**A Sign of the Times:**

**The Importance of General Mental Ability Increases over Time in the Modern Workplace**

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**Abstract**

Widely accepted theories of dynamic performance suggest that general mental ability (GMA) decreases in its importance for performance the longer one is on the job. While this perspective was true at the time, the nature of work has changed considerably in the last half century. Changes in labor market demands, increased automation of job tasks, the rise of the knowledge economy, and a heightened focus on continuous learning all suggest that cognitive demands on workers have increased in recent years. Moreover, job training does not end after onboarding; modern workers are required to continuously update their skill set in order to perform effectively. These fundamental changes to the nature of work suggest that the relationship between GMA and job performance may not function the same way in the modern world of work as it did in prior decades. To better understand the temporal limits to dynamic theories of job performance, we conducted a meta-analysis on the relationship between job or training performance, job tenure, and GMA. Based on data from 37 primary studies, comprising 73 correlations and a pooled sample size of approximately 25,000 (N = 25,275), we find that the relationship between GMA and job performance decreases over tenure for earlier studies and increases over tenure for later studies. Practically, this finding holds important implications for personnel selection. Overall, these results may suggest that other theories within the organizational sciences are time-bound, which begets a more general need to re-evaluate dated theories of job performance.

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Researchers investigating the dynamic nature of performance have long agreed that its correlation with general mental ability (GMA) decreases as a function of an employee’s time on the job (i.e., Alvares & Hulin, 1972; Dunham, 1974; Fleishman, 1960; Fleishman & Hempel, 1954; Hempel & Fleishman, 1955; Parker & Fleishman, 1959; Fleishman & Rich, 1963; Ghiselli & Haire, 1960; Guion, 1961; Humphreys, 1968). This finding has been confirmed in field and laboratory studies (Henry & Hulin, 1987), and is so well-established that it is routinely mentioned in introductory industrial-organizational psychology, human resource management, and staffing textbooks (e.g., Gatewood & Feild, 2001; Polyhart, Schneider, & Schmitt, 2006). Indeed, the most recent edition of the *Handbook of Psychology* refers to this decrease in the GMA-performance relationship over time as “the most ubiquitous finding in longitudinal studies of performance prediction” (Cortina & Lunchman, 2013; p. 164). This trend has major implications for our fundamental understanding regarding the importance of GMA to performance, suggesting familiarity with and routinization of job-related tasks erodes the importance of GMA.

Declines in the importance of GMA to performance with increased tenure are based on work by Ackerman (1986; 1988; 1992) regarding skill acquisition that were generalized to learning across career stages (Kanfer & Ackerman, 1989; Murphy, 1989). This theory states that in the *transition* stage, learning is highly important, making GMA critical to performance. This stage occurs when an employee first begins a new job or when the tasks of the job change substantially, such as the introduction of new technology. As time on the job increases, persons become more comfortable with tasks and enter the maintenancestage in which skill usage becomes routinized; thus, the importance of GMA fades (Murphy, 1989).

In the relatively short time since publication of these influential theories, the world of work has undergone major changes (Howard, 1995; Hoffman et al., 2020). For instance, management practices devoted toward continuous learning and employee adaptability have gained popularity (National Academy of Science, 1999). Similarly, empirical evidence has documented increases in the job characteristics of skill variety and autonomy since 1975 (Wegman et al., 2017). Given these broad contextual changes in the modern workplace, “transition stages” occur continuously, requiring employees to adapt to frequent and rapid changes in the requirements of their work. Further, employees must also adapt independently of formal training and supervision programs due to their new-found autonomy. Indeed, researchers have cited learning orientation and adaptability to be increasingly important worker characteristics (e.g., Cascio & Aguinis, 2008; Fried, Levi, & Laurence, 2008).

Despite these radical shifts in the nature of work, no theoretical or empirical research to date has sought to reconcile these changes with the classical perspective on the dynamic interplay of GMA and work performance. In this article, we propose that although the perspective that GMA becomes less important as job tenure increases was generally correct when formulated, modal shifts in the nature of the workplace suggest otherwise. In particular, we propose that the importance of GMA *does not* decline with job tenure in the modern workplace. Rather, we suggest GMA becomes *more* important to performance over time. We argue that although classical perspectives on the GMA-performance relation were correct in their time, the radical shifts in the nature of work over the past two decades requires a reexamination of this fundamental finding in applied psychology. To test this idea, we present a meta-analysis that examines whether the moderating influence of job tenure on the GMA-performance relation has changed direction over the years.

