Zero : Jurnal Sains, Matematika, dan Terapan
E-ISSN : 2580-5754; P-ISSN : 2580-569X
Volume 9, Number 3, 2025
DOI: 10.30829/zero.v9i3.26769
Page: 959 - 969

Classifying Alumni Satisfaction in Integrity Zone Universities Using CART: Evidence from Indonesian Higher Education

[1] Nurhasanah
Department of Statistics, Syiah Kuala University, Banda Aceh, 24415, Indonesia

[2] Eka Baqtini
Department of Statistics, Syiah Kuala University, Banda Aceh, 24415, Indonesia

[3] Evi Ramadhani
Department of Statistics, Syiah Kuala University, Banda Aceh, 24415, Indonesia

[4] Nany Salwa
Department of Statistics, Syiah Kuala University, Banda Aceh, 24415, Indonesia

[5] Latifah Rahayu Siregar
Department of Statistics, Syiah Kuala University, Banda Aceh, 24415, Indonesia

Article Info

Article history:

Accepted 26 December 2025

Keywords:

Alumni satisfaction;
Area under the curve (AUC);
Classification and regression tree (CART);
Integrity zone;
Service quality.

ABSTRACT

This study examines alumni satisfaction within the Integrity Zone framework in Indonesian higher education using survey data collected from 315 alumni out of a total population of 1,483 graduates. Alumni satisfaction was dichotomized into satisfied and dissatisfied groups and analyzed using the Classification and Regression Tree (CART) method to identify the most influential service related factors. The results indicate that employee sincerity, service timeliness, completeness of information, adequacy of facilities, and institutional transparency particularly the availability of anti-corruption information are the key determinants of alumni satisfaction. The CART model achieved an Area Under the Curve (AUC) value of 0.73, indicating fair discriminative ability according to standard classification guidelines. These findings provide practical insights for improving service quality and integrity-oriented governance in higher education institutions.

Corresponding Author:

Nurhasanah,
Department of Statistics
Faculty of Mathematics and Natural Sciences, Syiah Kuala University
Email: nurhasanah@usk.ac.id

1. INTRODUCTION

Service quality is a critical component in strengthening governance and enhancing stakeholder satisfaction within higher education institutions. In Indonesia, the importance of high quality academic and administrative services is institutionalized through the Integrity Zone (Zona Integritas, ZI) program, as regulated in the Minister of Administrative and Bureaucratic Reform Regulation (Permen PAN RB) No. 52 of 2014. The ZI framework aims to establish corruption-free and clean-serving bureaucratic units by promoting transparency, accountability, and ethical governance. Higher education institutions implementing this program are therefore expected to enhance service effectiveness not only for students but also for alumni, who represent a strategic stakeholder group in institutional evaluation and long-term development. In this context, one faculty participating in the ZI initiative has produced 1,483 alumni during the period 2017–2021, providing an appropriate setting for empirical assessment.

In higher education, service quality comprises both tangible elements, such as facilities, infrastructure, and administrative systems, and intangible dimensions, including reliability, responsiveness, assurance, and empathy. Previous studies consistently demonstrate that these dimensions significantly influence alumni satisfaction and perceptions of institutional performance. Tangible resources, such as classroom infrastructure and academic facilities, alongside human factors including lecturer professionalism and administrative responsiveness, shape alumni evaluations of their overall educational experience. These findings indicate that alumni satisfaction reflects the combined effects of interpersonal interaction, operational performance, and institutional governance.

Recent empirical research has increasingly applied machine-learning classification techniques to model satisfaction outcomes in educational contexts. Methods such as Naïve Bayes (NB), Classification and Regression Trees (CART), K-Nearest Neighbor (KNN), Support Vector Machine (SVM), and Neural Networks have been used to categorize service quality perceptions [1], [2]. While probabilistic methods such as NB often achieve high predictive accuracy, CART offers a key methodological advantage through its interpretability. By producing hierarchical decision rules, CART enables the identification of dominant variables and interaction patterns, particularly in datasets characterized by non-linear relationships and mixed measurement scales. Comparative studies have shown that although CART may yield comparable accuracy to other classifiers, its transparency provides clearer analytical insights into the determinants of satisfaction [3].

Despite the growing body of literature on service quality and satisfaction in higher education, several important gaps remain. First, most existing studies rely on linear or correlation-based analytical models that assume simple relationships among variables, which may fail to capture the complex, non-linear interactions inherent in service quality assessment [4], [5], [6]. Second, prior research predominantly focuses on current students or general service users, while alumni—who represent long-term stakeholders and reflect the sustainability of institutional service performance—remain relatively underexplored. Third, empirical studies that integrate Integrity Zone (ZI) governance indicators, particularly transparency, procedural clarity, and anti-corruption dimensions, into satisfaction modeling are still scarce. As a result, the combined influence of service quality attributes and institutional integrity within the ZI framework has not been sufficiently examined using interpretable non-linear analytical approaches.

