

Predicting Student Performance in a Design Entrepreneurship and Leadership Course: Leveraging Academic Metrics

Dr. Sajid Khalifa

Effat University, Jeddah, Saudi Arabia

Predicting and understanding student performance is a critical challenge for design education programs, as it enables educators to identify at-risk students, allocate resources effectively, and enhance teaching strategies to support student success. This study investigates the use of academic metrics to develop a predictive model for student performance in a "Design Entrepreneurship and Leadership" course at Effat University. The academic record data collected includes student attendance, quiz grades, midterm exam grades, final exam grades, and assignment project grades. Using a multiple linear regression approach, this research examined the relative influence of these factors on the students' final course performance. The results indicate that quiz grades, midterm exam grades, and assignment project grades were the strongest predictors of student success, while attendance grades also contributed significantly to the model. The proposed predictive model provides valuable insights for design educators and program administrators. By understanding the key drivers of student performance, they can identify at-risk students early on and implement targeted interventions to improve learning outcomes. Additionally, the findings can inform curriculum development, assessment practices, and the allocation of resources within design program's other courses. This study contributes to the limited but growing body of research on predicting student performance in design-focused courses. By leveraging academic metrics, the researchers demonstrate a rigorous and data-driven approach to forecasting student success, which can be adapted and applied to a variety of design education contexts. The findings have important implications for enhancing the quality and effectiveness of design curricula, ultimately preparing students for the complex challenges they will face in the professional world.

Keywords: Design education, student performance prediction, multiple linear regression, academic metrics, design entrepreneurship, design leadership, curriculum development, assessment practices.

1. Introduction

The design program at Effat university and the course:

Effat University in Jeddah, Saudi Arabia offers a Bachelor of Science in Design program that

prepares students for careers in various design fields. The program covers two majors, namely, interior design, and product design, providing a well-rounded education in both the theoretical and practical aspects of design.

The curriculum includes courses in design fundamentals, technology and systems, design history, and design studio projects, giving students the opportunity to develop their creative skills and gain hands-on experience. The program also encourages interdisciplinary learning, allowing students to explore the intersection of design with other fields like business, technology, and sustainability.

Need for this research

Accurately predicting student performance in design-focused courses is crucial for improving educational outcomes and supporting student success [1,2]. Design education programs play a vital role in preparing the next generation of innovators, entrepreneurs, and leaders [3,4]; however, design students often navigate complex, multifaceted challenges that can impact their academic performance [5,6].

Prior research has explored the use of various academic metrics, such as attendance, quiz grades, exam scores, and project performance, to forecast student achievement in design-related disciplines [7,8]. However, the majority of these studies have focused on traditional design studio courses or engineering programs, leaving a gap in the literature regarding the specific context of design entrepreneurship and leadership courses [5,9].

This study aims to address this gap by developing a predictive model for student performance in a "Design Entrepreneurship and Leadership" course at Effat University, a leading institution for men and women in Saudi Arabia. By leveraging academic record data, including attendance, quiz grades, midterm exam grades, final exam grades, and assignment project grades, the researcher seek to identify the key factors that contribute to student success in this design-focused, entrepreneurial learning environment [10,11].

The findings of this study can provide valuable insights for design educators and program administrators, enabling them to implement targeted interventions, refine assessment practices, and enhance the overall quality and effectiveness of design entrepreneurship and leadership curricula [12,13]. This research contributes to the limited but growing body of literature on predicting student performance in design-focused courses, which can be adapted and applied to a variety of educational contexts [9,5].

2. Literature Review

The ability to accurately predict student performance in design-focused courses has been a longstanding area of interest for educators and researchers [2, 14]; however, students in these programs often navigate complex, multifaceted challenges that can impact their academic achievement [15, 16].

Past researchers have indeed made use of similar academic metrics, such as attendance, quiz grades, exam scores, and project performance, to forecast student success in design-related disciplines [17], [18]. For example, Alves et al. [2] investigated the impact of problem-based learning (PBL) approaches on student performance in engineering design courses, finding that

PBL fostered deeper conceptual understanding and improved project outcomes. Similarly, Beattie et al. [13] examined the relationship between student learning approaches (deep vs. surface) and academic achievement in accounting education, highlighting the importance of cultivating a deep, meaningful engagement with course material.