**General Mental Ability and the Changing Nature of Work**

Examples of great changes in the workplace over the past few decades are abundant: The rise of the knowledge economy, increased focus on continuous learning, flattened organizational structures, and heightened emphasis on service are hallmarks for understanding and studying employee performance. The “changing nature of work” is commonly cited as evidence that work and the workplace are fundamentally different than in years past (National Academy of Science, 1999). Researchers often reference such changes as rationale for studying corresponding changes in a variety of organizational phenomenon, such as organizational commitment (Solinger, van Olffen, & Roe, 2008), job design (Grant et al., 2010), and changes in selection systems (Murphy, 1999).

One reason for the increased importance of GMA in predicting job performance is the increased market demand for skilled laborers. In recent years, the proportion of jobs demanding high skills in the United States labor market has increased. Compared to low-skill and high-skill jobs, middle-skill jobs are made up of rule-based tasks that are relatively easy to automate. As a result, organizations have begun to replace middle-skill workers with machines and can outsource middle-skill jobs overseas (Autor et al., 2003). Occupations that are intensive in routine tasks now make up a smaller share of total employment, whereas occupations that require social and cognitive skills have grown (Boehm, 2014; Atalay et al., 2020). Occupations in the top two skill percentiles (80-100%) grew sharply between 1980 and 2005, whereas occupations requiring moderate skill levels (20-40%) conceded market share (Autor & Dorn, 2009).

With increased demand for knowledge work and skill-expansion, it is likely that GMA is more strongly associated with performance than ever and should also become more important as time on the job increases. In the information age, knowledge and information are crucial to organizational success (Felin, Zenger, & Tomsik, 2009). Knowledge workers hold jobs that involve the “creation, distribution, or application of knowledge” (Authur, Defillippi, & Lindsay, 2008; p. 365), and this industry has grown rapidly over the last century. Researchers estimated that in 1999 58% of men held technical/managerial occupations compared to only 21% in 1900 (Caplow, Hicks, & Wattenberg, 2001). More recent data from the United State Department of Commerce suggests that between 1997 and 2014 the manufacturing sector fell from 16.1% of gross domestic product (GDP) to 12.1% and the retail industry from over 7% to under 6% GDP. In contrast, the professional and business services industry rose from 9.8% to 11.9% GDP. In 2015, 31.9% of the United States labor force was employed as Managers and Professionals, and 23.9% was employed as Sales and Administrative Support (Sakamoto et al., 2020).

Atalay et al. (2020) created a database of newspaper job ads and used text analysis to describe changes in work in the United States between 1950 and 2000. They demonstrate that the frequency of words related to routine cognitive tasks and routine manual tasks has sharply declined during this time period, whereas mentions of nonroutine interactive tasks and nonroutine analytic tasks have increased. Interestingly, 88% of changes in tasks occurred *within* jobs, which suggests that the trend toward nonroutine tasks is not solely a result of an increase in the total share of nonroutine jobs in the economy. Because machines are taking over the manipulation or assembly of smaller parts or pieces of information, this means that jobs at all levels are increasingly cognitively loaded (Demerouti, 2020).

Over the last 50 years, workers’ time spent using information and communication technologies including Microsoft Office and general-purpose programming languages has risen. As new technologies enter the workplace, the number of nonroutine analytical tasks that employees engage in has increased considerably, as have the requirements for employees to acquire new knowledge (Atalay et al., 2018). Demerouti (2020) posits that this “technology-induced implementation of changes” (p. 3) is a source of job demands; it forces employees to continually change their work routines and learn new skills, which increases cognitive demand on employees. Rapid changes in technology and innovation mean that workers’ skills become quickly outdated. In order to keep up, organizations heavily invest in training programs and reimbursements for postsecondary education. It is estimated that companies in the United States spend 1.1 trillion dollars on postsecondary education and training for employees (Carnevale et al., 2015). Employee performance over time is therefore closely related to their ability to learn new skills, which suggests that the importance of GMA on job performance does not decline as job tenure increases.

