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Analysis of English Language Learners Educational Outcomes Using WSM Method: A Multi-Criteria Decision Making Approach

S. Yamuna

Karpaga vinayaga College of Engineering and Technology, Chengalpattu, Tamil Nadu, India.

Corresponding Author Email: yamuna.S076@gmail.com

Abstract: *This study examines the factors that influence Academic performance of English language learners (ELLs), using weighted sum method (WSM). It analyzed five key factors—school characteristics, teacher influence, student fixed effects, intercept values, and treatment approaches—in four student groups: all students, non-ELLs, former ELLs, and recently reclassified ELLs. Through an in-depth quantitative analysis using normalized data for all categories and standardized weights of 0.35, the study revealed important patterns regarding the relative importance of these factors. Student fixed effects were found to be the most influential factor with the highest priority score (1.09753), followed by teacher influence (1.05052), treatment approaches (0.88553), intercept (0.76822), and school characteristics (0.45418). Analysis of the normalized data showed differential impacts across different ELL categories, with recently reclassified ELLs showing higher treatment scores (95.743) and former ELLs showing stronger school performance (92.872). The weighted normalized outcome matrix emphasized the significant effectiveness of teacher influence on recently reclassified ELLs (0.35000) and the strong impact of student fixed effects on all students and former ELLs (0.35000). These results indicate that, while school-wide interventions are important, individual student characteristics and teacher quality are more important factors in determining ELL educational success. The findings have important implications for educational policy and practice, particularly regarding resource allocation and the development of targeted intervention strategies for different ELL groups. The study recommends maintaining strong teacher support systems and individualized approaches for students, continuing to develop effective treatment strategies, and underscoring the need for differentiated approaches to ELL education based on student classification and unique needs.*

Keywords: *English language learners (ELLs), weighted sum method (WSM), student fixed effects, educational assessment, multiple criteria decision making, teacher impact, intervention strategies, educational policy, performance assessment, language acquisition effects.*

