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RESEARCH ARTICLE

The Relationship between General Mental Ability and Workplace Deviance

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Abstract

General Mental Ability (GMA) refers to an individual's capability to reason, plan, solve problems, and comprehend complex ideas. In the context of work and organizational psychology, GMA is one of the best predictors of overall job performance, and especially task and contextual performance. However, the relationship between GMA and a third dimension of overall job performance, workplace deviance, remains inconclusive and under-researched. We investigated this hypothesis using a sample of 391 individuals from various occupational fields. Using novel Bayesian cumulative link mixed effects models, our results show that even after controlling for all Five-Factor Model factors, GMA has a significant, yet weak effect on workplace deviant behavior. Our findings emphasize the need for a more comprehensive exploration of the influence of GMA across diverse occupational sectors to fully understand its impact on workplace behavior.

Keywords

GMA, Intelligence, Workplace Deviance, Personality, Performance

General Mental Ability (GMA), or general intelligence, is a "...capability that, among other things, involves the ability to reason, plan, solve problems, think abstractly, comprehend complex ideas, learn quickly and learn from experience" (Gottfredson, 1997, p. 13). GMA has been linked to a series of favorable outcomes from various life domains, such as higher literacy levels, better general physical health, and lower odds of unemployment. Within the realm of work and organizational psychology, GMA has been recognized alongside work samples as the most stable predictor of overall job performance (e.g., Schmidt & Hunter, 2004) and of some of its dimensions, namely, task performance ($\hat{\hat{\rho}}$ = .69, Schmidt et al., 2008) and Organizational Citizenship Behaviors (OCB, $\hat{\hat{\rho}}$ = .23, Gonzalez-Mulé et al., 2014).

The influence of GMA on the remaining domain of job performance - Workplace Deviant Behaviors (WD) - remains a subject of ongoing research. For example, previous research has assumed a negative correlation due to the potential inhibitory effects of GMA on WD According to this argument, high-GMA individuals can reason better, learn faster, and also possess enough foresight to evaluate the consequences of their actions, which makes them less likely to engage in counterproductive or deviant behaviors. Empirical evidence to date has been less than

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conclusive. In particular, early meta-analytic efforts showed a near-zero effect size for the relationship between GMA and WD ($\hat{\bar{\rho}}$ = -.02, Gonzalez-Mulé et al., 2014).

However, these meta-analytic efforts were weakened by the state of the literature. For example, military and police samples accounted for over half of the available correlations. As these occupations are characterized by unique, stringent rule enforcement and high-integrity selection criteria, the relatively low remaining number of observations from other occupational sectors leaves a *de-facto* population gap in research (Robinson et al., 2011). In such high-integrity settings, the strict enforcement of rules may naturally lead to lower incidences of WDB, potentially causing a range restriction in the WDB variable itself. This situation suggests that the findings of the meta-analysis, heavily based on these sectors, might not fully represent the variations in WDB that occur in less regulated environments. Consequently, the generalizability of the relationship between GMA and WDB as observed in these contexts might be limited. To underscore the importance of this issue, we point to the fact that more recent research links overqualified workers (GMA proxy) to WD risk (Fine & Edward, 2017), while other studies (Cuadrado et al., 2021) show that GMA is indeed related to Counterproductive Academic Behavior (CAB), such as cheating or plagiarism (ρ = .19).

It is clear that our understanding of the role of GMA in work performance, particularly in relation to counterproductive or deviant behaviors, is far from complete. More primary studies, encompassing a wider range of occupational sectors, are needed to further elucidate these relationships. The current scarcity is evidenced by the latest two meta-analyses on workplace deviant behavior, where neither Liao et al. (2021), nor Mackey et al. (2021) have included GMA in the analysis.

In this paper we contribute to solving this gap in two ways: first, by providing further data on the subject and second, by analyzing the data using a modern approach, namely, Bayesian cumulative link mixed effects models (CLMMs), an approach that avoids distorted estimates, a risk inherent in the way ordinal data has been treated until now (Liddell & Kruschke, 2018; Taylor et al., 2022).

