

Academic Procrastination in E-Learning Environments: Assessment, Machine-Learning Classification, and an AI-Based Support Approach

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ABSTRACT

This study examined academic procrastination among university students in e-learning environments, its associations with demographic and educational characteristics, and the feasibility of using machine learning and artificial intelligence to support learner analysis and intervention. The study was applied in purpose and quantitative in approach and was conducted in five stages. Main data were obtained from 222 university students using a 22-item researcher-developed Academic Procrastination Questionnaire for E-Learning, developed from the content themes of the Solomon and Rothblum (1984) scale and contextualized for e-learning. Descriptive and inferential statistical procedures were used to examine procrastination and its associations with student characteristics. Decision Tree, Random Forest, and Support Vector Machine algorithms were then evaluated for auxiliary classification of procrastination into low, moderate, and high operational levels, using 49 demographic and educational features and excluding questionnaire items and derived scores to prevent information leakage. Finally, a preliminary intelligent support system was designed and evaluated through a seven-day intervention with 20 students divided into intervention and control groups. The mean academic procrastination score in the main sample was 59.57. Random Forest produced an accuracy of 0.4667 and an F1-score of 0.4697 on the held-out test set, exceeding the baseline accuracy of 0.3333. In the preliminary support evaluation, the intervention group's mean score decreased from 73.10 to 70.80, and the within-group change was statistically significant; the change also differed significantly from that of the control group. The findings support the feasibility of an integrated framework combining direct assessment, auxiliary machine learning, and intelligent support, while the small preliminary intervention sample and short duration require cautious interpretation and further evaluation in larger and longer studies.

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Introduction

E-learning has expanded the ways in which university education can be accessed, organized, and experienced. Its flexibility in time and place, digital access to learning resources, and opportunities for asynchronous and online interaction can increase learner autonomy, but they also transfer a larger share of planning and monitoring responsibility from the instructor to the learner. In asynchronous and technology-mediated settings, students must decide when to study, how to sequence activities, and how to respond to deadlines with less immediate external supervision. Research on self-regulation in online courses has therefore emphasized the importance of learners' ability to organize and monitor their academic behavior, while recent work has also documented challenges associated with online study in higher education ([Han et al., 2023](#); [Wu et al., 2025](#)).

Academic procrastination is particularly relevant to this environment because it concerns voluntary delay in initiating or completing intended tasks despite expecting that the delay may be undesirable ([Solomon & Rothblum, 1984](#); [Steel, 2007](#)). From a self-regulated learning perspective, procrastination is linked to failures or difficulties in planning, monitoring, motivation, and behavioral regulation rather than to time management alone ([Ferrari, 1998](#); [Steel, 2010](#); [Steel & Klingsieck, 2016](#); [Wolters, 2003](#)). Online courses can intensify these demands because the learner has greater control over when to engage with recorded content, assignments, and other learning activities. Empirical studies have consequently examined procrastination in online courses in relation to self-regulated learning and anxiety, and have shown that procrastination in digital settings is intertwined with motivational and emotional processes ([Afridi et al., 2023](#); [Cheng & Xie, 2021](#); [Liu et al., 2020](#); [Ma et al., 2022](#); [Wu & Fan, 2017](#); [Zimmerman, 1990](#)).

Measurement is a central issue in this area. Self-report instruments provide direct information about the learner's perception of delay-related behavior and its cognitive or motivational correlates, whereas behavioral approaches use traces such as assignment start time, submission timing, or sequences of activity recorded in learning systems ([Abdollahi et al., 2026](#); [Ghorbankhani & Salehi, 2025](#); [González-Brignardello & Paniagua, 2023](#); [Michinov et al., 2011](#); [Solomon & Rothblum, 1984](#); [Tan & Samavedham, 2022](#); [Tuckman, 1991](#)). These approaches are complementary but not interchangeable. A delayed action observed in a learning management system does not automatically establish psychological procrastination; students may delay for strategic reasons or may maintain adequate performance despite late starts. Recent work has explicitly distinguished different patterns of academic delay and has cautioned against treating every observed delay as procrastination ([Kim et al., 2025](#)). This distinction is especially important when machine learning models are trained on behavioral labels derived from system traces.

