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RECRUITERS' USE OF GPA IN INITIAL SCREENING DECISIONS: HIGHER GPAs DON'T ALWAYS MAKE THE CUT

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The relationship between college grade point average (GPA) and recruiters' initial screening decisions was examined using data from 548 job postings in a college recruitment program. Results indicate that in-major grade point average (GPA) is more strongly associated with screening decisions (ρ = 0.18, SD_ρ = 0.200) than is overall GPA (ρ = 0.06, SD_ρ = 0.187), but the magnitudes of the relationships varied across decision sets including a larger number of negative values than would be expected from sampling error alone. Subsequent examination of the bivariate data identified 6 different plot types suggesting that recruiters use a variety of GPA decision rules to initially screen applicants in college recruiting. The most common data plots found in 42% of the decision sets suggests that recruiters do not use GPA in screening decisions. But a surprising 81 of 548 decision sets indicated recruiters selected against applicants with high GPAs. Evidence that organizations recruiting for the same job produced different plot types suggests that the use of GPA data in initial screening decisions may be idiosyncratic to individual recruiters.

Recruiters indicate that grade point average (GPA) is an attribute used to initially screen college applicants for positions (e.g., Brown & Campion, 1994; Thoms, McMasters, Roberts, & Dombkowski, 1999). GPA is indicative of students' performance in their academic program and has been shown to be a valid predictor of job performance (ρ = .32; Roth, BeVier, Switzer, & Schippmann, 1996). Recently, Roth and Bobko (2000) demonstrated that initially screening applicant pools using a minimum grade point average (GPA) cutoff as a criterion may produce adverse impact due to differences in mean GPA across ethnic groups. They found that using GPA cut scores of 3.0, 3.25, and 3.5 for business se-

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niors resulted in relative success ratios (i.e., success ratios for Black applicants/success ratios for White applicants) of .32, .36, and .22, respectively. These values are well below .80, providing prima facia evidence of adverse impact based on the 4/5ths rule. Given the consequences of adverse impact for organizations and applicants, studying how GPA is actually used in college recruiting is important and timely. The current study extends research in this area by examining data from actual screening decisions made by college recruiters during their normal on-campus recruiting and selection efforts.

GPA and Screening Decisions

The belief that GPA is a primary factor in initial screening decisions is apparently widely held by students, career counselors, and recruiters. A number of studies indicate decision makers report using GPA in screening decisions (e.g., Brown & Campion, 1994; Gardner, Kozloski, & Hults, 1991; Hutchinson & Brefka, 1997; Posner, 1981; Rynes, Orlitsky, & Bretz, 1997; Thoms et al., 1999), though none examines the actual screening decisions of recruiters. Results of these studies suggest that GPA is not always the most important predictor of recruiters' screening decisions (e.g., Brown & Campion, 1994; Hutchinson & Brefka, 1997; Posner, 1981; Rynes & Gerhart, 1990). GPA appears to be only one of several screening mechanisms, and often not the primary mechanism, used by recruiters. Brown and Campion (1994) found evidence that the relative importance of GPA is not constant and may vary across jobs. The association between GPA and screening decision outcomes is reduced when consideration is given to other applicant attributes such as degree, academic major, work experience (Hutchinson & Brefka, 1997), communications ability, or future potential (Posner, 1981).

Two methodological features of past research may also cloud our understanding of how GPA is used in initial screening decisions. First, existing studies often rely on recruiters' retrospective reports (e.g., Brown & Campion, 1994; Gardner et al., 1991; Thoms et al., 1999). Research indicates that decision makers often do not do a good job of reporting their own decision processes (e.g., Motowildo, 1986; Stevenson, Busemeyer, & Naylor, 1990). Both Brown and Campion (1994) and Gardner et al. (1991) found a lack of congruence between what recruiters reported they used and what they actually used in making selection decisions. Similar results have been found in policy capturing research evaluating applicants in employment interviews (e.g., Dougherty, Ebert, & Callender, 1986; Graves & Karren, 1992; Hitt & Barr, 1989). Thus, relying on recruiters' retrospective reports that GPA is an important factor in their resume screening decisions may not be appropriate.

A second concern is the use of decision tasks that have questionable fidelity to real screening contexts (e.g., Hutchinson & Brefka, 1997; Posner, 1981; Rynes et al., 1997). Research in decision making demonstrates that context can influence decision outcomes (Stevenson et al., 1990). Features of research designs that reduce the fidelity of the decision task from that actually experienced by recruiters can be expected to affect the external validity of the research findings from these studies. Examples of design features that potentially reduce decision-context fidelity include the use of simplified or stylized resume content (e.g., Hutchinson & Brefka, 1997; Posner, 1981) or limiting the number of resumes that are evaluated (e.g., Thoms et al., 1999). Several studies required respondents to rank the importance of resume characteristics or rank the favorability/suitability of applicants rather than make true dichotomous screening decisions (e.g., Brown & Campion, 1994; Hutchinson & Brefka, 1997; Posner, 1981). Of the studies we examined, only Thoms et al. (1999) actually required respondents to make dichotomous decisions. This study, though, is one of several that relied on subjects who were not actual decision makers. Research designs have employed decision makers ranging from individuals with prior recruiting experience (e.g., Brown & Campion, 1994; Rynes et al., 1997) to college students (e.g., Thoms et al., 1999). These studies capture perceptions or insights into resume screening decisions, but how well these findings generalize to actual recruiting contexts is not known. Although GPA is likely to be involved in the decision-making process, we do not have empiric evidence of how recruiters actually use GPA in initial screening decisions. Thus, the purpose of the current study is to examine the relationship between college GPA and recruiters' initial screening decisions.

Method

This study examines the initial screening decisions made by corporate recruiters at a southeastern university from September 1998 through May 1999. We report data on a sample that includes the initial screening decisions of recruiters for 548 jobs. Given our focus on the recruiter's decision making, each job and all applicants for that job are referred to as a decision set. Each decision set centers on a job posting originated by a recruiting organization at the university's career services center. College students submitted resumes in response to job postings. No limits were placed on the number of job postings for which students could electronically submit resumes. Recruiters reviewed all submitted resumes and then determined which resumes warranted an invitation for an on-campus interview.