To address these gaps, this study applies the Classification and Regression Tree (CART) algorithm as a nonparametric and interpretable classification framework to model alumni satisfaction in a faculty implementing the Integrity Zone program. Alumni are classified into satisfied and dissatisfied groups based on survey responses capturing interpersonal, operational, and institutional integrity dimensions. From an applied mathematics and statistical modeling perspective, the key contribution of this study lies in demonstrating the effectiveness of CART in uncovering hierarchical decision structures and non-linear interaction patterns among service quality indicators, while maintaining transparency and interpretability of results [3], [7]. Model performance is evaluated using the Area Under the Curve (AUC) metric to assess discriminative capability, thereby providing both methodological and practical insights for evidence-based service improvement and integrity-oriented governance in higher education institutions [8].

2. RESEARCH METHOD

2.1 Research Design

This study employed a quantitative cross-sectional design using primary data obtained from the Integrity Zone (ZI) Alumni Satisfaction Survey conducted in 2021. The population consisted of 1,483 graduates, and a stratified sampling approach generated a final sample of 315 alumni (21%), ensuring proportional representation across five graduation cohorts. Although the sample is reasonably robust, potential selection bias may exist if non-respondents differ systematically from respondents.

2.2 Data Source and Variables

The study examined alumni satisfaction as the dependent variable, categorized into satisfaction levels based on responses to the alumni satisfaction survey. The independent variables consisted of multiple service-related indicators encompassing administrative quality, timeliness of service, completeness of information, staff performance, and institutional integrity. Each indicator was measured using a five-point Likert scale, ranging from 1 (strongly disagree) to 5 (strongly agree). Prior to analysis, data cleaning, validation, and encoding procedures were performed to ensure the accuracy, completeness, and consistency of responses.

The questionnaire items were derived from the Integrity Zone (ZI) Alumni Satisfaction Survey instrument routinely administered by the institution. The instrument was designed to capture key dimensions of public service quality, including administrative procedures, service timeliness, information transparency, staff performance, and institutional integrity. Prior to use, the questionnaire underwent internal review to ensure content relevance and clarity for alumni respondents. Internal consistency reliability was assessed using Cronbach's alpha, yielding satisfactory values that indicate acceptable internal consistency across the service quality indicators.

Based on the results of the Classification and Regression Tree (CART) analysis, several indicators were identified as the most influential predictors of alumni satisfaction. These included:

X1: Understanding of operational procedures (POB)
X9: Services meet alumni needs
X10: Timeliness and efficiency of services
X12: Availability of adequate facilities and information
X24: Employee sincerity in serving
X26: Compliance with working hours
X40: Availability of anti-corruption information media

These indicators represent key dimensions of institutional service quality that collectively contribute to alumni perceptions and satisfaction with university services.

2.3 Data Collection Procedure;

The CART algorithm was chosen for its ability to handle both categorical and continuous data, identify nonlinear relationships, and produce interpretable decision rules [9], [10], [11]. Data were gathered using an online questionnaire distributed to five alumni cohorts (2017–2021). Responses were screened for completeness, outliers, and inconsistencies before analysis.

Table 1. Population and Sample by Graduation Year (2017–2021)

Strata	Graduation Year	Population	Sample
1	2017	262	56
2	2018	296	63
3	2019	289	61
4	2020	331	70
5	2021	305	65
Total		1.483	315

The study population consisted of 1,483 alumni who graduated between 2017 and 2021. Data were collected through an online questionnaire, yielding 315 valid responses, corresponding to a response rate of approximately 21.2%. Stratified sampling was applied based on graduation year to ensure proportional representation across cohorts, as summarized in Table 1. While this approach improves cohort-level coverage, potential sources of bias remain, including non-response bias and the exclusive use of an online survey mode, which may underrepresent alumni with lower digital engagement. These limitations are acknowledged when interpreting the findings.

Data analysis employed the Classification and Regression Tree (CART) method, a nonparametric statistical approach designed to identify the most influential predictors of categorical outcomes. Because CART requires a categorical dependent variable, alumni satisfaction originally measured using a five-point Likert scale was dichotomized into "satisfied" and "dissatisfied" categories prior to modeling. Respondents with an average satisfaction score of 4.0 or higher were classified as satisfied, while those with scores below 4.0 were categorized as dissatisfied. This threshold was selected to reflect a substantively meaningful level of positive evaluation, as values of 4 and 5 indicate clear endorsement of service quality attributes in Likert-scale measurement. Although alternative thresholds or ordinal modeling approaches could influence class balance and model specification, preliminary inspection indicated that small variations around the cut-off did not materially alter classification patterns. Binary classification was therefore retained to enhance interpretability and align with the applied decision-making context of institutional service evaluation. [12], [13], [14].

