

Graduate
Management
Admission
Council™

Predicting Student Success in Quantitative Master's Programs: A Meta-Analysis



Abstract

The Graduate Management Admission Council (GMAC) conducted a meta-analysis to examine how well the Graduate Management Admission Test™ (GMAT™) scores and undergraduate grade point average (UGPA), both individually and together, predict academic performance in quantitative master's programs. Studies from 11 master's degree programs—six accounting and five finance—were combined. The results of the meta-analysis show that a student's GMAT Total Score (Total) and UGPA have the same predictive validity on academic performance (0.39) when used individually. The highest predictive validity (0.55), however, was achieved when the sub-scores from a GMAT exam (Verbal Reasoning, Quantitative Reasoning, Integrated Reasoning, Analytical Writing Assessment) and UGPA were combined. This suggests that quantitative master's programs should combine UGPA with GMAT sub-scores to improve selection rather than using UGPA alone.

Introduction

The GMAT exam is “the most trusted, proven, and well-understood predictor of academic success” in business school.¹ It does this by measuring capabilities across four domains: Verbal Reasoning (VR), Quantitative Reasoning (QR), Integrated Reasoning (IR), and Analytical Writing Assessment (AWA). The most recent review of the GMAT exam found that the skills being measured were relevant to a range of graduate business master's programs, including quantitative programs such as those focused on accounting and finance. For example, the skills measured by the QR section directly correlated with the skills required to memorize, understand, and apply accounting knowledge.² Additionally, data from GMAC demonstrate that GMAT scores are increasingly being accepted by quantitative master's programs worldwide as an admission criterion: as of August 2019, GMAT scores were accepted by 872 accounting and finance programs (522 accounting, 350 finance) in 35 different countries. Ten years ago, this figure stood at around 500.

GMAC's validity study is conducted to collect evidence of the effectiveness of different admissions criteria, such as the GMAT exam, to predict student performance. This validity study gives programs valuable information about how well the admissions process identifies those likely to succeed academically. A meta-analysis combines the results of multiple studies to provide a more holistic evaluation than that which would arise from an individual, program-specific study. In this paper, 11 validity studies for master's degree programs—six accounting and five finance—were combined to evaluate the effectiveness of different admissions criterion on predicting student performance.

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¹ GMAC. (2019). The GMAT™ Exam Advantage. Retrieved [September 13, 2019] from: <https://www.gmac.com/gmat-other-assessments/about-the-gmat-exam/the-gmat-advantage>.

² Yang, J.-W., & Wu, L. (2016). Cognitive skills of accounting students: Does language background matter? *Academy of Business Research Journal*, 3, 53–70.

Related Literature

Numerous predictive validity studies have explored the extent to which GMAT scores predict academic performance in accounting master's programs.³ These studies demonstrate that GMAT scores are positively associated with graduate grade point averages (GGPA). It must be noted, however, that among some accounting courses (e.g., financial statement analysis), the relationship between GMAT scores and academic performance was not obvious.⁴ Other studies have also explored the relationship between GMAT scores and performance in finance programs and courses.^{5,6} Indeed, findings from one study⁶ suggested that GMAT scores are better predictors of GGPA for finance programs than the UGPA.

While the literature suggests that, in general, GMAT scores are effective means to predict the GGPA for quantitative master's programs, the variability of predictive validity across studies makes it hard to know the real magnitude of the predictive validity. By parsing out variability across different studies, however, meta-analyses can show the overall predictive validity.

A further challenge facing validity studies is that they only evaluate data containing students admitted to the program. This could negatively bias the predictive validity (i.e., correlation coefficients) because correlation is a function of variance, and sampling solely from admitted students decreases the variance of scores, and in turn, this decreases the correlation.⁷ To adjust for the bias caused by range restriction, the method proposed by Hunter and Schmidt⁷ has been applied to give a better estimate of the correlation.

Purpose

This study sought to determine the overall correlation between admission criteria (i.e., GMAT scores, UGPA) and GGPA. A meta-analysis used data from 11 quantitative master's programs (six accounting and five finance).

