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The Impact of Prior English Learning on the Academic Success of Computer Science Students

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Abstract

This article examines the impact of students' prior experience with English on their academic success in a university English course. The study is based on a survey conducted among students majoring in Computer Science, Business Information Technology (BIT), and Software Technology and Design (STD) at the Faculty of Mathematics and Informatics (FMI), University of Plovdiv, at the beginning of their general English language course. We focus on students' self-assessed language competence at the start of the course and examine how these self-assessments correspond to their actual test results. Using high-performance machine learning methods, we identify background factors that influence academic achievement, including the number of years spent learning English, the type of high school attended, and informal exposure to English. The findings aim to support more effective and tailored approaches to teaching English in technical and scientific disciplines.

Keywords: English language learning; undergraduate students; self-assessment; academic achievement; machine learning; CART Ensemble; educational prediction

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1. Introduction

Research on English language learning has consistently shown that students' achievement is shaped by a complex interaction of social, motivational, and educational factors. Early foundational studies [1,2] emphasized the role of learner attitudes, environmental exposure, and instructional context in shaping foreign language outcomes. Subsequent work expanded this perspective by investigating how emotions, beliefs, and internal dispositions influence language development [3,4]. Taken together, this body of research highlights that English language performance cannot be fully understood without considering learners' prior experiences and psychological characteristics.

A considerable number of empirical studies have examined these influences in diverse educational settings. For example, El-Omari [5] surveyed 496 secondary-school students in Jordan and found that students' performance in English was shaped by measurable contextual factors such as the school environment, informal exposure, and family support. The study in [6] emphasized that several influential factors were located outside the immediate instructional setting and had been formed earlier in the learners' development, such as the home environment, early exposure to resources, and previous contact with English. Their results showed that these external conditions constituted a substantial part of the background that later shaped learners' outcomes. Our study followed a comparable logic, as all predictors used here reflected prior experience accumulated before the current learning situation, rather than characteristics of the instructional process itself. Thus, both studies highlighted the importance of influences that originated before formal instruction and continued to affect subsequent performance. It was reported in [3] that learners' results were associated not only with elements of the formal learning environment but also with conditions that had been established earlier, including previous contact with English and earlier opportunities to make use of the language. These forms of accumulated experience existed prior to the course under investigation and contributed to the observed outcomes. Similarly, the present study relied exclusively on predictors linked to learners' earlier experience, rather than variables originating from the ongoing instructional context. In this way, both investigations demonstrated that performance could be shaped by long-term external factors that preceded the immediate moment of learning. The results in [7] showed that a number of relevant influences were rooted in conditions formed before the educational setting in which the outcomes were measured. Their model illustrated how previously established characteristics could extend their effect into later stages of learning. This perspective aligned closely with the approach used in our study, where all explanatory variables referred to past learner experience, rather than to circumstances within the current learning environment. Consequently, both studies illustrated the broader tendency to examine performance as a result of factors originating prior to the instructional process. Although the three studies addressed different educational contexts, they shared a methodological orientation toward data-driven analysis. None of them employed machine-learning models in the strict algorithmic sense, yet all three relied on techniques that were standard precursors to or components of predictive modeling. Ref. [6] applied *t*-tests and hierarchical linear regression, which served to quantify the contribution of several external, previously accumulated factors to the observed outcomes. Ref. [7] used exploratory factor analysis and structural equation modeling, a framework that combined dimensionality reduction and multivariate path estimation, both of which were closely related to strategies used in supervised learning. Refs. [6,7] applied quantitative models, including MANOVA and hierarchical regression, to show that external conditions—such as school type, domain of study, and prior language experience—have both direct and indirect effects on English achievement. Ref. [3] used large-scale correlational analysis and multiple regression to estimate the joint influence of several background variables, representing classical statistical approaches that could be naturally extended into machine-learning pipelines.

In contrast to these works, our study attempted to examine a comparable predictive task—namely, the estimation of English-language performance—but explicitly based on machine-learning methods. By employing algorithmic models rather than solely inferential statistical procedures, we aimed to explore whether patterns derived from prior learner experience could yield stronger or more flexible predictive accuracy than traditional approaches.

Beyond psychological and social variables, researchers have also explored the influence of contextual and technological factors. Qaddumi [8] reported generally neutral attitudes toward English among Palestinian university students, whereas his later study [9] showed that students benefiting from Moodle-supported instruction achieved higher reading, writing, and vocabulary scores. Recent work has also incorporated fuzzy logic and data-driven methods: [10] used Mamdani fuzzy inference systems to model perceptions of instructors, while [11,12] applied hierarchical regression and Random Forests to analyze demographic and performance patterns. These studies demonstrate a growing interest in computational approaches for capturing complex relationships in educational data.

Although the literature provides substantial insight into the factors affecting English language learning, several gaps remain. Most existing studies focus on secondary-school populations, rely on self-reported attitudes, or examine general English outcomes without

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considering the specific learning needs of students in technical fields. Moreover, while a few studies employ machine learning techniques, the use of ensemble tree-based models to identify the most influential predictors of English performance among university students in STEM/STEAME disciplines is still limited.

The present study addresses this gap by examining how prior English learning experience influences academic achievement in university-level English courses among first-year students enrolled in Informatics, Software Technology and Design (STD), and Business Information Technology (BIT) at the Faculty of Mathematics and Informatics (FMI), University of Plovdiv. Building on the literature, we investigate whether students' self-assessed competence aligns with their actual test performance and which background factors—such as years of study, school type, informal exposure, and personal attitudes—most strongly predict achievement.

To accomplish this, we apply a high-performance ensemble method, CART Ensemble and Bagging (CART-EBag), to both survey data and test results. Tree-based approaches are well suited to modeling nonlinear relationships and identifying the relative contribution of individual predictors, making them particularly appropriate for educational datasets that combine subjective and objective indicators.

We formulate the following research questions:

1. Which prior learning experiences and self-rated factors are the most predictive of students' actual performance in English?
2. Do objective factors (such as school type or major) lose influence over time compared to subjective factors such as frequency of practice and self-rating?
3. Does academic success in an English for Specific Purposes (ESP) course depend primarily on achievement in a general English course?

From these questions arise the central hypotheses:

H1: *Students' final English results are significantly associated with measurable background variables such as years of study, type of high school, frequency of English practice, and self-evaluated competence.*
H2: *Machine learning models based on both objective (test scores) and subjective data can effectively predict students' English language achievement.*

To test these hypotheses, we employ the CART-EBag algorithm on a combined dataset consisting of placement test scores, final course grades, and survey-based indicators of prior experience and self-assessment. This approach allows the discovery of statistically robust predictor–outcome relationships and provides insights that may support the development of more effective, data-informed instructional practices for students in STEAME-related fields.

The scope of this study does not include an analysis of learner motivation or emotional variables. Instead, the results are derived from a combination of subjective self-reported information and objective empirical measures of students' English language performance.

2. Materials and Methods

The primary methods applied in this study rely on ensemble machine learning techniques derived from decision-tree algorithms, such as Classification and Regression Trees (CART). A key advantage of tree-based methods is their capacity to determine the relative importance of each predictor, thereby enhancing the interpretability and explanatory power of the resulting models. Model performance is assessed using standard statistical indicators, including Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), and the coefficient of determination (R^2). Statistically robust models are characterized by low prediction errors and high R^2 values, reflecting strong predictive ability and an adequate fit to the observed data.

