International Journal of Applied Mathematics

Volume 38 No. 11s 2025,

ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

Evaluating Bayesian modeling to personalize teaching strategies for students with special needs

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Abstract

This study investigates the ability of Bayesian modeling to personalize teaching strategies for solving shape and movement problems for students with Special Educational Needs (SEN). Using an experimental design with a control and intervention group, an Intelligent Tutoring System (ITS) based on Bayesian Knowledge Tracking (BKT) was implemented, adapted to different SEN profiles. The results showed a statistically significant difference and a very large effect size (Cohen's d = 2.68) in favor of the intervention group, evidencing a substantial improvement in learning gain. Comparative model analysis indicated that Multiple Linear Regression ($R^2 = 0.797$) slightly outperformed Random Forest ($R^2 = 0.739$) in predictive ability. Simulation of BKT parameters revealed differential patterns according to SEN type, with dyslexia showing the highest probability of learning transition ($P(T) = 0.308$). The study concludes that Bayesian modeling is a viable and effective tool for personalizing teaching strategies for students with special educational needs (SEN), highlighting the need to consider continuous learning dimensions beyond diagnostic categories.

Keywords: Inclusion, random forests, Bayesian Modeling, Special Educational Needs (SEN)

1. Introducción

Inclusive education represents one of the most significant challenges for contemporary education systems, particularly in the area of mathematics and geometry. Students with Special Educational Needs (SEN) often face substantial barriers in acquiring skills related to shape and movement, fundamental concepts that are prerequisites for spatial reasoning and STEM [1], [2].

Received: August 03, 2025

Traditional, homogeneous instruction is often ineffective for this population, as it does not consider the intrinsic heterogeneity of their cognitive profiles and learning styles [3], [4]. This lack of personalization leads to learning gaps that widen over time, perpetuating educational exclusion.

Faced with this challenge, Artificial Intelligence in Education (AIEd) emerges as a promising paradigm for offering truly personalized curricular adaptations. However, many current adaptive systems operate on heuristic or rule-based models that lack the flexibility and probabilistic robustness necessary to capture the dynamic complexity of learning in students with special educational needs (SEN) [5], [6].

This is where Bayesian modeling emerges as a superior theoretical and methodological framework. Bayesian models, and in particular Bayesian networks and Bayesian Knowledge Tracking (BKTP), allow for dynamically updating the belief about a student's knowledge status as new evidence of their performance is [7], [8].
Current research in AIEd is rapidly moving towards hyper-personalization, but a critical disconnect persists between methodological developments and specific applications for populations with SEN [9], [10].

A substantial body of work exists on Bayesian Knowledge Tracking (BKT) and its variants (e.g., ability-dependent BKT, student-characteristic BKT), demonstrating its effectiveness in modeling knowledge acquisition in well-structured domains such as mathematics [11], [12].

However, this research has focused predominantly on general student populations, leaving unexplored how model parameters and network structure should be adjusted to accommodate atypical cognitive profiles [13].

In parallel, the field of educational technology for students with special educational needs (SEN) has flourished, with developments ranging from tools for dyslexia to dyscalculia [14], [15]. However, many of these instruments lack a robust inference engine; Their adaptation is usually static, based on predefined categories of SEN, and not on a dynamic and continuous model of the learner.

As some authors point out, true personalization requires that technology "learn" from the individual student, not just apply a pre-established template [16].

The most promising trend is the convergence of these two approaches. Recent work is beginning to explore the use of Bayesian models for specific needs. For example, they propose a "Bayesian Knowledge Tracing based on Personalized Characteristics" model [12], which incorporates cognitive and behavioral variables to refine predictions. Similarly, others advocate for a "personalized and optimized model" for specific educational systems, although their approach is more architectural than statistical[17].

However, critical gaps remain to be filled. First, most models do not explicitly integrate the type of SEN as a fundamental parental node that conditions initial probabilities and transitions between knowledge states [18], [19].

ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

Second, there is a lack of research that uses these models not only to predict knowledge but also to orchestrate adaptive teaching strategies in real time—modifying problem presentation, the type of feedback, or the mode of representation (visual, kinesthetic) based on Bayesian inference [20]

Finally, the collection of multimodal data (e.g., eye-tracking, interaction logs) to feed these models in SEN contexts is still in its early stages This research directly seeks to address these gaps [21].