Prior to model construction, the dataset was divided into training (70%) and testing (30%) subsets to enable an unbiased evaluation of predictive performance. To address class imbalance in the training data, a random oversampling technique was applied to the minority class to ensure balanced class representation during model learning. CART has been widely used in educational analytics to classify academic outcomes such as student performance, graduation likelihood, and course completion, demonstrating its effectiveness in handling categorical predictors and non-linear relationships [1], [10], [15], [16]. This empirical evidence further supports the suitability of CART for modeling alumni satisfaction based on multidimensional service quality indicators. To address class imbalance, random oversampling was applied exclusively to the training dataset through simple random duplication of minority-class observations, without synthetic feature generation or interpolation (i.e., no SMOTE-based methods).

2.4 Analytical Methods or Algorithms

This study employed the Classification and Regression Tree (CART) algorithm as the primary analytical framework for identifying the most influential predictors of alumni satisfaction. CART is a nonparametric, recursive partitioning technique that classifies data by iteratively splitting it into homogeneous subgroups based on predictor variables [17]. Unlike traditional linear regression models, CART does not assume normality, homoscedasticity, or linear relationships among variables, making it well-suited for complex educational datasets that exhibit non-linear and hierarchical structures.

- Analytical Framework

The CART model operates by selecting a predictor variable and a corresponding split point that minimize impurity within each node. The CART model splits the dataset based on the Gini impurity, as shown in Equation (1):

$$G = 1 - \sum_{i=1}^{k} \mathrm{p}_i^2$$

where p represents the proportion of observations belonging to class i within a node, and k denotes the number of classes. The algorithm recursively partitions the data to form a decision tree that maximizes within-node homogeneity and predictive accuracy.

- Model Training and Validation

Model tuning involved adjusting several hyperparameters such as the minimum split size, complexity parameter (cp), and maximum tree depth to optimize classification accuracy while preventing overfitting. The parameters used in this study are summarized in Table 2. After tree construction, a cost-complexity pruning process was applied to remove non-contributing branches and enhance model generalizability.

Table 2. CART Hyperparameters Used in Model Tuning

Parameter	Description
Minimum Split (minsplit)	Minimum number of observations required to split a node.
Minimum Bucket (minbucket)	Minimum number of observations in any terminal node.
Maximum Depth (maxdepth)	Maximum depth allowed for the decision tree.
Complexity Parameter (CP)	Complexity threshold used for pruning the tree.

Hyperparameter tuning was conducted to control tree complexity and improve generalization performance. Several values of the minimum number of observations required to split an internal node (*minsplit*) were evaluated, specifically 5, 10, and 15. These values were selected to examine the trade-off between model complexity and interpretability. Other parameters, including the minimum number of observations in terminal nodes (*minbucket*) and maximum tree depth, were constrained to prevent overfitting, while cost-complexity pruning (*cp*) was applied during model optimization using default software settings. The optimal CART configuration was determined based on the highest Area Under the Curve (AUC) value obtained from the validation results, ensuring an objective and performance-driven parameter selection.

The resulting model's performance was evaluated using the Classification Performance Summary and Area Under the Curve (AUC) metrics to assess both classification accuracy and discriminative capability. The CART method was selected for this study due to its interpretability, flexibility in handling categorical and continuous data, and ability to capture non-linear interactions among predictors key advantages over traditional regression-based approaches.

Similar applications of CART have been documented in educational analytics, including student performance prediction [11], [14], learning engagement classification [18], and institutional service evaluation [1]. The model's ability to uncover key predictors from large, heterogeneous datasets makes it suitable for exploring satisfaction dynamics in higher education [9]. All statistical analyses were conducted using the R statistical computing environment (R Foundation for Statistical Computing), employing standard packages for classification tree modeling and performance evaluation.

- Assumptions and Robustness Checks

  As a nonparametric method, CART requires no assumptions about the distribution or scale of the predictors. However, to ensure robustness, data balancing was applied to mitigate class imbalance across satisfaction levels. Model accuracy and stability were assessed using confusion matrices, classification accuracy, and misclassification error rates on the testing dataset.

Methodologically, the application of the CART algorithm in this research represents a valuable contribution to satisfaction analysis. Traditional regression models often assume linear and independent effects among predictors, potentially overlooking complex, non-linear interactions. CART, by contrast, uncovers hierarchical relationships and interaction effects that better represent human decision-making patterns. The tree generated in this study showed that combinations of sincerity, timeliness, and transparency yield higher satisfaction probabilities than any single factor alone[19]. This observation echoes the conclusions of Krishna, et al. [1], who demonstrated that CART effectively captures multi-dimensional patterns in satisfaction classification. The interpretability of the tree structure also enhances its managerial utility: administrators can directly visualize which attributes most strongly determine satisfaction, making it easier to prioritize interventions.