We used point biserial correlations to measure the level of association between reported GPA and invitation for an on-campus interview. In order to develop the best estimate of the level of association, we felt it was appropriate to limit the sample to those decision sets that would provide the best opportunity to estimate that value. Consequently, we limited our sample to those decision sets with at least 50 submitted resumes and where at least 10% of those resumes resulted in an invitation for an interview. The requirement for a minimum of 50 applicants was implemented to reduce the influence of sampling error. A minimum of 10% invitations was chosen because the upper bound of a point biserial correlation is reduced the more the split on the dichotomous variable (i.e., invited/not invited) deviates from a 50/50 split (Howell, 1997, p. 282). Eliminating decision sets with extremely low selection ratios excludes those decision sets where the observed correlations will be most severely attenuated. Of 1,156 available data sets, 548 met these criteria. These decision sets incorporated 59,173 of the 93,794 resumes submitted by the 2,319 students pursuing on-campus interviews through the career services center.

The number of resumes submitted compared to the number of students (i.e., 59,173 resumes by 2,319 students) indicates that students, on average, submitted resumes for 26 jobs. This creates a lack of strict independence of resume observations across the 548 decision sets. However, because the focus of this analysis is not on each unique resume but rather on recruiters' use of resume data and subsequent decision making, we do not believe the lack of independence of resume observations across decision sets found in these data are problematic for this analysis (e.g., Kenny & Judd, 1986; 1996). The critical issue is not whether there is independence of the individual resumes but whether there is independence among the decision maker's perceptions of them. The independence of recruiters' perceptions of resume data is much more likely because few recruiters were responsible for screening more than one decision set and no two decision sets contain the same subset of resumes.

Even if a violation of independence does exist, it is not likely to meaningfully bias estimates of the association of GPA with screening decisions. Although it is possible to estimate and test for the amount of bias, criteria discussed by Kenny and Judd (1996) argue for not using a bias correction procedure in this instance. They conclude the magnitude of this bias is relatively small when sample sizes are appreciable and the correction procedure is cumbersome, particularly when values of ρ other than zero are expected. We do recognize that the lack of strict independence may result in an underestimation of the true variability in point biserial correlations across decision sets. Thus, variance outcomes reported here should be interpreted as lower bound estimates.

Measures

The two variables examined are reported GPA and whether the individual received an invitation for an on-campus interview (i.e., screening decision). Grade point average is most commonly reported as "overall" GPA representing an individual's performance on all course work taken as part of a degree program. A second form is "in-major" GPA that represents an individual's performance in a subset of classes specific to his or her area of specialization. It is not clear what GPA data recruiters use when different forms of GPA are reported on a resume (i.e., overall, in-major, or both). Therefore, we considered four possible decision rules that recruiters might employ and developed GPA measures consistent with each.

First, it is possible that recruiters use either overall GPA or in-major GPA as the sole screening device, ignoring other forms of GPA data when they are reported. Two measures, GPA(O) and GPA(I), represent overall or in-major GPA, respectively. A potential problem with recognizing only one form of GPA data is that the decision maker can often be left with a large number of resumes that do not report the desired form of GPA data. For example, a large number of resumes in our sample do not report in-major GPA data. We believe it is unlikely that recruiters that use GPA would ignore other forms of GPA data when their preferred form is not present. Therefore, we considered two additional GPA measures. GPA(O+) is used to describe the decision rule where overall GPA is preferred (i.e., used when both are present), but in-major GPA is used when overall GPA is not reported. GPA(I+) is used to describe the decision rule where in-major GPA data is preferred, but overall GPA data is used when in-major GPA is not reported.

During the normal course of campus recruiting, recruiters were given the opportunity to review the resumes submitted by all applicants in order to determine which applicants would be invited for on-campus interviews. Recruiters' screening decisions were captured electronically by career services personnel and recorded in a database. Screening outcomes were recorded for every resume in each decision set and coded 1 = *invited* or 0 = *not invited*.

Analyses

A point biserial correlation was calculated between GPA and screening outcome in each decision set prior to using meta-analytic techniques (Hunter & Schmidt, 1990) to aggregate the correlations across decision sets. Calculating correlations within each data set prior to aggregation is preferred to the alternative of aggregating data and then constructing one overall correlation because it maintains the integrity of the individual decision sets (cf. Carlson, Scullen, Schmidt, Rothstein, & Erwin, 1999). The alternative method could be used if all decision makers could be expected to have used GPA data in the same way (i.e., they employed the same decision model), and the means and standard deviations of these variables were the same in each decision set. It is not clear a priori whether either of these conditions is likely to be met in this data.

Correcting for Decision Set Artifacts

We performed corrections for two types of artifacts—range restriction in GPA data and variations in selection ratios (i.e., differing splits in the dichotomous variable) across decision sets. If a large percentage of individuals who failed to report GPA data on their resumes did so because their GPAs were low, this would result in direct range restriction and attenuate the observed point biserial correlations in each study. However, if range restriction is common to most decision sets, it is a component of the decision-making context and the correction for range restriction would not be necessary. But irrespective of whether decision sets in general show evidence of range restriction, differences in the level of range restriction across decision sets are likely to exist and increase variance in outcomes. Therefore, we corrected each correlation for direct range restriction (e.g., Hunter & Schmidt, 1990), but did so using the average standard deviation of GPA found in our sample of decision sets (i.e., SD = 0.43).

Selection ratios (i.e., the percent of individuals invited for interviews) differed across decision sets. Earlier, we described how decision sets with selection ratios less than .10 were removed from the analysis. This eliminated those correlations based on data with the most severe deviations from a 50/50 split on the dichotomous variable. However, differences in selection ratios across studies still remain and these differences are associated with different levels of attenuation in the observed point biserial correlations that could cause correlations to appear to vary across decision sets when they actually may not. To remove this source of artifactual variation, we corrected each individual correlation to its biserial counterpart and then reattenuated all biserial correlations to a common 75/25 split. This matches the average overall 25% selection ratio found in our sample.

Finally, we did not correct for attenuation due to error of measurement in either variable. Although error of measurement exists in all data, the amount of measurement error in these objective measures was assumed to be minimal. Failing to remove the resulting small downward bias this introduces is not believed to materially affect the results of this analysis.

