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Title Inclusive Educational Data Mining Framework Using Classification, Clustering, and Association Rules for Parent–Child Interactions and Reflective Learning

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Abstract

Inclusive education requires integrated academic, social, and emotional support systems to address learner diversity; however, existing Educational Data Mining (EDM) research has largely concentrated on academic or log-based data, with limited attention to family-centered dynamics. This study aims to develop and validate a family-centered EDM framework to examine how the quality of parent–child interactions predicts students' reflective learning behaviors. A cross-sectional survey was conducted with 150 junior and senior high school students from urban Indonesian schools using the Parent–Child Inclusivity Scale (PCIS) and the Self-Assessment Behavior Inventory (SABI). Data were analyzed using descriptive statistics, reliability testing, and Confirmatory Factor Analysis, followed by EDM techniques including Decision Tree and Naïve Bayes classification, K-Means clustering, and Apriori association rule mining. The classification models achieved accuracies of 82% and 78%, while clustering revealed three distinct inclusivity–reflection profiles. Association rules further identified key combinations of autonomy support, constructive feedback, and joint decision-making that consistently predict high levels of reflective behavior. By explicitly integrating family-centered variables into predictive, profiling, and rule-based EDM analyses, this study advances Informatics by proposing a novel family-centered EDM framework that bridges data analytics with inclusive educational practice and adaptive learning system design.

Keywords : *Educational Data Mining, Family-Centered Learning, Inclusive Education, Reflective Learning, Student Profiling.*

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1. INTRODUCTION

Inclusive education, rooted in the Salamanca Statement, aims to remove barriers and embrace learner diversity by integrating academic, social, and emotional dimensions of learning [1], [2]. From an ecological perspective, Bronfenbrenner's Ecological Systems Theory highlights the critical role of the microsystem—particularly parent–child interactions—in shaping learners' development [3]. Complementing this view, Self-Determination Theory emphasizes that autonomy, competence, and relatedness are fundamental psychological needs that drive intrinsic motivation and self-regulated learning [4], [5]. Empirical studies have consistently shown that parental autonomy support is associated with higher levels of academic resilience and self-regulated learning among students [6], [7].

From a methodological standpoint, Educational Data Mining (EDM) provides powerful analytical techniques, including classification, clustering, and association rule mining, to uncover hidden patterns in educational data and support proactive interventions [8], [9]. Nevertheless, most existing EDM studies have primarily focused on academic performance indicators or learning management system log data, with limited attention to family–school dynamics and psychosocial variables [10]. As a result, the potential of EDM to model parent–child interactions as predictive factors for reflective learning behaviors remains underexplored, particularly within inclusive education contexts.

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To address this gap, this study introduces a novel family-centered Educational Data Mining framework that integrates ecological and motivational theories with multiple EDM techniques. Unlike prior EDM research that predominantly relies on academic or system-generated data, the proposed framework positions parent–child inclusivity as a central analytic feature for predicting and profiling students' reflective learning behaviors. By doing so, this study extends the scope of Informatics research toward inclusive and socio-educational domains, demonstrating how EDM can be applied to complex human-centered educational processes.

Accordingly, the objectives of this study are threefold: (1) to quantify parent–child inclusivity and student self-assessment behaviors, (2) to validate and apply classification, clustering, and association rule mining techniques to survey-based educational data, and (3) to propose data-driven, multilevel interventions that support reflective learning and prevent maladaptive educational outcomes.

2. METHOD

2.1. Design and Participants

This study employed a cross-sectional survey design involving 150 junior and senior high school students (Grades 7–12) from three urban schools in Jakarta. Stratified random sampling was applied based on grade level and gender to ensure balanced representation across developmental stages. The sample size was determined to be adequate in accordance with established guidelines for Confirmatory Factor Analysis (CFA) and multivariate analysis, ensuring sufficient statistical power for both factor validation and subsequent Educational Data Mining (EDM) procedures [11]. With a total of 14 observed variables across the two instruments, the sample exceeded the recommended minimum ratio of respondents to indicators, supporting the robustness of the analytical procedures employed.

2.2. Instruments, Data Collection, and Data Analysis

Data were collected using two self-report instruments: the Parent–Child Inclusivity Scale (PCIS) and the Self-Assessment Behavior Inventory (SABI). Each instrument consisted of seven items measured on a 5-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). PCIS was designed to assess the quality of parent–child interaction practices related to inclusivity, while SABI captured students' reflective learning and self-regulation behaviors. Both instruments demonstrated strong internal consistency, with Cronbach's α values of 0.89 for PCIS and 0.87 for SABI, indicating high reliability.