In addition to shifts in the types of jobs available, the complexity of changes in global economies, rapid pace of technology, and need for collaboration have resulted in increased pressure for adaptation in all jobs (Sessa & London, 2006). The National Academy of Science (1999) notes the cognitive complexity of work seems to be increasing, and employees must constantly update and master their skills to prevent becoming obsolete. Indeed, Wegman et al. (2017) found skill variety to have increased over time, and Fried, Levy, and Lawrence (2008) proposed employees’ capacity for learning has become a critical predictor of performance, even more so than job knowledge. Finally, with changes to organizational structures (e.g., flattened hierarchies, autonomous team design) decision-making authority is more diffuse, with lower-level employees granted greater control and more responsibility (Cappelli et al., 1997). Wegman et al. (2017) found support for this in that the modern workplace is characterized by greater levels of autonomy compared to organizations of the past.

Cognitive ability allows workers to acquire job-related knowledge (Schmidt et al., 1986). Murphy’s (1989) dynamic model of job performance is based on the premise that the types of activities employees engage in that are most reliant on their cognitive ability occur during the transition stage. While this model was a useful framework for understanding the GMA-performance relationship at the time, the premise no longer holds; employees are increasingly asked to learn new roles, new technologies, and contribute to cross-functional teams. We provide an updated model that describes the process by which GMA affects job performance in Figure 1. As opposed to the earlier Murphy (1989) model, our new model suggests that the GMA continues to affect job performance at all stages of employment, given that training and reskilling is a continuing process throughout an employees’ job tenure.

In the terminology of Murphy (1989), modern employees likely experience longer and more rapidly occurring transition phases, leading to an increased importance of GMA over tenure. Thus, we propose the following hypothesis:

*Hypothesis*: The relationship between GMA and performance decreases as tenure increases for earlier studies; the relationship will increase over job tenure for more recent studies.

*Hypothesis*: The relationship between GMA and performance will increase as a function of both an employee’s tenure and the year a study was conducted.

**Method**

**Literature Search and Criteria for Inclusion**

Literature searches were conducted to identify studies reporting correlations between each trait and performance that also included the sample’s average job tenure by examining studies used in prior meta-analyses and searches of databases. For a study to be included it had to use workers as participants, explicitly measure GMA, as well as job or training performance, utilize a predictive design with an expressed point of entry into a new job, new position, or time after an organizational intervention such as training. Concurrent designs were only included if the time period between entry and criterion measurement was clearly designated. A list of articles used are provided in Table 1.

**Preliminary Data Analysis**

In total, 73 correlation coefficients were collected from 37 studies, resulting in a pooled sample size of 25,275. Meta-analysis procedures were conducted using the “psychmeta” package (Dahlke & Wiernik, 2019). Furthermore, the current study used techniques developed by Raju, Burke, Normand, and Langlois (1991) to correct for measurement error and range restriction. The weighted mean uncorrected correlation coefficient was .15, with the 95% Confidence Interval ranging from .11 to .18. The mean correlation after application of correction was ρ=.19, *SD*ρ=.20, with the 95% Credibility Interval ranging from .14 to .23.

**Moderators**

Job tenure was used as a moderator, operationalized as days on the job. To evaluate the influence of time as a moderator, we utilized the year of the study’s publication minus two years as an estimate of the year of data collection (Twenge, 2001; Twenge & Campbell, 2001). Finally, criterion types were coded as either representing job performance or training performance to account for potential variability due to the type of criterion. The median days worked on the job (i.e., job tenure) was 365 days, with *M=*804.76, *SD=*1351.35. The median adjusted year of data collection (i.e., year of publication minus two) was 2007, with *M=*2003.44, *SD=*14.02. Of the 73 correlations, roughly half (54.8%) were job performance as opposed to training performance (see Table 1).