General Mental Ability and Workplace Deviant Behavior

Defined as "...voluntary behavior that violates significant organizational norms and, in so doing, threatens the well-being of the organization or its members, or both" (Bennett & Robinson, 2000), workplace deviance (WD) has a longstanding tradition in organizational research, perhaps due to the high economic and moral costs that are associated with it (Bennett et al., 2018). From a theoretical perspective, WD is a part of the larger umbrella term of Counterproductive Work Behaviors (CWB) that includes behavioral sets such as bullying or retaliatory actions (Mackey et al., 2021). In this respect, workplace deviance is unique because it involves actions that violate organizational norms, meaning they are behaviors that are uncommon and frowned upon (Thrasher et al., 2020). For example, WD includes acts such as stealing from colleagues, falsifying receipts for personal gain, or using illegal drugs or consuming alcohol on the job. Predicting workplace deviance has obvious upside potential in applied psychology, with general mental ability being a strong candidate, due to its powerful predictive capacity on overall job performance.

Historically, initial queries into the relationship between GMA and WD originate from an attempt to generalize findings from criminological literature to job-related deviance (e.g., Marcus et al., 2009). The main reasoning lines used to link general mental ability to lower levels of norm violating behavior generally revolve around the inhibitory effects of GMA on deviant behavior. For example, it is argued that high-GMA individuals can better reason, learn, and evaluate the consequences of their actions, which makes them less likely to engage in deviant behaviors. Furthermore, people low in reasoning abilities may take more risks and engage in behaviors that more intelligent individuals would avoid due to their ability to anticipate negative long-term consequences (Dilchert et al., 2007). However, empirical evidence shows a non-significant link ($\hat{\rho}$ = -.02, Gonzalez-Mulé et al., 2014). There are several interpretations that might explain the observed null effect.

First, range restriction can significantly impact primary studies that are developed in this domain. Participants in these studies are employees, i.e., one has to be an employee before being eligible to participate in a study on workplace deviance. Having a job is therefore a gateway to the study, but having a job is also associated with higher GMA than not having one. This means that these workplace studies systematically exclude people with lower GMA - and in turn the same reasoning explains why criminology studies do find one: this particular audience is not excluded from studies with inmates as participants.

Second, as already noted, the quality and characteristics of the primary studies will always shape the conclusions of a meta-analysis. Gonzales-Mulé et. al (2014) meta-analysis contains about 30 correlations, and more than half of them are based on military and police samples, i.e., samples coming from environments where deviant behavior is severely punished and integrity tests and other connected overt and covert indicators are used both as part of the selection process and for workplace monitoring.

Furthermore, the Gonzales-Mulé et. al (2014) paper appears to have significantly influenced the research trajectory on the topic. Following its publication, we observed a notable decline in subsequent studies in this area, with only two exceptions identified. Fine and Edward (2017) investigated the counterproductive work behaviors of overqualified employees; this study has limitations for the present topic because over-qualification was measured strictly in terms of GMA (which is actually a proxy for over-qualification and not a direct indicator), and because the related job requirements were identical (i.e., all participants were employed in the same job). The results of this study showed small or no effects of the investigated relationship (see p. 403). Fine et. al. (2015) also investigated our focal relationship on a military sample, again (as probably expected) with no significant effects. At the same time, indirect evidence points to a stronger relationship than the zero or almost-zero effect reported in these studies: For example, Cuadrado and his colleagues (2021), in his meta-analysis on academic deviance pointed out that lower GMA is significantly associated with academic deviance.

Personality and Workplace Deviant Behavior

The link between personality traits and workplace deviance is stronger and much better documented than the GMA-deviance relationship. In fact, a number of both broad and narrow personality traits are among the best predictors in the domain of individual differences that were ever found for deviant behaviors (cf. Dilchert et al., 2007). When focusing on broad personality traits, components of the Big Five model, like conscientiousness and agreeableness were found to be (negatively) related to CWB, and albeit with a lower strength emotional stability has also been highlighted (Barrick et al., 2003; Berry et al., 2007; Penney et al., 2011). In the same area of broad personality traits, core-self evaluations (CSE), a broad but fundamental personality domain that is a compound of the narrow traits of self-esteem, generalized self-efficacy, neuroticism, and locus of control, have also been linked (negatively) to CWB (Chang et al., 2012). Turning to narrow personality traits, several variables were associated with CWB: all three components of the dark triad of personality (i.e., machiavellism, narcissism, and psychopathy; O'Boyle et al., 2011), self-control (Tangney et al., 2004), locus of control (O'Brian & Allen, 2008; Spector, 1988) and others.