While these studies provide valuable insights into the factors that influence student performance in traditional design studio courses or engineering programs, there is a notable gap in the literature regarding the specific context of design entrepreneurship and leadership courses [9, 15]. These specialized programs often integrate design thinking, business acumen, and leadership development, presenting unique challenges and opportunities for student learning and achievement [19, 10].

To address this gap, Arbaugh [11] examined the relationship between virtual classroom characteristics and student satisfaction in internet-based MBA courses, underscoring the importance of creating engaging, interactive learning environments. Additionally, Baran [12] explored the transformative potential of pedagogical approaches that emphasize connection, participation, and active learning in higher education settings.

Furthermore, Hou [9] investigated the integration of community engagement with problem-based learning in education, demonstrating the benefits of fostering real-world, contextual learning experiences. Similarly, Dym et al. [15] proposed a framework for engineering design thinking, teaching, and learning, highlighting the need for holistic, interdisciplinary approaches that nurture creativity, critical thinking, and problem-solving skills.

Taken together, these studies suggest that predicting student performance in design-focused, entrepreneurial learning environments requires a comprehensive understanding of the unique challenges and opportunities inherent in these programs ([16], [2]). By leveraging academic record data and exploring the interplay between various factors, researchers can develop robust predictive models that inform educational practices and support student success ([17], [18]).

Hypothesis

- Academic metrics such as midterm exam grades, final exam grades, and assignment project grades will be the strongest predictors of student performance in the "Design Entrepreneurship and Leadership" course.
- Attendance and quiz grades will also contribute significantly to the predictive model for student performance in the "Design Entrepreneurship and Leadership" course.
- The predictive model, which leverages academic metrics, will provide valuable insights for design educators and program administrators to identify at-risk students early on and implement targeted interventions to improve learning outcomes.
- The findings from this study will inform curriculum development, assessment practices, and the allocation of resources within the design program's other courses.
- The rigorous, data-driven approach used in this study to predict student success can be adapted and applied to a variety of design education contexts, contributing to the limited but growing body of research on this topic.

3. Methodology

This study utilized a multiple linear regression analysis to examine the relationship among various academic performance indicators and the “Actual-Final Grade” for a group of 22 students in phase one.

The independent variables included in the model were:

- Attendance [Out of 100]
- Quiz 1 [Out of 100]
- English competency [Out of 100]
- Midterm [Out of 100]
- Reflection paper [Out of 100]
- Final project [Out of 100]
- Position paper [Out of 100]
- VP (Value Points initiative)_SPRING2024 [Out of 100]

The dependent variable was the “Actual-Final Grade”, which represented the students' final course performance.

The regression analysis was conducted using Excel software. Several key regression statistics were examined to assess the model's overall fit and explanatory power:

- **Multiple R:** This statistic measures the strength of the correlation between the independent variables and the dependent variable. A value close to 1 indicates a strong positive correlation.
- **R Square:** Also known as the coefficient of determination, this metric quantifies how much of the variation in the dependent variable is explained by the independent variables in the model. Values closer to 1 indicate better model fit.
- **Adjusted R Square:** This statistic adjusts the R Square value to account for the number of predictors in the model, providing a more accurate assessment of the model's predictive power.
- **Standard Error:** This represents the average amount that the observed values vary from the predicted values. Lower values indicate greater precision in the model's predictions.
- **F-statistic and Significance F:** These statistics test the overall significance of the regression model.

A low Significance F value (below 0.05) indicates the model is a good fit for the data.

The regression coefficients for each independent variable were also examined to understand the direction and magnitude of their relationship with the Actual-Final Grade. The statistical

significance of these coefficients was assessed using p-values, with a threshold of 0.05 used to determine statistical significance at the 95% confidence level.

Finally, the residuals from the regression model were analyzed to ensure there were no clear patterns or systematic biases, further confirming the appropriateness of the model. The range and distribution of the residuals were examined to ensure they fell within reasonable bounds.

This rigorous statistical approach provides a comprehensive assessment of the relationships between the academic performance indicators and the Actual-Final Grade, and lays the foundation for further experimentation and refinement of the model.

Data Preparation

The data has been collected and used from the real course outcomes and the dataset includes the results for 22 students for Spring 2024 batch that will be used as variables for further investigation for the phase one of the study.