The use of educational data mining and machine learning has nevertheless created opportunities to move from descriptive analyses toward computational estimation of learner states. Research has used assignment submission behavior, temporal patterns, and other learning-management-system indicators to predict or classify procrastination-related behavior ([Albreiki et al., 2021](#); [Cerezo et al., 2017](#); [Yağcı, 2022](#); [Yang et al., 2020](#)). Other studies have compared multiple machine learning models or applied ensemble methods to identify patterns associated with academic delay ([Imhof et al., 2023](#); [Izourane et al., 2026](#); [Sartana et al., 2025](#)). Reviews of educational machine learning emphasize that model performance is strongly dependent on the quality and meaning of the input features, the definition of the target variable, and the characteristics of the study context ([Alalawi et al., 2023](#)). Thus, machine learning can be useful as an auxiliary analytical tool, but model output should not be treated as equivalent to a validated psychological assessment unless that equivalence has been established.

A second development concerns the use of artificial intelligence to support learning behavior rather than only predict it. Recent research has explored data-driven feedback, intelligent feedback systems, digital interventions, and chatbot-supported approaches to self-regulation and procrastination. [Rakhmetov et al. \(2025\)](#), for example, examined an AI-based feedback system intended to support self-regulated learning in digital education platforms, whereas [Lee et al. \(2025\)](#) evaluated a mobile intervention augmented with a semigenerative chatbot for university students. Structured self-regulation training has also been examined as an intervention for students with procrastination tendencies ([Keyvan et al., 2025](#)). These studies indicate a movement from prediction toward support, but the stages of psychometric assessment, computational estimation, decision rules, interaction, and intervention have often been examined separately.

The literature reviewed in the thesis suggests a limitation in integrating these approaches. Psychometric studies establish measurement quality, psychological studies clarify relations with self-regulation and motivation, learning-management-system studies analyze behavioral traces, and machine learning extends computational estimation. Yet

the measurement, estimation, decision, and support stages are often examined separately ([Imhof et al., 2023](#); [Keyvan et al., 2025](#); [Rakhmetov et al., 2025](#)).

The present study was designed in response to this integration gap. It combines direct assessment of academic procrastination in e-learning with an operational three-level classification, auxiliary machine learning based only on demographic and educational information, and a preliminary intelligent support system that uses direct assessment, model output, operational learner profiles, activity status, and rule-based decisions to select support. The system also includes a conversational component that generates textual feedback from the information supplied by the system rather than making the support decision itself. This distinction preserves a separation between direct measurement and computational estimation and limits the risk of information leakage in the machine learning stage.

Accordingly, the study addressed five connected questions: What is the observed level and distribution of academic procrastination among university students using e-learning? How is procrastination associated with selected demographic and educational characteristics? To what extent can Decision Tree, Random Forest, and Support Vector Machine algorithms classify the operational level of procrastination from non-questionnaire features? Which input features have greater relative importance in the classification models? And, as a preliminary feasibility evaluation, are measurable changes in procrastination observed during a seven-day intelligent support program, together with evidence of system use and interaction? The study therefore positions machine learning as an auxiliary component within a broader support framework rather than as a substitute for direct assessment or a diagnostic instrument. This position is also consistent with recent studies emphasizing the context dependence of academic procrastination and learner characteristics ([Rad et al., 2025](#); [Zhao et al., 2025](#)).

Method

Sample and Sampling Method

The study population comprised students enrolled in universities and other higher education institutions in Iran who were using e-learning during the study period. Data collection was conducted from 29 May to 4 June 2026, coinciding with wartime conditions in Iran. During this period, university instruction was conducted virtually through electronic platforms. A convenience sampling procedure was used. The questionnaire was administered electronically through the Porsline platform, and the survey link was distributed through social networks and messaging applications. A total of 225 responses were collected; three invalid responses were excluded, leaving 222 valid cases for the main analysis. The final sample included 127 women (57.21%) and 95 men (42.79%). Most participants were bachelor's students (166, 74.77%), followed by master's students (52, 23.42%) and doctoral students (4, 1.80%). Participants ranged in age from 18 to 54 years, with a mean age of 24.43 years ($SD = 6.60$). Regarding daily e-learning use, 76 students (34.23%) reported less than 2 h, 83 (37.39%) reported 2–4 h, 44 (19.82%) reported 4–6 h, and 19 (8.56%) reported 6–8 h. By university type, participants were distributed across Islamic Azad universities ($n = 99$, 44.59%), public universities ($n = 48$, 21.62%), non-profit universities ($n = 41$, 18.47%), and virtual universities ($n = 34$, 15.32%).