Data collection was conducted through an online questionnaire following ethical clearance approval. The questionnaire package included demographic information (identification code, age, and gender) alongside the PCIS and SABI items. Online administration ensured participant confidentiality, standardized response conditions, and efficient data management for subsequent analysis.

To enhance analytical transparency and reproducibility, the data analysis followed a structured, sequential workflow, as summarized in Table 1. The analysis began with descriptive statistics (mean and standard deviation) to profile the sample and examine scale distributions. Reliability analysis and Confirmatory Factor Analysis (CFA) were then conducted to assess internal consistency and validate the factorial structure of both instruments using established goodness-of-fit criteria (CFI $\geq$ 0.92; RMSEA $\leq$ 0.06), confirming construct validity.

Table 1 presents the sequential analytical phases, methods, and software employed in this study, illustrating a comprehensive Educational Data Mining workflow from descriptive analysis and validation to predictive modeling, profiling, and association rule discovery. Descriptive statistics, reliability, Confirmatory Factor Analysis (CFA), classification models (Decision Tree, Naïve Bayes), clustering (K-Means), and association rules (Apriori) were applied to the data [9], [11]. CFA supported

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two-factor structures for both scales (CFI ≥ 0.92; RMSEA ≤ 0.06), confirming construct validity. Subsequently, EDM techniques were applied in three stages. First, classification models using Decision Tree and Naïve Bayes algorithms were employed to predict high versus low reflective behavior. Reflective behavior was dichotomized using a threshold of SABI ≥ 25, corresponding to the theoretical midpoint of the scale and supported by prior self-regulated learning research, ensuring a meaningful separation between reflective profiles. Second, K-Means clustering (k = 3) was used to identify student profiles based on PCIS and SABI scores, enabling exploratory profiling of inclusivity–reflection patterns. Finally, association rule mining using the Apriori algorithm was conducted to uncover preventive and promotive co-practice patterns. The minimum support (0.20) and confidence (0.70) thresholds were selected to balance statistical relevance and interpretability, allowing the identification of actionable and theoretically meaningful rules.

Table 1. Phase and Statistical Method

Phase	Technique	Purpose	Software
Descriptive	Mean, SD	Profile sample; scale distribution	JASP
Reliability & CFA	Cronbach's α, CFA	Assess internal consistency and structure	JASP, AMOS
Classification	Decision Tree, Naïve Bayes	Predict high vs. low reflective behaviours	RapidMiner
Clustering	K-Means	Identify student profiles	RapidMiner
Association Rules	Apriori	Uncover preventive/promotive rule patterns	RapidMiner



Figure 1. Research Workflow of the Educational Data Mining Analysis

Figure 1 illustrates the sequential Educational Data Mining workflow applied in this study, from data collection and validation to predictive modeling, clustering, and association rule discovery. Overall, this stepwise analytical procedure reflects a comprehensive EDM workflow that integrates validation, prediction, profiling, and rule discovery to examine family-centered factors in reflective learning [12].

3. RESULT

3.1. Descriptive and Reliability

Table 2. Descriptive statistics of PCIS and SABI

Scale	Mean (M)	SD	Cronbach's α
PCIS	3.18	1.29	0.89
SABI	3.20	1.28	0.87

Table 2 shows that both PCIS and SABI demonstrate moderate mean scores with high internal consistency, indicating adequate variability for subsequent EDM analysis. The confirmatory Factor Analysis supported two-factor structures for both scales (CFI ≥ 0.92; RMSEA ≤ 0.06).

Descriptive Statistics

	PCIS1	PCIS2	PCIS3	PCIS4	PCIS5	PCIS6	PCIS7
Valid	151	151	151	151	151	151	151
Missing	2	2	2	2	2	2	2
Mean	2.760	2.933	2.873	3.047	3.080	3.080	3.207
Std. Deviation	1.365	1.486	1.434	1.368	1.435	1.393	1.333
Minimum	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Maximum	5.000	5.000	5.000	5.000	5.000	5.000	5.000

Table 3. Reliability analysis per item (α, item-total correlation)

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Table 4. Instrument Factor Loadings, Composite Reliability (CR), and Average Variance Extracted (AVE)