3. RESULT AND ANALYSIS

3.1 Descriptive Statistics

A total of 315 valid responses were obtained from alumni graduating between 2017 and 2021. The descriptive analysis indicates a high level of alumni satisfaction across graduation cohorts from 2017 to 2021. As summarized in Table 3, satisfaction rates exceeded 90% for all cohorts, with the highest satisfaction observed among the 2017 cohort (98.21%) and the lowest among the 2021 cohort (92.31%). Overall, 95.56% of respondents were classified as satisfied, while 4.44% were classified as dissatisfied. These results indicate a generally positive evaluation of academic services among alumni respondents.

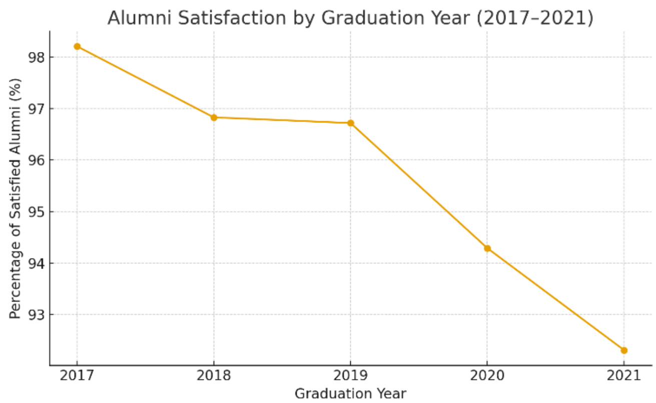

Figure 1. Distribution of alumni satisfaction levels across graduation years (2017–2021).

Figure 1 illustrates the downward trend in satisfaction percentages across graduation years, which is further detailed in Table 3.

Table 3. Cross-Tabulation of Satisfaction Levels by Graduation Year

Graduation Year	Satisfied (f)	%	Dissatisfied (f)	%
2017	55	98.21	1	1.71
2018	61	96.83	2	3.71
2019	59	96.72	2	3.28
2020	66	94.29	4	5.71
2021	60	92.31	5	7.69
Total	301	95.56	14	4.44

Note: *Satisfied = respondents with mean Likert score ≥ 4; Dissatisfied = respondents with mean score < 4.*

Such patterns indicate that while institutional reforms under the Integrity Zone (ZI) program have been effective in maintaining strong satisfaction levels, continuous adaptation to evolving alumni expectations remains essential. The persistence of high satisfaction across cohorts also reinforces the reliability of the survey instrument and provides a stable basis for deeper analytical modeling using CART.

Unlike conventional service quality studies, which focus on responsiveness and tangibility, this variable captures the ethical dimension of service quality. Its importance suggests that alumni satisfaction is not only a reaction to functional performance but also an evaluation of institutional integrity and moral accountability. Gomes and Jelihovschi [12] argued that transparency, ethical communication, and shared values are essential for fostering alumni commitment, while Magasi and Bwemelo [20] emphasized that ethical credibility strengthens alumni trust and advocacy. In the context of the Integrity Zone (ZI) framework, the visibility of anti-corruption information likely serves as a symbolic assurance of institutional honesty and good governance, which resonates with the public service values of fairness and accountability.

The findings reveal that alumni satisfaction is influenced by a combination of interpersonal, operational, and institutional integrity factors. Employee sincerity emerged as the strongest predictor, followed by service timeliness and completeness of information. These results are consistent with prior studies emphasizing that empathy, responsiveness, and transparency remain critical determinants of satisfaction in higher education [21], [22], [23].

3.2 Training–Testing Data Partition and Class Balancing

Table 4. Number of Training and Testing Data

Category	Frequency	Percentage (%)
Training Data	221	70.16
Testing Data	94	29.84
Total	315	100

Prior to model construction, the dataset was divided into training (70%) and testing (30%) subsets to enable unbiased evaluation of predictive performance, as shown in Table 4. Because the initial distribution of satisfaction classes was imbalanced, a random oversampling technique was applied to the training dataset to ensure balanced class representation. The effect of this balancing procedure is presented in Table 5, which shows an equal number of observations in both satisfaction categories after resampling.

Table 5. Number of Training Data Before and After Balancing

Description	Satisfied	Dissatisfied
Before	211	10
After	211	211

The balancing process increased model stability and improved the ability to identify patterns within the minority (dissatisfied) group. This step is particularly important in satisfaction studies, where respondents typically skew toward positive ratings. Table 5 presents the class distribution before and after the balancing procedure applied to the training data. Classification performance is subsequently evaluated using a Classification Performance Summary framework, as summarized in Table 6.

