

Applying Binary Logistic Regression to Map Cognitive Styles Based on Students' Errors in Algebraic Thinking Generalization Problems According to Newman's Theory

Nanda Arista Rizki¹, Gyta Krisdiana Cahyaningrum^{2*}, Mutiara Mumtaza³

¹Universitas Mulawarman, nanda.arista@fkip.unmul.ac.id

²Universitas Mulawarman, gytacahyaningrum@fkip.unmul.ac.id

³Universitas Mulawarman, aramumtz@gmail.com

*corresponding author

Submitted: 21 November 2025; Revised: 8 March 2026; Accepted: 15 April 2026

ABSTRACT

Algebraic generalization problems pose a significant challenge, requiring teachers to recognize influencing factors like Field Independent (FI) and Field Dependent (FD) cognitive styles. The purpose of this study was to apply binary logistic regression to map students' cognitive styles, either FI or FD, based on their error patterns when solving algebraic thinking generalization problems. These errors were classified using the five categories of Newman's Theory: Reading (R), Comprehension (C), Transformation (T), Process Skill (S), and Encoding (E). This exploratory correlational study involved 40 tenth-grade students from SMA IT Granada Samarinda. Cognitive style (the dependent variable) was measured using the GEFT, while the Newman error categories (the independent variables) were identified from a generalization instrument adopted from TIMSS (2003–2019). The results found that 23 out of 40 students made mistakes, consisting of 9 FI students and 31 FD students. The binary logistic regression results showed that the Process Skill (S) error was the strongest predictor for the FI style, with an odds ratio of 18.025. This means that students who make an S error are 18 times more likely to be classified as FI. This finding leads to the conclusion that FI students struggle with the details of procedural implementation, despite possessing a strong strategic understanding. Binary logistic regression proved effective as a diagnostic tool to support more personalized mathematics learning strategies.

Keywords: *Binary logistic regression, Algebraic thinking generalization problems, Cognitive styles, Students' errors*

Penerapan Regresi Logistik Biner untuk Memetakan Gaya Kognitif Berdasarkan Kesalahan Siswa dalam Soal Generalisasi Berpikir Aljabar Menurut Teori Newman

ABSTRAK

Soal generalisasi aljabar memberikan tantangan yang signifikan, sehingga menuntut guru untuk mengenali faktor-faktor yang memengaruhinya, seperti gaya kognitif Field

Independent (FI) dan Field Dependent (FD). Tujuan dari penelitian ini adalah menerapkan regresi logistik biner untuk memetakan gaya kognitif siswa, baik FI maupun FD, berdasarkan pola kesalahan mereka saat menyelesaikan soal generalisasi berpikir aljabar. Kesalahan-kesalahan ini diklasifikasikan menggunakan lima kategori Teori Newman, yaitu Membaca (Reading/R), Pemahaman (Comprehension/C), Transformasi (Transformation/T), Keterampilan Proses (Process Skill/S), dan Encoding (E). Penelitian korelasional eksploratif ini melibatkan 40 siswa kelas sepuluh dari SMA IT Granada Samarinda. Gaya kognitif (variabel terikat) diukur menggunakan Group Embedded Figures Test (GEFT), sementara kategori kesalahan Newman (variabel bebas) diidentifikasi dari instrumen generalisasi yang diadopsi dari TIMSS (2003–2019). Hasil penelitian menemukan bahwa 23 dari 40 siswa melakukan kesalahan, yang terdiri dari 9 siswa FI dan 31 siswa FD. Hasil regresi logistik biner menunjukkan bahwa kesalahan Keterampilan Proses (S) adalah prediktor terkuat untuk gaya FI, dengan nilai odds ratio 18,025. Ini berarti siswa yang membuat kesalahan S memiliki kemungkinan 18 kali lipat lebih besar untuk diklasifikasikan sebagai FI. Temuan ini menyimpulkan bahwa siswa FI berjuang dengan detail implementasi prosedural, walaupun mereka memiliki pemahaman strategis yang kuat. Regresi logistik biner terbukti efektif sebagai alat diagnostik untuk mendukung strategi pembelajaran matematika yang lebih terpersonalisasi.

Kata Kunci: *Regresi logistic biner, Masalah generalisasi berpikir aljabar. Gaya kognitif, Kesalahan siswa*

How to cite: Rizki, N. A., Cahyaningrum, G. K., & Mumtaza, M. (2025). Applying Binary Logistic Regression to Map Cognitive Styles Based on Students' Errors in Algebraic Thinking Generalization Problems According to Newman's Theory. *Jurnal Riset Pendidikan dan Inovasi Pembelajaran Matematika (JRPIPM)*, 10(1), 48-58. <https://doi.org/10.26740/jrpijm.v10n1.p48-58>

License



This work is licensed under a [Creative Commons Attribution 4.0 International License](https://creativecommons.org/licenses/by/4.0/).