TABLE 1

Overview of the Reporting of GPA and Descriptive Statistics for the Four GPA Measures and Screening Outcomes

		In-major GPA		
		Reported	Not reported	Totals
Overall GPA	Reported	15,982	22,746	38,728
	Not reported	7,208	13,237	20,445
	Totals	23,190	35,983	59,173
GPA Measure		*N*	*Mn*	*SD*
GPA(O)		38,728	3.23	.454
GPA(I)		23,190	3.24	.387
GPA(O+)	(38,728 + 7,208)	45,936	3.23	.442
GPA(I+)	(23,190 + 22,746)	45,936	3.30	.428
Screening outcome		59,173	.25	.430

Notes: GPA(O) uses only overall GPA data. GPA(I) uses only in-major GPA data. GPA(O+) and GPA(I+) include all resumes that report any form of GPA data. GPA(O+) uses overall GPA when it is available or in-major GPA when overall GPA is not available. GPA(I+) reverses the decision rule using in-major GPA data when it is present and overall GPA when in-major GPA is not.

Results

Table 1 provides a breakdown of the number of resumes that reported each type of GPA data. Of the 59,173 resumes in our final sample, 65% (N = 38,728) reported an overall GPA, 39% (N = 23,190) reported in-major GPA, and 27% (N = 15,982) reported both. The remaining 22% (N = 13,237) did not report any type of GPA data and, because GPA could not have played a role in the screening process for these resumes, they were not included in the analyses of their respective decision sets. The majority of the resumes analyzed came from students in the colleges of business and engineering—representing 50.4% and 40.8% of all resumes, respectively. All GPA values are on a 4.00 scale.

The means and standard deviations for each GPA measure—GPA(O), GPA(I), GPA(O+), and GPA(I+)—and screening outcomes are reported in Table 1. Means were similar for all four GPA measures, ranging from the low end of M = 3.23 (SD = 0.442) for GPA(O) to M = 3.30 (SD = 0.428) for GPA(I+). The higher mean and lower standard deviation in these data as compared to data for all university seniors (i.e., M = 2.72, SD = 0.52) provides evidence that range restriction did in fact exist. As noted above, the mean screening decision (M = 0.25, SD = 0.430) indicates that 25% of all resumes in our sample resulted in invitations for on-campus interviews.

As reported in Table 2, the mean observed point biserial correlations between GPA and screening decision are somewhat different for the four

TABLE 2

Results of the Analysis of Point Bi-Serial Correlations Between Reported GPA and Screening Decisions Across 548 Decision Sets Using Four Different Measures of GPA

Screening decision rule	K	N	r_{pb}	SD_r	ρ	S^2_{rc}	S^2_e	SD_ρ
GPA(O)	548	38,728	.05	0.213	.06	0.050	0.01428	0.190
GPA(I)	548	23,190	.16	0.208	.18	0.063	0.02298	0.200
GPA(O+)	548	45,936	.06	0.202	.07	0.047	0.01199	0.187
GPA(I+)	548	45,936	.08	0.201	.09	0.049	0.01192	0.193

Notes: K = Number of decision sets; N = total number of resumes; r_{pb} = mean observed point biserial correlation; SD_r = standard deviations of observed point bi-serial correlations; r = estimated true point biserial correlation; S^2_{rc} = variance of corrected point biserial correlations; S^2_e = estimated sampling error variance; SD_ρ = standard deviation of the true correlations. GPA(O) uses only overall GPA data. GPA(I) uses only in-major GPA data. GPA(O+) and GPA(I+) include all resumes that report any form of GPA data. GPA(O+) uses overall GPA when it is available or in-major GPA when it is not available. GPA(I+) reverses the decision rule using in-major GPA data when it is present and overall GPA when it is not.

GPA measures. The weakest relationship was found for GPA(O) with $\rho = 0.06$ ($SD_\rho = 0.190$) and GPA(O+) with $\rho = 0.07$ ($SD_\rho = 0.187$). On the other hand, GPA(I) and GPA(I+) exhibited stronger associations with screening decisions, $\rho = 0.18$ ($SD_\rho = 0.200$) and $\rho = 0.09$ ($SD_\rho = 0.193$), respectively. These results provide evidence that when these data exist, recruiter's screening decisions are more strongly associated with in-major GPA than with overall GPA. Unfortunately, only 39% of resumes contained in-major GPA data upon which screening decisions could be made.

A finer-grained depiction of the relationship between GPA and screening outcomes is reported in Table 3. As shown, resumes are categorized into eight 0.25 GPA-point ranges from 2.00–4.00 and a "No GPA" category using GPA(O), GPA(I), and GPA(I+) data. Percentages for GPA(O+) data did not differ meaningfully from those for GPA(O) data and are not reported. We list the total number of resumes that report GPA values in each range and the percentage of those resumes that resulted in invitations for on-campus interviews. These data indicate that for GPA(O), the greatest success rates (i.e., 30.8%) occurred for GPAs between 3.01 and 3.25. For GPA(I), the greatest success rates (i.e., 38.3%) occurred for GPAs between 3.51 and 3.75. Success rates drop as GPA(O) and GPA(I) increase above or decrease below these values. Success rates are higher for GPA(I) than for GPA(O) in all ranges with the exception of GPAs ranging from 2.26 to 2.50 and from 2.76 to 3.25. These findings indicate that recruiters appear to be more attentive to in-major GPA than overall GPA. Even more interesting are the suc-

TABLE 3

Percentage of Resumes in Different GPA Ranges That Resulted in Invitations for On-Campus Interviews

	GPA(O)		GPA(I)		GPA(I+)	
GPA	*N*	% invited	*N*	% invited	*N*	% invited
3.76–4.00	6,427	24.7	2,780	36.5	8,524	26.9
3.51–3.75	5,739	26.9	2,763	38.3	6,992	29.8
3.26–3.50	6,236	29.7	5,192	34.2	8,823	29.8
3.01–3.25	6,032	30.8	5,096	27.3	7,697	26.2
2.76–3.00	7,711	26.0	5,030	21.1	8,679	22.3
2.51–2.75	4,254	17.1	1,610	20.1	3,475	17.4
2.26–2.50	1,992	19.0	668	13.0	1,469	15.0
2.25 or less	337	8.6	51	9.8	277	7.9
No GPA reported	13,237	20.4				