3.3 CART Classification Results

The CART model identified seven service quality indicators as splitting variables (X1, X9, X10, X12, X24, X26, and X40), with employee sincerity (X24) selected as the root node of the classification tree. This indicates that employee sincerity serves as the primary factor differentiating alumni satisfaction categories. The resulting classification tree structure is illustrated in Figure 2, which depicts the hierarchical decision paths generated by the CART algorithm based on the selected predictors.

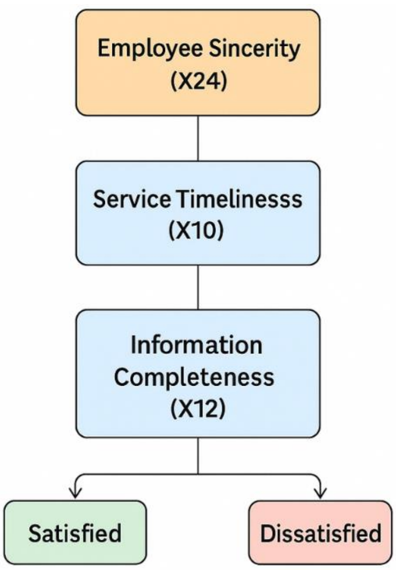

Figure 2. Full CART classification tree estimated from the data, illustrating the complete structure of splits and terminal nodes used to classify alumni satisfaction based on service quality indicators.

As shown in Figure 2, *Employee Sincerity (X24)* appears as the root node, confirming its dominant influence in predicting alumni satisfaction. Respondents who perceived staff sincerity and attentiveness as high were consistently classified as "Satisfied." When sincerity was rated lower, subsequent splits were determined by *Service Timeliness (X10)* and *Information Completeness (X12)*, which jointly refined the prediction outcomes. The tree structure highlights the interaction between interpersonal and procedural service factors. To enhance interpretability, a simplified decision path is presented to illustrate the dominant classification rules derived from the CART model.

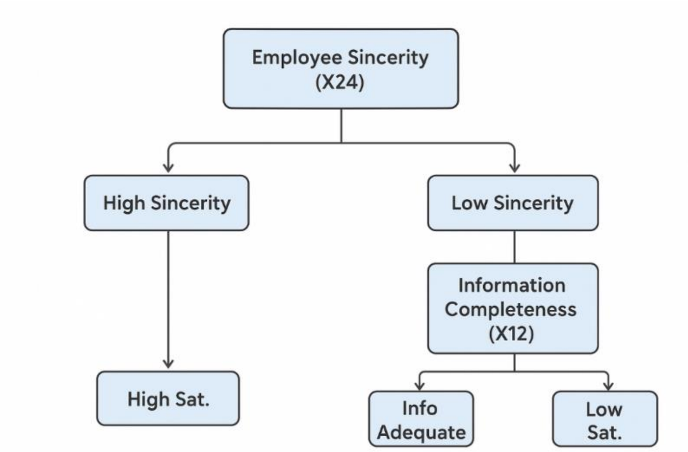

Figure 3. Simplified CART decision path illustrating how employee sincerity (X24) and information completeness (X12) determine alumni satisfaction outcomes.

Figure 3 presents a simplified conceptual representation of the CART decision logic, highlighting the dominant split at X24 (employee sincerity) and the secondary split at X12 (information completeness), which jointly determine the predicted satisfaction outcome. The simplified diagram clarifies the dominant pathways identified by the CART algorithm.

Table 6. Classification Performance Summary of the CART Model

Actual \ Predicted	Satisfied	Dissatisfied	Sensitivity	Specificity
Satisfied	TP = 81	FN = 8	0.91	0.40
Dissatisfied	FP = 3	TN = 2	0.40	0.91

Based on the classification performance summary presented in Table 6, the CART model demonstrates an acceptable level of classification capability. The model shows high sensitivity in identifying satisfied alumni, indicating that most satisfied cases are correctly classified. In contrast, classification performance for dissatisfied alumni is more limited, reflecting the smaller number of observations in this category and resulting in lower sensitivity but higher specificity. This pattern suggests that the model is particularly effective in capturing factors associated with satisfaction, while distinctions for dissatisfaction should be interpreted with caution.

3.4 Classification Performance Evaluation

Model performance was evaluated using a classification performance summary and Receiver Operating Characteristic (ROC) analysis. The Classification Performance Summary results are presented in Table 6, showing the distribution of correctly and incorrectly classified observations across satisfaction categories. The CART model correctly classified the majority of satisfied alumni, with fewer misclassifications observed for the dissatisfied group. This indicates acceptable sensitivity for identifying satisfied cases and reasonable specificity for distinguishing dissatisfied cases, given the imbalanced nature of satisfaction outcomes. Model discrimination was further assessed using the ROC framework. As summarized in Table 8, the CART model achieved an Area Under the Curve (AUC) value of 0.73, indicating fair discriminative performance in distinguishing between satisfied and dissatisfied alumni across different classification thresholds.

