Graduate Management Admission Council™

Predicting Success in Part-Time MBA Programs: A Study of Executive Assessment™

Abstract

In this study, the predictive validity of the Executive Assessment™ (EA™) scores and undergraduate grade point average (UGPA) were analyzed for four part-time MBA (PTMBA) programs. The results show that the predictive validity varies across different programs. Additionally, on average, EA Total score has the highest predictive validity, followed by Quantitative Reasoning, Integrated Reasoning, and Verbal Reasoning. The UGPA did not show much predictive validity, however, we recommend further study based on a larger sample size.

Introduction

The Executive Assessment (EA) was created by the Graduate Management Admission Council™ (GMAC™) to meet the needs of both the Executive MBA (EMBA) programs and their applicants. It assesses the skills that are relevant and essential to success in the MBA programs.[1] Specifically, EA measures these domains: Verbal Reasoning (VR), Quantitative Reasoning (QR), and Integrated Reasoning (IR). Although the VR and QR sections of EA are shorter than those found in the Graduate Management Admission Test™ (GMAT™) exam, they still reliably measure the essential skills required for candidates to excel in MBA programs.

A previous study has found that EA scores have good predictive validity of the students' graduate GPA in EMBA programs.[2] Given that many PTMBA programs are interested in using EA as their admission criteria, validity evidence suggesting that EA scores are robust and appropriate admission criteria for PTMBA programs is much needed.

Validity is defined as the extent to which the interpretation of test scores can be supported by evidence (AERA, APA, & NCME, 2014),[3] which can directly affect how we use the scores for their intended purpose. The development process for EA provides two sources of validity evidence—the content and construct are appropriate to aid in the selection of successful students into PTMBA programs.[2]. The most visible source of validity evidence typically comes from predictive validity, which demonstrates the extent to which scores used in admission predict program measurable success. For example, a positive correlation between EA scores and students' graduate GPA in PTMBA can indicate predictive validity.

GMAC provides its predictive validity study service (VSS) free to all member schools. The validity studies not only offer the schools the validity evidence of the EA scores but also help them to identify those who are likely to succeed academically in their programs. In this report, we analyzed the predictive validity of EA scores and UGPA for four participating PTMBA programs and aggregated the results to show the overall predictive validity of EA scores and UGPA.

[1] *How is the Assessment Structured?* (n.d.). Retrieved April 26, 2020, from https://www.gmac.com/executive-assessment/about/assessment-structure

[2] Talento-Miller, E. (2017). *Summary of validity studies from the initial uses of the Executive Assessment*. Reston, VA: Graduate Management Admission Council.

[3] American Educational Research Association, American Psychological Association, National Council on Measurement in Education, & Joint Committee on Standards for Educational and Psychological Testing (U.S.). (2014*). Standards for educational and psychological testing*. Washington, DC: American Educational Research Association.

Methodology

Data Collection

Four PTMBA programs from different US regions joined the study in the fall of 2019. They submitted the students' EA section scores and Total score and first-semester graduate GPA (FSGGPA). Not every data entry includes EA scores, therefore, the actual sample size for Programs A, B, C, and D is 29, 12, 27, and 24, respectively. Moreover, Program A did not include the UGPA in its dataset, and one outlier from Program C was removed from the study. The descriptive statistics of the scores included in this study are summarized in Table A.1 (see Appendix A).

Predictive Validity

Pearson correlational analyses were used to evaluate how well the admission criteria (e.g., EA section and Total score, and UGPA) can predict students' FSGGPA for the four programs. All individual correlations were tested for statistical significance. Those correlations vary across programs, however, because of differences in the curriculum and the makeup of the student body. In addition, within each school, data sampling error can also influence the values of the correlation. Therefore, the meta-analysis was used to obtain the average correlations between the admissions criteria and the FSGGPA across the four programs. A random-effect model[4] that takes into account between-program and within-program variance was used. The details of the process for obtaining the weighted mean correlation ($\bar{r}$) of different predictors and their confidence interval are discussed in Appendix A.