Methods

General Procedure and Sample Recruitment

Participants

The data was collected online with the help of a survey company, that operates a large panel of participants in Romania. The sample drawn comprises 391 individuals, with an average age of M = 33.70 and with a standard deviation (SD) of 5.68. The sample is balanced in terms of gender distribution, including a number of 216 (55%) male participants, with the remaining 175 (45%), female.

Scales and Instruments

General Mental Ability

General mental ability was measured with the General Ability measure for Adults (GAMA, Naglieri & Bardos, 1997). The GAMA is a 66-items, self-administered, timed (25 minutes) test that uses nonverbal items grouped into four templates (matching, analogies, sequences, construction), and is scored based on the tenets of Classical Test Theory: each item provides an unweighted contribution (0 or 1) to the raw total score. The raw total score is then transformed into a standardized score based on age-specific norms. Psychometric data such as reliability and validity evidence for GAMA is presented by Iliescu & Livinti (2008), Ispas et al. (2010), and Naglieri & Bardos (1997). For the present study, the split-half reliability of the GAMA is .89.

Workplace Deviant Behavior

WDB was measured using the questionnaire developed by Bennett and Robinson (2000). The instrument measures a wide range of workplace deviant behaviors from taking property from work without permission to discussing confidential company information with unauthorized individuals, using 19 items. Examples are: “Told someone about the lousy place where you work” or “Made an ethnic, religious, or racial remark or joke at work. Responses were collected on a 7-point frequency scale, ranging from 1 = “daily” to 7 = “never”. The full scale had M = 2.38, SD = 0.94, and α = .92.

Personality Measures

The five domains of the Five-Factor Model, i.e., Neuroticism, Extraversion, Openness, Agreeableness and Conscientiousness were measured with the NEO-FFI (Costa & McCrae, 1992). The NEO-FFI is a 60-item questionnaire measuring each of the five domains with 12 items on a 5-point Likert response scale from 1 = “strongly disagree” to 5 = “strongly agree”. The internal consistency of the five personality scores (N, E, O, A, and C) was .86, .76, .76, .75 and .74 respectively.

Data Analysis

While ordinal data, such as Likert scales, are modeled in routine fashion using metric models, this choice is ultimately inappropriate since it is prone to consistently produce Type I and II errors, even to the point of systematic effect inversions (Liddell & Kruschke, 2018). To address these issues, we analyzed the data using Bayesian cumulative link mixed effects models (CLMMs). These account for the unequal psychological distances between response categories, respect the discreteness of ratings or accommodates easily for non-normal information (Bürkner & Vuorre, 2019), while increasing accuracy of the estimated parameters by accounting for subject and item variability. Furthermore, Bayesian inference was preferred over the frequentist implementation since it offers a complete posterior distribution of the parameters of interest and therefore quantifies uncertainty more naturally (McElreath, 2020), is more flexible and will perform very well even in small or moderate sample sizes (Liddell & Kruschke, 2018) that are pervasive in psychological science.

Results

The analysis was run under R, version 4.3.1 (R Core Team, 2023) and RStudio (version 2023.06.0). The models were fit and analyzed using *rstan* for Markov Chain Monte Carlo probability sampling (Stan Development Team, 2018) interfaced with *brms* (version 2.17.0, Bürkner, 2018). Tidyverse implementations drew inspiration from the work of Kurz (Kurz, 2022) and the reporting follows the Bayesian Analysis Reporting Guidelines (BARG, Kruschke, 2021) as well as the recommendations by Veríssimo (2021).

For the CLMM, we standardized the predictors, and we initialized four chains for each parameter, with a total of 8000 steps with a burn-in of 2000, the rest being saved. Chain convergence was observed (*potential scale* *reduction factor*; $\hat{R}$ = 1), with good stationarity, overlapped and well mixed, representative of the posterior distributions. For all β parameters we used a weakly-regularizing – N(0, 1) – prior and for the second level σ an Exponential(1) was applied. The priors for the thresholds were set at equally distributed probability mass points on the latent continuous distribution. The full model containing the likelihood, priors, by item and by person varying intercept is:

$$p\left(\text{rating} = k \middle| \{\tau_k\}, \mu_{ij}\right)$$

$$= \Phi\left(\tau_k - \mu_{ij}\right)$$

$$- \Phi\left(\tau_{k-1} - \mu_{ij}\right)$$

$$\mu_{ij} = b_0 + b_{1\mathrm{O}_{ij}} + b_{2\mathrm{C}_{ij}} + b_{3\mathrm{E}_{ij}} + b_{4\mathrm{A}_{ij}}$$

$$+ b_{5\mathrm{N}_{ij}} + b_{6\mathrm{GMA}_{ij}} + u_i$$

$$+ v_j$$

$$\tau_1 \sim \mathcal{N}(-1.07,1)$$

$$\tau_2 \sim \mathcal{N}(-0.57,1)$$

$$\tau_3 \sim \mathcal{N}(-0.18,1)$$

$$\tau_4 \sim \mathcal{N}(0.18,1)$$

$$\tau_5 \sim \mathcal{N}(0.57,1)$$

$$\tau_6 \sim \mathcal{N}(1.07,1)$$

$$b_0, b_1, b_2, b_3, b_4, b_5, b_6 \sim \mathcal{N}(0,1)$$

$$u_i, v_j \sim \mathcal{N}(0, \sigma_u)$$

$$\sigma_u, \sigma_v \sim \mathcal{E}xp(1)$$

While Table 1 reports means, dispersion data and frequentist Pearson correlations for each variable of interest, Table 2 presents the summary information on the posterior distributions of the mixed-effect threshold cumulative model predicting response categories as a function of the FFM and GMA data. Further information regarding model specification and diagnostics (chain information, auto-correlation plots) or posterior-predictive checks are also included in the ESM.

First, the results show that the effect of FFM on Workplace Deviance varies in significance depending on the dimension, but remains overall weak, with the slope for Conscientiousness, β = -.16, 89% CrI[-.25, -.07], and for Agreeableness, β = -0.12, 89% CrI[-.21, -.03]. These coefficients are a bit smaller, but in line with previous meta-analytic reports on FFM and deviant behavior in the workplace (e.g., Thrasher et al., 2020). Two other FFM factors, Extraversion, β = -.04, 89% CrI[-.12, .04] and Neuroticism, β = .03, 89% CrI[-.08, .13], have posterior θ distributions that fall almost completely within the Region Of Practical Equivalence with 91% and 87% respectively (ROPE set at -.1 to .1 *SD*, Kruschke & Liddell, 2018). As such, they are not significant, however we cannot safely accept the null due to the remaining uncertainty. Interestingly, FFM-Openness shows a small, positive effect with a β of .15, 89% CrI[.07, .24]. As for the central variable of interest of this study, the effect of GMA has a probability of 100 [*pd*] of being negative (Median= -.22, 89% CrI[-.29, -.14]), and can be considered to be small and significant (with 0% in ROPE). Figure1 shows the effect of GMA on self-rated response categories of WD. At lower levels of GMA, all response categories from the WD scale seem to be almost equally probable. However, as GMA increases there is also a steady increase in the probability of observing a “Never” response, while there is a slow decline in the other categories. As GMA passes the +1*SD* mark, “Never” becomes more likely to be observed.

Table 1. *Means, Standard Deviations, and Frequentist Pearson Correlations for the Variables of Interest*

	M	SD	1	2	3	4	5	6
1. Openness	35.70	7.73						
2. Conscientiousness	48.27	5.93	.07					
2. Extraversion	44.66	6.70	.28**	.26**				
4. Agreeableness	40.60	7.25	.05	.25**	.17**			
5. Neuroticism	33.03	9.80	.24**	-.52**	-.17**	-.51**		
6. GMA	104.06	10.41	.02	.05	.04	.09+	-.06	
7. WD	2.38	0.94	.17**	-.24**	-.07	-.19**	.25**	-.24**

Note. N = 391. M and SD are used to represent mean and standard deviation, respectively. WD = Workplace Deviance Behaviors. GMA = General Mental Ability. + indicates p < .10. * indicates p < .05. ** indicates p < .01.