Notes: Results for GPA(O+) are not meaningfully different than those for GPA(O) and are not reported. GPA(O) refers to those resumes that reported an overall GPA. GPA(I) refers to those resumes that reported in in-major GPA. GPA(I+) incorporates all resumes that included some form of GPA data and is based on a decision rule that uses in-major GPA if it is available, but will use overall GPA data from those resumes that do not include an in-major GPA but do include an overall GPA.

cess rates for resumes not reporting any GPA data. These are reported in the last line of Table 3. Of the 13,237 resumes that did not report any GPA data, 20.4% resulted in invitations for on-campus interviews. In essence, those not reporting GPA values were slightly more likely to be invited for an on-campus interview than those reporting GPA(O) or GPA(I) less than 2.76.

Variance in Results Across Decision Sets

Irrespective of the GPA measure used, there is substantial variability in the magnitude of the association between GPA and screening outcomes (i.e., SD_ρ values range from 0.187 to 0.200). This suggests there are real differences in how decision makers use GPA data. Figure 1 presents a histogram showing the distribution of corrected point biserial correlations across the 548 decision sets for GPA(I) and GPA(I+) data. Several features of this figure are noteworthy. First, approximately 26% and 39% of the corrected point biserial correlations are negative for GPA(I) and GPA(I+) data, respectively. That correlations between GPA and screening decisions would ever be negative is an unexpected finding. Further, a perfect association between GPA and screening decisions in these data would be represented by a point biserial correction of .73. A review of the data in Figure 1 shows that only 27 of 548 point biserial correlations in the GPA(I) and 2 of 548 in the GPA(I+) data

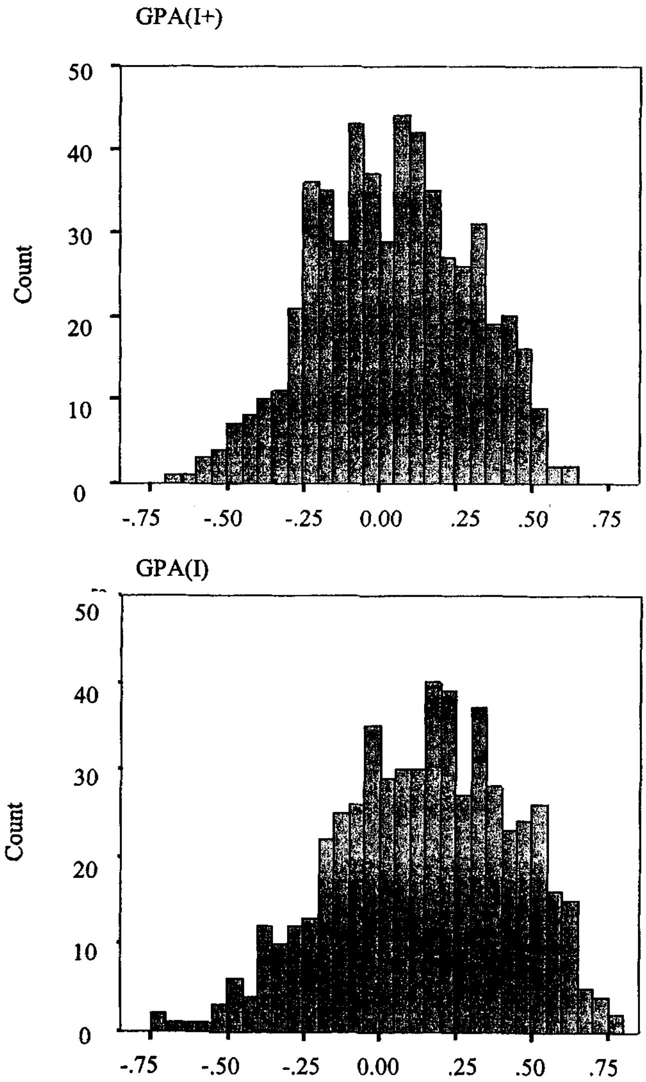

Figure 1: **Distribution of Corrected Point Biserial Correlations of GPA(I) and GPA(I+) with Screening Decision Outcomes Across the 548 Decision Sets.**

Notes: The height of each bar represents the number of point biserial correlations in each .05 correlation interval. GPA(I) refers to those resumes that reported in in-major GPA. GPA(I+) incorporates all resumes that included some form of GPA data and is based on a decision rule that uses in-major GPA if it is available, but will use overall GPA data from those resumes that do not include an in-major GPA but do include an overall GPA.

are greater than $r_{pb} = .60$. Thus, perfect associations between GPA and screening outcomes appear to be rare in actual screening decisions.

Plotting GPA and Screening Decision Relationships

In order to further understand the variability in the magnitude of the association between GPA and screening outcomes across decision sets, we constructed bivariate plots of GPA and screening outcomes data for each of the 548 decision sets. These plots show the GPA values of the applicants that were not invited versus the GPA levels of the applicants that were invited to on-campus interviews. A comparison of the plots revealed that those based on GPA(O), GPA(O+), and GPA(I+) data were very consistent but plot types based on GPA(I) data differed. Where GPA(I) produced different plot types compared to other GPA data types, the differences generally coincided with smaller numbers of data points in the plots. Because GPA(I) data was reported less frequently on resumes, some GPA(I) plots included fewer than five invite data points. When plots contained larger numbers of data points, GPA(I) plots were similar to those for the other GPA data types. Because plot types did not differ meaningfully across GPA data types, we only coded plots based on GPA(I+) data.

Two of the authors independently coded each of the 548 decision sets for GPA data types. A preliminary review of the bivariate data plots suggested three plot types reflecting a maximum cutoff plot, a minimum cutoff plot, and no relationship plot. An initial coding of decision sets using these three plot types resulted in interrater agreement of slightly over 80%. The discrepancies in coding of the decision sets were resolved by recognizing three additional plot types reflecting nonabsolute minimum and maximum cutoffs and a midrange target. Each of the 548 decision sets was recoded against the six plot types resulting in 98% interrater agreement. Remaining discrepancies were resolved through discussion.