1. Introduction

Algebraic thinking skills are crucial in mathematics learning. Algebraic thinking skills can directly or indirectly support students in solving various everyday problems using their thinking skills (Sari & Nasution, 2023). Algebra learning requires students to shift from concrete operations to symbolic and abstract thinking, making it an important prerequisite for understanding advanced concepts. However, based on the results processed by the Trends in International Mathematics and Science Study (TIMSS), Indonesian students who completed algebra questions at the reasoning level had a correct answer percentage of 18%. In contrast, the correct answer percentage for questions at the application level was only 1% (Hadi & Novaliyosi, 2019). The difficulties experienced by most students in understanding algebraic concepts are reflected in the various mistakes that often occur during the learning process. The types of errors commonly made include organizing, generalizing, and modeling (Wihda, 2021). These errors occur not only due to weak conceptual mastery but also due to teaching approaches that fail to consider the diversity of students' thinking or cognitive styles. These errors often recur and are structured, thereby hindering a deep understanding of algebra (Ilyas et al., 2017; Rohmah, 2021).

Algebraic difficulties arise not only from weak procedural skills, but also from metacognitive failures, when students simply imitate steps without reflecting on the strategies and objectives of each procedure. This condition often results in transformation and encoding

errors that are not easily overcome by repeated practice alone, because the root of the problem lies in students' lack of awareness of their own thought patterns. These metacognitive deficiencies mean students may possess the correct procedural knowledge but fail to monitor and regulate its application effectively. Consequently, the reliance on rote memorization without genuine strategic reflection inhibits true mastery of complex algebraic processes (Alam & Mohanty, 2024).

The cognitive styles commonly used are Field Independent (FI) versus Field Dependent (FD), which explain how individuals process information. FI students tend to break problems down into separate elements, while FD students consider the overall context (Shodikin et al., 2020). The lack of recognition of these styles in teaching practices often results in interventions that are uniform and ineffective, especially when dealing with the diversity of thinking styles within a single class. Recognizing this diversity is crucial because a teaching method effective for FI students may be detrimental to FD students, thus necessitating personalized approaches (Volkotrubova et al., 2024).

Newman's Error Analysis offers a powerful diagnostic framework for educators to pinpoint the precise source of student difficulties in solving mathematical word problems. This model sequentially categorizes errors into five distinct types, allowing teachers to trace a student's thought process. The first hurdle is Reading (R), where a student may be unable to decode words or symbols. Following this is Comprehension (C), where the student reads the words but fails to grasp the overall meaning or what is being asked. Next, a Transformation (T) error occurs when the student understands the problem but chooses an incorrect mathematical strategy or operation. Even with the right plan, a Process Skill (S) error can happen during the calculation itself, such as a mistake in addition or multiplication. Finally, an Encoding (E) error occurs when the student finds the correct answer but fails to express it in the required format, such as with the correct units (Wihda, 2021).

Although informative, Newman's analysis is descriptive and does not provide a probabilistic picture of students' thinking styles (Simon Antero et al., 2022). Binary logistic regression provides the solution by transforming Newman's error patterns into predictor variables to predict the probability of FI and FD tendencies. This model enables teachers to obtain not only categorical classifications but also the degree of confidence that a student belongs to FI or FD, which is highly useful in identifying the "gray zone" where intervention is more needed. By quantifying the relationship between specific errors and cognitive styles, this approach moves beyond simple error identification toward predictive educational diagnostics.

In the context of SMA IT Granada Samarinda, where general algebra questions were taken from the TIMSS bank (2003–2019), the application of this probabilistic model is expected to provide empirical data that can be directly utilized by teachers (Rasdiansastra et al., 2022). The Group Embedded Figures Test (GEFT) instrument was used to measure cognitive style with high reliability, while the TIMSS questions recorded error patterns in binary format for analysis. Although several studies have examined algebraic errors or cognitive styles separately, integrating both into a single probabilistic model is still rare. This gap indicates the need for research that maps the direct relationship between types of algebraic errors and cognitive styles, so that learning interventions can be adaptive and measurable. Against this backdrop, this study maps FI–FD cognitive style tendencies based on patterns of algebraic thinking errors in generalization questions according to Newman's Theory using binary logistic regression analysis. It is hoped that the results of this study will not only enrich the theoretical knowledge of mathematics education but also serve as a practical tool to help teachers design more personalized, effective, and responsive learning strategies tailored to students' needs. Hence, this research aimed to apply binary logistic regression in mapping students' cognitive styles based on Newman's theory on generalization.