Table 1. Analysis of students’ predicted and actual results

Students	Attendance [Out of 100]	Quiz 1 [Out of 100]	English competency [Out of 100]	Midterm [Out of 100]	Reflection [Out of 100]	Final Project [Out of 100]	Position Paper [Out of 100]	VP_SPRING2024 [Out of 100]	Actual-Final course Grade [Out of 100]
1	57.9	85	90	75	90	81.65	95	100	80.47
2	75	65	65	70	60	94.15	100	100	73.33
3	100	92.5	95	80	100	81.65	100	100	90.08
4	78.9	77.5	95	88.75	100	93.35	100	80	90.12
5	52.8	72.5	70	65	80	0	0	0	34.14
6	95	90	90	87.5	90	93.35	100	100	90.42
7	88.1	92.5	90	88.75	100	93.35	100	98	90.72
8	52.8	30	60	63.75	75	82.9	80	38	61.12
9	88.9	80	70	82.5	80	90.85	95	100	88.11
10	100	82.5	98	100	100	94.15	100	100	95.08
11	100	67.5	75	83.75	85	94.6	95	60	85.17
12	90	87.5	90	80	90	94.6	95	50	86.92
13	72.5	95	90	90	95	87.5	100	100	88.53
14	60.5	90	90	92.5	100	90.85	95	90	89.7
15	89.5	95	90	90	95	87.5	95	100	90.97
16	90	82.5	95	92.5	100	93.35	100	100	91.67
17	100	100	100	100	100	96.25	100	100	99
18	67.5	80	90	82.5	95	82.9	80	24	80.66
19	100	92.5	95	97.5	100	96.25	100	100	95.25
20	81.6	90	85	82.5	85	90.85	85	100	86.5
21	83.3	90	70	70	85	90.85	85	98	85.49
22	80	47.5	60	67.5	50	75	95	92.6	72.13

As seen in Table 1, there are following dependent and independent variables:

Dependent Variable:

- Final Course Grade (out of 100 points – actual grade out: 100%)

Independent Variables:

- Attendance [Out of 100 – actual grade: 5%]
- Quiz 1 [Out of 100 – actual grade: 10%]
- English competency [Out of 100] – This is from the instructor, based on his observation for class participation and interaction.
- Midterm [Out of 100 – actual grade: 20%]
- Reflection paper [Out of 100 – actual grade: 5%]
- Final project [Out of 100 – actual grade: 20%]
- Position paper [Out of 100 – actual grade: 5%]
- VP_SPRING2024 [Out of 100 – actual grade: 5%]

Results of multiple regression model

To demonstrate that using the “Average” of independent variables would not deliver the desired predictive result, a test was conducted which showed over 13.6% error in the results. As it can be confirmed from Table 1, the average of available independent variables alone does not provide a robust model for predicting final course grades. The analysis indicates a need for a sophisticated estimating approach, and therefore, a multiple regression method was adopted for further investigation, with the expectation of developing a model with stronger explanatory and predictive capabilities compared to a simple average-based approach; following are the results obtained for the regression statistics from Table 2 to Table 4.

Multiple Linear Regression Statistics:

Table 2 Summary Regression Statistics

SUMMARY OUTPUT	
Regression Statistics	
Multiple R	0.991095
R Square	0.98227
Adjusted R Square	0.971358
Standard Error	2.370027
Observations	22

Table 3 Summary Regression Statistics

ANOVA					
	df	SS	MS	F	Significance F
Regression	8	4045.391	505.6739	90.02514	3.99E-10
Residual	13	73.02139	5.61703		
Total	21	4118.413			

	Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%	Lower 95.0%	Upper 95.0%
Intercept	-5.98557	4.181073	-1.43159	0.175863	-15.0182	3.04709	-15.0182	3.04709

Attendance [Out of 100]	0.114723	0.046161	2.485276	0.027337	0.014998	0.214448	0.014998	0.214448
Quiz 1 [Out of 100]	0.194211	0.067484	2.877874	0.012946	0.04842	0.340002	0.04842	0.340002
English competency [Out of 100]	-0.05149	0.13868	-0.37128	0.716409	-0.35109	0.248111	-0.35109	0.248111
Midterm [Out of 100]	0.211344	0.109692	1.926716	0.076159	-0.02563	0.448318	-0.02563	0.448318
Reflection [Out of 100]	0.136108	0.101532	1.340544	0.203026	-0.08324	0.355455	-0.08324	0.355455
Final Project [Out of 100]	0.216037	0.101903	2.120028	0.053818	-0.00411	0.436185	-0.00411	0.436185
Position Paper [Out of 100]	0.215269	0.117979	1.824636	0.091114	-0.03961	0.470147	-0.03961	0.470147
VP_SPRING2024 [Out of 100]	0.015991	0.03844	0.415996	0.684198	-0.06705	0.099037	-0.06705	0.099037