Ideal representations of the six plot types are presented in Figure 2. In each plot shown in Figure 2, GPA is presented on the vertical axis and the two possible screening outcomes are indicated on the horizontal axis. In each plot, applicants that were not invited were found in the full range of GPA values, but systematic differences occur in the distribution of GPA values for invited applicants. The six plot types reflect minimum cutoffs, maximum cutoffs, or no relationship between GPA and screening outcomes.

Plot A: Minimum cutoff. In Plot A, only applicants with higher GPA values were selected. All GPA values for those invited for on-campus interviews are above a minimum score that falls somewhere around the midpoint of the GPA score ranges. This minimum cut score did not ap-

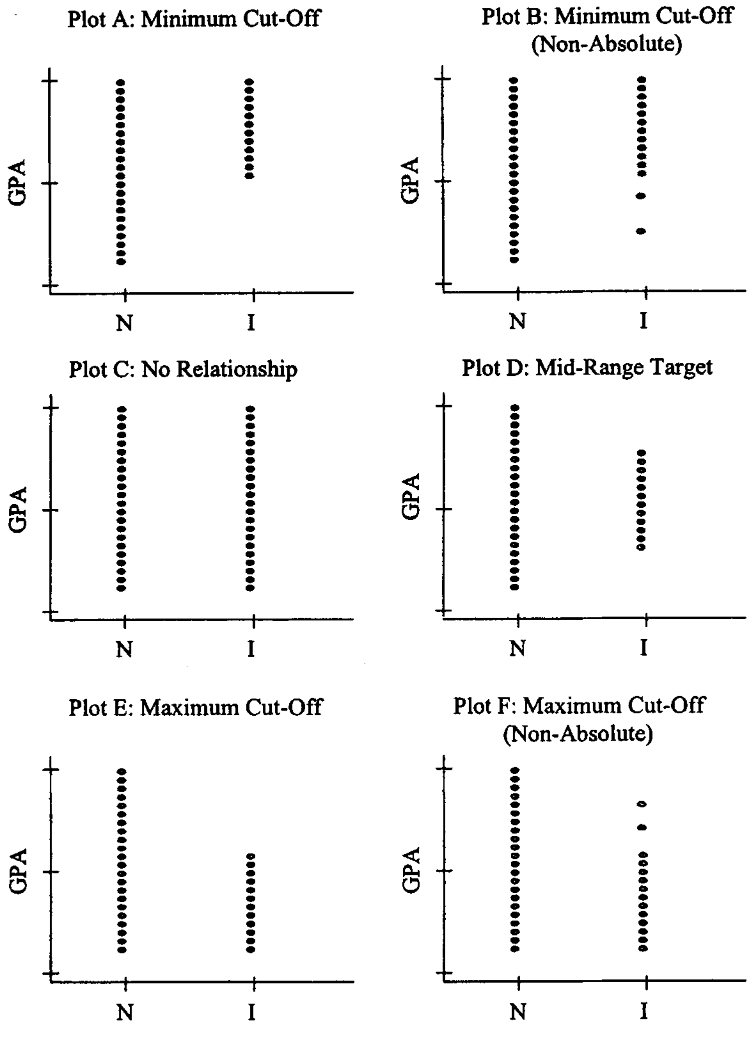

Figure 2: **Plot Types: GPA and Screening Decision**

Notes: Six different types of plots of bivariate relationships between grade point average (GPA) and initial screening decision outcome (N = not invited for on-campus interview; I=Invited for on-campus interview) were identified. Each graph in the figure represents the prototypical pattern of data points characteristic of each plot type is presented.

pear to be consistent across data sets, ranging from values as high as 3.50 to as low as 2.90. In each instance, although a number of applicants with lower GPA values were available, none were invited for interviews. That is indicative of a decision rule where GPA is used to screen resumes applying a minimum cut score. Only applicants with GPAs above a minimum cut score were invited, but applicants with a GPA below the cut score were excluded from receiving an invitation.

Plot B: Minimum cutoff (nonabsolute). Plot B is similar to Plot A in that it also appears to be indicative of the use of a minimum cut score, however, in this instance the minimum cut score does not appear to be inviolate. That is, although the vast majority of applicants selected have GPA values above the apparent minimum cut score, a few applicants with GPA values below the cut score have been selected. This pattern of data points is consistent with a screening decision rule that first uses a minimum GPA value as a cut score and then in a subsequent step reviews those applicants that did not have the minimum GPA to determine whether these applicants possessed other compensatory characteristics that would warrant invitations.

Plot C: No relationship. Plot C differs from the two earlier plots in that the distribution of GPA values is the same for both the uninvited and invited outcome groups. That is, the distribution of GPA values of the individuals invited mirrors that of those individuals not invited. This suggests that, in these data sets, no relationship exists between GPA level and screening decisions. Both high and low GPA individuals appear to be equally likely to receive invitations for on-campus interviews.

Plot D: Midrange target. In Plot D all individuals invited for on-campus interviews possessed midrange GPA scores. No applicants with very high or very low GPAs (i.e., typically the upper and lower quartiles) received invitations. This could be indicative of a decision rule where preference is given to applicants with midrange GPA but applicants both well above or well below the average are not considered.

Plot E: Maximum cutoff. Plot E was perhaps the most surprising to observe. In these plots, only applicants with GPA scores below a maximum value were invited. That is, in these plots there appears to be a "maximum" cut score and any individual with a GPA above that level is screened out. All applicants invited for on-campus interviews in these decision sets had GPA scores below a maximum cut score.

Plot F: Maximum cutoff (nonabsolute). Although Plot E suggests a maximum cut score is inviolate, Plot F suggests the use of a decision rule where high GPA applicants may have been excluded on a first pass through the applicant pool, but they may be examined for compensatory factors in subsequent rounds of evaluation. This results in very few high GPA applicants receiving invitations for interviews.