1. INTRODUCTION

Within this framework, both science experiments and standardized science tests are considered cognitively demanding. However, science experiments are also seen as embedded in a context that facilitates student understanding. The cognitive demands described in the framework relate to the information processing required to understand and use specific types of language. These cognitive processes are further described in terms of academic functions such as use, analysis, synthesis, and evaluation. When reexamining the distinction between social language and academic English (AE), critics have argued that these classifications alone do not fully capture the complexities of language use in school settings. [1] One group was taught word pronunciation and memorized definitions. Another group worked with the same word list but created One group created They predicted the meanings of words using semantic maps. The second group created a grid to explain word relationships and anticipated their meanings. Similarly, the third group followed the second group's approach, but additionally completed cloze sentences. All groups had to write summaries of social science chapters on the second and subsequent days third days of the lessons, and to rewrite them several weeks later. [2] Although there is little information on how to identify and address learning disabilities in for Extensive research has been conducted on English language learners (ELLs), examining various aspects of their education and language acquisition on this identifying, assessing, and intervening with learning disabilities among native English speakers. Therefore, it is important to explore how this knowledge can be used to guide future efforts with ELL students. It is essential to determine effective methods for distinguishing between learning disabilities and the language-related challenges that these students face as they learn English. Researchers need to outline the key steps needed to achieve these goals. [3] This article aims to review the literature on The process of identifying learning disabilities in English language learners (ELLs) emphasizes the challenges and considerations involved in accurately distinguishing language acquisition difficulties from true learning disabilities challenges that need to be addressed to improve the accuracy of identification procedures. The discussion begins with a summary of recent research on English-speaking individuals with learning disabilities that challenges traditional assumptions. It then explores additional issues in assessing English language learners with learning disabilities and presents two initiatives aimed at developing comparable assessment tools. [4] A student's situation depends on The Level The extent to which English is similar to or different from a learner's native language. For example, prior understanding of print concepts can influence the learning process. An English language learner's learner (An English language learner It would be helpful for an English language learner A Native Spanish ELL may be used to printing concepts similar to English, such as reading from left to right. On the other hand, a native Arabic ELL may face different challenges have developed different print conventions print conventions, such as reading from right to left, which may affect their approach to learning English literacy. [5] Engaging in classroom mathematical discourse is more than just using technical language; it embraces how mathematically competent individuals communicate and behave when discussing mathematics. Gee illustrates this point with the example of a biker bar – fitting into such an environment is more than just knowing the names of motorcycle parts or models. Similarly, participating in mathematical discourse goes beyond memorizing words; it involves understanding how to think, communicate, and interact within the mathematical community. [6] There are many ways to foster Improving the literacy skills of English language learners (ELLs). Some strategies are specifically designed for this group, such as including their home language in instruction or providing targeted feedback on grammatical errors that may occur due to limited English proficiency. In addition, many effective teaching practices that benefit all students can be applied with greater intensity to ELLs. These include ensuring adequate repetition and reinforcement, differentiating instruction for individuals and small groups, and providing appropriate scaffolding to support learning. [7] The survey was conducted to collect data on several key areas, including respondents' backgrounds, the structure of their caseloads, challenges faced in providing services to Employment of English Language Learners (ELLs), Translators, and types of assessment methods used with ELLs. In addition, the survey solicited input on areas in which respondents would like to receive further training and their preferred models for receiving such professional development (see the appendix for the full survey). The study specifically focused on analysing respondents' backgrounds in relation to the challenges they identified in providing services to ELLs. [8] These challenges These Issues include the continued use of ineffective conflict models for diagnosis, the need for improved identification methods, ongoing debates over program structures ranging from content-based to self-contained models, and Overrepresentation of specific racial and ethnic groups learning disabilities (LD) category. This article primarily addresses the latter issue, focusing specifically on students with mild learning disabilities and those classified as having LD. It provides an overview of how this issue has been addressed over time. [9] Before implementing this change in my teaching, I usually start the first session with a brief "getting to know each other" activity, followed by a direct dive into the textbook. First, I introduce myself, and then the students take turns giving short self-introductions, usually completing the activity within half an hour before starting the listening exercises. However, after realizing the importance of providing students with a clear purpose and goal at the beginning of a lesson, I decided to dedicate the first session to helping them identify their learning needs, set expectations, and understand the value of the lesson. [10] Academic language functions (such as describing, identifying, classifying, ordering, explaining, predicting, and interpreting) can be taught alongside scientific Inquiry and process skills, including observing, measuring, inferring, predicting, communicating, and identifying relationships, are essential for learning. Effective teachers demonstrate and encourage the use of a variety of academic language activities in scientific The purpose of inquiry is to guide students through the processes of formulating questions, developing hypotheses, designing experiments, collecting and analysing data, drawing conclusions, and effectively communicating their findings. [11] To answer the third research question, "Which critical milestones on the path to four-year colleges pose difficulties for ELLs, and why?" we conducted a multigraph analysis using various demographic, family, educational, and school-related predictors for each milestone. The approach of examining predictors for each language background group was inspired by Cabrera and La Nasa (2001), who conducted similar analyses for students from different socioeconomic status (SES) levels. However, instead of running separate regressions for each group, as Cabrera and La Nasa did, we used a single multigraph analysis for each dependent variable. This allowed us to statistically test for differences between groups regarding the impact of each predictor. [12] This study aims to provide Empirical research examines The relationship between using blogs and process-oriented writing methods by examining students' blogging experiences in a process writing context. Specifically, using a quasi-experimental design, the study examines whether providing opportunities for blogs to publish drafts, receive feedback from teachers and peers, provide feedback to others, view peer feedback, and extend self-study time improves students' writing performance. In addition, it would be useful to examine some current tests It is used in the United States to analyse how language on these exams can affect scores achieved by English language learners (ELLs). [13] Examining the language used in assessments is critical to understanding its impact on English language learners' (ELL) scores. In New York, high school students must pass state-level Regents exams to graduate. Originally designed as Honours exams to assess college readiness, these exams became a graduation requirement for all students following The No Child Left Behind Act (NCLB) was enacted and implemented which aims to improve educational standards across the country state. [14] This study presents a meta-analysis of research comparing the effectiveness of instructional programs for English language learners (ELLs), providing a comprehensive overview of the topic. Unlike previous literature reviews, our methodology included a broad range of previously unconsidered studies, without excluding any based on design quality. Despite differences in our dataset and approach, our findings are consistent with major reviews conducted to date. We note that instructional programs that incorporate students' native languages demonstrate a clear benefit. As a result, we conclude that state and federal policies that restrict or discourage native language use in ELL programs are not justified by a fair interpretation of the evidence. [15]