Table 4 Summary Regression Statistics

RESIDUAL OUTPUT					
Observation	Predicted Actual-Final Grade [Out of 100]	Residuals	Observation	Predicted Actual-Final Grade [Out of 100]	Residuals
1	80.32043	0.149566	12	87.54343	-0.62343
2	78.32205	-4.99205	13	90.12837	-1.59837
3	89.84357	0.236434	14	88.47701	1.222991
4	88.56681	1.553186	15	91.00232	-0.03232
5	35.17392	-1.03392	16	91.92366	-0.25366
6	91.7935	-1.3735	17	98.42373	0.576267
7	93.08072	-2.36072	18	78.54204	2.117959
8	62.22873	-1.10873	19	96.69623	-1.44623
9	86.14713	1.962874	20	85.00727	1.492725
10	94.67434	0.405662	21	83.30086	2.189144
11	85.85069	-0.68069	22	68.53319	3.596814

Interpretation of results – Phase 1

Based on running the multiple regression analysis in Excel software,

- Multiple R of 0.991095117 indicates an extremely strong positive correlation between the independent variables and the dependent variable (Actual-final grade).
- R Square of 0.982269531 means that the model explains 98.23% of the variation in the Actual-Final grade.
- The Adjusted R Square of 0.971358473 suggests that the model has good predictive power and is not overfitted.
- The Standard Error of 2.370027437 is relatively low, indicating a high level of precision in the model's predictions.
- The 22 Observations provide a sufficient sample size for the analysis.

ANOVA - Analysis of Variance:

The Regression model is highly significant, with an F-statistic of 90.02514163 and a Significance F value of 3.98624E-10, which is well below the typical 0.05 threshold. This indicates that the overall model is a good fit for the data and the independent variables collectively have a significant impact on the Actual-Final Grade.

Coefficients:

- Attendance [Out of 100]: This variable has a positive coefficient of 0.11472324, meaning that a 1-unit increase in attendance is associated with a 0.115-unit increase in the Actual-Final Grade, holding all other variables constant. The p-value of 0.027337033 suggests this relationship is statistically significant at the 95% confidence level.
- Quiz 1 [Out of 100]: This variable has a positive coefficient of 0.194211194, indicating that a 1-unit increase in Quiz 1 score is associated with a 0.194-unit increase in the Actual-Final Grade, all else equal. The p-value of 0.012946088 confirms this as a significant predictor.
- English competency [Out of 100]: This variable has a negative coefficient of -0.051489218, implying that a 1-unit increase in English competency is associated with a 0.051-unit decrease in the Actual-Final Grade, holding other factors constant. However, the p-value of 0.716409059 suggests this relationship is not statistically significant.
- Midterm [Out of 100]: This variable has a positive coefficient of 0.211344372, meaning that a 1-unit increase in Midterm score is associated with a 0.211-unit increase in the Actual-Final Grade, all else equal. The p-value of 0.076159221 indicates this is marginally significant at the 90% confidence level.
- Reflection [Out of 100]: This variable has a positive coefficient of 0.13610811, suggesting that a 1-unit increase in Reflection score is associated with a 0.136-unit increase in the Actual-Final Grade, holding other variables constant. However, the p-value of 0.203025715 shows this relationship is not statistically significant.
- Final Project [Out of 100]: This variable has a positive coefficient of 0.216037103, meaning that a 1-unit increase in Final Project score is associated with a 0.216-unit increase in the Actual-Final Grade, all else equal. The p-value of 0.053817788 indicates this is marginally significant at the 90% confidence level.
- Position Paper [Out of 100]: This variable has a positive coefficient of 0.215268553, suggesting that a 1-unit increase in Position Paper score is associated with a 0.215-unit increase in the Actual-Final Grade, holding other factors constant. The p-value of 0.091114492 shows this is also marginally significant at the 90% confidence level.
- VP_SPRING2024 [Out of 100]: This variable has a positive coefficient of 0.015991068, meaning that a 1-unit increase in VP_SPRING2024 score is associated with a 0.016-unit increase in the Actual-Final Grade, all else equal. However, the p-value of 0.684198341 indicates this relationship is not statistically significant.