TABLE 4

Subgrouping Correlations of GPA(I+) and Screening Decision by Plot Type

Plot type	K	%	N	ρ	SD_ρ
A. Minimum cutoff (3.0)	103	18.8	10,578	.32	.122
B. Minimum cutoff (not absolute)	133	24.2	16,960	.20	.152
C. No relationship	231	42.1	23,758	−.01	.098
D. Mid-range target (min and max cutoff)	33	6.0	3,837	−.05	.050
E. Maximum cutoff	24	4.3	2,290	−.23	.088
F. Maximum cutoff (not absolute)	24	4.3	2,206	−.22	.192
Overall GPA(I+)	548		59,174	.09	.193

Notes: K = Number of decision sets; %= percentage of plot types of the 548 decision sets; N = total number of resumes; ρ = estimated true point biserial correlation; SD_ρ = standard deviation of the true correlations.

These six plot types were sufficient to code the data from all decision sets. Table 4 provides a recap of the frequencies (K) that each plot type was found in these data. An interesting finding was the frequency of the no relationship plot. A total of 231 of the 548 decision sets (42%) were consistent with Plot C, suggesting GPA data were not used to initially screen applicants for on-campus interviews. Plots that indicate a decision rule applying a minimum cut score for GPA (i.e., Plots A and B) were found in 236 out of the 548 decision sets. In this analysis, 103 of 548 decision sets (19%) were consistent with Plot A. Another 133 of 548 (24%) were consistent with Plot B.

The remaining plots were used less frequently, but were unexpected prior to examination of the plots and, therefore, are perhaps the most interesting. In these data, 33 decision sets were consistent with Plot D, 24 were consistent with Plot E, and an additional 24 were consistent with Plot F. All are indicative of decision rules that result in selecting against individuals with high GPA levels. Therefore, in almost 15% of the decision sets, decision makers screened out applicants with high GPAs.

Plot Types and the Relationship of GPA to Screening Decision

An examination of the plot types in Figure 2 provides insight into the observed variance in the relationships between GPA and screening outcomes. In Plots A and B, the absence of points in the lower right portion of the plot suggests that these plots will produce a positive relationship between GPA and screening outcomes. The higher the cut score and the greater the percentage of individuals in the decision set above that score that are selected, the stronger the relationship is likely to be. Plots C and D, on the other hand, are unlikely to produce a strong relationship between GPA and screening decision. Particularly in Plot C, the absence of any discernable pattern would suggest the association between GPA and screening decision is near zero. In Plot D, both upper and lower cut scores may have been used to identify those individuals to invite. This should produce relationships that are nonlinear (i.e., curvilinear) and would not be captured well by the zero-order correlation of GPA and screening decision. Plots E and F are likely to produce strong negative relationships between GPA and screening outcomes. In these plots, screening success (i.e., receiving an invitation for an on-campus interview) is more strongly associated with a low GPA than a high GPA. This suggests that some variance in the magnitude of the relationship of GPA and screening outcomes across decision sets may be due to the use of different screening decision rules as implied by different data plots.

To determine to what extent these differences account for variance in outcomes across decision sets, we examined plot type (i.e., inferred decision rule) as a moderator of the relationship of GPA to screening outcomes. We grouped decision sets by plot type and then meta-analyzed the correlations for each plot type using the methods described earlier. The results of this analysis are reported in Table 4. As shown in Table 4, the average relationships between GPA and screening decision do differ in the expected directions. In general, stronger and more consistent relationships were produced from the plots that used strict minimum or maximum cutoff decision rules (i.e., Plots A and E) as compared to those that applied these decision rules less consistently. The mean corrected correlation for each plot type and the standard deviation of the corrected correlations for each plot type are as follows: Plot A, $\rho = .32$, $SD_\rho = .122$; Plot B, $\rho = .20$, $SD_\rho = .152$; Plot C, $\rho = -.01$, $SD_\rho = .098$; Plot D, $\rho = -.05$, $SD_\rho = .050$; Plot E, $\rho = -.23$, $SD_\rho = .088$; Plot F, $\rho = -.25$ $SD_\rho = .192$.

The use of these decision rules does appear to account for a portion of the variance in the relationship between GPA and screening outcomes across decision sets. A comparison of SD_ρ values in Table 4 indicates that grouping by inferred decision rule does result in a meaningful reduction in variance in outcomes. The SD_ρ values for each of the subgroups range from $SD_\rho = .050$ to $SD_\rho = .192$, all of which are lower than the $SD_\rho = .193$ for GPA(I+) data for all decision sets combined.

Choice of Decision Rule

Given that several different decision rules appear to exist, we attempted to determine whether certain factors influenced the choice of decision rule. Specifically, we examined the extent to which the size of the applicant pool, the job for which applicants are being evaluated, and the recruiting organization were related to plot types. We first examined whether initial screening decisions may differ simply as a function of the

TABLE 5

Plot Types by Applicant Pool Size

Sample size	N	Plot A	Plot B	Plot C	Plot D	Plot E	Plot F
50–99	333	64	65	150	17	22	15
100–149	131	27	37	49	7	2	9
150–199	44	7	13	20	4	–	–
200–299	29	4	13	7	5	–	–
300+	11	1	5	5	–	–	–
Totals	548	103	133	231	33	24	24

Notes: Sample size = total number of resumes screened within a decision set; N = total number of decision sets; Plot A is minimum cutoff; Plot B is minimum cutoff (nonabsolute); Plot C is no relationship; Plot D is midrange target; Plot E is maximum cutoff; Plot F is maximum cutoff (nonabsolute).

size of the applicant pool. For example, when applicant pools are very large, the task of evaluating applicants becomes more difficult and the use of a simple screening tool for initially screening applicants may make this task more tractable for most decision makers. Therefore, it may be likely that the use of GPA as a screening device (i.e., either minimum or maximum cut score) may be more prevalent in larger decision sets. In addition, we examined whether differences in job requirements may also contribute to differences in the use of GPA data for initially screening applicants. For example, if a candidate's capacity to perform a job is highly related to learning the specific knowledge and skills acquired in a degree program, then perhaps GPA might be more important in the screening of individuals for those jobs. Finally, we examined whether the use of GPA decision rules were consistent *within* organizations.