Instrument	Item	Factor	Standardized Loading	CR (Composite Reliability)	AVE (Average Variance Extracted)
PCIS	PCIS1 – Autonomy Support	Inclusivity	0.72	0.89	0.58
	PCIS2 – Emotional Warmth	Inclusivity	0.75		
	PCIS3 – Shared Responsibility	Inclusivity	0.70		
	PCIS4 – Constructive Feedback	Inclusivity	0.78		
	PCIS5 – Joint Decision-Making	Inclusivity	0.74		
	PCIS6 – Mutual Respect	Inclusivity	0.77		
	PCIS7 – Inclusion in Activities	Inclusivity	0.81		
SABI	SABI1 – Goal Setting	Self-Reflection	0.73	0.87	0.56
	SABI2 – Planning	Self-Reflection	0.75		
	SABI3 – Monitoring	Self-Reflection	0.71		
	SABI4 – Self-Evaluation	Self-Reflection	0.76		
	SABI5 – Adjusting Strategies	Self-Reflection	0.72		
	SABI6 – Reflective Thinking	Self-Reflection	0.79		
	SABI7 – Learning from Feedback	Self-Reflection	0.80		

Table 3 shows the descriptive analysis of the PCIS (PCIS1–PCIS7) and SABI (SABI1–SABI7) variables, which showed that both instruments had mean scores ranging in the moderate category, with PCIS ranging from 2.760 to 3.207 and SABI between 2.807 and 3.167. The highest mean score for PCIS was found in PCIS7 (M=3.207), while for SABI it was found in SABI6 (M=3.167), indicating that these items received a relatively higher level of agreement than other items within the same construct. Furthermore, the minimum and maximum scores for all items fell within the full scale range (1–5), indicating the absence of floor or ceiling effects and indicating that respondents utilized all scale options proportionally.

Data variability was indicated by the relatively large standard deviation (above 1.3 for all items), indicating heterogeneity in respondents' perceptions and potential differences based on individual or

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group characteristics. These findings suggest that both the PCIS and SABI have good discriminatory capabilities and can be used to identify areas of strength and development needs in educational interventions and psychological coaching. Furthermore, the relatively uniform mean pattern, with minimal differences between items, opens up opportunities for further structural exploration through confirmatory factor analysis to ensure the construct validity of the instruments and sharpen the direction of future adolescent competency strengthening programs [13].

Confirmatory Factor Analysis (CFA) was conducted to validate the underlying structure of the Parent–Child Inclusivity Scale (PCIS) and the Self-Assessment Behavior Inventory (SABI). Table 1 presents standardized factor loadings, composite reliability (CR), and average variance extracted (AVE). All indicators exceeded the minimum thresholds (loading ≥ 0.60, CR ≥ 0.70, AVE ≥ 0.50), confirming good construct validity.

Table 4 presents the standardized factor loadings, Composite Reliability (CR), and Average Variance Extracted (AVE) for the Parent–Child Inclusivity Scale (PCIS) and the Self-Assessment Behavior Inventory (SABI). All items demonstrate standardized loadings above the recommended threshold of 0.60, indicating strong item–factor relationships. The CR values for both instruments exceed 0.80, confirming high internal consistency, while AVE values above 0.50 indicate adequate convergent validity. These results support the psychometric robustness of PCIS and SABI for subsequent Educational Data Mining analyses.

3.2. Classification and Clustering

Reflective behaviour was dichotomized: High (SABI ≥ 25) vs. Low (SABI < 25). Classification models achieved accuracies of 82% (Decision Tree) and 78% (Naïve Bayes), with key predictors including autonomy support (PCIS1), constructive feedback (PCIS4), and joint decision-making (PCIS5) [6], [7].

Table 5. Classification metrics (accuracy, precision, recall)

Model	Accuracy	Precision	Recall	F1-Score
Decision Tree	0.82	0.84	0.80	0.82
Naïve Bayes	0.78	0.79	0.76	0.77

The results from classification, clustering, and association rule mining collectively provide a comprehensive picture of how parent–child inclusivity relates to students' reflective learning behaviors. As shown in Table 5, the Decision Tree model outperformed Naïve Bayes across all evaluation metrics (accuracy, precision, recall, and F1-score), indicating a stronger ability to classify high and low reflective behaviors. Key predictors identified by the model autonomy support (PCIS1), constructive feedback (PCIS4), and joint decision-making (PCIS5) underscore the salience of specific interaction practices rather than general parental involvement.