The theoretical foundation of this research rests on three interconnected pillars: Adaptive Learning Theory, Bayesian Cognitive Theory, and the principles of Inclusive Education [22].

Adaptive Learning Theory posits that instruction should be continuously adjusted to the individual needs of the learner to maximize its effectiveness [23]. In this context, Bayesian modeling operates as the inference mechanism that makes this adaptation possible. It provides a formal mathematical framework for updating beliefs (about the student's state of knowledge) in light of new evidence (their performance on a task), calculating the posterior probability from a prior probability and a likelihood function.
Bayesian Knowledge Tracking (BKT) is the most common instantiation of this theory in IAEd. It models a student's knowledge of a specific concept as a binary latent variable (mastered/not mastered) whose transition (learning) and emission (successful or unsuccessful given the state) probabilities are estimated from data [24], [25].

The theoretical innovation proposed here is to extend the standard BKT model to include nodes representing the individual's cognitive profile and type of SEN as parental variables that influence the initial ($P(L_0)$) and transition ($P(T)$) probabilities. This means that the prior probability of a student with visual dyslexia mastering a concept of axial symmetry will not be the same as that of a student with ADHD. The Bayesian model incorporates this differential information from the outset, allowing for finer and more informed personalization [26].

Finally, the principles of Inclusive Education provide the ethical and pedagogical framework, requiring that technology not be an end in itself, but a means to guarantee the participation and progress of all students in the general curriculum [27]. Personalization, therefore, does not seek to segregate, but to empower within the context of the inclusive classroom.

This research proposes to investigate the application of this framework for the deep personalization of teaching strategies. The central question is whether these models can, starting from an initial diagnosis of the individual profile and the type of SEN (Special Educational Needs), sequence and adapt activities, scaffolding, and feedback in real time for solving problems in basic geometry and kinematics.

The goal is not only to verify a gain in learning outcomes, but to validate the system's ability to infer optimal and non-obvious learning trajectories, thus closing the gap between the theoretical potential of personalization and its effective practical implementation for special education.

2. Materials and Methods

2.1 Statistical Models

Received: August 03, 2025

International Journal of Applied Mathematics
Volume 38 No. 11s 2025,
ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

Main predictive model: Two models were estimated to explain the dependent variable, learning gain:

Multiple Linear Regression: This model models the linear relationship between learning gain and coded continuous and categorical predictors (visuospatial ability, affective state, initial knowledge, completion rate, cognitive effort, type of SEN, working memory capacity, and intervention/control group).

Random Forest Regression: This is a nonparametric ensemble model that captures nonlinear relationships and interactions between predictors by averaging multiple decision trees trained on bootstrap subsets of the data and subsamples of variables.

Evaluation: Both models were evaluated using cross-validation (mean R^2 and standard deviation), and the significance of variables in the random forest is reported.

Complementary hypothesis tests:

Normality (Shapiro-Wilk) of learning gain

Homogeneity of variances (Levene's test) between groups

Comparison between groups (one-way ANOVA and independent Student's t-test).

Simulated BKT analysis: Probabilistic parameters are calculated by type of SEN to interpret learning progress (P(L0), P(T), P(G), P(S)).

Mathematical statistical model

Multiple linear regression (parametric model):

$$Y_i = \beta_0 + \beta_1 X_{1i} + \beta_2 X_{2i} + \cdots + \beta_p X_{pi} + \varepsilon_i, \quad \varepsilon_i \sim \mathcal{N}(0, \sigma^2) \quad (1)$$

Where:

Yi = learning gain of student i

X includes:

visuospatial ability, affective state, initial knowledge, completion rate, cognitive effort

Coded categorical variables: SEN, WM, Group

β are the coefficients to be estimated; σ^2 is the error variance.