Residual Output:

The Residuals range from -4.992049274 to 3.59681356, with a mix of positive and negative values, suggesting the model is fitting the data well overall.

The largest residual in absolute value terms is 4.992049274, which is relatively small compared to the scale of the Actual-Final Grade (out of 100); the observed results in educational research are generally expected to be within 10% points of the actual or true value being measured, however, in this research it is restricted to within 5% points of the actual value being measured in this phase one.

The residuals do not appear to exhibit any clear patterns or systematic biases, further indicating a good model fit.

Overall, this regression model provides a robust and informative analysis of the relationship between the various academic performance indicators and the Actual-Final Grade. The high R-squared value, significant F-statistic, and several statistically significant predictors suggest the model has strong explanatory and predictive power. However, some variables like English competency and VP_SPRING2024 do not appear to be significant predictors, and therefore they will be removed for the next stage of experimentation while, marginal significance of the Midterm, Final Project, and Position Paper variables will be further tested for their effectiveness.

Interpretation of results – Phase 2

In the Phase 2 test, two variables - English competency and VP_SPRING2024 - were removed, and a regression analysis was conducted. The results showed that the actual and predicted values for all students had less than a 5% error, except for student number 2 which had a 5.1% error. Considering the data set of 22 students, this equates to an overall error of 4.54%, which is deemed an acceptable error value for an educational prediction model of this nature. This refined multiple regression approach demonstrated improved predictive accuracy compared to the initial average-based method.

Table 5 Result of Second Regression Statistics Test

Students	1	2	3	4	5	6	7	8	9	10	11
Actual-Final Grade [Out of 100]	80.47	73.33	90.08	90.12	34.14	90.42	90.72	61.12	88.11	95.08	85.17
Predicted Actual-Final Grade [Out of 100]	80.42	78.43	89.83	88.71	35.13	91.92	92.81	61.96	85.59	94.59	85.88
Students	12	13	14	15	16	17	18	19	20	21	22
Actual-Final Grade [Out of 100]	86.92	88.53	89.70	90.97	91.67	99.00	80.66	95.25	86.50	85.49	72.13
Predicted Actual-Final Grade [Out of 100]	88.49	90.02	88.21	90.86	91.75	98.60	79.41	96.58	85.01	82.68	68.70

In the Phase 2 test, two variables - English competency and VP_SPRING2024 - were removed, and a regression analysis was conducted. The results showed that the actual and predicted values for all students had less than a 5% error, except for student number 2 which had a 5.1% error. Considering the data set of 22 students, this equates to an overall error of 4.54%, which is deemed an acceptable error value for an educational prediction model of this nature. Although number of authors have suggested the percentage errors in the range of 10-20% is acceptable for regression models in educational contexts [20, 21, 22].

This refined multiple regression approach demonstrated improved predictive accuracy compared to the initial average-based method.

Based on above analysis, following manual formula is developed to predict the final grade for the course Design Entrepreneurship and Leadership, which will be tested against the legacy data from the past years.

$$\text{Predicted Actual-Final Grade} = (-6) + 0.11473 \times \text{Attendance (Att)}$$

$$+ 0.194211194 \times \text{Quiz 1 (Qui)}$$

$$+ 0.211344372 \times \text{Midterm (MT)}$$

$$+ 0.13610811 \times \text{Reflection (Ref)}$$

$$+ 0.216037103 \times \text{Final Project (FP)}$$

$$+ 0.215268553 \times \text{Position Paper (PP)}$$

$$\text{Predicted Final Grade} = (-6) + 0.11 \times \text{Att} + 0.2 \times \text{Qui} + 0.2 \times \text{MT} + 0.09 \times \text{Ref} + 0.22 \times \text{FP} + 0.22 \times \text{PP} \tag{1}$$

Above equation manually predicts the Final grade based on the variables input. When tested against the legacy data for the years 2020 till 2024, following errors were notices given in Table 6.