2. Research Method

This study used an exploratory correlational design. The main focus was to explain the influence of errors based on Newman's theory on students' cognitive style tendencies using binary logistic regression. The study was conducted at SMA IT Granada Samarinda. The study population included all 109 students in the 10th grade at SMA IT Granada Samarinda. From this population, 40 students were selected as the sample using purposive sampling. The sample selection was based on the student's willingness to participate in the study. The sample consisted of two classes, namely class X-A3 ikhwan with 18 students and class X-B2 akhwat with 22 students.

The study used two main instruments, i.e. GEFT and generalization-type questions test which is summarized in Table 1. Data collection was conducted by distributing a test instrument consisting of one generalization-type question with three assessment indicators to the selected students. Next, students' answers were coded according to the classification of errors in Newman's five errors. The collected data will be analyzed using binary logistic regression analysis techniques.

Table 1. Research Instruments

Instrument	Purpose	Description and Scoring	Data Type and Role
1. Group Embedded Figures Test (GEFT)	To identify students' cognitive style (Field Independent/FI or Field Dependent/FD).	<ul style="list-style-type: none"> • Source: Developed by Witkin. • Format: 25 complex images; students find simple shapes. • Sections: Three sections (first section is practice, scores not counted; second and third sections are scored). • Scoring: 1 point for each correct answer in sections 2 & 3; 0 for incorrect. Total score ranges from 0 to 18. 	Dependent Variable <ul style="list-style-type: none"> • FD: Score 0–9 • FI: Score 10–18
2. TIMSS Generalization-Type Questions	To assess student errors based on Newman's Error Theory in the context of algebraic generalization.	<ul style="list-style-type: none"> • Source: Adopted from TIMSS questions (2003–2019). • Focus: Contains generalization-type algebraic thinking components. • Coding: Each error type was coded in a binary format (1 = error occurred, 0 = error did not occur). 	Independent Variables (Predictors in the logistic regression model)

3. Results and Discussion

The first research results, which can be seen in Table 2, showed that 23 out of 40 students made mistakes in Reading (R), Comprehension (C), Transformation (T), Process Skill (S), and Encoding (E). This proportion indicated that more than half of the students still have difficulty in solving algebraic generalization problems, suggesting the need for more targeted learning interventions. This finding was in line with previous research showing that Newman's error analysis can reveal various types of difficulties students have in solving mathematical problems.

Based on Table 2, there was a different pattern of errors between students with Field Independent (FI) and Field Dependent (FD) cognitive styles. Some students also made more than one type of error, i.e., one FI student who made errors in the Process Skill (S) and Encoding (E) stages, five FD students who made errors in the Comprehension (C) and Transformation

(T) stages, and one FD student who made errors in Reading (R), Comprehension (C), and Transformation (T).

Table 2. Cross-tabulation of Error Types and Cognitive Styles

Error Type	FI	FD
Reading (R)	0	1
Comprehension (C)	2	14
Transformation (T)	0	9
Process Skill (S)	2	0
Encoding (E)	1	1
Number of students who made mistakes	4	19
Number of students	9	31

Students with FI cognitive styles showed relatively limited but specific error patterns. Of the 9 FI students, only four students (44.4%) made errors, with a predominance in the Process Skill stage (2 students) and Encoding stage (1 student). This reflected the characteristics of FI students, who were generally able to understand and transform problems well but experienced difficulties in the stage of implementing mathematical procedures and writing final answers (Hasan, 2020). FI students tend to be more analytical and able to separate important information from distracting contexts, thus rarely making errors in the early stages of problem-solving (Wulan & Anggraini, 2019). Conversely, students with FD cognitive style showed a broader and more complex distribution of errors. Of the 31 FD students, 19 students (61.3%) made errors with diverse patterns. The dominant errors occurred at the Comprehension stage (14 students) and Transformation stage (9 students), indicating FD students' difficulties in understanding the meaning of the question and transforming it into a mathematical model.