2. MATERIALS AND METHOD

School: A school is an institution (or, for in-person learning, a physical building) created to provide educational settings in which students are taught, typically led by teachers.
Teacher: Teachers are fundamental to society, acting as role models, providing guidance and commitment, and empowering youth through education. Teachers' impact is crucial in shaping the future of nations are able to grow socially and economically.
Student Fixed effects: Fixed-effects estimation relies only on Data obtained from individuals with multiple observations are used to estimate the effects of variables that differ across these observations. It assumes that the influence of unmeasured, invariant variables can be represented by time-invariant, individual-specific dummy variables.
Intercept: The point of The point of intersection of a line or curve is the point where it meets the axes on a graph. When a line intersects the x-axis, it is referred to as the x-intercept, and when it intersects the y-axis, it is called the y-intercept.
Treatment: Treatment involves the provision, organization, or supervision of health care and related services by one or more medical professionals. It may also include the coordination or management of care by a provider in conjunction with a third party parties, as well as discussions among health care providers about a patient's care.
All Students: All students mean Treatment involves the provision, coordination, or supervision of health care and related services by one or more health care providers. It also includes the management or coordination of care by a provider in collaboration with a third party as well as consultations between health care professionals regarding the care of a patient.
Non-ELLs: English Language Learners (ELLs) are students who are not fluent in English, and they face challenges in understanding and using the language effectively face challenges in learning effectively in the language. They usually come from families and backgrounds Where English is not the first language, personalized or modified instruction is required for both English language development and academic subject's skills.
Former ELLs: In architecture, an L refers to a wing of a building that is perpendicular (at right angles) to the main part of the building. The term comes from the shape of the letter L. Ls are commonly added to existing buildings.
Recently Reclassified ELLs: Reclassification is the process by which a student is moved from EL status to the Level of Fluent English Proficiency (RFEP) status. This can occur at any time during the school year, once the student has met all the necessary criteria.

WSM method: The Weighted Sum Method (WSM) is one of the most widely used and simplest techniques in Multi-Criteria Decision Making (MCDM). It is especially popular due to its intuitive structure, ease of implementation, and clear interpretation of results. WSM is primarily applied when decision-makers need to evaluate and rank multiple alternatives based on several criteria that may differ in importance. The method converts complex, multidimensional decision problems into a single aggregated score for each alternative, enabling straightforward comparison and selection. At its core, the WSM assumes that each decision criterion contributes independently to the overall performance of an alternative. Each criterion is assigned a **weight** that reflects its relative importance in the decision-making process. These weights are typically normalized so that their sum equals one. The alternatives are then evaluated against each criterion, and their performance scores are multiplied by the corresponding weights. The final score for each alternative is obtained by summing these weighted values.

Mathematically, the Weighted Sum Method can be expressed as:

$$S_i = \sum_{j=1}^{n} w_j \times x_{ij}$$

where
Si is the overall score of alternative *i*,
wj is the weight of criterion *j*, and
xij is the performance value of alternative *i* with respect to criterion *j*.

