance

B. Preprocessing

	A	B
1	EDUCATION & PERFORMANCE	AVERAGE PERCEPTION VALUE
2	D3 [VERY GOOD]	4
3	S1/D-IV [VERY GOOD]	4
4	S1/D-IV [GOOD]	3
5	S1/D-IV [GOOD]	3
6	S1/D-IV [VERY GOOD]	4
7	D3 [GOOD]	3
8	D3 [GOOD]	3
9	D3 [VERY GOOD]	4
10	S1/D-IV [LESS GOOD]	2
11	D3 [GOOD]	3
12	D3 [VERY GOOD]	4
13	D3 [VERY GOOD]	4
14	D3 [VERY GOOD]	4
15	S1/D-IV [VERY GOOD]	4
16	S1/D-IV [VERY GOOD]	4
17	S1/D-IV [VERY GOOD]	4
18	S1/D-IV [VERY GOOD]	4
19	D3 [GOOD]	3
20	S1/D-IV [VERY GOOD]	4
21	S1/D-IV [GOOD]	3
22	S1/D-IV [VERY GOOD]	4
23	D3 [VERY GOOD]	4
24	D3 [GOOD]	3
25	S2 [GOOD]	3
26	S2 [VERY GOOD]	4

Data | Preprocessing

Fig 2. Data Preprocessing

In Figure 2, it can be seen that the data has been preporecessed so that all that remains is education & performance, average perception value

C. Modeling and Analysis

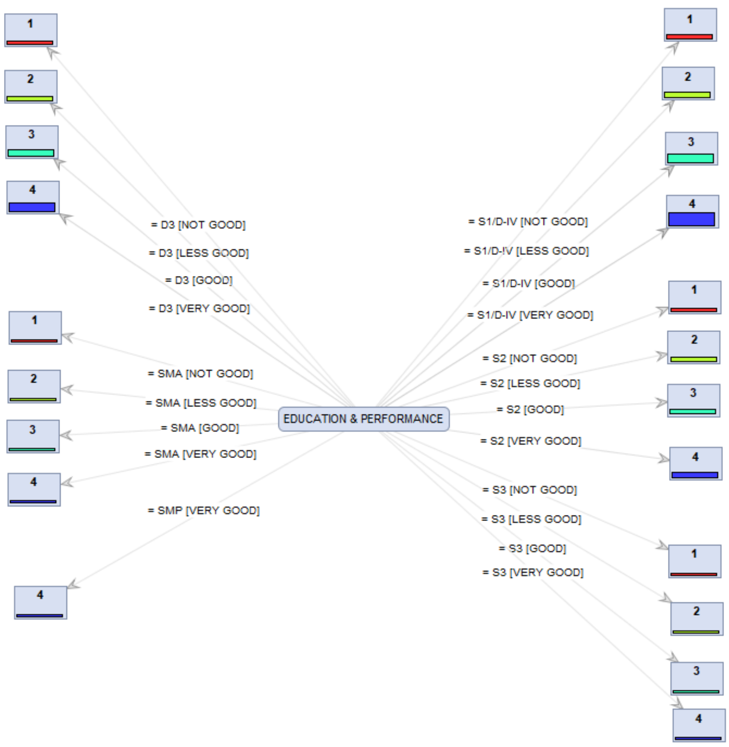

Fig 3. Model Decision Tree

Based on Figure 3, respondents with middle school education rated (4 = VERY GOOD). Respondents with high school education rated (1 = NOT GOOD, 2 = LESS GOOD, 3 = GOOD, 4 = VERY GOOD). Similarly, respondents with D3, S1/D-IV, S2, and S3 education levels provided ratings within the same range: (1 = NOT GOOD, 2 = LESS GOOD, 3 = GOOD, 4 = VERY GOOD).