Table 2. *Posterior Summary, Parameter Decision and Convergence Statistics for the Described Model, Fixed Effects Only*

		HDI					
Parameter	Median	lower	upper	*pd*	% in ROPE	$\hat{R}$	*ESS*
Threshold[1]	-.41	-.64	-.21	1.00	0%	1.00	1,997
Threshold[2]	.36	.13	.56	.99	1.4%	1.00	2,004
Threshold[3]	.85	.61	1.05	1.00	0%	1.00	2,006
Threshold[4]	1.65	1.42	1.85	1.00	0%	1.00	2,033
Threshold[5]	2.26	2.03	2.47	1.00	0%	1.00	2,059
Threshold[6]	2.97	2.73	3.19	1.00	0%	1.00	2,239
Openness	.15	.07	.24	1.00	14.6%	1.00	2,356
Conscientiousness	-.16	-.25	-.07	1.00	10.6%	1.00	2,409
Extraversion	-.04	-.12	.04	.78	90.6%	1.00	2,333
Agreeableness	-.12	-.21	-.03	.98	33.0%	1.00	2,551
Neuroticism	.03	-.08	.13	.66	87.2%	1.00	2,193
GMA	-.22	-.29	-.14	1.00	0%	1.00	2,755

Note. Median = Posterior median; HDI = 89% highest density interval with lower and upper bounds; pd = Probability of Direction; Region of practical equivalence (ROPE) range = -.01 to 0.1 SD; % in ROPE = Percent of the highest density interval within ROPE; ESS = Effective sample size; $\hat{R}$ = Gelman-Rubin Statistic.

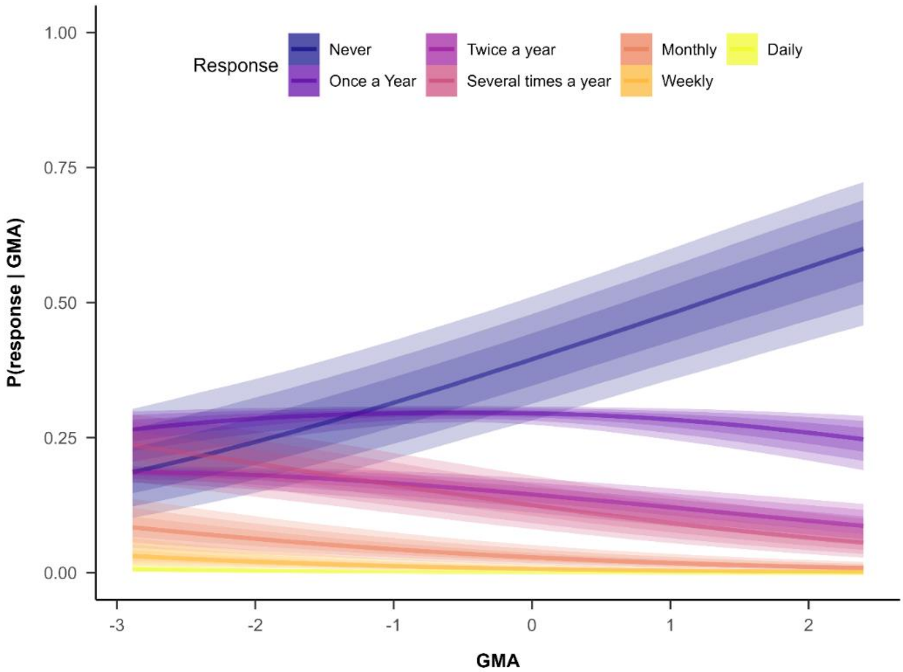

Figure 1. Effect of GMA on self-rated Workplace Deviant Behavior. The plot indicates separate predictions for each response category. Transparent bands indicate 50, 75 and 89% credible intervals.

Discussion

The main objective of the current paper was to bring further empirical evidence for the nuanced relationship between General Mental Ability (GMA) and tendencies for deviant behavior in the workplace. This relationship has seen dormant interest in the existing literature of organizational psychology. The last comprehensive meta-analysis on this topic was conducted almost a decade ago (Gonzalez-Mulé et al., 2014) and while its findings showed a non-significant relationship, a substantial gap still persists in the literature offering avenues for further research.

For example, previous studies relied heavily on samples from military and police sectors, where deviant behavior is strictly penalized, monitored and controlled for, possibly suppressing the true relationship between GMA and WD. While the sample homogeneity hypothesis (Marcus et al., 2009), suggests GMA will be a better predictor of WD in occupationally homogenous groups, this is due to better control of the confounding variables. However, the specific nature of military and law enforcement jobs might suppress this effect.