2.1. Machine Learning Model: CART Ensemble and Bagging

CART is a method for building decision trees that can be used for both classification and regression [13]. To reduce CART's tendency toward overfitting, a technique called Bagging (bootstrap aggregating), developed by [14], is applied. By combining multiple models trained on different bootstrap subsets, Bagging achieves lower variance and better generalization.

The algorithm includes the following steps: drawing multiple subsets with replacement (bootstrap sampling); training a CART tree on each subset; and aggregating predictions through averaging (for regression) or voting (for classification). For performance evaluation, cross-validation (CV) is the most commonly used method.

This results in an ensemble model that is more stable and robust, while still retaining the interpretability of individual CART trees, even though the transparency of the ensemble decreases [14].

Establishing the influence of predictors in CART combined with Bagging is achieved through variable importance measures. The most commonly used approaches are Mean Decrease in Impurity (MDI) and Permutation Importance (MDA). The former reflects the accumulated improvement in splitting criteria, while the latter measures the deterioration in accuracy when predictor values are randomly shuffled [15]. Bagging allows these estimates to be made directly using out-of-bag (OOB) observations.

However, when variables are highly correlated or have differing variances, MDI may be biased; therefore, permutation importance is considered the more reliable method [16].

The primary hyperparameters of the Arcing ensemble include: the number of trees (T), the form of cross-validation (CV), the minimum parent- and child-node sizes (m1, m2), and the number of predictors randomly selected at each split.

2.2. Evaluation Measures and Statistical Tools

In order to evaluate the created models, we use the following statistical measures: RMSE, MAPE, and the coefficient of determination.

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{t=1}^{n}\left(Y_t - \hat{Y}_t\right)}{n}},\ \mathrm{MAPE} = \frac{1}{n}\sum_{k=1}^{n}\left|\frac{P_k - Y_k}{Y_k}\right|,\ \mathrm{R}^2 = \frac{\left(\sum_{k=1}^{n}\left(P_k - \overline{P}\right)\left(Y_k - \overline{Y}\right)\right)^2}{\sum_{k=1}^{n}\left(P_k - \overline{P}\right)^2 \sum_{k=1}^{n}\left(Y_k - \overline{Y}\right)^2},$$

where Y_k and P_k denote the dependent and predictor variables, respectively, and $\overline{Y}$, $\overline{P}$ represent their means; n is the sample size.

2.3. Methodological Framework

The present study adopts a quantitative and pedagogically grounded research design aimed at identifying relationships between students' previous English learning experiences, their self-assessed competence, and their actual academic performance in university-level English courses. The research was conducted among first-year students in Informatics-related majors at the Faculty of Mathematics and Informatics (FMI), University of Plovdiv—specifically, Informatics, Software Technology and Design (STD), and Business Information Technology (BIT).

Upon admission, all students sit for an entrance examination, which determines placement in a degree program. At the beginning of the academic year, they also take a placement test in English administered by the faculty's English instructors to assign them to groups of similar proficiency.

The overarching objective is to examine how students' previous experience influences their academic results and whether self-perceived competence aligns with objectively measured performance.

The study's specific tasks include:

1. Collecting and systematizing data on students' prior English learning, motivation, and attitudes;
2. Comparing self-reported information with actual test and course results;
3. Identifying the most influential predictors of academic achievement using machine learning techniques.

Methodologically, the study integrates pedagogical principles of individual differences with data-driven modeling. It combines subjective survey-based data with objective assessment results within a coherent analytical framework.

2.4. Data Collection Instruments

The main data collection tool is a questionnaire survey consisting of both closed and open-ended items grouped into thematic areas:

- background information (gender, age, school type, years of English study);
- prior English learning (school, private courses, self-study, certificates);
- frequency and context of English language use;
- self-assessment of the four language skills (reading, writing, listening, speaking);
- attitudes toward group work, online learning, and use of digital resources.

Responses to closed questions were collected on a five-point Likert scale, while open questions invited free-text explanations. The questionnaire was prepared in English and distributed electronically through a university platform. A second survey was administered after the first semester, asking students to self-assess their progress in English. The complete questionnaires used in the study are provided in Appendix A.

In the Bulgarian education system, all assessments use a numeric grading scale from 2 to 6, where 2 = fail, 3 = pass (satisfactory), 4 = good, 5 = very good, and 6 = excellent.

2.5. Analytical and Computational Methods

The integrated dataset combined survey responses with objective indicators—placement test scores, midterm grades, and final results. To investigate the factors influencing test scores or student self-assessment, we use the CART-EBag algorithm to build a robust statistical model that best describes the data.

For this purpose, for a given target variable, we construct a set of models by varying their hyper-parameters:

- number of trees in the ensemble ($T = 30, 40, 50, 60, 70, 80$);
- training with 5-fold or 10-fold cross-validation (CV);
- minimum number of observations in parent and child nodes ($m1$:$m2$ = 10:5, 5:5, 3:3);
- number of randomly selected predictors for each tree, typically equal to 3.

During the modeling process, we monitor the relative variable importance (MDI and MDA) and interactively remove those with the lowest contribution. Model selection is guided both by statistical performance indicators and by stabilization of predictor importance weights and their ranking across the ensemble.

Statistical analyses were performed using Salford Predictive Modeler 8.2 (SPM; Minitab LLC, State College, PA, USA) [17] and IBM SPSS Statistics, version 29.0 IBM Corp., Armonk, NY, USA [18], on a laptop (Lenovo Group Ltd., Beijing, China; Intel Core i7 processor, Intel Corporation, Santa Clara, CA, USA, CPU 3.3 GHz).

2.6. Methodological Rationale

The choice of CART-EBag methods in this study is motivated by several methodological and practical considerations. First, decision-tree-based models are well suited for capturing

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complex, nonlinear relationships and interaction effects among predictors—patterns that traditional linear models may fail to identify. Second, the Bagging (Bootstrap Aggregating) procedure substantially enhances model robustness and predictive stability. Third, CART-based ensemble methods offer advantages in interpretability by providing direct measures of predictor importance. Finally, CART-EBag methods are computationally efficient, flexible with respect to data types, and insensitive to monotonic transformations of predictors, which makes them particularly appropriate for heterogeneous predictor distributions.

3. Context of English Language Instruction and Collected Data

We studied the English language results in the first year of study of students in computer science-related majors.

3.1. English Language Education at FMI

At the Faculty of Mathematics and Informatics, English is a mandatory subject during the first academic year for all students. Instruction is divided into two sequential courses: General English (first semester) and English for Specific Purposes (ESP) (second semester). General English develops grammar, vocabulary, and communication skills through paraphrasing, summarizing, note-taking, proofreading, and discussions on academic and cultural topics. ESP focuses on professional and technological communication, terminology, and soft skills such as presenting and writing in an IT context. Continuous assessment is based on:

- Class participation and attendance (30%);
- Homework and project work (40%);
- Final test (30%).

All courses are taught in small groups (around 20 students) to ensure interaction and feedback.

3.2. Participants and Data

The study sample consisted of 61 first-year students majoring in Informatics, BIT, and STD. Students were assigned to English groups according to their placement test results. The combined dataset included demographic variables, self-assessment data, placement and final test scores, and grades in both General English and ESP courses (denoted as GRADE 1 and GRADE 2).