³ Buckless, F., & Krawczyk, K. (2016). The relation of student engagement and other admission metrics to Master of Accounting student performance. *Accounting Education*, 25(6), 519–533; Jin, J., Kwon, S.-K., & Yun, J. K. (2004). Predictors of Student Performance in the Accounting Master's Program. *Journal of Accounting & Finance Research*, 12(4), 71–79. <https://doi.org/10.1080/09639284.2016.1218778>; Krausz, J., Schiff, A., Schiff, J., & Hise, J. Van. (2005). The impact of TOEFL scores on placement and performance of international students in the initial graduate accounting class. *Accounting Education*, 14(1), 103–111. <https://doi.org/10.1080/0963928042000256671>; Morris, M., & Maxey, S. (2014). The Importance of English Language Competency in the Academic Success of International Accounting Students. *Journal of Education for Business*, 89(4), 178–185. <https://doi.org/10.1080/08832323.2013.819315>.

⁴ Krausz, J., Schiff, Y., Schiff, J., & Hise, V. J. (2002). Predicting Success in Graduate Financial Statement Analysis Courses – Do Traditional Predictors of Accounting Success Apply? *The Accounting Educators' Journal*, 14.

⁵ Bertus, M., Gropper, D. M., & Hinkelmann, C. (2006). Distance education and MBA student performance in finance classes. *Journal of Financial Education*, 32, 25–36. <https://www.jstor.org/stable/41948532>.

⁶ Borde, S. F. (2007). A better predictor of graduate student performance in finance: is it GPA or GMAT? *Financial Decisions*, 6, 1–9.

⁷ Hunter, J. E., & Schmidt, F. L. (1990). *Methods of meta-analysis: Correcting error and bias in research findings*. Newbury Park, CA: Sage Publications.

Methodology

Data sources

Validity Study Service

Data used in the analysis were collected through the GMAC Validity Study Service, a free service that helps programs evaluate their admissions processes. Participating programs provided GMAC with a dataset that included admissions criteria variables (e.g., GMAT scores and UGPA), and indicators of academic performance (either mid-program or final graduate GPA). In return, GMAC researchers evaluated the predictive validity of the variables, both individually and jointly, using correlation and regression methods.

The dataset

Data from 11 individual validity studies (2013-2018) were used to develop the meta-analysis.⁸ Offered by seven different universities—all but one in the United States—six of the programs focus on accounting, the remaining five on finance. Combined, these 11 programs represent 1,666 students, the largest citizenship group being those from the United States (43 percent).

The predictors used in this study were the UGPA, Total, VR, QR, IR, and AWA. The program type (i.e., accounting or finance), sample size (N), the year of the study, and the predictive validity for different admissions criteria are shown in Table 1. Note that only five programs have predictive validity values for IR as this section of the GMAT is relatively new (2012). Additionally, Study C did not have a predictive validity value for UGPA because the school did not provide that information.

⁸ Note that a meta-analysis is usually based on a large number of studies, often in the hundreds. Using only 11 studies may therefore limit the findings.

Table 1. Predictive Validity by Program

Study	N	Year	Program type	UGPA	Total	VR	QR	IR	AWA
A	128	2013	Accounting	0.45	0.50	0.40	0.29	--	0.02
B	161	2013	Finance	0.36	0.33	0.32	-0.08	--	0.28
C	120	2013	Accounting	--	0.31	0.23	0.25	--	-0.11
D	93	2013	Finance	0.44	0.24	0.18	0.17	--	0.10
E	257	2013	Accounting	0.60	0.44	0.52	0.14	--	0.36
F	224	2014	Finance	0.22	0.19	0.19	0.06	--	0.22
G	124	2016	Finance	0.27	0.41	0.31	0.20	0.05	0.01
H	145	2016	Accounting	0.10	0.37	0.26	0.28	0.17	0.21
I	238	2016	Accounting	0.54	0.51	0.48	0.26	0.29	0.22
J	56	2018	Finance	0.28	0.30	0.23	0.38	0.27	-0.15
K	120	2018	Accounting	0.46	0.52	0.52	0.29	0.28	0.03

Restriction of Range Correction

The methods to calculate predictive validity for individual and multiple predictors are discussed in this section. As mentioned before, program-level predictive validity studies take account of only the admitted student data. This results in lower variance among GMAT scores and UGPA, and hence, lower correlation coefficients. Therefore, the adjustment to the biased correlation is needed. The formula for computing the adjusted correlation (r^*) between a predictor and the GGPA⁷ is:

$$r^* = \frac{U*r}{\sqrt{(U^2-1)*r+1}}, (1)$$

$$U = \frac{\sigma_{pop}}{\sigma_{obs}}, (2)$$

where r is the observed bivariate correlation between a predictor and the GGPA, and σ_{pop} and σ_{obs} the standard deviations of a particular admission criterion for the population and sample, respectively.