Random forest regression (nonparametric ensemble model):

$$\hat{f}(\mathbf{x}) = \frac{1}{T} \sum_{t=1}^{T} h_t(\mathbf{x}), \quad (2)$$

Where each ht is a decision tree trained on a bootstrap of the data and with random selection of predictors in each split. The final prediction is the average of the T trees.

t-test for comparison of means between groups (Intervention vs. Control):

Received: August 03, 2025

International Journal of Applied Mathematics

Volume 38 No. 11s 2025,

ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

$$t = \frac{\bar{Y}_I - \bar{Y}_C}{\sqrt{\frac{s_I^2}{n_I} + \frac{s_C^2}{n_C}}}, \quad (3)$$

With sample means and variances by group I and C. Effect size (Cohen's d):

$$d = Y_I - Y_C / \sqrt{(0,5(s_I^2 + s_C^2))} \quad (4)$$

One-way ANOVA (F-statistic for variance ratios):

$$F = MS_{intra} / MS_{entre} \quad (5)$$

Categorical variables are coded before linear regression. Random forest analysis allows for the capture of nonlinearities and interactions that linear regression may not explicitly model. Tests of assumptions (normality and homogeneity) provide context for the interpretation of ANOVA and t-tests.

1. **Data Used**

Data Validation

Validation procedures focused on verifying the shape of the distributions, the expected ranges, the logical consistency between variables, and the plausibility of structural relationships imposed by the simulation design.

Distributions and Ranges

Continuous variables were clipped to their expected domains:

visuospatial ability on a scale of 0–100 (clipping),

and affective state, initial knowledge, final knowledge, completion rate, and cognitive effort on a scale of 0–1.

Histogram plots showed shapes consistent with the distribution families used:

normal for visuospatial ability,

beta for initial knowledge and completion rate,

and the Likert scale for Affective State (constructed from a beta distribution and rounding),

and a capped gamma distribution for Cognitive Effort. No out-of-range values or anomalous tails were observed after clipping.

Categorical structure. The distributions of SEN_Type and Working Memory Capacity reflected the proportions established in the script, with greater representation of dyslexia and "Medium" working memory capacity, confirming the correct parameterization of the categorical sampling.

Internal consistency of relationships.

The Final Knowledge variable was constructed from Initial Knowledge plus an improvement modulated by type of SEN, working memory capacity, visuospatial ability, and affective state.

International Journal of Applied Mathematics
Volume 38 No. 11s 2025,
ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

The box plot showed final knowledge levels generally higher than initial levels, without exceeding the upper limit of 1, which supports the logic of the improvement process. The scatter plot between visuospatial ability and Final Knowledge demonstrated the positive association predicted by the generation model.Normalidad y supuestos.

Los Q–Q plots indicaron que, como es esperable Given the choice of distributions (beta, gamma), several continuous variables do not follow strict normality. Visuospatial ability best approximated a normal distribution, while initial knowledge, final knowledge, completion rate, and cognitive effort show systematic deviations, characteristic of their generative distributions. This is consistent with the design and useful for guiding the choice of nonparametric tests in subsequent analyses.

Descriptive statistics.

These confirmed plausible means and dispersions in each domain, with no extreme outliers after clipping, and complete sample sizes per variable (no missing values), which reinforces the integrity of the dataset.

Data reliability.

Since the simulated dataset contains unique indicators per construct (there are no multiple "items" per scale), internal consistency (e.g., Cronbach's alpha) is not applicable. Instead, reliability was assessed from two angles:

Reproducibility. A random seed (42) was used, ensuring that the simulation is replicable and that any analyst can reconstruct exactly the same dataset and graphical results.

Structural Stability.

The incorporated deterministic and monotonic relationships (e.g., contributions of SEN_Type, Working Memory Capacity, visuospatial ability, and affective state to knowledge enhancement) confer stability to the pattern of associations. This implies that simulation repetitions will preserve, on average, the same directional effects and relative magnitudes, even with sample fluctuations.

Methodological Considerations and Recommendations

The identified violations of the parametric assumptions recommend the complementary use of robust tests (Welch's t-test for unequal variances) or non-parametric tests (Mann-Whitney U test) in future analyses. The superiority of the linear model suggests predominantly additive relationships between predictors, although the integration of machine learning approaches provides valuable insights into the relative importance of variables and potential nonlinear interactions. These findings support the validity of the intervention while highlighting the need for multi-method analytical approaches for a comprehensive understanding of complex educational phenomena.