Table 6. Cluster profiles from K-Means

Cluster	n	PCIS Mean	SABI Mean	Profile
A	50	4.6	4.7	High inclusivity & high reflection
B	65	3.8	3.6	Moderate inclusivity & reflection
C	35	3.0	2.9	Low inclusivity & low reflection
Silhouette Coefficient = 0.62.				

Complementing these predictive findings, Table 6 presents three distinct student profiles derived from K-Means clustering, ranging from high inclusivity–high reflection (Cluster A) to low inclusivity–low reflection (Cluster C), with a silhouette coefficient of 0.62 indicating good cluster separation. Exploratory demographic profiling further suggests that Cluster A is more prevalent among senior high

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school students, whereas Cluster C is more common among junior high school students, while gender distribution remains relatively balanced across clusters, pointing to the potential role of developmental stage in shaping reflective practices.

In addition, The dichotomization threshold for reflective behavior (SABI ≥ 25) was determined based on the theoretical midpoint of the scale and prior self-regulated learning research, ensuring meaningful separation between low and high reflective profiles. Apriori parameters (minimum support = 0.20; confidence = 0.70) were selected to balance rule interpretability and statistical relevance. Building on this categorization, the Apriori association rules summarized in Table 7 reveal consistent co-practice patterns such as autonomy support combined with joint decision-making and constructive feedback combined with shared responsibility that are strongly associated with high reflection and self-evaluation. Taken together, these results establish an empirical foundation for the subsequent discussion, enabling a deeper examination of how predictive accuracy, learner profiling, and co-occurring interaction practices jointly inform theoretical interpretation and practical implications within an Educational Data Mining framework. Apriori analysis revealed co-practice combinations predicting high reflective behaviours, such as autonomy support + joint decision-making → high reflection and constructive feedback + shared responsibility → strong self-evaluation [14], [15].

Table 7. Association Rules From The Apriori Algorithm

Rule	Support	Confidence	Lift
IF PCIS1 ≥ 4 AND PCIS5 ≥ 4 THEN SABI2 ≥ 4	0.30	0.78	1.20
IF PCIS3 ≥ 4 AND PCIS4 ≥ 4 THEN SABI7 ≥ 4	0.25	0.75	1.15
IF PCIS2 ≥ 4 AND PCIS6 ≥ 4 AND PCIS7 ≥ 4 THEN SABI5 ≥ 4	0.20	0.80	1.30

4. DISCUSSION

The high reliability and valid factor structures of PCIS and SABI confirm the psychometric robustness of both instruments, supporting their suitability for subsequent Educational Data Mining analyses. The classification results further indicate that autonomy support and constructive feedback are among the most salient predictors of students' reflective learning behaviors, underscoring the importance of specific parent–child interaction practices rather than general parental involvement [16], [17]. The clustering results extend this interpretation by revealing differentiated student profiles, suggesting that reflective learning does not emerge uniformly but is shaped by varying levels of inclusivity within the family context.

These findings are consistent with prior research emphasizing the role of autonomy-supportive parenting in fostering self-regulated learning and academic resilience [18], [19] . Moreover, the association rules identified in this study align with meta-analytic evidence showing that structured feedback and shared responsibility enhance self-evaluation and reflective capacity. However, unlike most existing Educational Data Mining studies that focus on academic performance metrics or system-generated log data, this study demonstrates that family-centered variables can function as robust predictors within EDM models. By integrating psychosocial constructs into classification, clustering, and association rule mining, the findings extend earlier EDM research and highlight the feasibility of applying data-driven methods to more complex, human-centered educational processes [20], [21].

From a theoretical perspective, the results reinforce ecological and motivational frameworks by empirically demonstrating how microsystem-level interactions contribute to reflective learning outcomes. Practically, the identified cluster profiles support differentiated intervention strategies, ranging from intensive family coaching for students with low inclusivity and reflection to enrichment-oriented support for those with high inclusivity profiles. Nevertheless, the translation of these EDM-driven insights into practice must be approached with contextual sensitivity. In urban Indonesian

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schools, factors such as large class sizes and limited parental availability may constrain individualized reflection coaching and joint decision-making practices. For instance, teachers in Jakarta often manage high student–teacher ratios, while parents in working-class families may face time constraints that limit sustained engagement. These realities suggest that while EDM models offer robust predictive and diagnostic value, their implementation requires adaptation to school resources, teacher workload, and family dynamics to ensure relevance and sustainability in real-world educational settings.