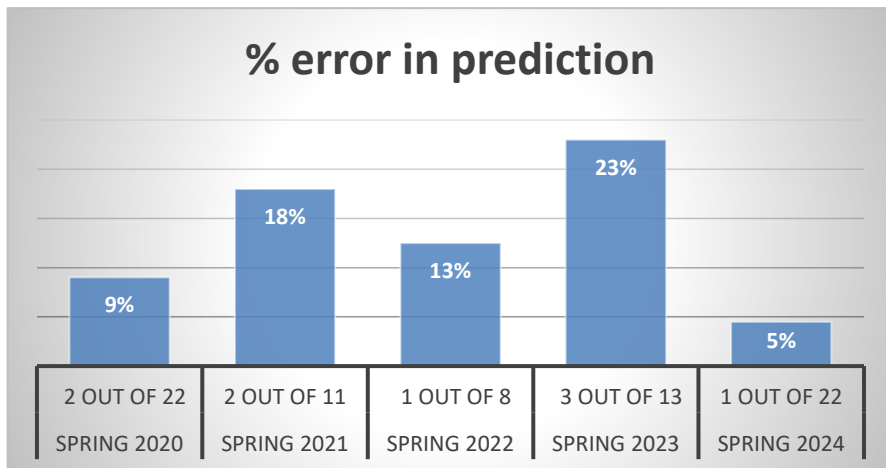


Figure 1 % error identified after the application of equation 1

This led to combining the data for all semesters and re-run the regression analysis to receive a stronger and better estimating model; accordingly following is the output from the regression analysis in Table 7 to:

Table 7 Summary Regression Statistics

Regression Statistics	
Multiple R	0.949689
R Square	0.901909
Adjusted R Square	0.893379
Standard Error	3.548151
Observations	76

ANOVA					
	df	SS	MS	F	Significance F
Regression	6	7987.066	1331.178	105.7382	8.62E-33
Residual	69	868.6668	12.58937		
Total	75	8855.733			

Table 8 Summary Regression Statistics for all semesters

	Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%	Lower 95.0%	Upper 95.0%
Intercept	-11.2439	3.79819	-2.96034	0.004209	-18.8211	-3.66675	-18.8211	-3.66675
Attendance [Out of 100]	0.11805	0.035819	3.295716	0.001553	0.046593	0.189508	0.046593	0.189508
Quiz 1 [Out of 100]	0.109536	0.026406	4.148125	9.4E-05	0.056857	0.162214	0.056857	0.162214
Midterm [Out of 100]	0.290863	0.034982	8.314746	5.31E-12	0.221077	0.360649	0.221077	0.360649
Reflection [Out of 100]	0.164752	0.039151	4.208155	7.62E-05	0.086649	0.242855	0.086649	0.242855
Final Project [Out of 100]	0.27428	0.04504	6.089702	5.67E-08	0.184427	0.364132	0.184427	0.364132
Position Paper [Out of 100]	0.158191	0.04559	3.469824	0.000902	0.06724	0.249141	0.06724	0.249141

$$\text{Predicted Final Grade} = (-11.2) + 0.12 \times \text{Att} + 0.1 \times \text{Qui} + 0.3 \times \text{MT} + 0.17 \times \text{Ref} + 0.27 \times \text{FP} + 0.16 \times \text{PP} \quad (2)$$

Based upon the new regression data, equation 2 was developed and tested for various students final outcome; Table 8 shows the regression results after applying the equation 2. The maximum error for overall data was reported as 13%, which can be further improved based on more data availability or through integrating data mining process.

Table 9 Summary Regression Statistics for all semesters

Actual-Final course Grade [Out of 100]	88.5	89.7	91.0	91.7	99.0	80.7	95.3	86.5	85.5	72.1	82.3	88.4	82.0
Predicted	88.1	87.8	89.4	92.1	98.0	79.4	96.5	83.4	80.0	66.4	84.6	87.7	84.3
Error	0.4	1.9	1.6	-0.4	1.0	1.3	-1.3	3.1	5.5	5.8	-2.4	0.7	-2.3
Actual-Final course Grade [Out of 100]	67.0	76.1	76.5	91.8	82.3	89.6	77.5	85.3	89.5	59.5	60.9	84.5	74.6
Predicted	76.5	73.6	69.3	87.9	78.2	87.9	70.6	84.9	85.1	65.5	67.0	82.4	76.4
Error	-9.5	2.4	7.3	3.9	4.1	1.7	6.9	0.4	4.4	-6.0	-6.1	2.1	-1.8
Actual-Final course Grade [Out of 100]	70.3	85.4	78.7	78.6	90.0	76.0	87.2	87.4	84.7	86.0	78.4	89.5	64.0
Predicted	68.7	80.7	78.8	77.0	86.1	70.6	83.0	83.7	84.4	81.8	83.3	84.2	64.8
Error	1.6	4.8	-0.1	1.6	3.9	5.4	4.2	3.7	0.3	4.2	-4.9	5.3	-0.8
Actual-Final course Grade [Out of 100]	83.8	89.6	93.1	78.3	76.0	68.2	72.3	60.3	80.1	62.9	80.0	89.5	79.7
Predicted	80.7	87.0	90.1	78.0	76.8	66.9	70.8	70.6	82.2	58.3	77.5	86.1	81.0
Error	3.1	2.5	3.0	0.2	-0.7	1.3	1.5	-10.4	-2.2	4.6	2.5	3.4	-1.2
Actual-Final course Grade [Out of 100]	70.1	74.5	77.4	81.8	78.7	60.3	73.7	91.8	75.6	83.8	80.4		
Predicted	69.3	79.3	79.4	80.3	74.8	56.4	75.5	89.1	73.1	77.9	82.1		
Error	0.8	-4.8	-2.0	1.6	3.9	3.9	-1.8	2.7	2.5	5.8	-1.8		