This result demonstrates that the decision rules generated by CART capture the underlying structure of the data, reflecting consistent patterns between service attributes and alumni satisfaction. Such performance reliability supports the use of CART in categorical outcome studies, particularly when interactions among predictors are non-linear or hierarchical. Furthermore, the Classification Performance Summary serves as the foundation for calculating the model's *Area Under the Curve (AUC)*, which provides a comprehensive measure of classification accuracy presented in the subsequent section (Table 7).

Table 7. AUC Interpretation Guidelines (adapted from Hosmer & Lemeshow, 2000)

AUC value	Interpretation
0.90–1.00	Excellent
0.80–0.90	Good
0.70–0.80	Fair
0.60–0.70	Poor
0.50–0.60	Fail

Note: Adapted from Hosmer, D. W., & Lemeshow, S. (2000). *Applied Logistic Regression* (2nd ed.). Wiley.

The CART model achieved a correct classification rate of approximately 78%, indicating moderate predictive strength (AUC = 0.73). As shown in Table 8, the highest AUC value (0.730) was obtained when minsplit = 5. The AUC interpretation in Table 7 follows the guidelines proposed by Hosmer and Lemeshow (2000), which classify values between 0.70 and 0.80 as indicating fair discriminative ability. Although the predictive performance is acceptable, further improvements could be achieved through additional predictor variables or methodological triangulation.

Table 8. AUC Values for Three Minsplit Configurations

No	Minsplit	AUC Value
1	5	0.730
2	10	0.725
3	15	0.718

3.5 Discussion

This study applied a CART-based classification approach to examine alumni satisfaction within an Integrity Zone (ZI) faculty context and demonstrated that satisfaction outcomes are shaped by hierarchical interactions among interpersonal quality, operational efficiency, and institutional integrity. Rather than being driven by isolated service attributes, alumni satisfaction emerges from combinations of service dimensions that interact in a non-linear structure. This pattern supports the suitability of interpretable tree-based models for evaluating complex service quality phenomena in higher education [12].

Instead of reiterating individual predictors identified in the Results section, this discussion emphasizes the broader structural insights revealed by the CART model. The tree structure indicates that relational attributes, procedural reliability, and governance-related signals jointly form decision pathways that distinguish satisfied from dissatisfied alumni. This finding reinforces prior evidence that alumni perceptions are influenced by both human-centered and system-centered dimensions of service quality, rather than by single factors acting independently [12], [13].

Within this structure, interpersonal interaction particularly staff sincerity plays a pivotal role by shaping how other service attributes are interpreted. This result is consistent with the SERVQUAL framework, which identifies empathy and responsiveness as central components of perceived service excellence, and aligns with empirical studies showing that staff attitudes significantly affect alumni satisfaction and institutional loyalty [4], [12]. Importantly, this suggests that relational quality remains critical even as administrative services become increasingly standardized or digitalized.

Operational reliability further strengthens satisfaction pathways by reinforcing institutional professionalism and accountability. Timely service delivery, adherence to working hours, and the provision of complete and accessible information collectively contribute to perceptions of organizational discipline and trustworthiness. These findings are consistent with previous studies highlighting the role of procedural clarity and transparent communication in sustaining satisfaction within higher education service systems [8], [12].

The inclusion of integrity-related indicators, particularly transparency and access to anti-corruption information, highlights the governance dimension of alumni satisfaction. Within the Integrity Zone framework, satisfaction is influenced not only by service efficiency but also by perceptions of ethical commitment and institutional credibility. Governance reforms that emphasize openness and accountability may therefore contribute indirectly to alumni trust and long-term engagement [13], [24].

From a methodological standpoint, alternative modeling approaches could be considered for alumni satisfaction analysis. Logistic regression models with interaction terms may capture linear effects and predefined relationships among predictors, while ensemble learning methods such as random forests or gradient boosting are widely recognized for improving predictive accuracy through the aggregation of multiple decision trees. However, these approaches often reduce model transparency, making it more difficult to extract explicit decision rules relevant for institutional policy formulation. In contrast, the single CART model adopted in this study offers transparent, rule-based insights that clearly reveal hierarchical relationships among service quality indicators. Given the applied context of this research, where interpretability and actionable guidance are prioritized over marginal gains in predictive accuracy the use of CART represents a pragmatic and methodologically appropriate choice [12].