3.3. Integration of Data and Pedagogical Context

Survey responses and test data were merged for statistical analysis. This integration allowed us to compare self-reported competence and motivation with objective achievement measures. The methodology reflected a holistic pedagogical approach: understanding how prior learning experiences shape university performance and how data-driven insights can inform more effective language instruction for Computer Science students.

4. Preliminary Analysis of Student Performance

The sample included 61 students (44 male and 17 female) enrolled in Computer Science programs at the Faculty of Mathematics and Informatics, University of Plovdiv "Paisii Hilendarski". They were distributed across three majors within the field of Informatics and Computer Science: Informatics (30 students), Business Information Technology (BIT) (14 students), and Software Technology and Design (STD) (17 students).

Most respondents (52) were between 18 and 20 years old, while nine fell in the 20–25 range. By place of residence, 22 came from large cities, 33 from small towns, and six from villages. All participants studied English during secondary school: 25 for 11–15 years,

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27 for 6–10 years, and only 9 for 1–5 years. Eleven graduated from language schools, 16 from mathematics high schools, 13 from vocational schools, 16 from general high schools, and five from other types of schools.

In terms of intensity, 57.3% had English lessons 3–5 times per week, while 73.8% reported receiving additional instruction outside the regular school curriculum. Ten students held internationally recognized English language certificates. Nearly 70% of the respondents had travelled abroad, most often for excursions.

4.1. Distribution of Self-Reported Competence Levels

A key part of Survey 1 was students' self-assessment of the four language skills—reading (Figure 1a), writing (Figure 1b), listening (Figure 1c), and speaking (Figure 1d). Figure 1 presents bar charts of the distribution of these four indicators.

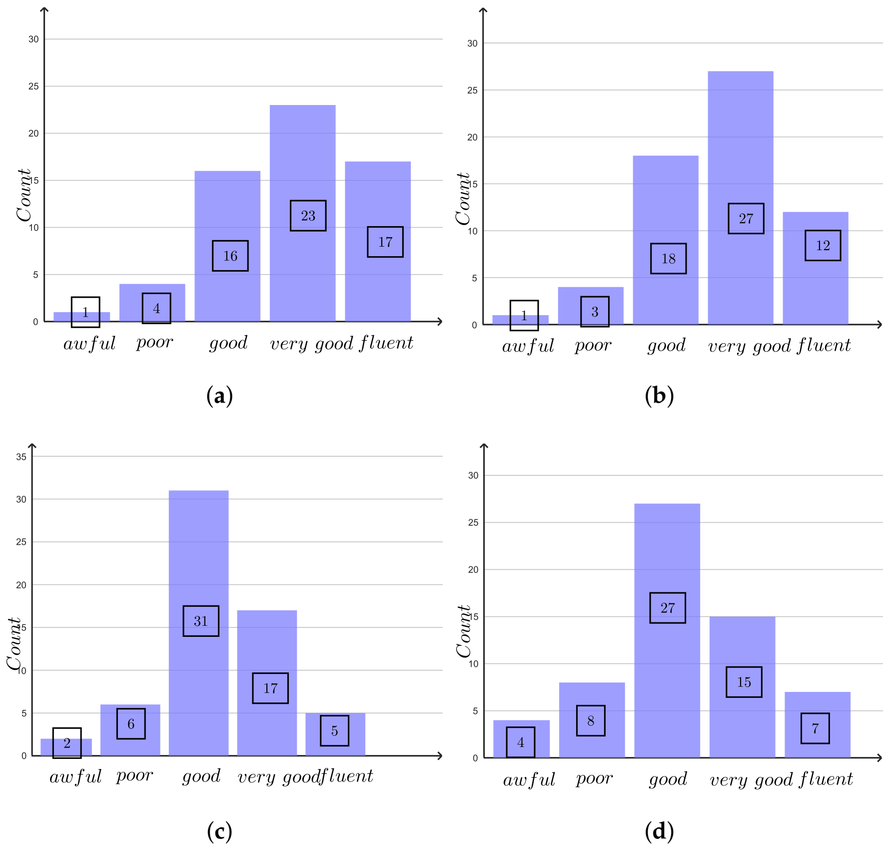

Figure 1. Bar charts of the distribution of students' self-assessments of the four language skills: (**a**) Reading. (**b**) Listening. (**c**) Writing. (**d**) Speaking.

The self-assessments were coded on a scale from 2 to 6, as follows: 2—awful, 3—poor, 4—good, 5—very good, and 6—fluent. Each student's average self-assessment was calculated as the arithmetic mean of the four coded scores. Descriptive statistics for these variables are presented in Table 1. The mean values show that the highest self-assessment is for reading (4.84, 95% CI $[4.59, 5.08]$), followed by listening (4.75, 95% CI $[4.53, 4.98]$). For both skills, the median is 5.00, indicating that more than half of the participants perceive themselves as very good in these areas. Lower mean scores are observed for speaking (4.21) and writing (4.28), with a median of 4.00, which suggests some difficulties in these productive skills. The standard deviations (0.878–1.035) indicate moderate variability in the responses, with the greatest dispersion found in speaking. The overall average self-assessment across all four skills is 4.52 (95% CI $[4.30, 4.74]$), with a median of 4.5, indicating that participants generally evaluate their language competence positively, but with distinctly higher results in receptive skills (reading and listening) compared to productive skills (speaking and writing).

Table 1. Descriptive statistics of students' self-assessments of the four language skills.

	Mean	95% Confidence Interval for Mean	Median	Std. Deviation
Self-evaluation of reading	4.84	(4.59, 5.08)	5.00	0.969
Self-evaluation of listening	4.75	(4.53, 4.98)	5.00	0.888
Self-evaluation of speaking	4.21	(3.95, 4.48)	4.00	1.035
Self-evaluation of writing	4.28	(4.05, 4.50)	4.00	0.878
Average self-evaluation	4.52	(4.30, 4.74)	4.50	0.842

4.2. Descriptive Statistics of English Course Results

Table 2 presents the descriptive statistics of the placement test, GRADE 1, and GRADE 2. The mean score for the Placement test is 4.48, while the median (4.8) is slightly higher, indicating a mild negative skewness; in other words, most students scored above the mean, but a few lower results pulled the average down. The standard deviation (0.829) shows moderate dispersion around the mean.

The mean grade for GRADE 1 is 5.26, with a narrow confidence interval (5.09–5.43). The median (5.37) is close to the mean, suggesting a relatively symmetric distribution. The standard deviation is the smallest of the three, which indicates the least variation in results.

For GRADE 2, once again, the median is higher than the mean, showing negative skewness: more results are above the mean, but a few weaker performances lower the average. The standard deviation (0.947) is the highest among the three groups, which means that the results are more dispersed and heterogeneous.

The table also shows that average results improve from the placement test (4.48) to GRADE 1 (5.26) and remain relatively high for GRADE 2 (5.17), though with greater variability. This suggests, on the one hand, progress in achievement, but also a wider spread of results in GRADE 2, with more weaker performances present.

Table 2. Descriptive statistics of the placement test, GRADE 1, and GRADE 2.