Results

The correlations across the four programs are summarized below in Table 1. The results show that EA scores had robust correlations with FSGGPA. The correlations between UGPA and FSGGPA, however, were negative or close to nothing. These strange results could be due to the small sample size and the missing data (the students who did not have UGPA scores were not at random). EA scores are significant predictors of FSGGPA for certain programs. Specifically, EA Total score was a significant predictor for Programs A and D, as was the IR score for Program A, the QR score for Program C, and the VR score for Program D. The variability in levels of significance could be also due to the small sample size for each program. Regardless, the results suggest that EA scores, in comparison to UGPA, are better predictors of academic performance.

[4] Hedges, L. V., & Olkin, I. (1985). *Statistical methods for meta-analysis*. Orlando, FL: Academic Press; Hedges, L. V., & Vevea, J. L. (1998). Fixed- and random-effects models in meta-analysis. *Psychological Methods*, 3, 486–504.

Table 1. Predictive Validity by Program

Program	N	Total	IR	QR	VR	UGPA
A	29	0.46*	0.47*	0.36	0.08	—
B	12	0.23	0.12	0.22	0.39	-0.16
C	26	0.37	0.26	0.45*	0.12	0.02
D	24	0.54*	0.3	0.4	0.45*	-0.28

*Note: * indicates the correlation is significant ($p < 0.05$).*

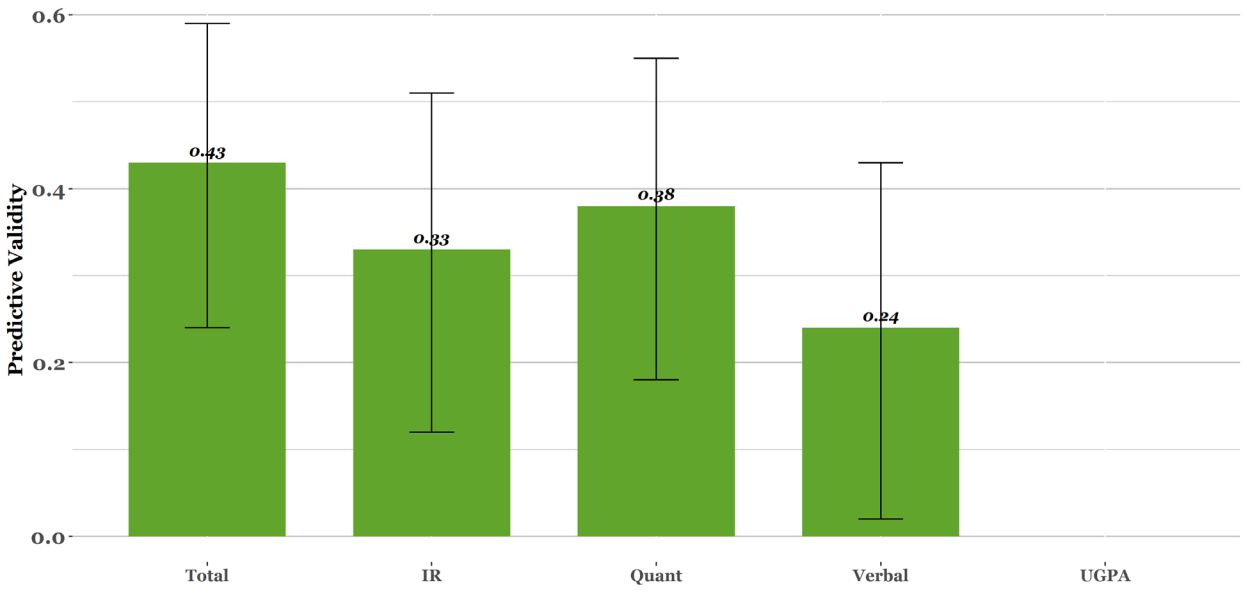
The weighted mean correlation ($\bar{r}$) and 95 percent confidence interval of the correlation for each predictor are shown in Table 2 and Figure 1. The most noticeable observation of the study was that except for UGPA, predictive validity values of the other admissions criteria were all significantly above 0.2. EA Total score had the highest predictive validity ($\bar{r} = 0.43$) values, followed by QR ($\bar{r} = 0.38$), IR ($\bar{r} = 0.33$), and VR ($\bar{r} = 0.24$). The predictive validity of UGPA on average was no different than zero ($\bar{r} = -0.08$), which could be caused by the small sample size and instances of missing data. Many previous validity studies indicated that the UGPA was a useful predictor of the graduate GPA in MBA programs. For more reliable evidence, a future study with a larger sample size is recommended.