Table 3. Cross-tabulation of Gender and Cognitive Styles

Gender	FI	FD
Ikhwan (Male)	3	9
Akhwat (Female)	1	10
Number of students who made mistakes	4	19
Number of students	9	31

Based on Table 3, which showed the cross-tabulation between gender and students' cognitive styles, there was an interesting distribution between male (Ikhwan) and female (Akhwat) students in relation to FI and FD. The data indicated that out of the total 40 students who participated in the study, there were 12 male students and 11 female students, with an uneven distribution of cognitive styles between the two genders. Male students (Ikhwan) showed dominance in the FD cognitive style with nine students (75%) compared to FI, which had only three students (25%). Conversely, female students (Akhwat) showed an even more extreme dominance in the FD cognitive style, with ten students (90.9%) and only one student (9.1%) classified as FI. This pattern indicated that the majority of students in this study, both male and female, tended to have the FD cognitive style.

Before performing binary logistic regression analysis, assumption testing must first be carried out. The first assumption test was that there was no multicollinearity among explanatory variables. This test used the correlation matrix in Figure 1 and the VIF values in Table 4. Based on Figure 1, the correlation values between two features were still below the critical threshold for multicollinearity. The highest observed correlation value was between the Process Skill (S) and Encoding (E) variables at 0.474, which was still well below the critical threshold of 0.8 set by Gujarati (1995). Other correlations showed even lower values.

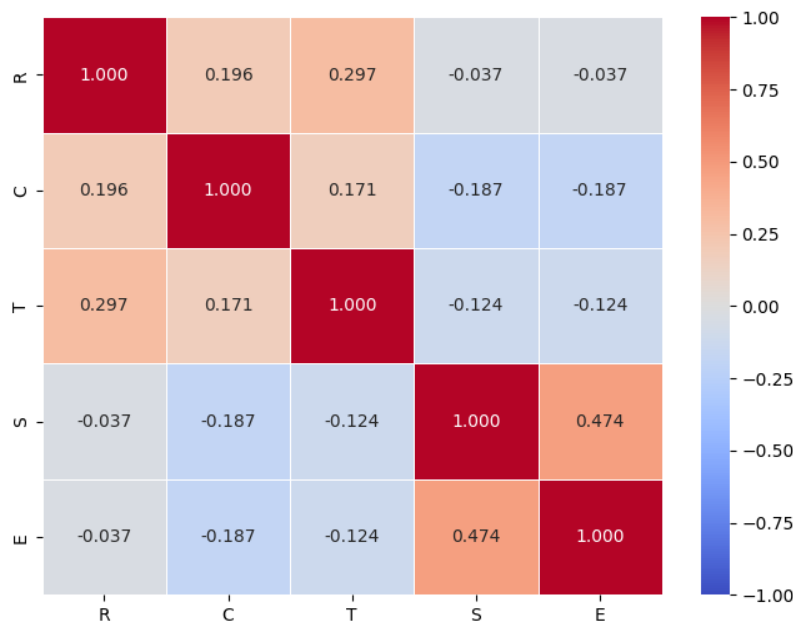


Figure 1. Correlation heatmap of error types

Table 4 showed that all Newman error variables have very ideal VIF values for the binary logistic regression model, as they have VIF values below 10, indicating no significant correlation between independent variables. The interpretation of the correlation matrix and VIF values indicated that each Newman error variable provides relatively independent information and does not overlap excessively in explaining variations in students' cognitive styles.

Table 4. Variance Inflation Factor (VIF) of Error Types

Feature	VIF
Reading (R)	1.144
Comprehension (C)	1.231
Transformation (T)	1.298
Process Skill (S)	1.333
Encoding (E)	1.333

The next test was to test the overall significance of the model using the Omnibus (Chi-squared) test, which was presented in Table 5. The selection of a significance level ($\alpha = 0.10$) in this test was specifically considered, given the exploratory nature of the study and the limited sample size.

Table 5. Overall Model Testing Results and By Observation Data

P Value for Omnibus Test	P Value for Hosmer-Lemeshow Test
0.0403	0.9895

This leniency in the α value was applied to reduce the likelihood of a Type II error in detecting potential predictors. Since the P value=0.0403 < 0.10 in the Omnibus test, it can be concluded that the resulting binary logistic regression model was significant overall. Meanwhile, in the Hosmer-Lemeshow test, since the P value = 0.9895 > 0.10, it can be concluded that the resulting binary logistic regression model was consistent with the observed data.

The next stage of the research was the establishment of a binary logistic regression model. The coefficients, odds ratios, and p-values for each variable forming the model are presented in Table 6.