	Mean	95% Confidence Interval for Mean	Median	Std. Deviation
Placement test	4.48	(4.27, 4.69)	4.80	0.829
GRADE 1	5.26	(5.09, 5.43)	5.37	0.679
GRADE 2	5.17	(4.93, 5.41)	5.40	0.947

5. Results

We analyzed the results obtained by the students during their first year of study, the responses from the surveys, and the relationships between them. The results were structured into four studies. In the first study, we showed that there was a relationship between students' self-assessed English proficiency and the other survey questions. In the second analysis, we examined whether the results of the entrance test preceding the training in General English were related to the first survey, including self-assessment as a predictor. In the third study, we found a relationship between the results of the students in their efforts to obtain a final grade in the subject and both the data from the survey and their results from the entrance test. In the fourth study, we analyzed the influence of all available information—survey responses, entrance test performance, and results of the first English course—on students' preparation for the exam in specialized English.

5.1. Examining Factors Influencing Students' Self-Assessments

The self-assessment of the four core language skills (reading, listening, speaking, and writing) is an important element in the process of learning English as a foreign language. It helps learners recognize their strengths and weaknesses and develop self-regulated learning skills. As noted in [19], when learners actively engage in self-assessment, they develop a deeper understanding of the criteria for success. Reference [20] also emphasized that self-assessment is a crucial tool for enhancing language awareness and achieving higher communicative competence.

In this section, we investigated which factors influenced students' self-assessments by applying the ensemble method with CART Ebag decision trees. As the dependent variable, we used the average of students' self-assessments across the four language skills.

Models were built with all 12 predictors described in Table 3. The Bagging model M1, which showed the best statistical performance (RMSE = 0.3, MAPE = 0.057, R^2 = 0.888), was achieved with T = 40 trees in the ensemble. It should be noted that the relative influence of the predictors remained stable across variations of the ensemble hyperparameters. Table 3 presents the relative importance of the selected predictors.

Table 3. Relative influence of predictors in the CART-EBag model M1.

Variable	Description	Relative Influence
SelfEval (dependent variable)	Average self-evaluation	
TimePractice	Frequency of English practice	95%
GroupDiscussion	Level of comfort when participating in group discussions in English	80%
YearLearn	Years of learning English	38%
IntensiveStudy	Intensity of English study	35%
Major	Major	30%
TypeSchool	Type of high school graduated from	22%
Background	Family background	20%
Abroad	Time spent abroad	10%
Certificate	Possession of a language certificate	10%
TypeStudy	Type of language study	10%
Age	Age	10%
Gender	Gender	10%

The strongest factors shaping students' self-assessments are:

TimePractice (95%)—frequency of English practice is the decisive factor, showing that the more regularly learners use the language, the higher their self-assessment.

GroupDiscussion (80%)—participation and comfort in English discussions is the second most significant factor, highlighting the importance of communicative environments and real-life language use.

Moderately important factors include:

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YearLearn (38%) and IntensiveStudy (35%)—years of study and intensity of English learning at school have a moderate influence, suggesting that duration and workload alone do not guarantee higher self-assessments without practical application.

Less influential factors are:

Major (30%)—the specific major has a negligible effect.

TypeSchool (22%) and Background (20%)—the type of high school and family background have relatively little influence, suggesting that social and educational context matters but is not decisive.

The remaining factors—Abroad, Certificate, TypeStudy, Age, Gender (each 10% importance)—appear to have no significant effect on the dependent variable. Possessing a certificate, spending time abroad, or personal characteristics such as age and gender do not appear to significantly influence how students evaluate their language proficiency.

We first modeled the dependent variable SelfEval with all predictors and then removed the insignificant ones. We selected a model with $T = 40$ trees in the ensemble. The statistical indicators of the new model M2 showed improved performance: RMSE = 0.289, MAPE = 0.054, $R^2 = 0.896$.

The influence of the predictors is presented in Table 4 (Figure 2).

Table 4. Relative influence of predictors in the CART-EBag model M2.

Variable	Description	Relative Influence
SelfEval (dependent variable)	Average self-evaluation	
TimePractice	Frequency of English practice	98%
GroupDiscussion	Level of comfort when participating in group discussions in English	80%
YearLearn	Years of learning English	40%
IntensiveStudy	Intensity of English study	35%
Major	Major	30%
Background	Family background	20%
TypeSchool	Type of high school graduated from	12%

TimePractice remained the most significant factor (98%; see Figure 2), clearly establishing it as the decisive predictor of self-evaluation.

On the Y-axis is the degree of significance (Var. Importance), i.e., the importance of the predictor, measured by how much the use of a given variable reduces the error, as shown in Figure 2 (e.g., Gini Impurity or MSE in regression). If the first variable had an influence of 100%, the others are expressed relative to it. On the X-axis are the variables included in the analysis. The blue bars (the box plot) show the variation in the importance of the corresponding predictor, calculated across the different trees in the ensemble. The longer the bar, the greater the fluctuations in the predictor's importance, meaning that in some trees of the ensemble, it had a strong effect, while in others, its influence was weak. Columns with a wide range indicate that the importance of this predictor is less stable across the trees. The pink squares + green line (Mean) represent the average importance of each predictor, averaged across all trees in the ensemble.

We also examined two additional variables that played an important role in the analysis. The first concerned how often students practice English, and the second how comfortable they felt in group discussions.

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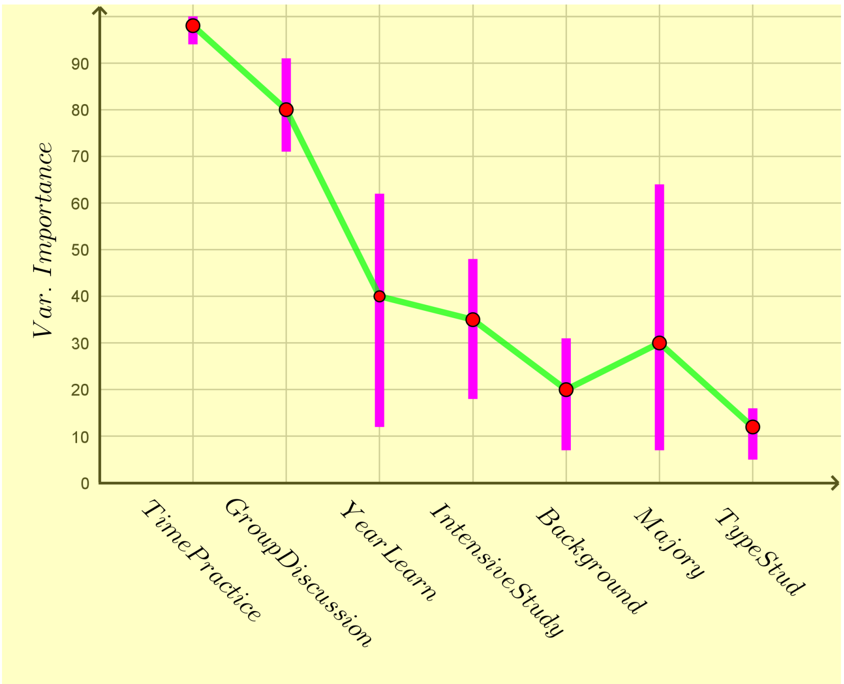

Figure 2. Relative variable importance for Table 4.

Figure 3 presents the frequency distributions of TimePractice. As can be seen, 65.5% of the respondents reported practicing English all the time, almost every day, or daily.