4. Discussion

The results of this study provide valuable insights into the key factors that influence student performance in the "Design Entrepreneurship and Leadership" course at Effat University. The multiple linear regression analysis revealed that midterm exam grades, and assignment project grades were the strongest and moderate predictors of student success, while attendance and quiz grades also contributed significantly to the model.

These findings align with prior research in design education, which has highlighted the importance of both summative assessments (e.g., exams) and formative assessments (e.g., projects, quizzes) in supporting student learning and achievement ([7], [8]). The significant impact of attendance and quiz grades suggests that these assessments effectively capture students' mastery of course concepts and their ability to apply design, entrepreneurial, and leadership principles in a high-stakes setting in the view of their punctuality and commitment through attendance.

Similarly, the marginal influence of assignment project grades underscores the value of authentic, hands-on learning experiences in design-focused, entrepreneurial courses ([12], [15]). By engaging in real-world design challenges and entrepreneurial projects, students have the opportunity to develop critical thinking, problem-solving, and leadership skills that are essential for success in the professional world.

Furthermore, the contribution of attendance to the predictive model is consistent with existing literature, which has emphasized the positive relationship between student engagement and academic performance ([17], [18]). Regular class attendance allows students to actively participate in discussions, receive feedback from instructors and peers, and maintain momentum in their learning, all of which can enhance their overall course outcomes.

While the influence of quiz grades was statistically significant, the relative impact compared to other factors, suggests that these formative assessments could also play a more supportive role in reinforcing key concepts and providing ongoing feedback, rather than serving as primary drivers of student success ([13], [12]).

5. Conclusion

This study has successfully developed a predictive model for student performance in the "Design Entrepreneurship and Leadership" course at Effat University, using a multiple linear regression approach and academic record data. The key findings indicate that midterm exam grades, and assignment project grades are the marginal predictors of student success, while attendance and quiz grades also contributes significantly to the model.

These results have important implications for design educators and program administrators. By understanding the key factors that influence student performance in this specialized senior course, they can implement targeted interventions to support at-risk students, refine assessment practices, and enhance the overall quality and effectiveness of the curriculum. For example, the researcher suggests that early identification of students who are struggling with exams or project work could enable the implementation of tailored support, such as individual tutoring, peer-to-peer mentoring, or adjustments to teaching strategies in addition to making a special assessment arrangement, such as open book test.

Furthermore, the findings can inform the allocation of resources and the development of support structures within the design program, ensuring that students receive the necessary guidance, feedback, and opportunities to thrive in the design entrepreneurship and leadership course. This data-driven approach to understanding and predicting student performance can be adapted and applied to a variety of design education contexts, contributing to the limited but growing body of research in this field.

Future studies could explore additional factors, such as student demographics, learning styles, or motivational factors, that may further enhance the predictive power of the model, in addition to using other mathematical modelling techniques. Further more, longitudinal analyses tracking student performance across multiple design courses could provide deeper insights into the long-term trajectories and success of design students.

Overall, this study demonstrates a rigorous and data-driven approach to forecasting student success in a design entrepreneurship and leadership course, with the ultimate goal of improving educational outcomes and preparing the next generation of design innovators, entrepreneurs, and leaders.