One of the key strengths of WSM is its relative simplicity. The method is easy to understand even for decision-makers without advanced mathematical backgrounds. This makes it particularly suitable for practical applications in engineering, management, manufacturing, human resource evaluation, material selection, and policy analysis. Because of its transparency, WSM allows stakeholders to clearly see how each criterion and its weight influence the final decision. Another important feature of WSM is its ability to handle relative comparisons among alternatives. The method works best when all criteria are expressed in comparable units or have been normalized beforehand. Normalization is essential because decision problems often involve criteria measured in different units, such as cost, time, quality, efficiency, or performance indices. Common normalization techniques include linear normalization or min–max scaling, which transform raw data into dimensionless values typically ranging between 0 and 1. The Weighted Sum Method is particularly effective in situations where criteria are independent and trade-offs between them are linear. This means that an increase in one criterion can compensate proportionally for a decrease in another. For example, in employee performance evaluation, higher productivity may compensate for slightly lower attendance, provided the assigned weights reflect organizational priorities. This linear compensatory nature makes WSM flexible but also introduces limitations when non-linear relationships or strong interdependencies exist among criteria. Despite its advantages, WSM has certain limitations. One major challenge is its sensitivity to the assignment of weights. Since weights represent subjective judgments, different decision-makers may assign different importance levels to the same criteria, leading to variations in results. Therefore, determining accurate and consistent weights is crucial. To reduce subjectivity, WSM is often combined with structured weighting techniques such as expert judgment, entropy methods, or pairwise comparison approaches. Another limitation is that WSM assumes all criteria are either benefit-type (higher values are better) or appropriately transformed if they are cost-type (lower values are better). If cost criteria are not properly converted, the aggregation may produce misleading results. Additionally, WSM is less suitable for problems involving uncertainty, vagueness, or imprecise data unless it is extended using fuzzy, grey, or neutrosophic frameworks. In practical applications, WSM is frequently used as a baseline or benchmark method. Its results are often compared with those obtained from more advanced MCDM techniques such as WPM, TOPSIS, or MOORA to validate decision consistency. In many studies, WSM serves as an initial screening tool that provides quick insights before applying more complex decision models.

3. RESULTS AND DISCUSSIONS

TABLE 1. English language learners

	All Students	Non-ELLs	Former ELLs	Recently Reclassified ELLs
School	12.875	27.185	92.872	53.482
Teacher	29.746	83.526	37.456	29.531
Student Fixed effects	95.539	73.861	29.184	89.429
Intercept	72.483	63.638	72.947	86.324
Treatment	83.192	91.687	83.172	95.743

Table 1 shows data on English language learners (ELLs) analyzed using the WSM method across various groups: all students, non-ELLs, former ELLs, and recently reclassified ELLs. The values reflect various factors, including school, teacher, student fixed effects, intercept, and treatment, highlighting their impacts on each category.

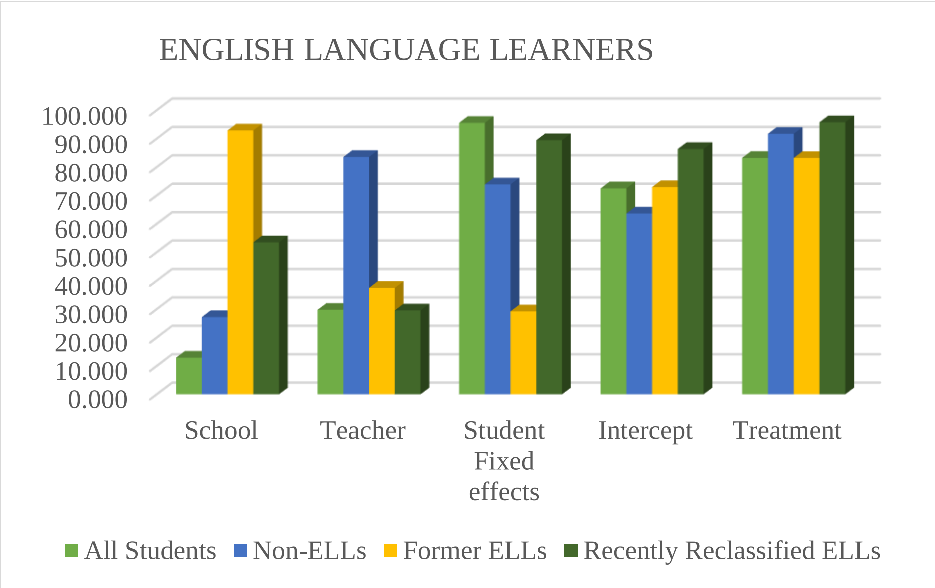

FIGURE. 1 English language learners

Figure 1 presents data on English language learners using the WSM method in different groups. School scores are lowest for ELLs (12.875) and highest for former ELLs (92.872). Teacher scores are highest for non-ELLs (83.526), while student fixed effects are highest for ELLs (95.539). Recently reclassified ELLs have higher treatment scores (95.743).