**Moderator Analysis**

Weighted hierarchical linear modeling (WHLM) was utilized to address our hypothesis concerning the moderators, using estimated error variances for each correlation coefficient to ensure more accurate estimates were given greater weight. WHLM was chosen for moderator analysis because it allowed us to account for the fact that the 73 coefficients in our study are nested within a set of 37 articles. Only the model intercept (i.e., the grand mean) was allowed to vary randomly; all other effects were estimated as fixed. All models were estimated using the ‘lme4’ (Bates et al., 2015) package in R, which uses random effects maximum likelihood (REML) in parameter estimation. Models were evaluated in steps, beginning with the main effects of all variables, then adding all two-way interactions involving Criterion Type, followed by our main hypothesis test of the two-way interaction between Job Tenure and Year. Finally, a three-way interaction was evaluated to determine whether the interaction between Job Tenure and Year was dependent on whether the criterion was a measure of job or training performance. The best model was then determined by examining: (a) Akaike’s Information Criterion (AIC), which is a relative fit statistic that penalizes the likelihood statistic for the number of parameters in the model; and (b) the significance test for the difference in χ2 between each successive model.

After selection of the best model, variance explained can be evaluated by the marginal R2, which assesses the ratio of variance attributable to the fixed effects in a HLM relative to the sum of the fixed effect, random effect, and residual variance (Nakagawa et al., 2017). Finally, parameter estimates of the best-fitting model are evaluated. Tests for the significance of estimates are approximated here using Satterthwaite’s (1946) approach to calculating approximate degrees of freedom for conducting *t-*tests, which is often applied in multilevel models. Given the directional nature of our hypothesis, a one-way test of significance is conducted for the Year x Job Tenure fixed effect.

**Control Variable**

In addition to the above moderators, we also present a post-hoc analysis of our hypothesis tests controlling for job complexity to ensure that our results were not contingent on the idiosyncrasies of our sample of studies. Job complexity was measured using the Occupational Information Network (ONET)’s Specific Vocational Preparation metric (SVP). SVP is a categorical variable representing “the amount of lapsed time required by a typical worker to learn the techniques, acquire the information, and develop the facility needed for average performance in a specific job-worker situation” (ONET, 2020). SVP is determined by ONET analysts performing job analyses and is a standard metric for assessing occupational complexity (Oswald et al., 1999).

**Results**

The results for model comparisons can be found in Table 2. Results support the hypothesis for a two-way interaction between Year and Job Tenure as indicated by this model showing the lowest AIC of all candidate models, excluding the null model that contained no fixed effects, and showing a marginally significant Δχ2 test, Δχ2(1) = 3.39, *p* = .065, in comparison to the model without this interaction. The inclusion of a three-way interaction did not increase model-data fit, Δχ2(1) = 0.44, *p* =.505, suggesting the two-way interaction between Year and Job Tenure was the same for training and job performance criteria. The total variance explained by the fixed effects of the best-fitting model was 23.70%, with the two-way interaction between Year and Job Tenure contributing 12.60% incremental variance explained.

To estimate the relative importance of the Tenure x Year interaction term in comparison to the other fixed effects in our final model (e.g. Tenure, Year, and Criterion Type main effects), we computed effect sizes following the recommendation of Hodges (2007) and Westfall et al. (2014). For the present study, effect sizes were obtained for each fixed effect by dividing the regression coefficient by the square root of the sums of the residual variance and random intercept variance as follows:

Table 3 shows the model parameter estimates and effect sizes for the best fitting model. The intercept of the model represents the grand mean of corrected correlations between GMA and performance (μρ= 0.16) similar to that obtained from the meta-analytic procedure (0.15) and is significantly different from than zero, β=0.161, *t*(38)=3.10, *p*<.001. All other parameter estimates reflect the effects of the factor that are symmetric around μρ (as in standard ANOVA). As can be seen, only the two-way interaction effect is statistically significant, β=0.20, *t*(51)=1.764, *p*=.042. This effect is shown in Figure 2. As can be seen, the effect was consistent with our hypothesis that whereas in earlier studies the GMA-performance link weakened, later studies showed an increase in the GMA-performance link as days on the job increased. The limits of this model were tested by re-estimating all WHLMs with 5% and 10% of the highest and lowest GMA-Performance correlations and primary studies, respectively, removed from analyses (see Appendix). Finally, we sought to determine whether our results could be attributed to the idiosyncrasies of the jobs in our sample of studies. Therefore, we fitted a model containing the two-way interaction between Year and Job Tenure (i.e., the only significant factor in our best-fitting model) controlling for Job Complexity. As can be seen in Table 3, this interaction remained significant when controlling for job complexity.