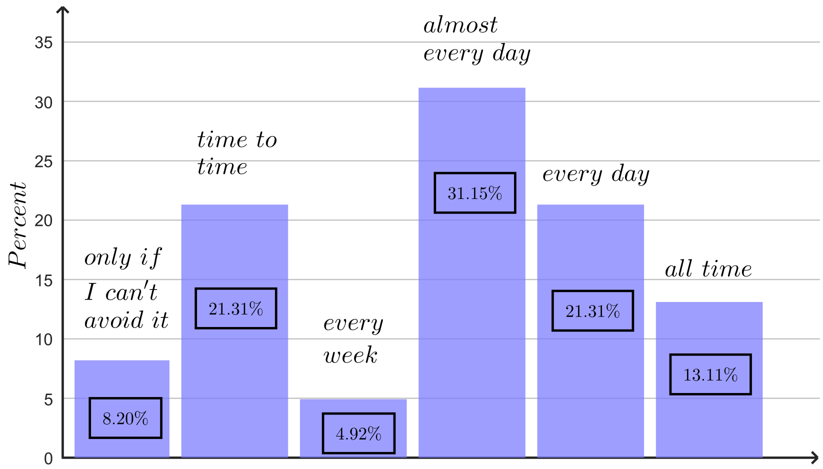

Figure 3. Bar chart of the variable TimePractice ("How often do you practice English?").

The second most important factor is GroupDiscussion (80%), showing that confidence in participating in group discussions is a strong and stable predictor. The box plot is moderately narrow, indicating a relatively consistent effect across all trees in the ensemble. Figure 4 shows that 57.4% of students reported feeling comfortable or very comfortable participating in group discussions in English.

YearLearn (40%) ranks as a moderately important factor, but with a wide variation, meaning that the effect of years of study is unstable—highly significant in some trees of the model and negligible in others. This depends on the randomly selected predictors used to construct each tree. IntensiveStudy shows a medium (35%) relative influence with a moderate range of variation. In other words, the intensity of English study at school has an effect, but not a consistently strong one—it may be useful for some groups but is not decisive overall. Weaker predictors include Major (30%) and Background (20%). For Major, there is again a significant variation in predictor importance, suggesting that its more substantial influence emerges only under certain conditions. By contrast, TypeSchool (12%) shows minimal effect, indicating that the mode of study (school only, additional lessons, or self-study) has little impact on how students evaluate their skills. It should be noted that varying the hyperparameters of the ensemble does not change the ranking of predictor influence. Moreover, this ranking remains consistent (with minor exceptions among the least influential factors) in both models M1 and M2, which demonstrates the stability and robustness of the models as well as of the determined predictor influences. In conclusion, the most important determinants of a high self-evaluation of English proficiency are regular practice and active participation in communicative situations.

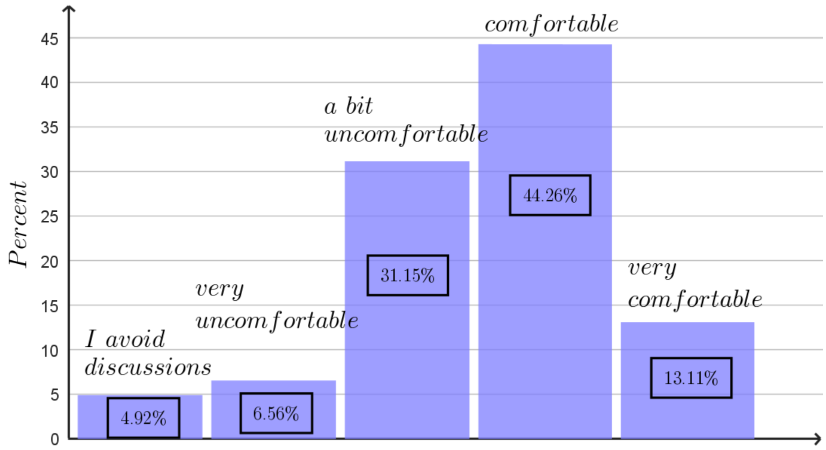

Figure 4. Bar chart of the variable GroupDiscussion ("How comfortable do you feel participating in group discussions in English?").

5.2. Examining the Factors Influencing Students' Placement Test Results

The placement test serves as the initial benchmark for assigning students to proficiency levels. Based on their prior language experience, knowledge, and skills, as demonstrated in the test, students are placed into groups of similar ability to ensure more effective and targeted instruction. Unlike most other academic subjects at the Faculty of Mathematics and Informatics, where students attend classes in their enrollment-based academic groups, English classes are organized by proficiency level as determined by the placement test.

The test itself is a standardized instrument designed explicitly for the needs of English language teaching at FMI. It contains 80 multiple-choice questions arranged in ascending order of difficulty, progressing from more straightforward to more complex tasks. The items assess students' knowledge of vocabulary and grammar through a range of task types. Developed by the English language instructors at FMI, the test provides a reliable and practical tool for placing learners into appropriate groups. The use of closed-ended questions allows for greater objectivity, faster evaluation, and comparability across a large student cohort. We constructed and examined a series of CART-EBag models with the dependent variable PlacementTestGrade—the students' placement test results. The best-performing model was obtained with T = 40 trees, training method: 10-fold cross-validation (CV10), a minimum number of observations in the parent and child nodes of each tree in the ensemble set to $m1{:}m2 = 5{:}5$, and three randomly selected predictors used for the construction of each tree. The performance indicators of the resulting model M3 were as follows: RMSE $= 0.182$, MAPE $= 0.033$, and $R^2 = 0.952$. The relative influence of the predictors on the placement test results is shown in Table 5.

From Table 5, students' Major exerts the most decisive influence on their performance in the placement test. This is expected, given that admission to different majors is determined by their entrance scores from secondary school. Next in importance is the average self-evaluation of language skills, which suggests that students' self-assessments are a reliable predictor of their placement results. Following these are TimePractice and GroupDiscussion, which is natural, considering their significance for the actual language use and confidence. They are followed by the intensity of English study at school (IntensiveStudy) and the number of years of learning (YearLearn). The appearance of these factors is logical, given that the placement test is a written exam, similar to the testing practices students often experienced in secondary school, which helped shape their attitudes and habits. We can conclude that the most decisive influence on the placement test results is the students' major, which is directly related to their admission score—determined by the entrance exam and their overall high school performance—and is followed by their self-assessment and the amount of practice they have completed.

Table 5. Relative influence of predictors in the CART-EBag model M3 on students' placement test results.

Variable	Description	Relative Influence
PlacementTestGrade (dependent variable)	Placement test result	
Major	Major	100%
SelfEval	Average self-evaluation	50%
TimePractice	Frequency of English practice	45%
GroupDiscussion	Level of comfort when participating in group discussions in English	35%
IntensiveStudy	Intensity of English study	25%
YearLearn	Years of learning English	15%

5.3. Investigating the Factors Influencing Students' Results in GRADE 1 (Final General English Score)

At the end of the first semester, students receive a grade in the General English course. In this case, the dependent variable is the examination test taken at the end of the course, which we denote as ScoreGrade1. The predictors include the previously examined dependent variables SelfEval and PlacementTestGrade, as well as TimePractice, GroupDiscussion, YearLearn, IntensiveStudy, Major, TypeSchool, Background, Abroad, Certificate, and TypeStudy.