To adjust the correlation, the population variance of an admissions criterion is required. Assuming the population in each study consists of all the examinees who sent scores to the program, their

characteristics (enrollment year, gender, etc.) were matched to those of the sample. For instance, if examinees in the sample enrolled in the program in fall 2017, the population would be all examinees who sent scores to the program prior to the enrollment date (i.e., from July 2016 to June 2017).

Additionally, the correlation between multiple admission criteria and the GGPA was also adjusted to remove bias arising from only evaluating data from admitted students. Multiple linear regression (R) was used to determine how well multiple admissions criteria can jointly predict the GGPA. This was obtained from the adjusted correlation matrix, which included adjusted correlations between the predictors and the GGPA, as well as the (population) correlations among predictors.

Finally, Total, VR, QR, AWA, and IR scores as well as UGPA were used as the predictors. Because the Total is derived from VR and QR scores, separate analyses of the predictors—Total, or VR and QR scores—were carried out.

Meta-Analysis

The correlations between the admissions criteria (e.g., GMAT scores and UGPA) and the GGPA vary across programs because of differences in the curriculum and the student body. In addition, and within each study, the sampling error can also influence the values of the estimated correlation. A random-effect model⁹ that takes into account between-study and within-study variance was used. The details of the process for obtaining the weighted mean predictive validities (\bar{r}) of different predictors and their confidence interval are discussed in the appendix.

Results

The most noticeable observation of the study was that nearly all predictive validity values for the admissions criteria, either alone or in combination, were significantly above 0.1, suggesting all the studied predictors were meaningful to a certain extent. When used alone, both Total and UGPA had the highest predictive validity ($\bar{r} = 0.39$) values, followed by VR ($\bar{r} = 0.34$), IR ($\bar{r} = 0.21$), QR ($\bar{r} = 0.19$), and AWA ($\bar{r} = 0.13$). The weighted mean and 95 percent confidence interval of the predictive validity values for each predictor and combined predictors are shown in Table 2 and Figure 1. Note that even though Total and UGPA had the same predictive validity on average, the confidence interval width was much smaller for Total than for UGPA. This could be caused by greater variation in the predictive validity of UGPA across programs resulting from diversity in candidate profiles (particularly what and where they studied).

Combining GMAT scores with UGPA produced the highest predictive validity values. Specifically, when Total was combined with UGPA, the predictive validity was 0.51; the same finding as when VR and QR scores were used instead. These show that whether Total or combined VR and QR are used does not influence predictive validity.

When IR and AWA scores were included in addition to Total and UGPA, predictive validity only increased marginally. If Total was combined with UGPA and IR, the predictive validity was 0.52; when Total was combined with UGPA, IR, and AWA, the predictive validity became 0.54. The highest predictive validity was obtained when UGPA was combined with VR, QR, IR, and AWA ($\bar{r} = 0.55$).

⁹ 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.