Table 6. Estimated Results of Binary Logistic Regression Model Parameters

Feature	Coefficient	Odds ratio	P value
Intercept	-0.888	0.412	1.000
Reading (R)	-0.165	0.848	1.000
Comprehension (C)	-0.636	0.530	0.395
Transformation (T)	-2.394	0.091	0.167
Process Skill (S)	2.892	18.025	0.068
Encoding (E)	-0.422	0.656	0.931

Based on Table 6, which displays the results of the binary logistic regression model parameter estimation, a comprehensive analysis of the relationship between Newman's errors and the prediction of FI students' cognitive styles can be performed. This model used five predictor variables representing the types of errors according to Newman's theory, i.e., Reading (R), Comprehension (C), Transformation (T), Process Skill (S), and Encoding (E). The Transformation (T) variable showed a fairly large negative coefficient of -2.394 with an odds ratio of 0.091 and a P value of 0.167, indicating that transformation errors tend to reduce the likelihood of students being classified as FI, although this is not statistically significant. Meanwhile, the Encoding (E) variable had a coefficient of -0.422 with an odds ratio of 0.656 and a p-value of 0.931, indicating a very weak and insignificant influence in the predictive model. Based on the coefficient values, the following regression model was obtained:

$$Logit(P(FI)) = -0.888 - 0.165R - 0.636C - 2.394T + 2.892S - 0.422E$$

$$P(FI) = \frac{1}{1 + e^{-(-0.888 - 0.165R - 0.636C - 2.394T + 2.892S - 0.422E)}}$$

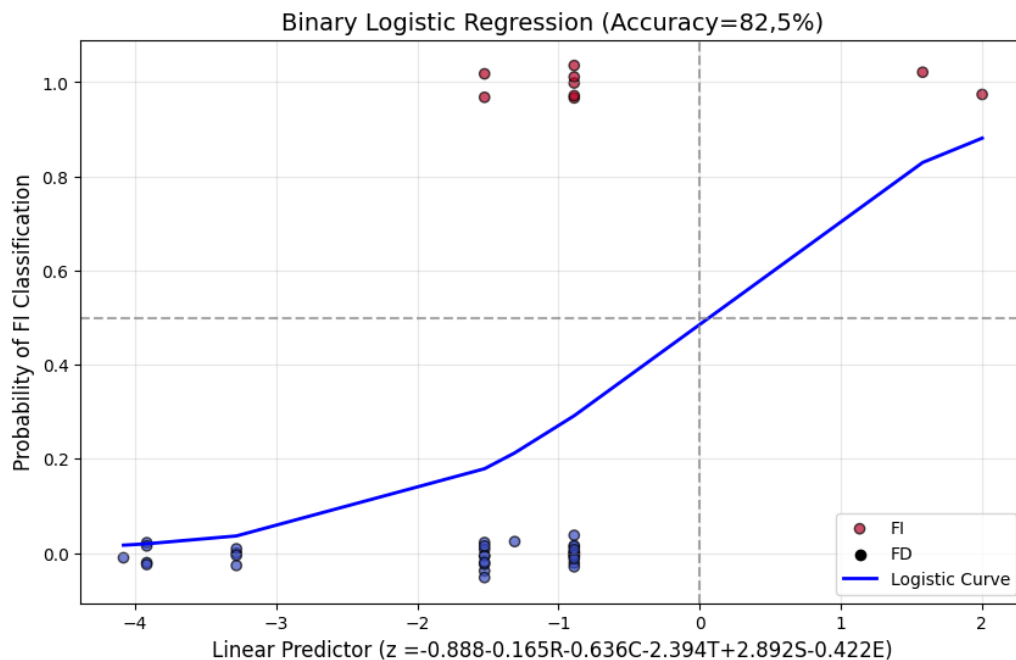


Figure 2. Binary Logistic Regression Curve for Cognitive Classification

The visualization of the binary logistic regression model in this study can be seen in Figure 2. The blue curve shown in Figure 2 was a classic sigmoid-shaped logistic function that shows how the probability of FI classification changes as the linear predictor value changes. The shape of this curve was consistent with the characteristics of the binary logistic regression model,

which uses the logit function to transform the linear relationship into probabilities bounded between 0 and 1. The largest coefficient was for the Process Skill (S) variable with a value of +2.892, which was consistent with previous findings that errors in Process Skill (S) increased the likelihood of students being classified as FI.

The significance of the prediction performance was validated using Fisher's Exact Test applied to the confusion matrix generated by the model. The matrix contained the distribution $\begin{bmatrix} 31 & 0 \\ 7 & 2 \end{bmatrix}$. Calculation of this matrix produced a p-value of $0.0462 < 0.10$, thus empirically proving that there was a statistically significant association between the actual cognitive style values of the students and the predicted values estimated by the binary logistic regression model.