We constructed and examined a series of CART-EBag models with the dependent variable ScoreGrade1—the students' final results in General English. The best-performing model was obtained with $T = 60$ trees, training method: 10-fold cross-validation (CV10), a minimum number of observations in the parent and child nodes of each tree in the ensemble set to $m1$:$m2$ = 3:3, and three randomly selected predictors used for the construction of each tree. The performance indicators of the resulting model M4 were: RMSE $= 0.455$, MAPE $= 0.076$, $R^2 = 0.834$. The relative influence of the predictors on these results is presented in Table 6 in percentages.

The most substantial relative influence is exerted by the average self-evaluation (SelfEval). This suggests that students with higher self-assessments are more motivated and confident and consequently achieve better results. The second most influential factor is PlacementTestGrade, which is expected, since stronger initial skills are likely to lead to higher final outcomes. The type of high school completed (TypeSchool) shows a relatively high influence of 40%, reflecting the degree to which students are trained to perform successfully in an academic environment. This is followed by TimePractice, GroupDiscussion, YearLearn, and Major, which exert a moderate influence. Weaker factors include IntensiveStudy, Background, and TypeStudy.

Table 6. Relative influence of predictors in the CART-EBag model M4 on students' GRADE 1 results.

Variable	Description	Relative Influence
ScoreGrade1 (dependent variable)	Final General English score	
SelfEval	Average self-evaluation	70%
PlacementTestGrade	Placement test result	50%
TypeSchool	Type of high school graduated from	40%
TimePractice	Frequency of English practice	38%
GroupDiscussion	Level of comfort when participating in group discussions in English	32%
YearLearn	Years of learning English	32%
Major	Major	30%

One notable finding in this model is the significantly reduced influence of Major. The chosen degree program reflects the motivation of students in their final year of high school to achieve high grades, perform well on external assessments, and succeed in competitive entrance examinations in order to be admitted to their desired major. However, the results after the first year of university indicate that this temporary motivation in secondary school does not play a substantial role in academic achievement at the bachelor's level.

In this model, it is evident that almost all selected variables affect the final assessment in General English, and they can be grouped into three categories:

- Self-evaluation and placement test—i.e., subjective and objective measures of language competence, which are the most significant predictors of final results;
- Educational background and engagement factors—such as the type of high school and frequency of practice, which also play an important role;
- Duration of learning and social background—which exert relatively weak influence.

This shows that the quality and intensity of study, as well as personal engagement, are more important than the sheer number of years spent learning English.

5.4. Investigating the Factors Influencing Students' Results in GRADE 2 (ESP)

After completing the first semester, students continue in the second semester with a course in English for Specific Purposes (ESP), focusing on English for Technology-related contexts. This subject is connected with the terminology and discourse features specific to the different majors. In computer science–related majors, the language is generally more straightforward in terms of grammar, but it nonetheless has its own distinctive features. Unlike the General English course, where students are grouped by proficiency level, in ESP, they are not regrouped by ability but continue to learn within their academic cohorts. At the end of the course, students take a final examination. In this case, the dependent variable is ScoreGrade2, and the predictors used are the same set of factors examined in the previous models. To construct a model and identify the influence of variables on students' final results in English for Specific Purposes, we built a series of CART-EBag models while varying different hyperparameters. The best statistical performance was obtained with model M5, with $T = 80$ trees in the ensemble, training method: 10-fold cross-validation (CV10), minimum number of observations in parent and child nodes of each tree set to $m1{:}m2$ = 3:3, and three randomly selected predictors used for the construction of each tree. The statistical indicators of the constructed model M5 were: RMSE $= 0.337$, MAPE $= 0.065$, $R^2 = 0.913$. The relative influence of the predictors on these results is presented in Table 7.

Table 7. Relative influence of predictors in the CART-EBag model M5 on students' results in GRADE 2 (ESP).

Variable	Description	Relative Influence
ScoreGrade2 (dependent variable)	Final result in ESP	
ScoreGrade1	Final result in General English	100%
SelfEval	Average self-evaluation	50%
PlacementTestGrade	Placement test result	48%
TimePractice	Frequency of English practice	35%
TypeSchool	Type of high school graduated from	32%
GroupDiscussion	Level of comfort when participating in group discussions in English	25%
Certificate	Possession of a language certificate	20%
SelfImprovement	Perceived improvement in English after the first semester	20%

5.5. Putting All Analysis Together (The Old Section Discussion)

Several new variables emerge as relevant for students' results in English for Specific Purposes, such as the type of high school, possession of an English certificate, and students' self-assessment of improvement after the first semester. These factors have a logical impact, considering the focus on specialized language learning. It is also noteworthy that the variable Major, which had a strong influence on placement test results, does not appear in this model. This suggests that the differences among students across degree programs become blurred and eventually disappear after one year of English language study at university.

By considering all results together (Table 8), we can draw a comprehensive picture of how students' outcomes depend on the predictors under study.

Table 8. SelfEval, Placement test, GRADE 1, and GRADE 2 together.

	ScoreGrade2	ScoreGrade1	PlacementTest	SelfEval
ScoreGrade1	100%			
PlacementTestGrade	48%	50%		
SelfEval	50%	70%	50%	
TimePractice	35%	38%	45%	98%
TypeSchool	32%	40%	insignificant	12%
GroupDiscussion	25%	32%	35%	80%
YearLearn	insignificant	32%	15%	40%
Major	insignificant	30%	100%	30%
IntensiveStudy	insignificant	25%	25%	35%

Self-evaluation (SelfEval) is most strongly influenced by the time devoted to practice (TimePractice, 98%) and the group discussion skills (GroupDiscussion, 80%). This suggests that students' self-perception of their knowledge is not merely subjective but is closely tied to concrete learning behaviors. The more time students invest in practice and the more they engage in collaborative learning, the more confident they feel in their own competence. These findings align with the theory of self-efficacy [21], which emphasizes that mastery experiences and social persuasion are key determinants of confidence, and with [22],which shows that cooperative learning enhances both motivation and achievement. By contrast, formal institutional factors—such as the type of school attended (TypeSchool), years of prior study (YearLearn), or declared major (Major)—play only a minor role. Thus, students appear to evaluate their knowledge primarily based on individual effort and peer interaction, rather than institutional context.

PlacementTestGrade is most decisively influenced by the students' chosen Major (100%). This indicates that students who deliberately select specific majors are more likely to demonstrate higher initial performance, likely due to better preparation. According to [23] educational choices such as major selection are strongly driven by motivational beliefs and goals, which in turn predict performance outcomes. Secondary but still meaningful influences are found from TimePractice (45%), GroupDiscussion (35%), and SelfEval (50%). Interestingly, the type of school is negligible here, showing that once students enter the university, their school background no longer determines their performance. Overall, entrance performance reflects a combination of prior preparation (major choice), study behaviors (practice and discussion), and self-perception, while institutional background fades in importance.

ScoreGrade1 (basic English knowledge) is primarily driven by self-evaluation (70%), showing that students' own assessment of their knowledge aligns closely with actual outcomes. This finding is consistent with [24], which highlights the strong link between self-efficacy and learning achievement. PlacementTestGrade also contributes significantly (50%), confirming that earlier acquired knowledge transfers effectively to this first stage of assessment [25]. TimePractice (38%) and TypeSchool (40%) also retain a noticeable influence, indicating that school preparation still matters during the foundational stage. GroupDiscussion (32%) and YearLearn (32%) play a moderate but non-negligible role. Therefore, success in the basic exam is influenced by both prior learning foundations and subjective self-assessment, while continuous effort and institutional support remain relevant.