Tools Used

Academic Procrastination Questionnaire:

Academic procrastination was measured using a 22-item researcher-developed Academic Procrastination Questionnaire for E-Learning. The instrument was developed based on the content themes and components of the academic procrastination scale developed by Solomon and Rothblum (1984) and was rewritten, expanded, integrated, and contextualized for e-learning environments. It was not treated as a direct translation or a shortened version of the original instrument. Items were rated on a five-point Likert scale ranging from 1 (never) to 5 (always). Items 20, 21, and 22 were reverse scored. The theoretical score range was 22–110, with higher scores indicating greater academic procrastination.

The content validity of the questionnaire was reviewed by the thesis supervisor and co-supervisor. In a pilot sample of 30 students, Cronbach's alpha was .945. Test–retest reliability was assessed with the same 30 participants, with the first administration conducted on May 17, 2026, and the second administration conducted on May 25, 2026, eight days later. The correlation between the total scores obtained in the two administrations was $r = .923$, $p < .001$. For the final sample of 222 students, Cronbach's alpha was .941.

Because no normative or diagnostic cut scores were available for this researcher-developed instrument, three operational levels of academic procrastination were defined based on the distribution of scores in the main sample.

The 33.33rd percentile was 51, and the 66.67th percentile was 66.67. Accordingly, scores of 51 or lower were classified as low, scores from 52 to 66 as moderate, and scores of 67 or higher as high. These categories were used solely for the descriptive and computational analyses of the present study and should not be interpreted as clinical, diagnostic, or general normative classifications.

Procedure

The study was applied in purpose and quantitative in approach and was implemented in five stages. First, academic procrastination in e-learning was assessed using the researcher-developed questionnaire. Second, procrastination scores and operational levels were examined in relation to demographic and educational variables. Third, machine learning models were evaluated for auxiliary classification of the operational procrastination level. Fourth, an intelligent support system was designed and implemented. Fifth, the system was examined preliminarily through a seven-day intervention and control procedure. The staged design kept direct measurement, statistical analysis, computational estimation, and support selection conceptually distinct.

For the statistical analyses, the total procrastination score was examined descriptively, and relationships with demographic and educational variables were analyzed using the statistical procedures documented in the thesis. For the machine learning stage, the operational procrastination level (low, moderate, or high) was defined as the target variable. Questionnaire items 1–22, the total procrastination score, and variables directly derived from the target were excluded from the model inputs to prevent information leakage. The final feature set contained 49 features. The data were divided into training and held-out test sets using stratification and random seed 42, and five-fold stratified cross-validation was conducted on the training set only.

Three algorithms were evaluated: Decision Tree, Random Forest, and Support Vector Machine (SVM). Random Forest was implemented with 200 trees, while SVM used an RBF kernel with standardization in a processing pipeline. The models were evaluated using accuracy, macro-averaged precision, macro-averaged recall, macro-averaged F1-score, and cross-validation accuracy. A baseline accuracy of 0.3333 was used for comparison. Feature importance was examined for the Decision Tree and Random Forest models and was interpreted as model-based importance rather than a causal effect.

The intelligent support system was designed to provide personalized support based on students' demographic and educational characteristics, directly assessed procrastination status, auxiliary machine-learning estimates, operational learner profiles, and recorded activity status. First, questionnaire responses were used to determine the direct procrastination score and operational level. Demographic and educational characteristics were also used as inputs to the Random Forest model to provide an auxiliary estimate of the procrastination level. The resulting information was combined with the learner's operational profile and activity status to select appropriate support through predefined rules. The system then provided textual feedback and conversational support through a large language model, while student activities and interactions were recorded to monitor progress and adjust subsequent support.

The preliminary evaluation was conducted as a seven-day procedure with 20 students divided into intervention and control groups. Both groups completed the questionnaire before and after the program. The intervention group used the support program and interactive system functions, whereas the control group continued their usual educational activities without dedicated system support. Change scores were calculated as posttest minus pretest. Within-group changes were examined using the Wilcoxon signed-rank test, and change scores between the two groups were compared using the Mann–Whitney U test.