Several considerations should be acknowledged when interpreting the findings. The high overall satisfaction level observed in the dataset may reflect a genuinely positive institutional climate but may also be influenced by response tendencies common in alumni surveys. In addition, although class balancing was applied during model training to improve stability, real-world satisfaction data are often inherently imbalanced. Consequently, the CART-derived rules should be interpreted as tools for pattern identification rather than as high-prioritizing staff sincerity training, enforcing service timeliness standards, and strengthening transparency precision predictive mechanisms.

In summary, alumni satisfaction in higher education reflects a complex synthesis of relational interaction, operational reliability, and institutional integrity. By integrating interpretable machine-learning methods with governance-oriented service indicators, this study extends existing service quality frameworks and underscores the strategic importance of transparency and ethical communication in shaping sustainable stakeholder perceptions. While ensemble based extensions such as random forests or gradient boosting may be explored in future studies to enhance predictive accuracy, their inclusion should be carefully balanced against the need for transparency and interpretability, particularly in applied institutional decision-making contexts.

4. CONCLUSION

From a practical perspective, the CART-derived decision rules offer a clear decision-support framework for institutional administrators. By translating key split variables into actionable guidelines such as prioritizing staff sincerity training, enforcing service timeliness standards, and strengthening transparency, through accessible anti-corruption information administrators can directly align policy interventions with the determinants most strongly associated with alumni satisfaction. The hierarchical structure of the model further enables decision-makers to identify which service improvements should be addressed first, supporting evidence based prioritization rather than ad hoc policy responses.

ACKNOWLEDGEMENT

The authors would like to express their sincere appreciation to Universitas Syiah Kuala for the institutional support provided during the completion of this research. The administrative and technical assistance from the Faculty of Mathematics and Natural Sciences is also gratefully acknowledged. No specific funding was received for this study.

5. REFERENCES

[1] D. Krishna, B. Rani, B. Madhavrao, and S. Chowdary, "Predicting student performance using classification and regression trees algorithm," *International Journal of Innovative Technology and Exploring Engineering,* vol. 9, pp. 3349-3356, 01/30 2020, doi: https://doi.org/10.35940/ijitee.c8964.019320.

[2] M. Siddik, H. Hendri, R. Putri, Y. Desnelita, and G. Gustientiedina, "Klasifikasi kepuasan mahasiswa terhadap pelayanan perguruan tinggi menggunakan algoritma naã¯ve bayes," *INTECOMS: Journal of Information Technology and Computer Science,* vol. 3, pp. 162-166, 11/19 2020, doi: https://doi.org/10.31539/intecoms.v3i2.1654.

[3] N. Insan, M. Hadijati, and I. Irwansyah, "Perbandingan metode classification and regression trees (cart) dengan naïve bayes classification (nbc) dalam klasifikasi status gizi balita di kelurahan pagesangan barat," *EIGEN MATHEMATICS JOURNAL,* vol. 3, no. 1, pp. 9-22, 06/26 2020, doi: https://doi.org/10.29303/emj.v3i1.68.

[4] S. Sudjoko, Masrum, and Kasbuntoro, "Alumni satisfaction in educational institutions: Does the quality service effect?," *Journal of Higher Education Theory and Practice,* vol. 22, no. 16, 11/24 2022, doi: https://doi.org/10.33423/jhetp.v22i16.5614.

[5] A. Supriyanto, B. Burhanuddin, S. Sunarni, R. Rochmawati, D. K. Ratri, and A. N. Bhayangkara, "Academic service quality, student satisfaction and loyalty: A study at higher education legal entities in indonesia," *The TQM Journal,* vol. 37, no. 5, pp. 1364-1384, 2024, doi: https://doi.org/10.1108/TQM-10-2023-0334.

[6] A. N. Litasari, "Examining the effects of higher education service quality (hesqual) on student loyalty and word-of-mouth at an indonesian private university," *Indonesian Journal of Economics, Business, Accounting, and Management (IJEBAM),* vol. 2, no. 4, pp. 92-108, 05/13 2024, doi: https://doi.org/10.63901/ijebam.v2i4.63.

[7] M. Hasan and Z. Hosen, "Influence of university service quality on student satisfaction and loyalty in bangladesh: With the mediating role of university reputation and external prestige," *The Journal of Quality in Education,* vol. 12, no. 19, pp. 169-181, 05/30 2022, doi: https://doi.org/10.37870/joqie.v12i19.319.

[8] G. Buchashvili, N. Jikia, and I. Mesiridze, "Alumni loyalty in higher education (case of three private university alumni of ba business administration programs)," *Journal of Education in Black Sea Region,* vol. 4, no. 2, pp. 51-70, 05/26 2019, doi: https://doi.org/10.31578/jebs.v4i2.170.