Table 2. Summary of Predictive Validity

	K	$\bar{r}$	95%L[A]	95%U[B]
Total	4	0.43*	0.24	0.59
IR	4	0.33*	0.12	0.51
Quant	4	0.38*	0.18	0.55
Verbal	4	0.24*	0.02	0.43
UGPA	3	-0.08	-0.39	0.24

[A]L: Lower bound
[B]U: Upper bound
*Note: * indicates the correlation is significant ($p < 0.05$).*

Figure 1. Predictive Validity Summary



Note: The 95 percent confidence interval of the predictive validity of each predictor or combination of predictors were overlaid as spreads.

Discussion

In this study, the predictive validity of EA scores and UGPA were investigated for each of the four PTMBA programs. The predictive validity was strong for EA scores but not for UGPA. Additionally, the overall predictive validity of EA scores and UGPA was examined. The study found that EA Total score has the highest predictive validity (0.43), followed by QR (0.38), IR (0.33), and VR (0.24). On the contrary, the predictive validity of UGPA was not significant. The findings of the study suggest that EA scores should be used in admission decisions for PTMBA programs. Furthermore, because the predictive validity of UGPA was insignificant, it is not recommended that UGPA be used as the sole admissions criterion.

A last note: The findings of the study should be cautiously interpreted and may not hold up to generalization due to the small number of programs.

Contact Information

For questions or comments regarding the study findings, methodology, or data, please contact Yanyan Fu, Research Manager, or Sung-Hyuck Lee, Senior Research Manager at vss@gmac.com.

Appendix A

Method for Obtaining Weighted Mean Correlation

First, the correlation r_i of the i^{th} study needs to be converted to z score using Fisher's z transformation because r_i is not normally distributed (Equation 1).

$$z_{r_i} = \frac{1}{2}\log\left(\frac{1+r_i}{1-r_i}\right). \quad (1)$$

Next, the weighted average $\bar{z_r}$ needs to be computed using Equations 2 and 3:

$$\bar{z_r} = \frac{\sum_{i=1}^{k} w_i z_{r_i}}{\sum_{i=1}^{k} w_i}, \quad (2)$$

$$w_i = n_i - 3, \quad (3)$$

Where w_i and n_i are the sample size and the weight for the i^{th} study, respectively, and k is the total number of the studies. The between-studies variance is computed using Equations 4 through 6. If τ^2 is negative, it will be set to 0.

$$\tau^2 = \frac{Q-(k-1)}{c}, \quad (4)$$

$$Q = \sum_{i=1}^{k} w_i\left(z_{r_i} - \bar{z_r}\right)^2, \quad (5)$$

$$c = \sum_{i=1}^{k} w_i - \frac{\sum_{i=1}^{k} w_i^2}{\sum_{i=1}^{k} w_i}. \quad (6)$$

After that, the new weight to adjust for the between-studies variance can be computed by the following Equation 7:

$$w_i^* = \left(\frac{1}{w_i} + \tau^2\right)^{-1}. \quad (7)$$

The new weighted average $\bar{z_r^*}$ can be computed with the new weight using Equation 2, and the standard error of $\bar{z_r^*}$ is calculated using Equation 8:

$$SE(\bar{z_r^*}) = \sqrt{\frac{1}{\sum_{i=1}^{k} w_i^*}}. \quad (8)$$

The 95 percent confidence interval of $\bar{z_r^*}$ is given by:

$$(\bar{z_r^*} - 1.96 * SE(\bar{z_r^*}), \bar{z_r^*} + 1.96 * SE(\bar{z_r^*})). \quad (9)$$

Finally, the z scores are transformed back to the correlation coefficient r using Equation 1.