An accuracy value of 82.5% indicated that the model was capable of correctly classifying 82.5% of the data for both cognitive style categories. Although this accuracy was relatively high, the accuracy metric alone was not sufficient to provide a comprehensive picture of the model's performance, especially when dealing with an unbalanced dataset. In the context of this study, the data distribution shows a significant imbalance between the number of FD students (31 students) and FI students (9 students), necessitating further analysis through precision and recall metrics, as shown in Table 7. The developed binary logistic regression model demonstrated excellent performance in identifying FD students with perfect recall (1.00) and high precision (82%). However, the model still has significant limitations in detecting FI students with low recall (0.22) despite perfect precision (100%). This pattern reflected the general characteristics of models on imbalanced datasets and requires further optimization strategies to improve performance balance between the two cognitive style classes.

Table 7. Performance Evaluation Matrix of Binary Logistic Regression Models Based on Cognitive Style

Group	Precision	Recall
FD	0.8158	1.0000
FI	1.000	0.2222

However, based on the Wald test in Table 6, only Process Skill (S) errors were significant because the P value was $0.068 < 0.100$. Meanwhile, the odds ratio value for Process Skill (S) was 18.025. This means that students who made errors in the Process Skill (S) stage were 18 times more likely to be classified in the FI category than students who did not make errors in that stage. Process Skill errors in Newman's theory occur when students are able to understand and transform problems correctly but encounter difficulties in performing mathematical procedures to reach a solution (Yus et al., 2019). These errors are characterized by the use of the correct formula but incomplete or inaccurate calculation processes, as well as errors in applying the correct statistical procedures (Rosmiati & Maya, 2021). Errors in transformation and process skills often result from carelessness in processing the provided information (Khusnah et al., 2022). FI students generally understand the problem structure and identify appropriate solution strategies but may encounter difficulties at the technical implementation stage (Prengki et al., 2024; Takdirmin & Mahmud, 2023). Overall, this binary logistic regression model provided important insights that specific error patterns, particularly at the Process Skill stage, can serve as strong indicators for identifying students with FI cognitive styles.

Dual processing theory explains that humans have two cognitive processing systems, namely Type 1 (intuitive, fast, automatic) and Type 2 (analytical, slow, controlled) (Borodin, 2016). FI students tend to use Type 2 processing, which is more analytical, while FD students rely more on Type 1 processing, which is intuitive. This was in line with the findings that FI students make mistakes at the Process Skill stage. They are good at analyzing problems (Type 2) but fail

at procedural implementation that requires automation (Type 1) (Hasan, 2020). FI students, although they can analyze problems well, may struggle with procedural implementation because they're too focused on the analytical aspects and don't automate basic procedures enough. Their working memory is overloaded by the analysis process, which interferes with procedural execution (Fatah & Risfina, 2023).

Indonesia has a strong collectivist culture with values such as social harmony, conflict avoidance, and group orientation. Research shows that societies with high collectivist cultural values tend to have behaviors that are more dependent on the social environment. This contributes to the dominance of the FD cognitive style (Saichu, 2023). In addition, the Indonesian education system, which still emphasizes teacher-centered learning and memorization, contributes to the development of the FD cognitive style. Students are accustomed to passively receiving information and following procedures set by teachers, thereby failing to develop independent analytical skills. Indonesia's culture, which prioritizes harmony and avoids direct confrontation, influences how students express their understanding. Students tend not to openly express confusion or mistakes, making it difficult for teachers to identify misconceptions and misunderstandings (Zakiya & Hariyadi, 2022).

In order to optimize mathematics learning in the context of Indonesian culture, an approach that integrates collective values with the development of individual analytical skills is needed (Santoso et al., 2025). Learning strategies must consider the dominance of the FD cognitive style while still providing room for development for students with FI potential, especially in overcoming procedural automation difficulties, which are their main weaknesses. Integrating ethnomathematics and a culture-based approach can serve as a bridge to create meaningful learning while developing students' cognitive diversity (Khasanah et al., 2021). The implication of this research for future mathematics education was the potential to utilize error analysis as a predictive tool for cognitive profiling. This approach empowered educators to design adaptive learning environments that specifically addressed the unique procedural or analytical needs of every student.

This exploratory research had several limitations that should be considered when interpreting the results. First, the sample size analyzed was relatively small, consisting of only 40 students from a single secondary school. This condition meant that the findings could not be widely generalized to populations with different educational characteristics. Second, there was a pronounced imbalance in the proportion of students with FD and FI cognitive styles. This class imbalance directly affected the recall of the statistical model that was developed. Further research replicating this model with a much larger and more balanced sample size was strongly recommended.