TABLE 2. Normalized

	Normalized			
School	0.13476	0.29650	0.31424	0.55217
Teacher	0.31135	0.91099	0.77915	1.00000
Student Fixed effects	1.00000	0.80558	1.00000	0.33022
Intercept	0.75867	0.69408	0.40007	0.34209
Treatment	0.87076	1.00000	0.35089	0.30844

This table shows the normalized values for different factors in an academic study. The normalization process adjusts each value to a fixed range between 0 and 1, for better comparison.

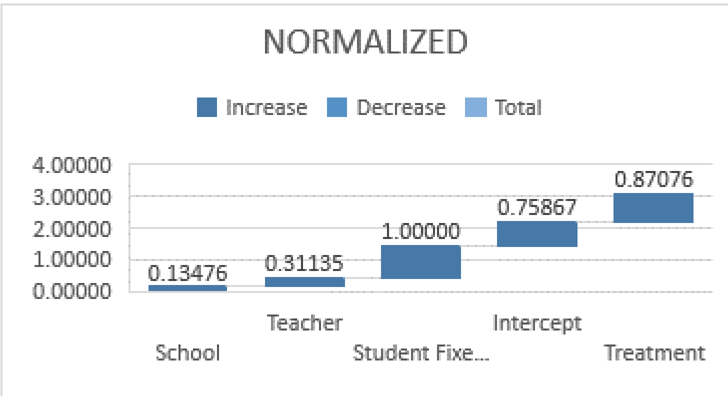

FIGURE. 2 Normalized

Figure 2 illustrates the normalized values across the various categories. School scores are lowest for all students (0.13476) and highest for recently reclassified ELLs (0.55217). Teacher scores peak for recently reclassified ELLs (1.00000). Student fixed effects are highest for all students (1.00000), while treatment scores are highest for non-ELLs (1.00000).

TABLE 3. Weight

	Weight			
School	0.25	0.25	0.25	0.25
Teacher	0.25	0.25	0.25	0.25
Student Fixed effects	0.25	0.25	0.25	0.25
Intercept	0.25	0.25	0.25	0.25
Treatment	0.25	0.25	0.25	0.25

Table 3 presents the weights assigned to the different factors using the WSM method. Each category—school, teacher, student fixed effects, intercept, and treatment—receives an equal weight of 0.35 across all groups (all students, non-ELLs, former ELLs, and recently reclassified ELLs). This uniform distribution indicates All factors are considered equally important the analysis.

TABLE 4. Weighted normalized decision matrix

	Weighted normalized decision matrix			
School	0.04717	0.10377	0.10998	0.19326
Teacher	0.10897	0.31885	0.27270	0.35000
Student Fixed effects	0.35000	0.28195	0.35000	0.11558
Intercept	0.26554	0.24293	0.14002	0.11973
Treatment	0.30477	0.35000	0.12281	0.10795

Table 4 shows The weighted normalized decision matrix is constructed using the WSM method. The values represent the weighted influence of the various categories – school, teacher, student fixed effects, intercept, and treatment – across different groups, including all students, non-ELLs, former ELLs, and recently reclassified ELLs.