Table A.1. Descriptive Statistics

Score Type	Group	N	Mean	SD	Min.	Max.
FSGGPA	Program A	29	3.20	0.41	1.98	3.85
	Program B	12	3.74	0.24	3.30	4.00
	Program C	26	3.45	0.35	2.92	3.92
	Program D	24	3.23	0.35	2.17	3.92
Total	Program A	29	151.79	5.27	144	165
	Program B	12	150.17	5.13	144	162
	Program C	26	148.38	5.89	136	158
	Program D	24	155.17	5.48	147	166
IR	Program A	29	10.86	3.13	5	18
	Program B	12	11.00	2.83	8	18
	Program C	26	9.69	2.51	5	18
	Program D	24	12.50	3.32	7	18
Quant	Program A	29	10.52	2.20	7	16
	Program B	12	9.50	1.17	8	11
	Program C	26	8.88	2.73	2	14
	Program D	24	10.96	2.07	8	16
Verbal	Program A	29	10.45	1.55	8	13
	Program B	12	9.75	2.09	5	13
	Program C	26	9.77	2.30	2	12
	Program D	24	11.71	2.48	8	18
UGPA	Program A	—	—	—	—	—
	Program B	11	3.34	0.34	2.93	4.00
	Program C	24	3.05	0.46	2.03	3.81
	Program D	10	3.27	0.42	2.19	3.80

Figure A.1. Histogram and Scatter Plot for EA Scores, FSGGPA, and UGPA in Program A

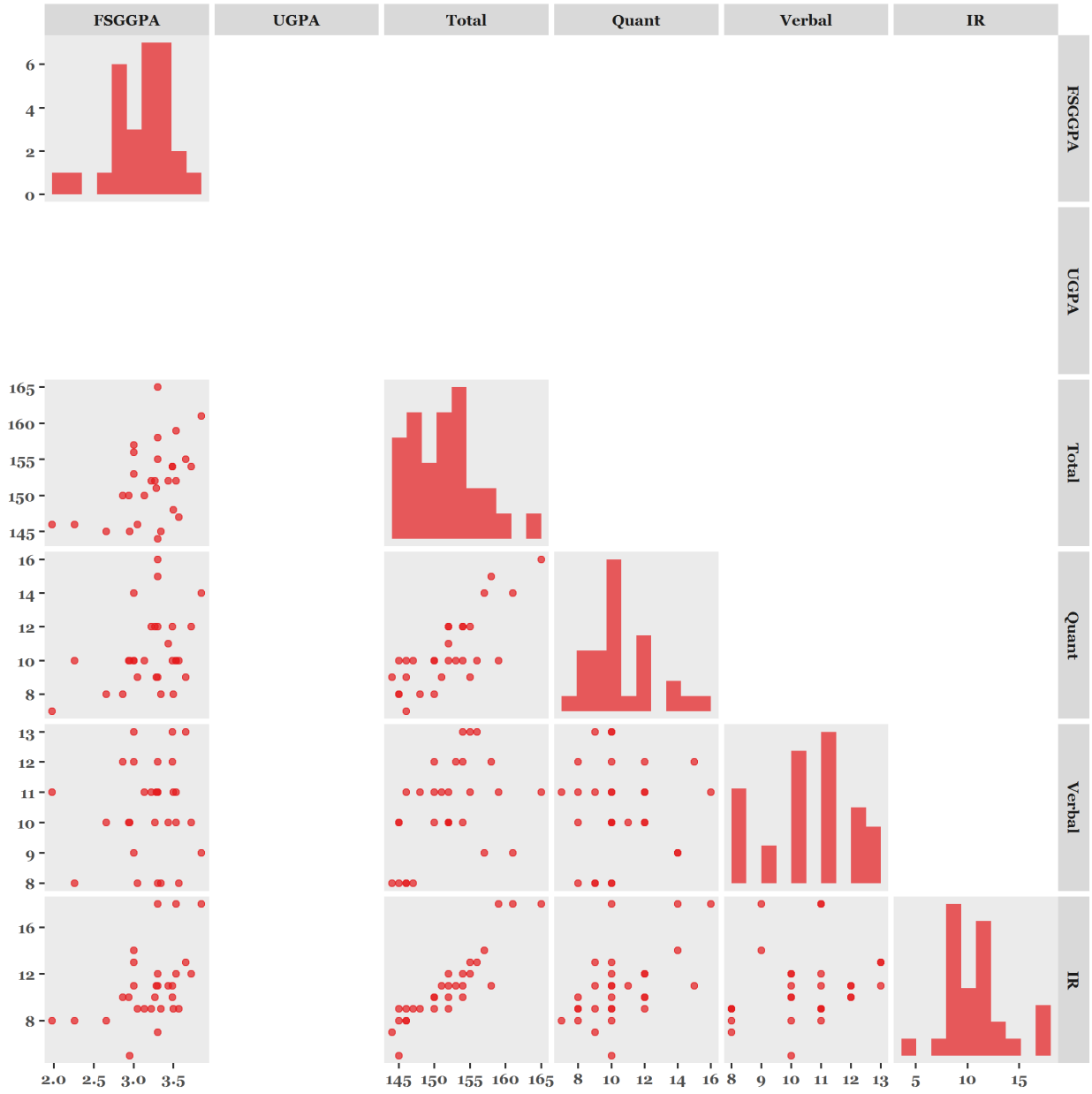


Figure A.2. Histogram and Scatter Plot for EA Scores, FSGGPA, and UGPA in Program B