Results

The final main sample comprised 222 valid cases, with no missing values or duplicate records. Academic procrastination scores ranged from 22 to 106, with a mean of 59.5721 ($SD = 18.0683$), a median of 59.5000, and a variance of 326.4631. Based on the operational, sample-derived cut points, 76 students (34.23%) were classified as having low procrastination, 72 (32.43%) as moderate, and 74 (33.33%) as high. Thus, the three operational categories were relatively balanced in frequency; however, these categories represent descriptive classifications specific to the study sample and are not normative or diagnostic levels.

Among the 22 questionnaire items, Item 1, which concerned delaying the viewing of recorded course videos until the final days of the semester, had the highest mean ($M = 3.387$, $SD = 1.189$). Item 15, concerning late submission of a student's share of an online group assignment, had the lowest mean ($M = 1.716$, $SD = 1.070$).

The normality tests did not provide sufficient evidence to reject the normality of the total procrastination score. The Shapiro–Wilk test yielded $W = 0.9912$, $p = .196905$, while the Kolmogorov–Smirnov test yielded $D = 0.0413$, $p = .827430$. Nevertheless, the inferential analyses were selected according to the type and measurement scale of the variables and the analytical procedures specified in the thesis. Spearman's rank-order correlation was used to examine the association between age and total procrastination score, whereas chi-square tests were used to examine associations between categorical variables and operational procrastination level.

Age was significantly and inversely associated with total academic procrastination score (Spearman's $\rho = -0.2844$, $p = .000017$), indicating that higher age was associated with lower procrastination scores in the study sample. Gender was not significantly associated with operational procrastination level, $\chi^2(2) = 5.2434$, $p = .072677$, Cramer's $V = .1537$. Daily e-learning use was significantly associated with operational procrastination level, $\chi^2(6) = 13.7686$, $p = .032331$, Cramer's $V = .1761$. Educational level was also significantly associated with operational procrastination level, $\chi^2(4) = 12.4326$, $p = .014408$; however, 33.33% of the cells had expected frequencies below 5, requiring cautious interpretation.

Semester was not significantly associated with operational procrastination level, $\chi^2(18) = 14.788$, $p = .676$. However, 53.33% of the cells had expected frequencies below 5, and the minimum expected frequency was 0.32; therefore, this result should also be interpreted cautiously. University type was significantly associated with operational procrastination level, $\chi^2(6) = 16.4759$, $p = .011415$, Cramer's $V = .1926$. Overall, these inferential results represent statistical associations observed in the study sample and should not be interpreted as evidence of causal relationships.

Tables

Table 1. Associations between demographic/educational characteristics and academic procrastination

Predictor	Criterion	Test statistic	p	Interpretation
Age	Total procrastination score	Spearman $\rho = -0.2844$	$p = .000017$	Significant
Gender	Operational level	$\chi^2(2) = 5.2434$; $V = .1537$	$p = .072677$	Not significant
Daily e-learning use	Operational level	$\chi^2(6) = 13.7686$; $V = .1761$	$p = .032331$	Significant
Educational level	Operational level	$\chi^2(4) = 12.4326$	$p = .014408$	Significant*
Semester	Operational level	$\chi^2(18) = 14.788$	$p = .676$	Not significant*
University type	Operational level	$\chi^2(6) = 16.4759$; $V = .1926$	$p = .011415$	Significant

Note. * Educational-level and semester chi-square results require caution because 33.33% and 53.33% of cells, respectively, had expected counts below 5. The analyses show association, not causation.

The machine learning target was the three-level operational classification. After leakage control and encoding, 49 features were available for modeling. On the held-out test set, the Decision Tree achieved accuracy = 0.4444, macro precision = 0.4751, macro recall = 0.4444, and macro F1 = 0.4470; its five-fold cross-validation accuracy mean was 0.3903 (SD = 0.0418). Random Forest achieved accuracy = 0.4667, macro precision = 0.4858, macro recall = 0.4667, and macro F1 = 0.4697; its five-fold cross-validation accuracy mean was 0.4243 (SD = 0.0622). SVM achieved accuracy = 0.4000, macro precision = 0.4046, macro recall = 0.4000, and macro F1 = 0.3986; its five-fold cross-validation accuracy mean was 0.3848 (SD = 0.0564). The baseline test accuracy was 0.3333. Thus, all three tested algorithms exceeded the baseline on held-out accuracy, while the overall classification performance remained modest. Random Forest was retained as the auxiliary model used in the support system.