References

1. Aljohani, O. (2016). A comprehensive review of the major studies and theoretical models of student retention in higher education. *Higher Education Studies*, 6(2), 1-18.
2. Alves, A. C., Sousa, R. M., Fernandes, S., Cardoso, E., Carvalho, M. A., Figueiredo, J., & Pereira, R. M. (2016). Teacher's experiences in PBL: Implications for practice. *European Journal of Engineering Education*, 41(2), 123-141.
3. Bridgstock, R. (2013). Not a dirty word: Arts entrepreneurship and higher education. *Arts and Humanities in Higher Education*, 12(2-3), 122-137.
4. Mohan Dass, Mohan & Sarfraz, Isra & Hewege, Chandana & Rajendran, Diana. (2018). An exploration of global employability skills: a systematic research review. *International Journal of Work Organisation and Emotion*. 9. 63. 10.1504/IJWOE.2018.10012435.
5. Dym, C. L., Agogino, A. M., Eris, O., Frey, D. D., & Leifer, L. J. (2005). Engineering design thinking, teaching, and learning. *Journal of Engineering Education*, 94(1), 103-120.
6. Goel, V., & Pirolli, P. (1992). The structure of design problem spaces. *Cognitive Science*, 16(3), 395-429.
7. Ojajuni, Opeyemi & Ayeni, Foluso & Akodu, Olagunju & Ekanoye, Femi & Adewole, Samson & Ayo, Timothy & Misra, Sanjay & Mbarika, Victor. (2021). Predicting Student Academic Performance Using Machine Learning. 10.1007/978-3-030-87013-3_36.
8. Fayolle, A., & Gailly, B. (2015). The impact of entrepreneurship education on entrepreneurial attitudes and intention: Hysteresis and persistence. *Journal of small business management*, 53(1), 75-93.
9. Hou, Su-I. "Integrating Problem-Based Learning with Community-Engaged Learning in Teaching Program Development and Implementation." *Universal Journal of Educational Research* 2, no. 1 (2014): 1-9.
10. Althubaiti, A. (2016). Information bias in health research: definition, pitfalls, and adjustment methods. *Journal of Multidisciplinary Healthcare*, 9, 211-217.
11. Arbaugh, J. B. (2000). Virtual classroom characteristics and student satisfaction with internet-based MBA courses. *Journal of Management Education*, 24(1), 32-54.
12. Baran, E. (2013). Connect, participate and learn: Transforming pedagogies in higher education.

- Bulletin of the IEEE Technical Committee on Learning Technology, 15(1), 9-12.
13. Beattie, V., Collins, B., & McInnes, B. (2002). Deep and surface learning: a simple or simplistic dichotomy? *Accounting Education*, 5(1), 1-12.
 14. O. Aljohani, "A comprehensive review of the major studies and theoretical models of student retention in higher education," *Higher Education Studies*, vol. 6, no. 2, pp. 1-18, 2016.
 15. C. L. Dym, A. M. Agogino, O. Eris, D. D. Frey, and L. J. Leifer, "Engineering design thinking, teaching, and learning," *Journal of Engineering Education*, vol. 94, no. 1, pp. 103-120, 2005.
 16. V. Goel and P. Pirolli, "The structure of design problem spaces," *Cognitive Science*, vol. 16, no. 3, pp. 395-429, 1992.
 17. V. Ramesh, P. Parkavi, and K. Ramar, "Predicting student performance: a statistical and data mining approach," *International Journal of Computer Applications*, vol. 63, no. 8, 2013.
 18. Moreau, Stéphanie & Coquin-Viennot, Danièle. (2003). Comprehension of arithmetic word problems by fifth-grade pupils: Representations and selection of information. *The British journal of educational psychology*. 73. 109-21. 10.1348/000709903762869941.
 19. R. Bridgstock, "Not a dirty word: Arts entrepreneurship and higher education," *Arts and Humanities in Higher Education*, vol. 12, no. 2-3, pp. 122-137, 2013.
 20. Dym, C. L., Agogino, A. M., Eris, O., Frey, D. D., & Leifer, L. J. (2005). Engineering design thinking, teaching, and learning. *Journal of Engineering Education*, 94(1), 103-120.
 21. Sheppard, S. D., Macatangay, K., Colby, A., & Sullivan, W. M. (2009). *Educating engineers: Designing for the future of the field*. Jossey-Bass.
 22. Teo, T. W., & Ke, K. J. (2014). Challenges in STEM teaching: Implication for preservice and in service teacher education program. *Theory Into Practice*, 53(1), 18-24.