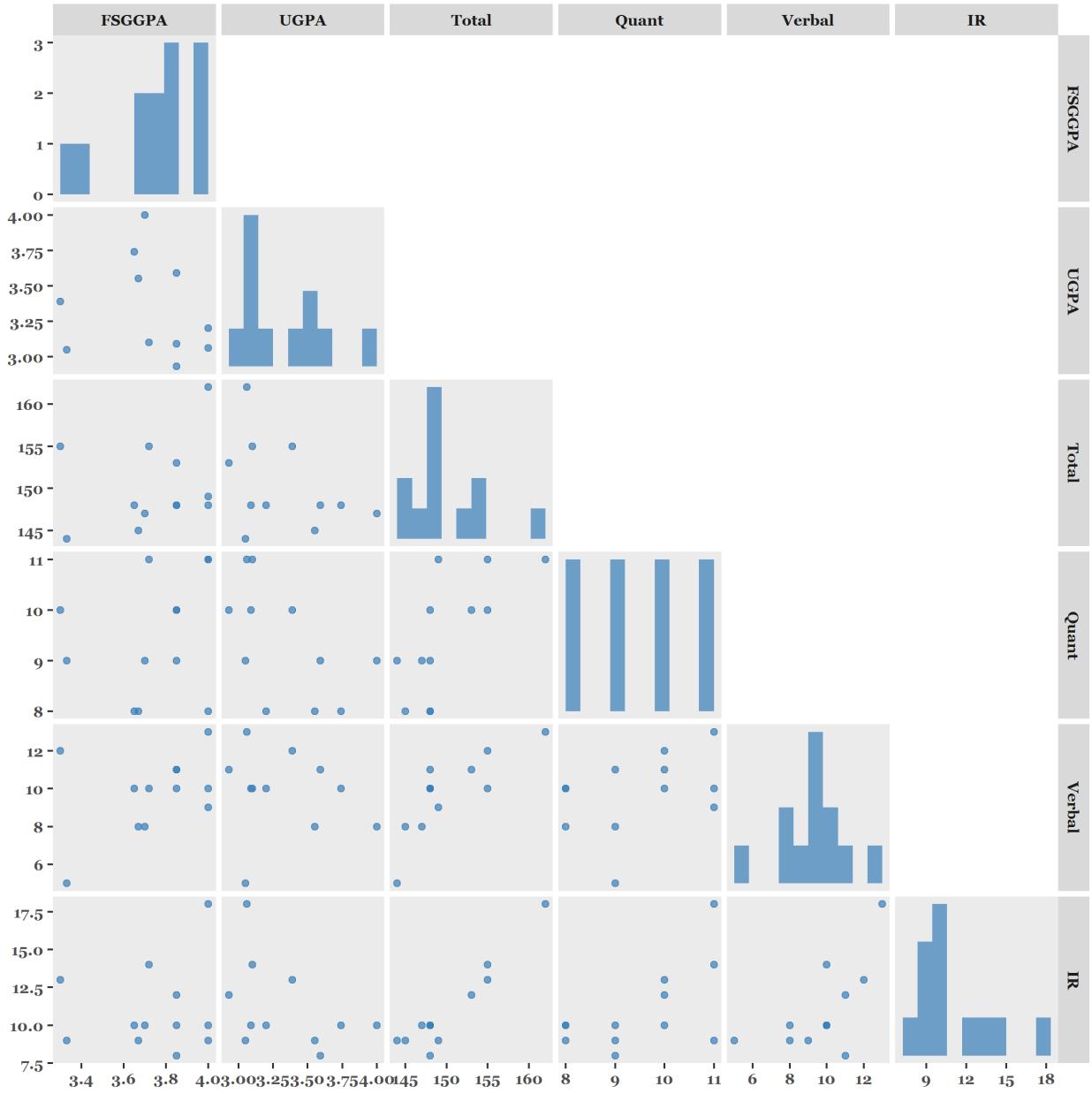


Figure A.3. Histogram and Scatter Plot for EA Scores, FSGGPA, and UGPA in Program C