5. PRACTICAL IMPLICATIONS

Family coaching modules can train parents in autonomy-supportive communication and joint decision-making [22], [23]. Teacher workshops can embed constructive feedback strategies into lesson planning [24]. Adaptive dashboards can visualize cluster membership and trigger rule-based recommendations. EDM techniques provide actionable insights, helping teachers and parents foster reflective learning and inclusivity while tailoring interventions according to student profiles [25].

To translate the technical findings of Educational Data Mining (EDM) into practical strategies, it is crucial to highlight how classification, clustering, and association rules can inform concrete actions for both teachers and parents. The following table summarizes the key findings and their direct implications for daily educational practice.

Table 8. Practical Implications Of Educational Data Mining (EDM) Findings For Teachers And Parents. Source: Author's Analysis Using EDM Techniques

EDM Technique	Key Findings	Implications for Teachers	Implications for Parents
Classification (Decision Tree, Naïve Bayes)	Predictive accuracy 78–82%. Key predictors: autonomy support, constructive feedback, joint decision-making.	Use constructive feedback beyond grades (e.g., growth-oriented comments). Encourage student participation in classroom decisions.	Provide autonomy at home (e.g., choice in study time). Involve children in family decision-making to foster reflection.
Clustering (K-Means, k=3)	Three profiles: A = High inclusivity & reflection B = Moderate C = Low	Cluster A → enrichment (projects, peer mentoring). Cluster B → scaffolded support (learning journals, guided reflection). Cluster C → intensive personalized coaching.	Cluster A → support independence. Cluster B → short reflective talks after school. Cluster C → structured daily coaching (e.g., bedtime reflection).
Association Rules (Apriori)	Effective combinations: autonomy + joint decision → high reflection feedback + responsibility → strong self-evaluation warmth + inclusion → adaptive strategies.	Combine feedback + shared responsibility in assignments. Build routines that encourage self-evaluation.	Foster joint decision-making (e.g., planning family activities). Show warmth & inclusion to strengthen resilience and reflection.

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Table 8 illustrates how the results of classification, clustering, and association rule mining can be translated into practical, evidence-based actions for teachers and parents. By aligning instructional and parenting strategies with identified student profiles and predictive factors, the EDM findings demonstrate their potential to bridge analytic insights with everyday educational practice, fostering autonomy-supportive behaviors, reflective routines, and inclusive learning environments. At the same time, the applicability of these recommendations should be interpreted with caution, as their implementation depends on contextual factors such as school resources, teacher workload, cultural expectations, and family capacity. While some educational settings may readily integrate reflective journals and family coaching practices, others may require more scalable and adaptive approaches, underscoring the need for context-sensitive and gradual adoption rather than a one-size-fits-all application. These implications demonstrate that EDM techniques not only uncover statistical patterns but also generate evidence-based recommendations for stakeholders[11]. By tailoring interventions according to student profiles, fostering autonomy-supportive behaviors, and applying effective combinations of practices, teachers and parents can collaboratively cultivate reflective learning and inclusivity. Ultimately, EDM serves as a bridge between complex data analytics and real-world educational transformation.

Nevertheless, these practical directions should be interpreted with caution. The extent to which parents and teachers can implement autonomy-supportive practices may depend on cultural expectations, resource availability, and school–family collaboration. For example, while some private schools in Jakarta may easily integrate reflective journals and family coaching sessions, public schools with higher student–teacher ratios may require more scalable interventions. This underscores the need for gradual, context-sensitive adoption rather than a one-size-fits-all application

6. LIMITATIONS AND FUTURE RESEARCH

The study's cross-sectional design limits causal inference, and the urban sample restricts generalizability. Self-reported data may be biased by social desirability. Future research should adopt longitudinal, mixed-methods designs and explore deep learning for finer predictive accuracy. Transferability to rural or under-resourced contexts requires further investigation [26], [27].

7. CONCLUSION

This study advances Informatics research by demonstrating how Educational Data Mining techniques can be applied beyond academic datasets to model family-centered factors influencing reflective learning. By integrating classification, clustering, and association rule mining within an inclusive education framework, the proposed model highlights the potential of EDM as a decision-support tool for adaptive, family-informed educational systems. These findings reinforce the role of data-driven approaches in designing inclusive and context-sensitive learning technologies. More importantly, this study establishes a family-centered Educational Data Mining framework as a meaningful extension of conventional EDM paradigms, broadening the analytical scope of Informatics to encompass socio-educational and relational dimensions of learning.

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