In examining whether applicant pool size was associated with specific types of data plots, we grouped decision sets by sample size and identified the number of decision sets of each plot type in each size category. The results of this analysis are reported in Table 5. These data indicate that minimum cut score plots became slightly more prevalent as the size of the applicant pool increased. Plots E and F did not occur in any decision set with more than 150 applicants. However, the no relationship decision rule was common throughout each of the various applicant pool sizes and was just as common as the minimum cut score plots in larger applicant pools.

Next, we examined whether certain types of jobs were associated with particular data plots (i.e., inferred decision rules). Decision sets were grouped into 18 families of closely related jobs. Only those job families with 8 or more positions were analyzed. The results for the analysis of job families are reported in Table 6. For this analysis, minimum cutoff plot types (Plots A and B) and maximum cutoff plot types (Plots E and F) were collapsed. The dominant decision rule for each job is indicated in bold type. From these data, it appears that minimum cutoffs

TABLE 6
Percent of Plot Types by Job Family

Job family (N)	% A & B	% C	% D	% E & F
Software technician (43)	**65**	30	–	5
Information technology (19)	**63**	21	16	–
Hardware technician (18)	**61**	22	6	11
Consultant (19)	**58**	37	5	–
Analyst (14)	**57**	29	14	–
Mechanical engineer (11)	**55**	27	–	18
Technical staff (17)	**53**	47	–	–
Software design (15)	**53**	33	7	7
Management (19)	**51**	32	16	32
Programmer/analyst (18)	**50**	22	6	22
Finance (25)	**48**	40	4	8
Associate engineer (19)	**42**	**42**	5	11
Engineer (91)	35	**51**	7	8
Production engineer (26)	31	**54**	8	8
Information systems (32)	28	**44**	16	13
Productions/operations (15)	27	**73**	–	–
Accounting (11)	27	**73**	–	–
Sales (62)	21	**58**	5	16
Other (74)	55	35	4	5
Totals (548)	43	42	6	9

Notes: N = total number jobs within the job family; A & B is the minimum cutoff (absolute and nonabsolute) plot type; C is no relationship plot type; D is midrange target plot type; E & F is the maximum cutoff (absolute and nonabsolute). Only job families that included at least eight jobs were analyzed separately. The remaining jobs are grouped in the other category.

Numbers in bold refer to dominant decision rule with in the job family.

(Plots A and B) were more prevalent among the more technical jobs including engineering, information technology, software design, and consulting. Interestingly, though, the no relationship plot was equally common among these same job families. These jobs accounted for roughly 55% of the jobs screened. Six of the 18 jobs included instances of all six data plot types with the no relationship decision rule being the most prevalent. These jobs accounted for 45% of the jobs screened. Finally, the fewest number of different plot types were found in "operations/ manufacturing" jobs (N = 15), where only Plots B and C occurred.

To determine whether there were consistencies in the use of inferred decision rules within organizations, we examined those instances where a single organization recruited for two or more different jobs. Consistent plot types occurring for a firm would signal the potential that decision rules might be consistent within companies. Our data set included 102 organizations recruiting for two or more different jobs. A sample of these data for organizations that recruited for four or more positions across multiple jobs is reported in Table 7. Examination of these data

TABLE 7

Examples of Plot Type Distributions Within Organizations

No. of different jobs	No. of decision sets	Plot A	Plot B	Plot C	Plot D	Plot E	Plot F
8	10	7	3	–	–	–	–
7	8	2	–	2	2	2	–
6	7	1	1	4	–	1	–
6	6	2	2	2	–	–	–
4	5	1	2	1	1	–	–
3	5	3	1	–	1	–	–
4	4	1	1	1	–	1	–
4	4	–	2	1	–	1	–
4	4	–	2	2	–	–	–
4	4	–	4	–	–	–	–
4	4	–	–	4	–	–	–
3	4	–	2	2	–	–	–
3	4	–	–	3	1	–	–
3	4	4	–	–	–	–	–
3	4	–	–	3	1	–	–

Notes: These data are a subset of the 102 organizations recruiting for four or more positions. Plot A is minimum cutoff; Plot B is minimum cutoff (nonabsolute); Plot C is no relationship; Plot D is midrange target; Plot E is maximum cutoff; Plot F is maximum cutoff (nonabsolute).

found that of the 102 organizations, different data plots occurred in 76, suggesting different decision rules for the use of GPA in initial screening decisions. A more conservative view of the differences is produced if all minimum cut score and maximum cut score plots are collapsed (i.e., considering Plots A and B and Plots E and F to be the same). This reduced the number of instances with different plots types within organizations from 76 to 58. These findings indicate that a lack of consistency in plot types (i.e., inferred decision rules) existed in more than half (i.e., 57%) of these organizations.

We also examined plot types in instances where the same organization recruited more than once for the same job. An examination of our data revealed 51 instances where an organization recruited for the same job two or more times. Our findings indicate that different data plots occurred in 33 of the 51 (65%) organizations. When minimum and maximum data plot types are collapsed, the number of instances with different data plots is reduced to 23 (45%). Thus, even when recruiters in the same organization are recruiting for the same job, there appear to be inconsistencies in the use of GPA in screening decisions.

Discussion

The results of this study provide evidence that the use of GPA data appears to differ widely across screening decisions in college recruiting. The relatively modest average level of association between GPA and screening outcomes we found obscures important differences in how recruiters use GPA data on resumes to initially screen applicants for on-campus interviews in college recruiting. We found that the most common decision rule appears not to use GPA in initial screening decisions. This occurred in 42% of the 548 decision sets we examined. The no relationship plot was as common as the minimum cutoff plot. The most surprising finding was evidence that some recruiters appear to select against high GPAs. Three different plot types, a midrange target and two versions of maximum cutoff plots all provide evidence that recruiters did not select high GPA individuals. That these plots occurred approximately 15% of the time was unexpected. Finding these different plot types helps explain why there is so much variability in the magnitude of the relationships between GPA and screening outcomes in these data, as shown in Figure 1, and why individuals with the highest GPAs do not experience the greatest levels of success in gaining on-campus interviews.