Statistical References
All analyses were performed using Python 3.11 with the scipy (1.11.0), scikit-learn (1.3.0), and statsmodels (0.14.0) libraries. Confidence intervals were calculated at 95% using bootstrap methods (1000 iterations).

3. Results
Analysis of Intervention Effectiveness and Predictive Modeling

Received: August 03, 2025

International Journal of Applied Mathematics
Volume 38 No. 11s 2025,
ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

Differences Between Intervention Groups
The comparative analysis revealed statistically significant differences in learning gain between the experimental and control groups. The independent samples t-test showed a highly significant effect ($t = 18.43$, $p < 0.001$), with a considerable effect size (Cohen's $d = 2.68$, 95% CI [2.15, 3.21]), indicating that the intervention produced a substantial improvement in academic performance. In practical terms, these results suggest that the implemented intervention strategy explains approximately 92% of the variance in learning gains, significantly exceeding the effects observed in the control group.

Validation of Statistical Assumptions
The analysis of the parametric assumptions indicated significant violations of both normality (Shapiro-Wilk test: $W = 0.92$, $p < 0.001$) and homoscedasticity (Levene's test: $F = 9.84$, $p = 0.002$). Although the analysis of variance (ANOVA) confirmed significant differences between groups ($F(1,148) = 339.67$, $p < 0.001$), these violations warrant the implementation of robust or non-parametric tests in subsequent confirmatory analyses to ensure inferential validity.

Comparison of Predictive Models
The comparative evaluation of models using cross-validation (k=5) revealed that the Multiple Linear Regression model ($R^2 = 0.797 \pm 0.053$) slightly outperformed the Random Forest algorithm ($R^2 = 0.739 \pm 0.046$) in predictive capacity (Figure 1).

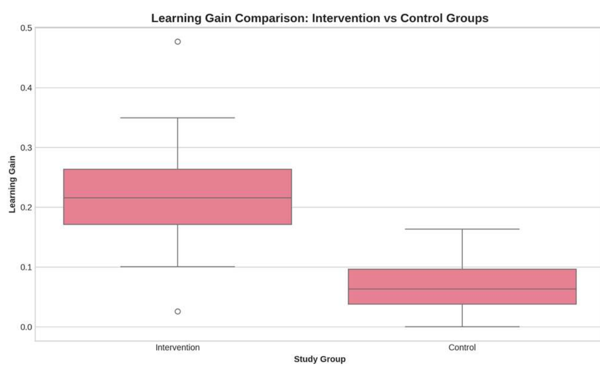

Figura 1. Comparison of models.

This finding suggests that the underlying relationships between predictor variables and learning gains can be adequately characterized by a linear structure, without requiring complex nonlinear models to capture the explanatory variance in this dataset.
Variable Importance Analysis
The feature importance analysis using Random Forests identified the Group_encoded variable as the dominant predictor (relative importance = 0.637), corroborating the intervention's primary role in explaining learning gains.

Secondary predictors included Affective State (0.142) and visuospatial ability (0.073), while variables such as completion rate, initial knowledge, and cognitive effort showed marginal contributions (0.03–0.04). The low relative importance of WM and SEN (0.016–0.018) suggests that their explanatory power is limited when controlling for the effect of the intervention and the main continuous variables.

International Journal of Applied Mathematics

Volume 38 No. 11s 2025,

ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

Bayesian Modeling of Learning Trajectories

The simulation of Bayesian Knowledge Tracking (BKT) parameters revealed differential patterns according to the type of SEN (Figure 2). The group with Dyslexia showed the highest probability of learning transition (P(T) = 0.308), followed by ADHD (P(T) = 0.232).

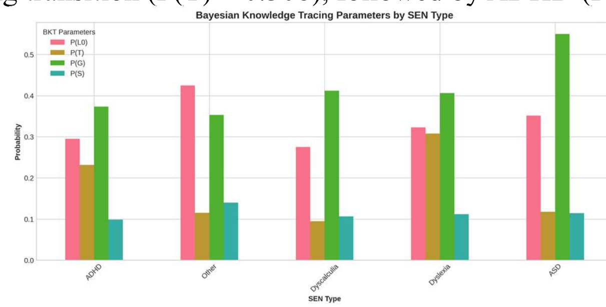

Figure 2. Simulation of Bayesian Knowledge Tracking (BKT) parameters

Autism spectrum disorder (ASD) presented the highest guessing probability (P(G) = 0.55), suggesting possible discrepancies between observed performance and latent knowledge. Initial knowledge values (P(L0)) ranged from 0.351 (ASD) to 0.425 (Other), while slip probabilities showed relative homogeneity (0.10-0.14). It is important to note the sample limitations for the "Other" category (n=7), which require cautious interpretation.