Table 2. Machine learning performance on the held-out test set and five-fold cross-validation

Model	Accuracy	Macro Precision	Macro Recall	Macro F1	CV Accuracy Mean (SD)
Decision Tree	0.4444	0.4751	0.4444	0.4470	0.3903 (0.0418)
Random Forest	0.4667	0.4858	0.4667	0.4697	0.4243 (0.0622)
SVM	0.4000	0.4046	0.4000	0.3986	0.3848 (0.0564)

Note. The test set contained 45 observations. The baseline accuracy was 0.3333. Random Forest used 200 trees; SVM used an RBF kernel with standardization.

Feature-importance analysis showed a similar pattern across the two tree-based models. In the Decision Tree, the highest relative importance values were for age (0.206237), daily e-learning use (0.116973), and semester (0.098133), followed by Psychology (0.087585), Islamic Azad university (0.084179), Computer Engineering (0.064093), non-profit university (0.061329), gender (0.047646), Architecture (0.037599), and virtual university

(0.032818). In Random Forest, the leading features were age (0.227919), semester (0.143114), daily e-learning use (0.121710), gender (0.062526), Computer Engineering (0.048289), Islamic Azad university (0.046592), educational level (0.037281), Psychology (0.032577), public university (0.027904), and non-profit university (0.026919). These values represent relative model importance and do not establish that any feature causes academic procrastination.

Table 3. Top relative feature-importance values for the tree-based models

Feature	Decision Tree	Random Forest
Age	0.206237	0.227919
Semester	0.098133	0.143114
Daily e-learning use	0.116973	0.121710
Gender	0.047646	0.062526
Computer Engineering	0.064093	0.048289
Islamic Azad university	0.084179	0.046592
Educational level	—	0.037281
Psychology	0.087585	0.032577
Public university	—	0.027904
Non-profit university	0.061329	0.026919

Note. Importance values indicate relative contribution to the models' decision process and do not imply causal or direct effects on procrastination.

The preliminary seven-day support evaluation included 20 students, with 10 in the intervention group and 10 in the control group. The intervention group's mean procrastination score decreased from 73.10 at pretest to 70.80 at posttest, a change of -2.30 points. The control group's mean increased from 60.50 to 61.00, a change of $+0.50$ points. The intervention-group Wilcoxon test produced a standardized statistic of -2.536 , $p = .011$, with an effect size of $.802$. The corresponding control-group statistic was 0.312 , $p = .755$, with an effect size of $.099$. The Mann–Whitney comparison of change scores produced $U = 23.000$, standardized statistic $= -2.081$, asymptotic $p = .037$, and exact two-tailed $p = .043$, with an effect size of $.465$. Given the small sample, the exact p value was treated as the primary result in the thesis. At the operational level, two intervention students (20%) moved down one level—one from high to moderate and one from moderate to low—while eight remained in the same level and none moved to a higher level. All 10 control students remained in the same operational level.

Table 4. Preliminary seven-day support evaluation

Group/Analysis	Statistic	Value
Intervention (n = 10)	Pretest mean	73.10
Intervention (n = 10)	Posttest mean	70.80
Intervention (n = 10)	Mean change	-2.30
Control (n = 10)	Pretest mean	60.50
Control (n = 10)	Posttest mean	61.00
Control (n = 10)	Mean change	$+0.50$
Within intervention	Wilcoxon z / p	$-2.536 / .011$
Within control	Wilcoxon z / p	$0.312 / .755$
Between-group change	Mann–Whitney $U / \text{exact } p$	$23.000 / .043$
Between-group change	Effect size	0.465

Note. Change = posttest – pretest. The exact two-tailed p value (.043) was treated as primary in the thesis because of the small preliminary sample. No random assignment is reported in the thesis.

System-use records provided additional descriptive evidence about feasibility. A total of 131 support-program records were registered. The most frequent operational profiles were pressure/guilt (35 records), task initiation (21), task difficulty (20), general procrastination (14), educational content (14), group activity (7), academic participation (7), help-seeking (6), and no specific profile (7). Across 67 daily monitoring records, 10 were complete (14.93%), 36 partial (53.73%), and 21 not started (31.34%). Fifty-five monitoring records contained actual time information, representing 2,805 total minutes, a mean of 51 minutes among non-missing observations, and a range of 0–240 minutes. The intelligent coach was used in 44 of the 67 monitoring records, while 23 records indicated no coach use. A separate conversation log contained 46 interaction records from eight students. These indicators document implementation and engagement patterns but were not used to establish the efficacy of the intervention.

intervention.