ScoreGrade2 (specialized English knowledge) is determined almost entirely by ScoreGrade1 (100%), making clear that without a strong foundation in basic English, specialized success is unattainable. Secondary influences include SelfEval (50%) and PlacementTestGrade (48%), indicating that self-confidence and initial knowledge still play a role, but only after a solid base is established. TimePractice (35%) and TypeSchool (32%) have a diminished effect, while GroupDiscussion (25%) plays only a minor role. Success in specialized English is therefore strongly path-dependent: foundational knowledge reflects later performance.

From these findings, several broader conclusions can be drawn:

- Self-perception is not trivial. Although subjective, SelfEval is a strong predictor of both basic exam success (ScoreGrade1, 70%) and entrance performance (PlacementTestGrade, 50%). This supports research showing that motivated and confident students tend to perform better [21,24].
- Study habits matter. TimePractice and GroupDiscussion consistently contribute to both self-assessment and measurable performance, though their effect is strongest in earlier stages and weakens in later, more specialized exams. This is consistent with evidence that cooperative and engaged learning improves outcomes [22,26].

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- School background plays only a temporary role. TypeSchool and YearLearn remain somewhat relevant for ScoreGrade1, but are negligible for PlacementTestGrade and ScoreGrade2.
- The choice of major is decisive at the initial stage. The major exerts its strongest influence immediately after enrollment (100% on PlacementTestGrade), but subsequent outcomes depend less on this factor and more on effort and foundational mastery [23].
- Strong foundations are essential. Specialized exam success (ScoreGrade2) is almost entirely determined by prior mastery of basic English knowledge (ScoreGrade1, 100%). This confirms findings that prior knowledge is a decisive predictor of advanced learning [25].

These results suggest that teachers and lecturers should encourage consistent practice and group discussions, as these strongly shape students' self-confidence and initial performance. At the same time, curricula should prioritize the development of basic knowledge (ScoreGrade1), since success at this stage is the critical determinant of advanced performance. Institutional profiling and background are less important than active student engagement and effective learning behaviors.

6. Discussion

The results demonstrated that models based on prior learner experience were able to produce stable and consistent predictions of English-language performance. The machine-learning algorithms outperformed traditional linear baselines, indicating that nonlinear relationships and interaction patterns were present in the dataset. These relationships could not have been captured adequately through classical statistical analysis alone.

Although previous studies such as [3,6,7] relied primarily on classical inferential methods, they similarly reported that external factors established prior to formal instruction played a substantial role in shaping outcomes. Our findings aligned with this general tendency: the most informative predictors in our models were also features representing accumulated experience rather than conditions of the current learning environment. Unlike the earlier studies, however, our investigation applied machine-learning techniques, which allowed the detection of complex, non-linear patterns among these prior-experience variables. This methodological distinction provided a more flexible framework for evaluating how long-term external influences contributed to performance.

The use of algorithmic models demonstrated several advantages:

- they handled multicollinearity effectively;
- they identified interaction patterns without requiring explicit specification;
- they allowed feature-importance analysis that highlighted the relative contribution of prior-experience variables;
- they maintained predictive accuracy even when the data structure was moderately heterogeneous.

These contributions extended previous findings by showing that predictive tasks in this domain benefited from computational modeling rather than relying exclusively on inferential methods.

The results suggested that performance in English could be reliably linked to factors formed before the current instructional process. This implied that future educational interventions might benefit from considering learners' accumulated experience rather than focusing solely on short-term instructional changes. Furthermore, the demonstrated success of machine-learning models indicated that predictive analytics could become a complementary methodological tool alongside traditional statistical procedures.

The dataset reflected a specific cohort, which limited the generalizability of the models. Future studies could expand the feature space, include longitudinal data, or compare machine-learning methods with causal-inference frameworks. A hybrid approach that integrates algorithmic prediction with structural modeling may further refine the understanding of how prior-experience factors contribute to English performance.

7. Conclusions

The analysis of the relative influence of the predictors shows clearly differentiated effects across the variables. The most significant factor is ScoreGrade1 (100%), making it the dominant predictor of performance in GRADE2. It is followed by the group of variables with approximately 50% influence, namely SelfEval and PlacementTestGrade. The next group, with around 30% influence, consists of TimePractice and TypeSchool. The final group, with about 20% influence, includes GroupDiscussion, Certificate, and SelfImprovement.

The results of the study provide strong empirical confirmation of both research hypotheses. Regarding H1, the CART-EBag models demonstrate that students' academic outcomes in English are significantly influenced by measurable background and behavioral factors, with self-evaluation, frequency of English practice, comfort in group discussions, and—at earlier stages—the type of high school and years of prior study emerging as meaningful predictors. These findings show that while institutional background plays a limited and diminishing role, individual engagement and self-perceived competence strongly shape achievement. H2 is likewise confirmed, as the machine learning models combining subjective (survey data) and objective (test scores) indicators achieve high predictive accuracy (R^2 = 0.83–0.95) and stable variable importance rankings across hyperparameter variations, demonstrating their effectiveness and robustness. Overall, both hypotheses are fully supported: students' prior experience and learning behaviors are key determinants of their success, and ensemble decision-tree methods provide a reliable analytical framework for uncovering these relationships.

It is interesting to note that there is no single predictor that has a significant impact on students' success in their English language learning in the first year of study. It turns out that over the course of the first year, the influential factors change. Some predictors that have high importance at one stage lose that importance at later stages.

This study demonstrates that students' academic success in university English courses is shaped less by institutional background factors and more by individual engagement, self-perception, and the strength of their foundational knowledge. While the type of high school and years of study play a limited role, self-evaluation emerges as a significant predictor of both entrance performance and subsequent exam outcomes. Consistent practice and collaborative learning activities not only enhance students' confidence but also contribute to measurable performance gains, particularly in the early stages of study.

The analysis further highlights that specialized achievement in English depends almost entirely on mastery of basic knowledge, confirming the path-dependent nature of language learning. Entrance performance is strongly influenced by students' choice of major, suggesting that motivation and academic orientation are decisive at the point of transition to higher education, but diminish in importance once the course is underway.

These findings suggest that university English programs, especially in technical and scientific fields, should emphasize the development of foundational skills while also encouraging study habits and peer interaction that foster self-confidence. Targeted support at the basic level of instruction is crucial, as success at this stage determines later specialization. By focusing less on institutional background and more on learning behaviors, educators can design more effective and tailored approaches to support diverse cohorts of students in technical disciplines.

The present study is limited by its reliance on self-reported measures of language competence, which may introduce bias despite the strong predictive value of self-evaluation.

In addition, the analysis is based on a single faculty and three specific majors, which may constrain the generalization of the results to other disciplines or institutions. Future research should expand the scope to include larger and more diverse student populations, explore longitudinal effects across multiple semesters, and incorporate additional predictors such as informal language exposure or digital learning practices. Integrating qualitative methods, such as interviews or focus groups, may also provide richer insights into the mechanisms by which study habits and self-perception influence academic outcomes.