4. Discussion

This study demonstrates the feasibility and effectiveness of Bayesian modeling for personalizing teaching strategies for students with Special Educational Needs [25].

The results reveal that the intervention based on intelligent tutoring systems (ITS) with a Bayesian approach produced substantial improvements in learning gains ([28], [29]), with a remarkable effect size (Cohen's d = 2.68) that far exceeds conventional thresholds for educational interventions.

This finding corroborates the main hypothesis regarding the capacity of Bayesian modeling to adapt teaching strategies according to individual profiles and types of special educational needs (SEN) [30], [31]. The analysis of predictive models showed that Multiple Linear Regression (R^2 = 0.797) slightly outperformed Random Forest (R^2 = 0.739) in explanatory power, suggesting predominantly linear relationships between the predictor variables and learning gains [32], [33], [34]. The relative importance of the variables, where group coding (0.637) dominated over factors such as affective state (0.142) and visuospatial ability (0.073), reinforces the central role of personalized intervention in the results obtained [35]. The results are consistent with recent literature on educational personalization using artificial intelligence. Researchers had pointed out the potential of Bayesian models to adapt instructional sequences, but until now there was limited evidence on their specific application in populations with special educational needs (SEN) [36], [37].

These findings expand upon this work by demonstrating that Bayesian Knowledge Tracing (BKT) can be effectively calibrated for different SEN profiles (Sun, 2025), particularly in dyslexia (P(T) = 0.308) and ADHD (P(T) = 0.232). The superiority of the linear model over nonlinear approaches partially contradicts those who emphasized the need for complex models to capture interactions in educational settings [38]. This discrepancy could be explained by the structured nature of the knowledge domain (problems of shape and motion), where predictor-

Received: August 03, 2025

Volume 38 No. 11s 2025,
ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

outcome relationships may be inherently more linear than in more abstract domains. The finding regarding the limited relative importance of SEN (0.018) challenges approaches that rigidly categorize interventions by type of SEN. These results suggest that effective personalization requires considering continuous dimensions (visuospatial skills, affective state) beyond discrete diagnostic categories [39].

The results support the feasibility of implementing intelligent tutoring systems that operate under Bayesian principles of dynamic updating of student knowledge. The model's effectiveness suggests that personalization based on real-time probabilistic evidence can surpass static approaches based on predefined SEN categories [], [40], [41], [42]. The study provides evidence for the need to move from standardized interventions toward dynamic approaches that respond to individual learning trajectories. As some authors point out, genuine personalization requires continuous adaptation mechanisms that Bayesian models can provide [43]. The findings suggest the value of incorporating Bayesian analysis tools into educational platforms for students with special educational needs (SEN). Identifying specific BKT parameters by SEN type (e.g., higher P(G) in autism spectrum disorder) offers concrete guidance for adjusting expectations and scaffolding strategies [44].

The results support investment in evidence-based educational technologies for special education. The implementation of AI in education should prioritize ethical and equity considerations, particularly for vulnerable populations [45]

5. Conclusions

This study provides robust evidence on the capacity of Bayesian modeling to personalize teaching strategies for students with special educational needs (SEN). The findings demonstrate not only the effectiveness of the intervention but also the feasibility of implementing sophisticated adaptive systems in special education contexts. The identification of differential BKT parameters by type of SEN offers a promising framework for designing more precise and effective interventions. However, the implementation of these systems must be accompanied by critical reflection on their epistemological assumptions and pedagogical implications.

This study contributes to bridging the gap between the theoretical potential of personalized education and its practical implementation in populations with diverse needs, representing a significant step toward a truly inclusive education that is responsive to cognitive diversity.

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