Our findings contribute to this complexity by revealing a nuanced relationship between GMA and workplace deviance, suggesting a departure from the conclusions drawn in the Gonzales meta-analysis. For example, the meta-analysis conducted by Cuadrado (2021) reveals a significant negative correlation between lower GMA and Counterproductive Academic Behaviors such as cheating, plagiarism, or deception, with the reported effects sizes being in the same range as our results ($\hat{\bar{\rho}}$ = -.19).

Our study started on the assumption that the GMA effect will be more likely to be observable in samples outside the military/police domain and the results of this research provide further supporting evidence for this assertion. Indeed, our data shows that, when accounting for personality factors (notably Conscientiousness and Agreeableness – the two best personality based predictors of deviant behavior; Thrasher et al., 2020) GMA has a small, yet non-zero and significant effect on workplace deviance. Together with the results obtained by Cuadrado (2021), our findings suggest that this this research avenue should not yet be discarded.

In addition to the sample homogeneity hypothesis, the source of the ratings for workplace deviance might also play a moderating role. For example, in the aforementioned law-enforcement and military samples, deviance was measured predominantly using supervisory ratings. Despite the apparent benefits, measuring deviant behavior through supervisory ratings is not without drawbacks. For example the notion that supervisors have the observational opportunity for certain workplace deviant behaviors was challenged (Chan, 2009), because instances of workplace deviance are likely to happen when supervisors are absent (e.g., stealing or acts of aggression). Therefore, data obtained from supervisors may be a deficient representation of deviant behaviors in the workplace (Harris & Schaubroeck, 1988).

Just as is the case of Organizational Citizenship Behavior (Gunnesch-Luca & Moser, 2020), it is generally perceived that individuals are the most reliable sources for reporting the frequency of their own deviant behaviors, since they have firsthand knowledge of their actions, especially those that go unnoticed by others. This perspective is also backed by the Gonzales meta-analysis that revealed that people often admit to participating in more counterproductive behaviors than what is reported by observers.

Another possible factor that might come into play when using self-reports is that individuals high in GMA may be inclined to under-report their own deviant behavior. This may be because they are more capable of anticipating the adverse repercussions of confessing to such actions. In turn, this might accentuate the negative correlation between GMA and WD in self-reported instances compared to data obtained from other sources.

Yet another strength of this paper is the use of Bayesian cumulative link mixed effects models. The consequences of using metric methods for fitting ordinal data can be a serious issue, even to the point of threatening inferential validity (Liddell & Kruschke, 2018). Using ordinal models, we mitigate these problems by accounting for unequal psychological distances between responses and the discreteness of the answers, thereby providing unbiased estimates for the parameter of interest.

While our study has limitations, one of which is the heterogeneity of participants' jobs, this aspect also emerges as a significant strength. Initially, the varied job types among participants might seem to introduce variability that could challenge the uniformity of the findings. However, this diversity actually enhances the generalizability aof our results. Unlike studies that focus narrowly on specific sectors like law enforcement and military organizations, our diverse sample allows for a broader exploration and understanding of the relationship between General Mental Ability (GMA) and Workplace Deviance (WD) across different occupational settings. This approach provides valuable insights into how this relationship manifests in a wider range of work environments, offering a more comprehensive perspective for future research.

Second, it would have been ideal for workplace deviance indicators to be collected both in self-report and supervisor-reported manner; a triangulation of such a kind would have possibly given a glimpse into how our predictors converge or diverge with the "deviance" variable depending on its measurement.

Third, as previously commented in several instances, investigations into deviance and other similar constructs that have very low endorsement rates may be better suited to intensive studies of criterion-positive samples, i.e., samples containing individuals who, based on objective indicators, are known to have exhibited deviance in the workplace. This solves one of the major issues in our study, i.e., the very low endorsement rate of deviance items - the from a theoretical range of 1-7, the mean endorsement has been $M = 2.38$ ($SD = .94$), which makes the criterion barely notable and also contributes heavily to range restriction, which in turn may artificially hide a potentially stronger relationship.

Despite these limitations, we consider the results of this study interesting and timely, coming after a decade-long gap in research dedicated to the relationship between two important variables: GMA, the most important predictor of workplace performance and WD, a fascinating and critical workplace performance criterion.

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