Discussion

The present study aimed to examine academic procrastination among university students in e-learning environments, investigate its relationships with demographic and educational characteristics, evaluate the ability of machine-learning models to classify operational procrastination levels using non-questionnaire information, and preliminarily examine an intelligent support system. The findings showed substantial variation in academic procrastination, with a mean score of 59.57. Age was significantly and inversely associated with total procrastination, while daily e-learning use, educational level, and university type were significantly associated with operational procrastination level. Gender and semester were not significantly associated with the three operational categories. Among the machine-learning models, Random Forest achieved the highest test accuracy and macro F1-score, although overall predictive performance remained modest. The preliminary intervention also showed a reduction in procrastination in the intervention group and a significant difference in change scores between the two groups.

The mean score and distribution of students across the three operational categories indicate heterogeneity in procrastination experiences. Because the cut-off points were derived from the 33.33rd and 66.67th percentiles of the present sample, these categories should be interpreted as study-specific operational levels rather than normative or diagnostic classifications. At the item level, postponing the viewing of recorded course videos had the highest mean, suggesting that delayed engagement with asynchronous content may be particularly relevant in e-learning. This finding is consistent with research emphasizing the importance of self-regulation, planning, and learner autonomy in online education ([Cheng & Xie, 2021](#); [Han et al., 2023](#)). The presence of students with low procrastination scores also indicates that e-learning itself is not sufficient to explain procrastination; rather, procrastination is likely shaped by interacting individual and contextual factors ([Steel, 2007](#); [Steel & Klingsieck, 2016](#)).

Age showed a significant inverse relationship with academic procrastination, indicating that older students tended to report lower procrastination scores. Greater educational and life experience may be associated with more developed planning and task-management skills, although this explanation cannot be established causally by the present correlational design. Previous meta-analytic evidence has likewise indicated that academic procrastination tends to decrease with age ([Steel, 2007](#)). In contrast, gender was not significantly associated with operational procrastination level. This result suggests that gender had limited explanatory value in the present sample, while previous research has highlighted psychological variables such as self-efficacy, emotional regulation, and self-regulation as important correlates of procrastination ([Liu et al., 2020](#); [Rad et al., 2025](#)).

Daily e-learning use was significantly associated with operational procrastination level. However, time spent online should not be interpreted as a direct cause of procrastination, because similar amounts of online activity may reflect regular engagement, fragmented participation, or intensive last-minute study. Previous research based on learning-management-system data has shown that temporal and participation patterns can provide useful information about procrastination-related behavior ([Cerezo et al., 2017](#); [Tan & Samavedham, 2022](#); [Yang et al., 2020](#)). Educational level and university type were also significantly associated with operational procrastination, although the educational-level result requires caution because 33.33% of cells had expected frequencies below five. Likewise, the significant association with university type was modest in magnitude. These findings may reflect differences in academic structure, learning conditions, and student characteristics rather than direct institutional effects. Semester, by contrast, was not significantly associated with operational procrastination, suggesting that academic progression alone does not necessarily correspond to systematic differences in procrastination.

The machine-learning results complement these inferential findings. Although all three models exceeded the 0.3333 baseline on the held-out test set, their predictive performance remained limited. Random Forest obtained the highest accuracy (0.4667) and macro F1-score (0.4697), with a cross-validation accuracy of 0.4243 (SD = 0.0622). These results indicate that demographic and educational characteristics contain some predictive information but are insufficient for accurate classification of procrastination. This is consistent with educational machine-learning research showing that predictive performance depends strongly on the richness and relevance of the input features ([Alalawi et al., 2023](#); [Ersozlu et al., 2024](#)). Studies specifically focused on procrastination have also shown the value of behavioral indicators such as assignment initiation and submission timing ([Akram et al., 2019](#); [Imhof et al., 2023](#); [Yang et al., 2020](#)).

Feature-importance analysis identified age, semester, and daily e-learning use among the leading variables in the tree-based models. These findings suggest that such characteristics may be useful for learner profiling, but their importance should not be interpreted as evidence of causality. The fact that semester was relatively important in the

tree-based models despite its non-significant chi-square association further demonstrates that statistical association and predictive contribution represent different analytical concepts. Thus, feature importance is best used to identify potentially informative variables for future modeling rather than causal determinants of procrastination.