Importantly, this study demonstrates the value of applying machine learning methods in educational research. The CART Ensemble and Bagging approaches provided robust models that revealed nuanced relationships between prior experience, self-assessment, and academic outcomes, offering methodological innovation for the field of language education. The findings emphasize that success in English depends less on institutional background and more on consistent practice, self-confidence, and strong foundational knowledge. University language teachers in technical fields can use these insights to design courses that combine skill-building with reflection, promote active engagement, and provide early support in General English as the basis for later ESP achievement.

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Data Availability Statement: The original contributions presented in the study are included in the article; further inquiries can be directed to the corresponding author.

Conflicts of Interest: The authors declare no conflicts of interest.

Appendix A. Surveys' Questions

Appendix A.1. English Language Learning Survey PART 1

Dear students,

This survey seeks to explore your English learning experiences prior to university and assess how these experiences influence your motivation and achievement in your English studies at the University of Plovdiv. It also offers you an opportunity to reflect on your journey of learning English. Please remember that there are no right or wrong answers. Your responses will be kept strictly confidential and used solely for research purposes. The success of this study depends on your participation.

Thank you for your cooperation!

Part A: Demographic Information

Question 1: Student's name and surname

Question 2: Student's full number

Question 3: Gender

1. Male
2. Female
3. Prefer not to say

Question 4: Age

1. younger than 20
2. 20–25
3. 26–30
4. 31 or older

Question 5: Country of origin

1. Bulgaria
2. Other:

Question 6: Family background

1. Big city
2. Small town
3. Village
4. Other:

Question 7: Years of learning English

1. 1–5
2. 6–10
3. 11–15
4. more than 15

Question 8: Type of high school you graduated from:

1. Secondary School of Mathematics
2. Language School
3. General High School (Gymnasium, focused on academic education)
4. Technical School (Technikum, focused on professional skills)
5. Other:

Question 9: How intensively did you study English at school? (You may select more than one option.)

1. 1–2 periods per week
2. 3–5 periods per week
3. Over 5 periods per week
4. Additional classes at a private school or with a private tutor
5. Studied independently

Question 10: Do you have an English language certificate?

1. Yes, an internationally recognized one
2. Yes, issued by a local company
3. No

Question 11: If you have a language certificate, what is your score or language level? Write it down

Question 12: Have you been abroad before coming to study at Plovdiv University?

1. Yes
2. No

Question 13: What was the purpose of your visit abroad? (You may select more than one option.)

1. An excursion
2. A student exchange program
3. I lived (and studied) abroad

4. For business
5. N/A
6. Other:

Question 14: How long did you stay abroad (altogether)?

1. Less than a week
2. A few weeks
3. A few months
4. About a year
5. Longer than a year
6. N/A

Question 15: How did you feel about communicating in English while in a foreign country?

1. Confident and comfortable
2. A bit shy but effective
3. Very shy to the point of avoiding speaking
4. I did not communicate in English
5. N/A

Question 16: What kind of problems have you encountered while in a foreign country? (You may select more than one option.)

1. Difficulty understanding the local accent
2. Local people had difficulty understanding my accent
3. Finding the right words
4. Explaining the essence of what I had in mind
5. Culture-related misunderstandings (critical incidents)
6. N/A
7. Other:

Part B—Language Practice

Question 17: How often do you practice English?

1. All the time
2. Every day
3. Almost every day
4. Every week
5. From time to time
6. Only if I can't avoid it

Question 18: What kind of activities do you use English for most often? (You may select more than one option.)

1. Reading (books, news, articles, etc.)
2. Online shopping
3. Playing games/interacting with game teammates
4. Writing (emails, reports, creative writing, etc.)
5. Listening (to podcasts, the radio, music, etc.)
6. Watching videos/movies/TV shows
7. Social media or online forums
8. Speaking with friends or colleagues
9. Doing homework in your English studies
10. Other:

Question 19: How comfortable do you feel participating in group discussions in English?

1. Very comfortable
2. Comfortable
3. A bit uncomfortable
4. Very uncomfortable
5. I avoid group discussions in English

Question 20: I think it is necessary to know about the culture (e.g., customs, stereotypes, gestures, values) of English-speaking countries to learn the language well.

1. Strongly agree
2. Agree
3. Neither agree nor disagree
4. Disagree
5. Strongly disagree

Question 21: Understanding common gestures in English-speaking countries helps with language learning.

1. Strongly agree
2. Agree
3. Neither agree nor disagree
4. Disagree
5. Strongly disagree

Question 22: Knowing about cultural stereotypes affects my communication in English.

1. Strongly agree
2. Agree
3. Neither agree nor disagree
4. Disagree
5. Strongly disagree

Question 23: Learning about English-speaking values and traditions helps me use the language more naturally.

1. Strongly agree
2. Agree
3. Neither agree nor disagree
4. Disagree
5. Strongly disagree

Part C—Self-Evaluation of English Language Skills
Question 24: How would you evaluate your own English language skills?
Reading

1. Fluent
2. Very good
3. Good
4. Poor
5. Awful

Question 25: Listening with comprehension

1. Fluent
2. Very good
3. Good
4. Poor
5. Awful

Question 26: Speaking

1. Fluent
2. Very good
3. Good
4. Poor
5. Awful

Question 27: Writing

1. Fluent
2. Very good
3. Good
4. Poor
5. Awful

Question 28: My greatest language strengths lie in: (You may select more than one option.)

1. Extensive vocabulary
2. Grammar
3. Listening with understanding
4. Reading with understanding
5. Speaking
6. Expressing my thoughts clearly in writing
7. Writing texts of specific formats (e.g., articles, reports, business correspondence)
8. Making presentations/talking in front of large audiences

Question 29: My greatest language weaknesses are: (You may select more than one option.)

1. Extensive vocabulary
2. Grammar
3. Listening with understanding
4. Reading with understanding
5. Speaking
6. Expressing my thoughts clearly in writing
7. Writing texts of specific formats (e.g., articles, reports, business correspondence)
8. Making presentations/talking in front of large audiences

Thank you very much for your time!

Appendix A.2. English Language Learning Survey PART 2

Dear Students,

Thank you for participating in this follow-up survey. It is designed to evaluate your English language skills at the end of your first semester at the University of Plovdiv and to reflect on your learning experience. This survey will help us explore how your prior English learning experiences influence your motivation and achievements and identify ways to enhance your future learning opportunities. Your responses are invaluable for this research and for improving the English course. Please note that:

- There are no right or wrong answers.
- Your responses will remain strictly confidential and will be used solely for research purposes.

Your participation is crucial to the success of this study, and I deeply appreciate your cooperation.

Question 1: Student's name and surname

Question 2: Student's full number

Question 3: How would you evaluate your own English language skills after the first semester at FMI?

1. Significant improvement
2. Moderate improvement
3. Slight improvement
4. No change
5. Slight worsening

Question 4: In your opinion, what is the reason for that (lack of) change? (Select all that apply)

1. My participation in classwork
2. The homework assignments I completed
3. The project work I undertook
4. The test based on a short story
5. Collaboration with other students
6. The teacher
7. Other:

Question 5: What could motivate you to work harder in English during the second semester? (Select all that apply)

1. More engaging classwork assignments
2. More interesting homework assignments
3. Challenging project assignments
4. More opportunities for collaboration with other students
5. Studying specialized vocabulary
6. Studying grammar
7. Other:

Question 6: What are your recommendations for improving English classes or for the teacher? Write it down

Thank you once again for your time and valuable input!

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