Tree

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EDUCATION & PERFORMANCE = D3 [GOOD]: 3 {4=0, 3=731, 2=0, 1=0}
EDUCATION & PERFORMANCE = D3 [LESS GOOD]: 2 {4=0, 3=0, 2=315, 1=0}
EDUCATION & PERFORMANCE = D3 [NOT GOOD]: 1 {4=0, 3=0, 2=0, 1=76}
EDUCATION & PERFORMANCE = D3 [VERY GOOD]: 4 {4=1055, 3=0, 2=0, 1=0}
EDUCATION & PERFORMANCE = S1/D-IV [GOOD]: 3 {4=0, 3=1176, 2=0, 1=0}
EDUCATION & PERFORMANCE = S1/D-IV [LESS GOOD]: 2 {4=0, 3=0, 2=603, 1=0}
EDUCATION & PERFORMANCE = S1/D-IV [NOT GOOD]: 1 {4=0, 3=0, 2=0, 1=239}
EDUCATION & PERFORMANCE = S1/D-IV [VERY GOOD]: 4 {4=1899, 3=0, 2=0, 1=0}
EDUCATION & PERFORMANCE = S2 [GOOD]: 3 {4=0, 3=305, 2=0, 1=0}
EDUCATION & PERFORMANCE = S2 [LESS GOOD]: 2 {4=0, 3=0, 2=251, 1=0}
EDUCATION & PERFORMANCE = S2 [NOT GOOD]: 1 {4=0, 3=0, 2=0, 1=167}
EDUCATION & PERFORMANCE = S2 [VERY GOOD]: 4 {4=544, 3=0, 2=0, 1=0}
EDUCATION & PERFORMANCE = S3 [GOOD]: 3 {4=0, 3=40, 2=0, 1=0}
EDUCATION & PERFORMANCE = S3 [LESS GOOD]: 2 {4=0, 3=0, 2=19, 1=0}
EDUCATION & PERFORMANCE = S3 [NOT GOOD]: 1 {4=0, 3=0, 2=0, 1=10}
EDUCATION & PERFORMANCE = S3 [VERY GOOD]: 4 {4=36, 3=0, 2=0, 1=0}
EDUCATION & PERFORMANCE = SMA [GOOD]: 3 {4=0, 3=8, 2=0, 1=0}
EDUCATION & PERFORMANCE = SMA [LESS GOOD]: 2 {4=0, 3=0, 2=2, 1=0}
EDUCATION & PERFORMANCE = SMA [NOT GOOD]: 1 {4=0, 3=0, 2=0, 1=2}
EDUCATION & PERFORMANCE = SMA [VERY GOOD]: 4 {4=7, 3=0, 2=0, 1=0}
EDUCATION & PERFORMANCE = SMP [VERY GOOD]: 4 {4=2, 3=0, 2=0, 1=0}
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Fig 4. Description Tree

In figure 4, based on the level of education and performance of the respondents, there is an assessment distribution as follows: At the D3 education level, the respondents who gave a score of VERY GOOD (4) amounted to 1,055, GOOD (3) as many as 731, NOT GOOD (2) as many as 315, and NOT GOOD (1) as many as 76. At the S1/D-IV education level, 1,899 respondents rated VERY GOOD (4), 1,176 GOOD (3), 603 NOT GOOD (2), and 239 NOT GOOD (1). At the S2 education level, the respondents who gave a score of VERY GOOD (4) amounted to 544, GOOD (3) as many as 305, NOT GOOD (2) as many as 251, and NOT GOOD (1) as many as 167. At the S3 education level, the respondents who gave a score of VERY GOOD (4) amounted to 36, GOOD (3) as many as 40, POOR (2) as many as 19, and NOT GOOD (1) as many as 10. At the high school education level, respondents who gave a score of VERY GOOD (4) amounted to 7, GOOD (3) as many as 8, POOR (2) as many as 2, and NOT GOOD (1) as many as 2. Finally, at the junior high school education level, the respondents who gave a VERY GOOD score (4) amounted to 2.

4. CONCLUSION

Based on the results of the analysis using the Decision Tree algorithm on the Community Satisfaction Index (CSI) data in Public Service Mall (PSM) services, it can be concluded that the level of education affects the assessment of community satisfaction. Respondents with higher levels of education, such as D3, S1/D-IV, S2, and S3, tended to give better assessments, with most giving excellent (4) and good (3) scores. Meanwhile, respondents with lower levels of education, such as high school and junior high school, gave more varied assessments, but still gave many Very Good scores (4). This shows that the education factor can be an important indicator in predicting the level of public satisfaction with PSM services. This result provides insight for PSM managers to pay more attention to the characteristics of education in designing public services that are more in line with community expectations. For further research, it is recommended to explore other factors that can affect community satisfaction, such as age or experience using public services.