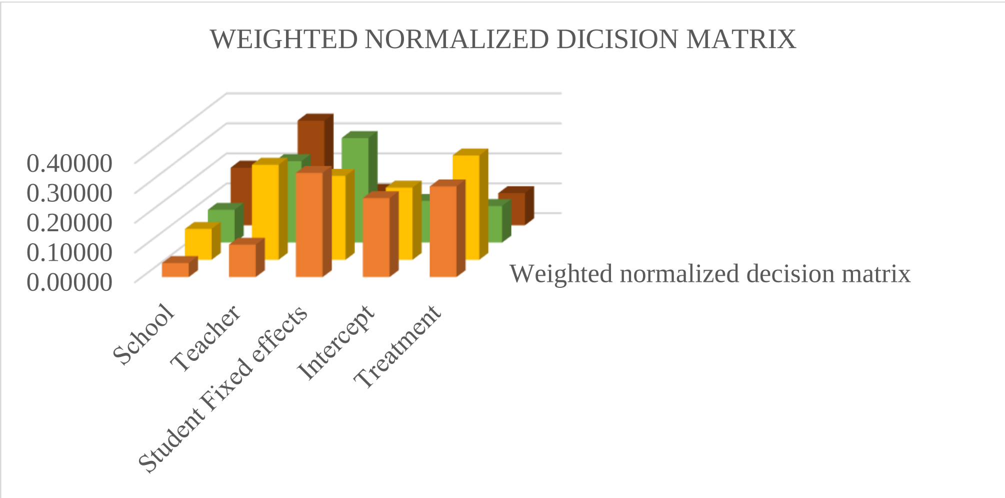

FIGURE. 4 Weighted normalized decision matrix

Figure 4 illustrates the creation of a weighted normalized decision matrix using the WSM method. School scores are lowest for all students (0.04717) and highest for recently reclassified ELLs (0.19326). Teacher scores peak for recently reclassified ELLs (0.35000), while student fixed effects are highest for all students and former ELLs. Intercept and treatment scores are highest for non-ELLs and gradually decrease for recently reclassified ELLs.

TABLE. 5 Preference score

	Preference Score
School	0.45418
Teacher	1.05052
Student Fixed effects	1.09753
Intercept	0.76822
Treatment	0.88553

Table 5 shows the option scores calculated using the WSM method. The highest score is for student fixed effects (1.09753), indicating its strong influence on the decision-making process. Teacher follows closely with a score of 1.05052, which also shows a significant impact. Treatment has a moderate score of 0.88553, reflecting its influence. The intercept and school scores are lower at 0.76822 and 0.45418, respectively, indicating that while they play a role in the decision matrix, their influence is less compared to student fixed effects and teacher. These scores highlight the relative importance of each factor in the overall analysis.

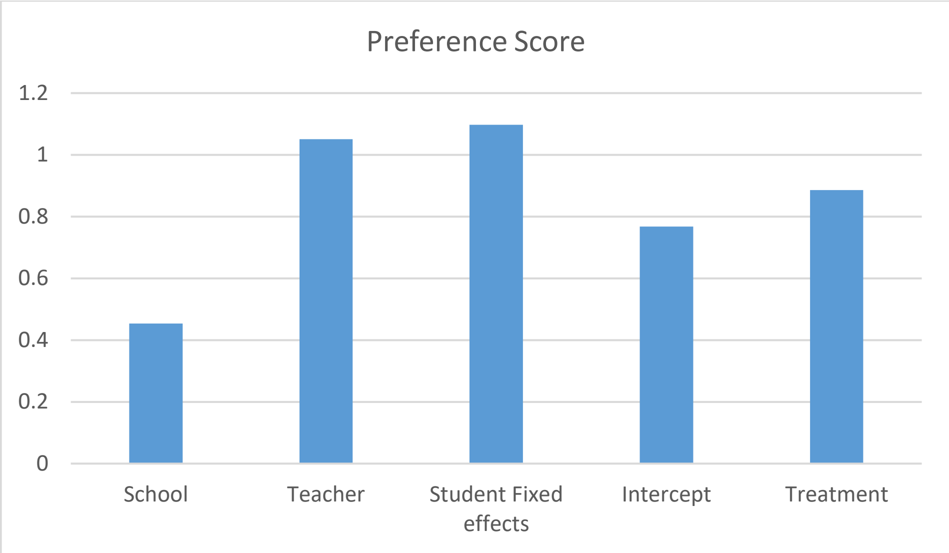

FIGURE. 5 Preference score

Figure 5 presents the priority scores using the WSM method. Student fixed effects lead with the highest score (1.09753), followed closely by teacher (1.05052), indicating their strong influence. Treatment (0.88553) and intercept (0.76822) show moderate scores, while school has the lowest score (0.45418), indicating its low impact.