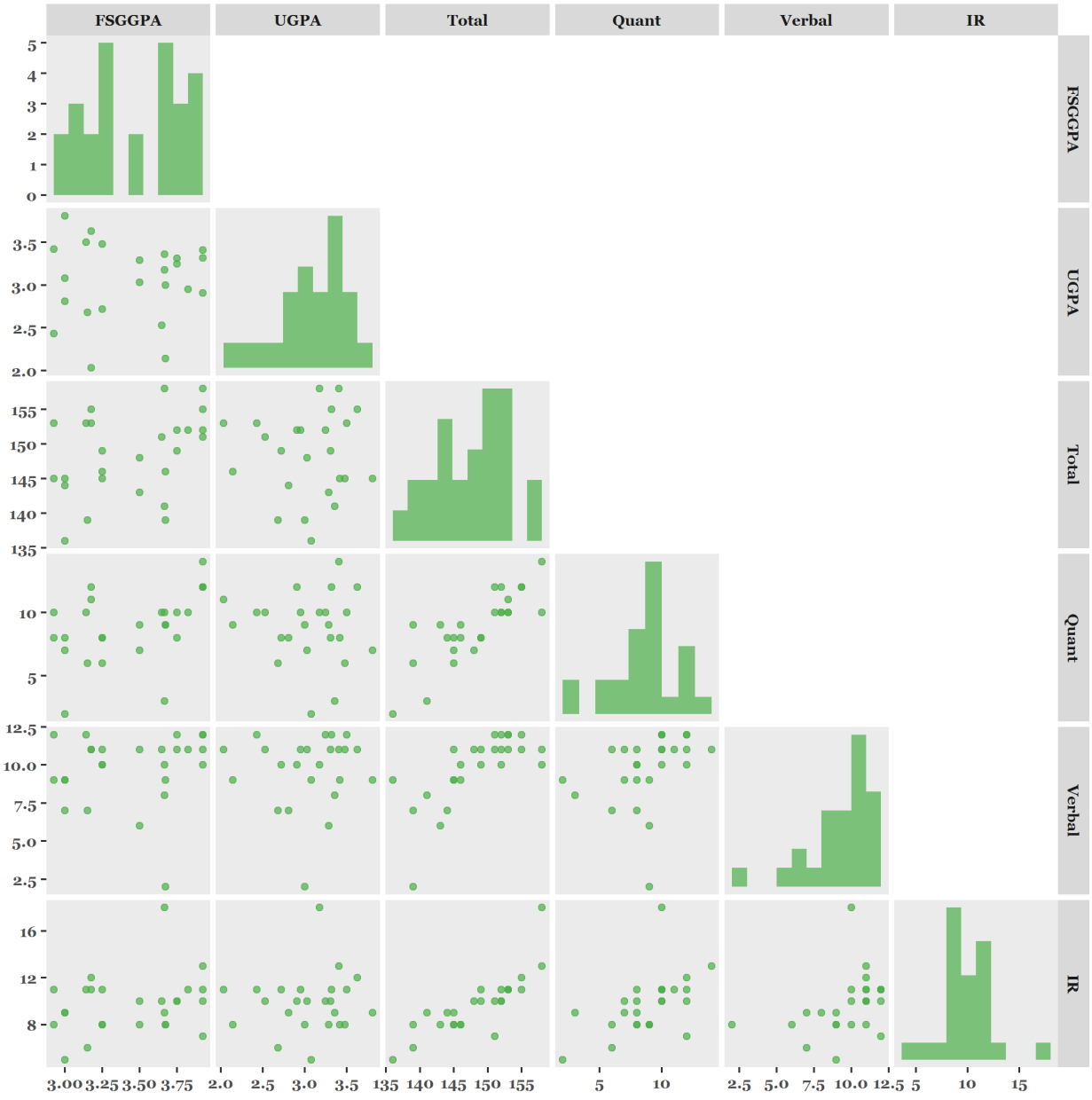


Figure A.4. Histogram and Scatter Plot for EA Scores, FSGGPA, and UGPA in Program D

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