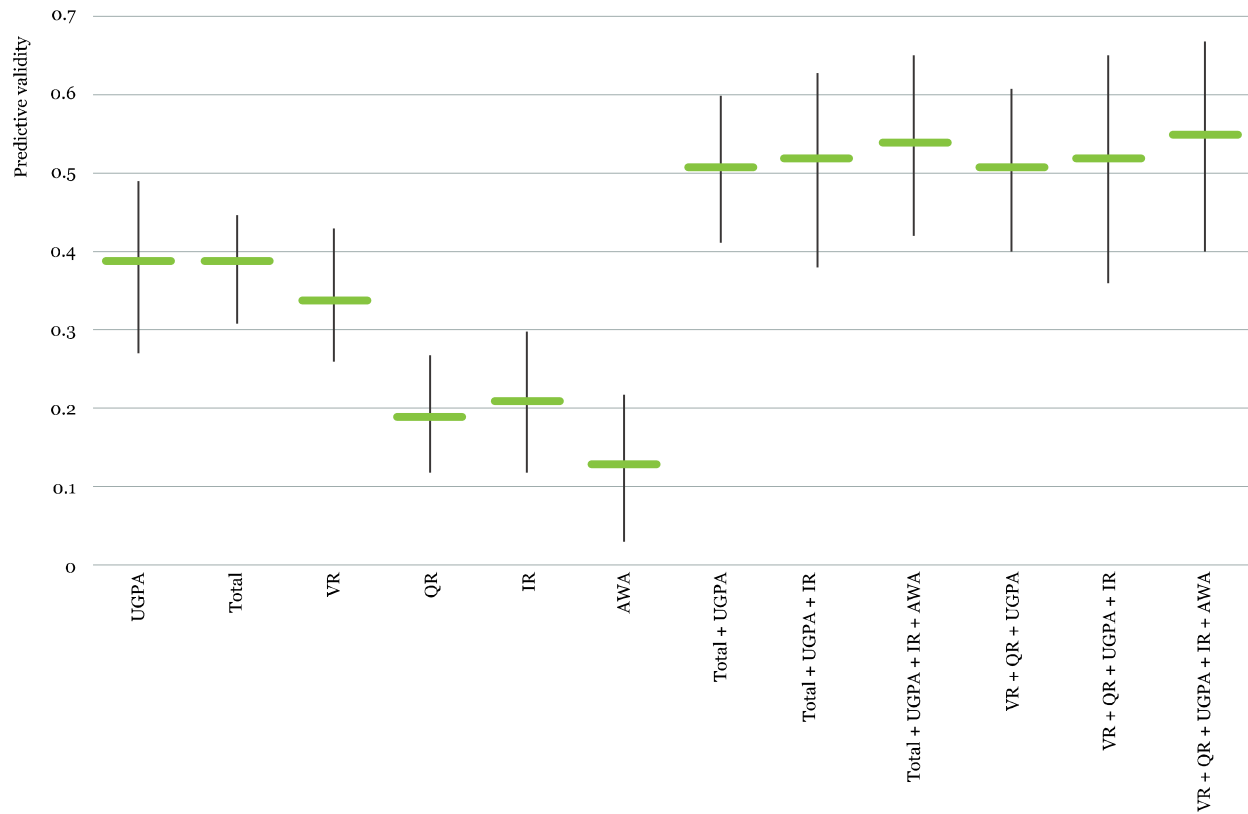
Table 2. Summary of Predictive Validity

	K	\bar{r}	95% L*	95% U**
UGPA	10	0.39	0.27	0.49
Total	11	0.39	0.31	0.45
VR	11	0.34	0.26	0.43
QR	11	0.19	0.12	0.27
IR	5	0.21	0.12	0.30
AWA	11	0.13	0.03	0.22
Total + UGPA	10	0.51	0.41	0.60
Total + UGPA + IR	5	0.52	0.38	0.63
Total + UGPA + IR + AWA	5	0.54	0.42	0.65
VR + QR + UGPA	10	0.51	0.40	0.61
VR + QR + UGPA + IR	5	0.52	0.36	0.65
VR + QR + UGPA + IR + AWA	5	0.55	0.40	0.67

*L: Lower bound

**U: Upper bound

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

Applying a meta-analysis approach, the overall predictive validity of GMAT scores and UGPA was examined for 11 quantitative master’s programs (six accounting and five finance). The study found that, when used alone, Total and UGPA have the highest individual predictive validity (0.39), followed by VR (0.34), IR (0.21), QR (0.19), and AWA (0.13). Combining Total and UGPA, however, produced a significantly higher predictive validity (0.51). The study also found that combining VR and QR with UGPA (0.51) provided as high a predictive validity as when combining Total and UGPA (0.51). Including AWA and IR in addition to UGPA and Total did not increase the predictive validity by much (0.54).

The findings of the study suggest that incorporating GMAT scores into the admissions process can help admissions decisions when combined with UGPA. Furthermore, because the predictive validity of UGPA varies considerably between programs, 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

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.

$$z_{r_i} = \frac{1}{2} \log \left(\frac{1+r_i}{1-r_i} \right). \quad (3)$$

Next, the weighted average \bar{z}_r needs to be computed using Equation 4:

$$\bar{z}_r = \frac{\sum_{i=1}^k w_i z_{r_i}}{\sum_{i=1}^k w_i}, \quad (4)$$

where weight w_i is $n_i - 3$, n_i is the sample size for the i^{th} study, and k is the total number of the studies. The between-studies variance is computed using Equations 5 and 6.

$$\tau^2 = \frac{Q-(k-1)}{c}, \quad (5)$$

$$Q = \sum_{i=1}^k (n_i - 3) (z_{r_i} - \bar{z}_r)^2. \quad (6)$$

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

$$w_i^* = \left(\frac{1}{n_i-3} + \tau^2 \right)^{-1}. \quad (7)$$

The new weighted average \bar{z}_r^* can be computed using Equation 4, 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:

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

The z scores can be transformed back to correlation using Equation 10:

$$r = \frac{e^{2z}-1}{e^{2z}+1}. \quad (10)$$