4. Conclusion

This study successfully demonstrated that binary logistic regression can be effectively used to predict students' cognitive styles based on patterns of errors in mathematical problem solving by Newman's theory. Among the 40 students who participated in the study, 23 students (57.5%) made errors at various stages of Newman's theory, with 9 students classified as Field Independent (FI) and 31 students as Field Dependent (FD). The developed model revealed a highly significant finding that errors at the Process Skill stage are the strongest predictor for identifying students with a Field Independent cognitive style. With a coefficient of 2.892 and an odds ratio of 18.025, students who made Process Skill errors are 18 times more likely to be classified as Field Independent compared to those who did not make errors at that stage. This finding was consistent with the characteristics of FI students, who can understand problem

structures and identify appropriate solution strategies but struggle during the procedural implementation stage.

The findings of this limited-scale research offer initial insights into the prospect of utilizing binary logistic regression as an additional support instrument for teachers to recognize the characteristics of students' cognitive styles in the classroom. Therefore, students who make Process Skill errors and are identified as Field Independent require a learning approach focused on strengthening procedural skills through structured practice, specific feedback on each step of the solution, and metacognitive reflection.

5. References

- Alam, A., & Mohanty, A. (2024). Unveiling the complexities of 'Abstract Algebra' in University Mathematics Education (UME): Fostering 'Conceptualization and Understanding' through advanced pedagogical approaches. *Cogent Education*, 11(1), 2355400. <https://doi.org/10.1080/2331186X.2024.2355400>
- Borodin, A. (2016). The Need for an Application of Dual-Process Theory to Mathematics Education. *CORERJ: Cambridge Open-Review Educational Research*, 3(1), 1–31. <https://doi.org/10.17863/CAM.41156>
- Fatah, A. H., & Risfina, A. M. (2023). Teori Pemrosesan Informasi dan Implikasinya Dalam Pembelajaran. *Jurnal Ilmiah Mandala Education*, 9(3), 1632–1641. <http://dx.doi.org/10.58258/jime.v9i3.5256>
- Gujarati, D. N. (1995). *Basic econometrics* (3rd ed.). Singapore: Mc Graw Hill Book Company.
- Hadi, S., & Novaliyosi, N. (2019). TIMSS Indonesia (Trends In International Mathematics and Science Study). *Prosiding Seminar Nasional & Call For Papers Program Studi Magister Pendidikan Matematika Universitas Siliwangi*. Retrieved from <https://jurnal.unsil.ac.id/index.php/snep/article/view/1096>
- Hasan, B. (2020). Proses Kognitif Siswa Field Independent Dan Field Dependent Dalam Menyelesaikan Masalah Matematika. *JPMI (Jurnal Pembelajaran Matematika Inovatif)*, 3(4), 323–332. <https://journal.ikipsiliwangi.ac.id/index.php/jpmi/article/view/4545>
- Ilyas, A., Folastris, S., & Solihatun. (2017). *Diagnosis kesulitan belajar & pembelajaran remedial*. Semarang: Jurusan Bimbingan dan Konseling, Fakultas Ilmu Pendidikan, Universitas Negeri Semarang.
- Khasanah, N., Mashuri, M. F., & Karmiyati, D. (2021). Manifestations of polyculturalism in Indonesia: A study of indigenous psychology. *Indigenous: Jurnal Ilmiah Psikologi*, 6(2), 1–13. <https://doi.org/10.23917/indigenous.v6i2.12436>
- Khusnah, K., Ekawati, R., & Shodikin, A. (2022). Student's error in solving change and relationship-PISA problem and its scaffolding. *Journal of Mathematical Pedagogy (JoMP)*, 4(1), 9-20. <https://doi.org/10.26740/jomp.v4n1.p9-20>
- Prengki, N., Jamilah, & Astuti, R. (2024). Analisis Kesalahan Siswa Menyelesaikan Soal Berdasarkan Metode Newman's Error Analysis Ditinjau Dari Gaya Kognitif. *Jurnal Math-UMB.EDU*, 11(2), 94–102. <https://doi.org/10.36085/mathumbedu.v11i2.5543>
- Rasdiansastra, W., Wibawa, G. A., & Abapihi, B. (2022). Analisis Faktor-Faktor Yang Mempengaruhi Kemampuan Membaca Siswa Dengan Metode Regresi Probit Ordinal (Studi Kasus Siswa SD Se-Sulawesi Tenggara). *Jurnal Matematika, Komputasi, Dan Statistika*, 2(2), 102–109. <https://doi.org/10.33772/jmks.v2i2.14>
- Rohmah, N. (2021). Media pembelajaran masa kini: Aplikasi pembuatan dan kegunaannya. *Awwaliyah: Jurnal Pendidikan Guru Madrasah Ibtidaiyah*, 4(2), 176–181. <https://doi.org/10.58518/awwaliyah.v4i2.771>