What leads recruiters to choose the decision rules that led to the distribution of plot types found in our data is not clear. Although there is some evidence of job and organization level influences on decision rules, there is sufficient variability in the screening outcomes within jobs and organizations to argue much of the variance may be due to factors related to individual recruiters. We were able to demonstrate that as the size of the applicant pool grows, recruiters are less likely to employ decision rules that select against high GPA. It is possible that decision rules that result in Plots D, E, and F may be due to differences in the competitiveness of particular positions/organizations rather than a perceived relationship between GPA and job performance. However, we were unable to examine this possibility with our data.

Our results also suggest future research should examine differences in the use of in-major versus overall GPA in initial screening decisions (i.e., GPA(O), $\rho = .06$, $SD_\rho = .190$ vs. GPA(I), $\rho = .18$, $SD_\rho = .200$). It may be that organizations view in-major GPA as a potentially more effective indicator of relevant job knowledge. In addition, less is known about the validity of in-major GPA for predicting job performance. If in-major GPA should be determined to be a more valid predictor of job performance for at least some jobs, organizations may begin requesting students report in-major GPA on their resumes. Given that current resume preparation tactics exclude in-major GPA data on more than half of student resumes its current role in screening decisions is necessarily limited.

Interestingly, in our analysis of data plot types we encountered no "pure" plots; that is, we found no data plots that suggested that selection for an on-campus interview was based exclusively on GPA. This finding can extend research on the potential for adverse impact due to group differences in GPA (e.g., Roth & Bobko, 1997; Sackett & Ellingson, 1997). These data indicate that the use of GPA in initial screening is not likely to lead to adverse impact in most screening decisions in college recruiting. Finding no evidence of "pure" GPA screens indicates adverse impact is less likely to occur because GPA is not directly translated to screening outcomes. However, in those instances where minimum cut scores are set very high, the magnitude of the association between GPA and screening outcomes could still approach levels that produce adverse impact.

This study does not address GPA's value as a screening device. A recent meta-analysis demonstrates that overall GPA has validity for predicting job performance with an observed correlation corrected for measurement error in the criterion and for range restriction of $\rho = 0.32$ (Roth, et al., 1996). This evidence could be used to defend organizations whose use of GPA as a screening device produces adverse impact. We also do not examine the association between GPA and decision makers' use of GPA in later screening or selection decisions. We believe that the impact of GPA on selection decisions is likely to be greater during initial screening than at later stages in the selection process. Later decisions in multiple hurdle screening processes are likely based on additional sources of information, potentially further diluting the influence of any one factor.

It is important to note that our analysis is based on data from human decision makers. The advent of Internet recruiting and computerized human resource information systems, though, is resulting in an increased interest in the use of computer algorithms for screening large numbers of resumes. Human decision processes appear to be compensatory, that is, they permit strengths in one area to compensate for weaknesses in another (Stevenson et al., 1990). If computer models use noncompensatory decision rules (i.e., each resume must possess each of the characteristics identified at a level equal to or greater than that specified), shifting from human decision makers to computer algorithms could increase the potential for adverse impact. While this analysis provides a basis for inferring recruiters' screening decisions, most do not appear to be heavily weighted on overall GPA. However, organizations shifting from human-based screening processes to computer algorithms may use GPA as a screening criterion, thus, ensuring that GPA will play a greater role in determining screening outcomes. Using GPA in noncompensatory computer algorithms for screening resumes could raise the potential for adverse impact. Organizations that are leading the shift to computerized applicant tracking and selection systems will need to understand this potential source of risk.

There are several potential limitations in human decision making associated with judgmental shortcuts that may influence the results of this study. Although this study examined recruiters' screening decisions, we cannot know with certainty whether all resumes for each job were screened. Some of the decision sets had as many as 600 resumes to be screened. There is anecdotal evidence that recruiters faced with screening large applicant pools may only screen a sufficient number of resumes to fill vacant interview slots. To the extent that recruiters did not screen all resumes in each decision set, the results of this study may not be an accurate representation of the relationship between GPA and screening decisions. We have no reason to believe that all resumes for each job were not screened and it seems unlikely that recruiters would risk the possibility of not screening for the most qualified applicants, though this is a possibility that should be considered in future research.

A second limitation concerns the recruiting context for the 548 jobs examined in this study. There is sufficient anecdotal evidence that career services personnel in college environments frequently provide students with guidance on reporting GPA on their resume. Often, this advice is based on specific GPA levels. What is less clear is whether career services may also play a role in recruiter's screening decisions by suggesting and/or discouraging the use of GPA screens. The extent to which career services personnel communicate expected policies to organizations recruiting on campus may potentially influence the use of GPA in recruiters' screening decisions. There is no evidence that career services personnel communicated either official or unofficial policies suggesting the use of GPA in screening decisions. Given the variability found in the current study, it is unlikely that the use of hard GPA screens were suggested or discouraged. Future research on resume screening decisions should examine the potential context effects of career services' practices on organizational recruiters.

Finally, some readers may be concerned that the selection criteria used to include decision sets in this analysis may have produced a sample that was in some way biased. We do not believe this is the case. The criteria we used for including decision sets in this analysis (i.e., eliminating sets with selection ratios below .10 or sample sizes less than 50) were established to remove those decision sets likely to produce correlations with large confidence intervals or that were most severely downwardly biased. The resulting 548 decision sets are representative of the variety of jobs and employers found in the full sample. Although these data depict decision making that occurred at a single university, the decision makers involved represent a wide range of organizations that also recruit on many other campuses. Therefore, we would expect results found here to generalize to initial screening decisions in other university settings.

Conclusion

This study demonstrates that there appears to be little consistency in the use of GPA as a screening tool in college recruiting. Although many decision sets support the general perception that recruiters use a minimum GPA cut score in screening—a view that is consistent with research indicating GPA is a valid predictor of job performance—more than half of the decision sets we examined appear to suggest decision rules that do not use GPA or that select against high GPA levels. Although selecting against high GPA would result in lower validity selection practices, and as a result lower utility in selection procedures, there are reasons to believe that such selection practices may be rational when other components of the staffing cycle—capacity to attract high quality applicants, the capacity to get high quality applicants to accept offers or to retain those individuals once they are on the job—are considered. Determining the rationality of these decisions, though, will require more comprehensive evaluations of staffing decisions.

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