TABLE. 6 Rank

	Rank
School	**5**
Teacher	**2**
Student Fixed effects	**1**
Intercept	**4**
Treatment	**3**

Table 6 presents the rankings of the various factors using the WSM method. Student fixed effects ranks highest at 1, indicating its primary importance in the analysis. Teacher follows in second place, reflecting its significant influence. Treatment ranks third, indicating moderate importance. Intercept ranks fourth, while school ranks lowest at fifth, indicating that it has the least impact on the overall decision-making process. These rankings emphasize the relative importance of each factor in the final analysis.

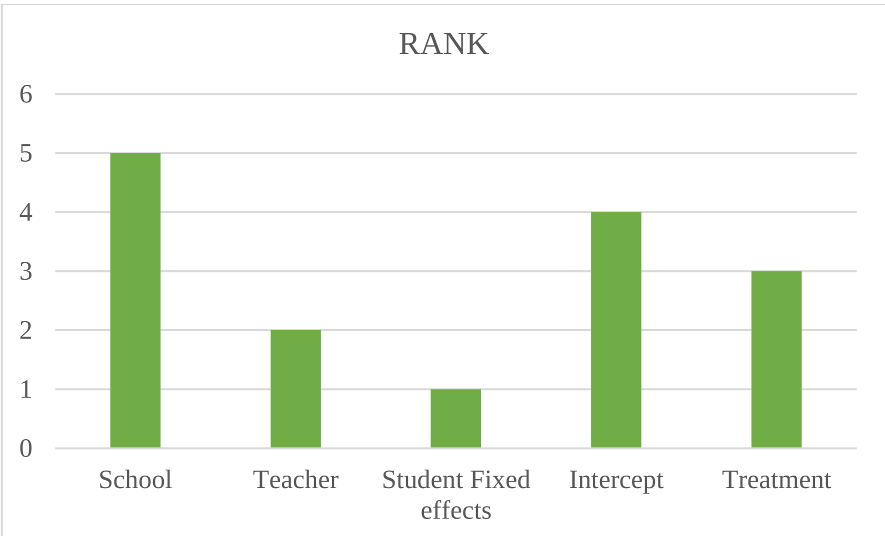

FIGURE 6. Rank

This ranking Indicates The relative importance of different factors analysis. Student fixed effects are ranked highest, indicating the greatest influence. Teacher follow-up is ranked highest, indicating a significant but somewhat smaller influence. Treatment is ranked third, indicating moderate importance. Intercept is ranked fourth, while School has the least influence of the factors.

4. CONCLUSION

This analysis clearly reveals that student fixed effects were the most influential factor, ranking first with a high preference score of 1.09753. This indicates that individual student characteristics and variables have a very significant impact on educational outcomes for English language learners. Teacher influence was the second most important factor, with a preference score of 1.05052, emphasizing the important role that educators play in ELL student success. Treatment approaches ranked third (0.88553), indicating that while intervention strategies are important, they may have less of an impact than student-specific factors and teacher quality. The intercept factor ranked fourth (0.76822), and school-level factors had the least impact, ranking fifth with a score of 0.45418. When examining the data normalized across different ELL categories, several patterns emerged. Recently reclassified ELLs had higher treatment scores (95.743), indicating that intervention strategies may be particularly effective for this group. Former ELL students had higher school scores (92.872), while non-ELLs had higher teacher scores (83.526). The study used a balanced approach by assigning equal weights (0.35) to all factors in all groups, which ensured an unbiased assessment of the various components that affect ELL education. This standardized weighting method ensures fair comparisons across categories and factors. The weighted normalized outcome matrix highlights the varying impacts of factors across student groups. For example, teacher influence had the strongest effect on recently reclassified ELLs (0.35000), while student fixed effects had the greatest impact on all students and former ELLs (0.35000). These results have significant implications for educational policy and practice. While school-wide interventions are valuable, they suggest that focusing on individual student needs and investing in teacher development can lead to better outcomes for ELL education. The findings also point to the potential benefits of targeted approaches for different ELL groups, as the effectiveness of various factors varies across these groups. Going forward, these insights will help educators and administrators make more informed decisions about resource allocation and intervention strategies for ELL students. The results particularly highlight the importance of maintaining strong teacher support systems and individualized student strategies while continuing to develop effective treatment approaches.

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