[9] N. K. Wardhani and W. Gata, "Improving the academic environment and teaching quality through data segmentation and decision trees," *Dinasti International Journal of Education Management And Social Science,* vol. 6, no. 6, pp. 5227-5243, 09/15 2025, doi: https://doi.org/10.38035/dijemss.v6i6.5288.

[10] A. Maesya and T. Hendiyanti, "Forecasting student graduation with classification and regression tree (cart) algorithm," *IOP Conference Series: Materials Science and Engineering,* vol. 621, no. 1, p. 012005, 2019/10/01 2019, doi: https://doi.org/10.1088/1757-899x/621/1/012005.

[11] A. Ahmed *et al.*, "Students' performance prediction employing decision tree," *CTU Journal of Innovation and Sustainable Development,* vol. 16, no. Special issue: ISDS, pp. 42-51, 10/25 2024, doi: https://doi.org/10.22144/ctujoisd.2024.321.

[12] C. M. A. Gomes and E. Jelihovschi, "Presenting the regression tree method and its application in a large-scale educational dataset," *International Journal of Research & Method in Education,* vol. 43, no. 2, pp. 201-221, 2020/03/14 2020, doi: https://doi.org/10.1080/1743727X.2019.1654992.

[13] X. Qiao and H. Jiao, "Data mining techniques in analyzing process data: A didactic," *Frontiers in Psychology,* Original Research vol. Volume 9 - 2018, 2018-November-23 2018, doi: https://doi.org/10.3389/fpsyg.2018.02231.

[14] A. D. Riyanto, A. M. a. Wahid, and A. A. Pratiwi, "Analysis of factors determining student satisfaction using decision tree, random forest, svm, and neural networks: A comparative study," *Jurnal Teknik Informatika (Jutif),* vol. 5, no. 4, pp. 187-196, 07/29 2024, doi: https://doi.org/10.52436/1.jutif.2024.5.4.2188.

[15] A. Ivanov, "Decision trees for evaluation of mathematical competencies in the higher education: A case study," *Mathematics,* vol. 8, no. 5, p. 748, 2020, doi: https://doi.org/10.3390/math8050748.

[16] N. Z. Zacharis, "Classification and regression trees (cart) for predictive modeling in blended learning," *International Journal of Intelligent Systems and Applications,* vol. 10, pp. 1-9, 2018, doi: https://doi.org/10.5815/ijisa.2018.03.01.

[17] S. N. M. Nawai, S. Saharan, and N. A. Hamzah, "An analysis of students' performance using cart approach," *AIP Conference Proceedings,* vol. 2355, no. 1, 2021, doi: 10.1063/5.0053388.

[18] E. Barnes, J. Hutson, and K. Perry, "Enhancing adult learner success in higher education through decision tree models: A machine learning approach," *Forum for Education Studies,* vol. 2, no. 3, p. 1415, 07/09 2024, doi: https://doi.org/10.59400/fes.v2i3.1415.

[19] C.-N. Chang, S. Lin, O.-M. Kwok, and G. K. Saw, "Predicting stem major choice: A machine learning classification and regression tree approach," *Journal for STEM Education Research,* vol. 6, no. 2, pp. 358-374, 2023/08/01 2023, doi: 10.1007/s41979-023-00099-5.

[20] C. Magasi and G. S. Bwemelo, "Influence of undergraduate experience on alumni loyalty to their alma mater in the tanzania's higher education context," *International Journal of Research in Business and Social Science,* vol. 11, no. 4, pp. 333-341, 2022 2022, doi: https://doi.org/10.20525/ijrbs.v11i4.1813.
[21] I. M. Pedro, L. N. Pereira, and H. B. Carrasqueira, "Determinants for the commitment relationship maintenance between the alumni and the alma mater," *Journal of Marketing for Higher Education,* vol. 28, no. 1, pp. 128-152, 2018/01/02 2018, doi: https://doi.org/10.1080/08841241.2017.1314402.
[22] I. H. Pedro and J. M. Andraz, "Alumni commitment in higher education institutions: Determinants and empirical evidence," *Journal of Nonprofit & Public Sector Marketing,* vol. 33, no. 1, pp. 29-64, 2021/01/01 2021, doi: https://doi.org/10.1080/10495142.2019.1656138.
[23] L. Divinagracia and R. A. Murro, "Alumni level of satisfaction on the services rendered by the college of education: Basis for service enhancement planning," *Sprin Journal of Arts, Humanities and Social Sciences,* vol. 3, no. 8, pp. 44-48, 08/29 2024, doi: https://doi.org/10.55559/sjahss.v3i8.370.
[24] L. Masserini, M. Bini, and M. Pratesi, "Do quality of services and institutional image impact students' satisfaction and loyalty in higher education?," *Social Indicators Research,* vol. 146, no. 1, pp. 91-115, 2019/11/01 2019, doi: https://doi.org/10.1007/s11205-018-1927-y.