The preliminary intelligent-support evaluation showed a decrease in the intervention group's mean procrastination score from 73.10 to 70.80, whereas the control group's mean increased from 60.50 to 61.00. The within-group change in the intervention group was significant ($z = -2.536$, $p = .011$), and the exact two-tailed Mann–Whitney comparison of change scores was also significant ($U = 23.000$, $p = .043$). Two intervention participants moved down by one operational level, while no participant moved to a higher level. This pattern is compatible with previous research on AI-supported feedback, chatbot-assisted interventions, and self-regulation training ([Keyvan et al., 2025](#); [Lee et al., 2025](#); [Rakhmetov et al., 2025](#)).

Nevertheless, the intervention findings should be interpreted as preliminary. The evaluation included only 20 students, lasted seven days, random assignment was not reported, and the intervention group had a higher pretest mean than the control group. Consequently, regression toward the mean, baseline imbalance, and other uncontrolled factors may have contributed to the observed change. The results therefore provide preliminary evidence of different short-term change patterns rather than conclusive evidence of causal intervention effectiveness.

A key contribution of the study is the integration of assessment, computational estimation, and support within a single framework. Direct questionnaire responses were used to determine the procrastination score and operational level; demographic and educational characteristics were processed through Random Forest as an auxiliary estimate; predefined rules then combined these results with operational learner profiles and activity status to select support. The language model generated feedback and conversational responses but did not independently determine the student's condition or intervention. This architecture preserves the distinction between psychological assessment, machine-learning estimation, rule-based decision-making, and AI-generated communication.

The system records further indicate implementation feasibility. During the seven-day period, 131 support-program records and 67 monitoring records were registered. The intelligent coach was used in 44 monitoring records, and 46 conversation records were generated by eight students. These data demonstrate that differentiated support, monitoring, and interaction could be recorded in practice; however, usage frequency should not be interpreted as evidence of effectiveness because these records were primarily descriptive.

Several limitations should be considered. Convenience sampling limits generalizability, and the researcher-developed self-report instrument may be influenced by individual response conditions. The sample-derived cut-off points should not be treated as normative or diagnostic. The machine-learning sample was relatively small for three-class classification with 49 features, limiting model stability and external generalizability. The intervention was also short and involved only 20 students without reported random assignment. Future studies should therefore use larger and more diverse samples, validate the instrument and models externally, incorporate dynamic LMS indicators such as login patterns, content viewing, task initiation, and submission timing, and examine psychological variables such as self-regulated learning, motivation, self-efficacy, and academic anxiety. Longer and randomized intervention studies are also needed to examine the sustainability of AI-supported changes in procrastination.

Overall, the findings indicate that academic procrastination in e-learning cannot be adequately explained by a single demographic characteristic or predicted accurately from static background information alone. Direct assessment remains important, whereas machine learning can provide complementary learner information and intelligent systems can translate assessment results into differentiated support. The principal value of the proposed framework therefore lies in connecting measurement, auxiliary prediction, decision-making, and personalized support within an integrated e-learning environment.

Conclusion

The present study investigated academic procrastination among students in e-learning environments using an integrated framework that combined direct assessment, analysis of learner characteristics, machine-learning-based auxiliary classification, and intelligent support. Academic procrastination varied considerably across students; age showed an inverse relationship with total procrastination, while daily e-learning use, educational level, and university type were associated with operational procrastination level. Gender and semester were not significantly associated with the operational categories.

The machine-learning results showed that demographic and educational characteristics provided limited predictive information. Although all three models exceeded the baseline, Random Forest achieved the highest held-out performance, with an accuracy of 0.4667 and macro F1-score of 0.4697. The preliminary seven-day support evaluation showed a reduction in the intervention group's mean procrastination score and a statistically significant difference in change scores between the intervention and control groups. Given the small sample, short duration, baseline difference, and absence of reported random assignment, these findings should be regarded as preliminary.

The main contribution of the study is the integration of direct psychological assessment, auxiliary machine-learning estimation, rule-based support selection, and AI-generated feedback within a unified e-learning framework. This approach positions machine learning as a complementary tool rather than a substitute for psychological assessment and provides a basis for future research using larger samples, richer behavioral data, and more rigorous longitudinal intervention designs.

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