REFERENCES

Asman Abnur. (2017). *PERATURAN MENTERI PENDAYAGUNAAN APARATUR NEGARA DAN REFORMASI BIROKRASI REPUBLIK INDONESIA NOMOR 14 TAHUN 2017 TENTANG PEDOMAN PENYUSUNAN SURVEI KEPUASAN MASYARAKAT UNIT PENYELENGGARA PELAYANAN PUBLIK*.

Fahlevi, R. A., Com, H., Asif Khan, M., Bhayangkara, U., & Raya, J. (2024). PENGARUH KUALITAS PELAYANAN DAN KUALITAS PRODUK TERHADAP KEPUASAN PELANGGAN MELALUI PROMOSI SEBAGAI VARIABEL INTERVENING DI PERUMDA TIRTA BHAGASASI BEKASI. In *Indonesian Journal of Economics and Strategic Management (IJESM)* (Vol. 2, Issue 3).

Hambali, F., Nurhana, G., Praadha Gitama, D., & Pranata, S. (2024). PENGARUH INSENTIF DALAM MENINGKATKAN KINERJA KARYAWAN PADA NINJA EXPRESS CIREBON. *Jurnal Witana (JW)*, *02*(01), 45–49. http://jurnalwitana.com/

Hendra, & Abdul Rozak. (2024). Analisis Kepuasan Masyarakat Terhadap Pelayanan Publik Berdasarkan Indeks Kepuasan Masyarakat Desa Cintaasih Kecamatan Cipongkor Kabupaten Bandung Barat. *JEMSI (Jurnal Ekonomi, Manajemen, Dan Akuntansi)*, *10*(4), 2424–2435. https://doi.org/10.35870/jemsi.v10i4.2629

Hidayat, M. S., & Ghofur, A. (2024). Pengaruh Latar Belakang Pendidikan Terhadap Sikap Toleransi di Kelurahan Sialangmunggu Pekanbaru. *JHESS : Journal Hub for Humanities and Social Science*, *1*(1), 38–63.

Mardiani, E., Rahmansyah, N., Ningsih, S., Lantana, D. A., Wirawan, A. S. P., Wijaya, S. A., & Putri, D. N. (2023). Komparasi Metode Knn, Naive Bayes, Decision Tree, Ensemble, Linear Regression Terhadap Analisis Performa Pelajar Sma. *INNOVATIVE: Journal Of Social Science Research*, *3*(2), 13880–13892.

Priscila Simanjuntak, L. (2024). Penerapan Data Mining Dalam Proses Hukum Pidana Bagi Pelaku Kekerasan Pada Wanita Menggunakan Algoritma C4.5. *ADA Journal of Information System Research*, *1*(2).

Purbolaksono, M. D., Irvan Tantowi, M., Imam Hidayat, A., & Adiwijaya, A. (2021). Perbandingan Support Vector Machine dan Modified Balanced Random Forest dalam Deteksi Pasien Penyakit Diabetes. *Jurnal RESTI (Rekayasa Sistem Dan Teknologi Informasi)*, *5*(2), 393–399. https://doi.org/10.29207/resti.v5i2.3008

Septhya, D., Rahayu, K., Rabbani, S., Fitria, V., Irawan, Y., & Hayami, R. (2023). Implementasi Algoritma Decision Tree dan Support Vector Machine untuk Klasifikasi Penyakit Kanker Paru. *MALCOM: Indonesian Journal of Machine Learning and Computer Science*, *3*(1), 15–19.

Zulfiana, R., Shofiah Hilabi, S., Nurapriani, F., Huda, B., Karawang, P., Jl HSRonggo Waluyo, K., Timur, T., & Barat, J. (2024). Peningkatan Minat Digital Skill Menggunakan Algoritma K-Medoids Clustering Pada Karyawan. *Journal of Information System Research (JOSH)*, *5*(3), 811–818. https://doi.org/10.47065/josh.v5i3.4994