- Rosmiati, F., & Maya, R. (2021). Analisis Kesalahan Siswa Dalam Menyelesaikan Soal Cerita Materi Aritmatika Sosial Dengan Tahapan Newman. *JPMI (Jurnal Pembelajaran Matematika Inovatif)*, 4(5), 1365–1374. <https://doi.org/10.22460/jpmi.v4i5.1365-1374>
- Saichu, A. (2023, July 5). Pengaruh Budaya Masyarakat dalam Sistem Pendidikan Nasional. Retrieved June 14, 2025, from KOMPASIANA website: <https://www.kompasiana.com/ahmadsaichu1876/64a5225f4addee0443046372/pengaruh-budaya-masyarakat-dalam-sistem-pendidikan-nasional>
- Santoso, H. S., Agustin, A. S., Kurniasih, A. W., & Agoestanto, A. (2025). Systematic Literature Review: Implementasi Budaya dalam Matematika pada Kurikulum Merdeka untuk Mencapai Pembelajaran yang Bermakna. *PRISMA, Prosiding Seminar Nasional Matematika*, 8, 122–133. <https://proceeding.unnes.ac.id/prisma/article/view/4308>
- Sari, N. A., & Nasution, E. Y. P. (2023). Analisis kemampuan berpikir aljabar siswa kelas IX A SMP Negeri 12 kota Sungai Penuh pada materi SPLDV. *Jurnal Riset Pembelajaran Matematika*, 5(2), 111–116. <https://doi.org/10.55719/jrpm.v5i2.580>
- Shodikin, A., Rohim, A., & Mustofah, M. (2020). Analisis Kemampuan Penalaran Matematis Dalam Menyelesaikan Soal Kubus Dan Balok Ditinjau Dari Gaya Kognitif Field Independent Dan Field Dependent. *Inspiramatika*, 6(1), 50-60. <https://doi.org/10.52166/inspiramatika.v6i1.2040>
- Simon Antero, E., Odanga Simon, E., Francisco Echanis, S., Castillo Dunghit, J., Laroza Silva, D., & Marzan Adina, E. (2022). Logistic Regression Approach in Analyzing the Learning Styles of Students in Science, Mathematics and English Online Classes. *Proceedings of the 13th International Conference on Education Technology and Computers*, 195–201. New York, NY, USA: Association for Computing Machinery. <https://doi.org/10.1145/3498765.3498796>
- Takdirmin, & Mahmud, R. S. (2023). Menguak Tantangan Matematika: Memahami Kesalahan Siswa Dari Perspektif Gaya Kognitif Field Dependent Dan Field Independent. *ELIPS: Jurnal Pendidikan Matematika*, 4(1), 116–125. <https://doi.org/10.47650/elips.v4i1.912>
- Volkotrubova, A., Kasymova, A., Hbur, Z., Kichuk, A., Koshova, S., & Khodakivska, S. (2024). An Integrative Approach to Organizing the Formation of Students' Cognitive Independence in Conditions of Intensification of Learning Activities. *Strategies for Policy in Science & Education/Strategii na Obrazovatel'nata i Nauchnata Politika*, 32(6). <https://doi.org/10.53656/str2024-6-2-int>
- Wihda, N. Z. (2021). *Analisis Kemampuan Berpikir Aljabar Siswa dengan Menggunakan Newman's Error* (Skripsi). UIN Syarif Hidayatullah Jakarta.
- Wulan, E. R., & Anggraini, R. E. (2019). Gaya Kognitif Field-Dependent dan Field-Independent sebagai Jendela Profil Pemecahan Masalah Polya dari Siswa SMP. *Journal Focus Action of Research Mathematic (Factor M)*, 1(2), 123–142. https://doi.org/10.30762/factor_m.v1i2.1503
- Yus, S. R., Syafari, & Minarni, A. (2019). Analysis of Students Failure in Mathematical Problem Solving Based on Newman Procedure at Middle Secondary School 3 Aceh Tamiang District. *American Journal of Educational Research*, 7(11), 888–892. <https://doi.org/10.12691/education-7-11-20>
- Zakiya, N., & Hariyadi, S. (2022). Nilai Budaya Kolektivisme dan Perilaku Asertif pada Suku Jawa. *Journal of Social and Industrial Psychology*, 11(2), 62–71. <https://doi.org/10.15294/sip.v11i2.64788>