**Discussion**

After decades of research, scholars concluded that as job tenure increases the importance of GMA to performance decreases (Murphy, 1989; Kanfer & Ackerman, 1989). However, our findings indicate that, in the modern world of work, this theory no longer holds. In fact, an opposite effect emerged, such that GMA increases in importance. These findings provide the first empirical evidence of which we are aware that changes in work context have changed how traits necessary for effectiveness influence performance. In line with our hypotheses, we found that in recent years GMA becomes *more* important to training and job performance over the course of the job.

These findings turn a long-held assumption about dynamic GMA-performance relationships on its ear, stressing the importance of time as a boundary condition on theory. Further, our findings stress the increasing importance of adaptability to performance in modern work. Generally, these results paint a picture of an increasingly complex work environment wherein survival will depend heavily on traits related to adaptation. Below we discuss the implications of our findings for theory, research, and practice. The findings are discussed in the context of three overarching implications: the need to revise existing theory to reflect modern work; increased importance of maintaining effective selection systems; performance; and fit and increased competition for highly intelligent employees.

**Theoretical Implications**

First, an important theoretical implication of our findings concerns the need to revise the current conceptions of performance. Since the inception of these theories, the world of work has become more complex, with changes including demands for knowledge work, skill expansion, and continuous learning, leading to the increased importance of GMA. Greater efforts are needed to understand successful performance in the modern work context. Future studies, particularly meta-analyses, should include time as a focal construct in multiple areas of inquiry. Given that the current study calls into question the established belief that the importance of GMA decreases with tenure, other established theories of performance at the macro level may need to be re-evaluated.

Murphy (1989) suggested that two questions ought to be answered in order to understand the relationship between GMA and job performance: What do people do with cognitive ability that results in high levels of job performance? And do these activities occur with the same frequency throughout one’s tenure? While the answer to the first question is likely the same today as it was in 1989, the question to the second answer certainly is not. At the time when Murphy’s dynamic model of performance was conceptualized, training and learning opportunities were concentrated in the initial stages of an employee’s tenure (Ackerman, 1986; 1978; 1992). In the modern world of work, employees are continually learning and updating their skillset. Thus, GMA continues to affect performance throughout one’s job tenure.

**Practical Implications**

Our findings point to the increased importance of effective selection systems. Selecting employees with high GMA will of course be beneficial to the organization, but according to our findings will also become even more important as time goes on. Despite much discussion from scholars, business leaders, and education experts on the identifying and/or developing capabilities associated with "greater adaptability", "mental agility", and "learning orientation" to effectively perform in unstable jobs (e.g., Cascio & Aguinis, 2008; Fried et al., 2008; Howard, 1995), our results suggest that GMA has the potential to fulfil this role. Thus, although there is certainly continued value in the identification of alternative constructs to capture this skill set, focusing on GMA is a viable approach to increase such skill sets. Now more than ever, it is important that organizations use procedures to identify intelligent applicants.

Relatedly, it is crucial that future research address adverse impact issues likely to arise from selecting employees based on GMA. Selection systems based on GMA alone generally lead to underrepresentation of women and minority members (APA Standards, 1999) creating a trade-off between selecting based on GMA and organizational diversity, with potential legal consequences. Although multiple approaches have been presented to reduce subgroup differences (e.g., Sackett, Schmitt, Ellingson, Kabin, 2001), greater efforts are needed to ensure effective and unbiased selection systems given the increasing importance of cognitive ability as time on the job increases.

These results highlight the effects of the changing context surrounding work. Indeed, changes in the work context point to a demands-abilities perspective on P-E fit (Edwards, 1996; Dierdorff et al., 2009; Kristof, 1996) in which fit is a function of employees’ ability to meet demands. Given Wegman et al.’s (2017) findings that modern work is more demanding in terms of learning, our finding that GMA is increasingly important over job tenure in more recent years is not surprising. The overarching implication of the demands-abilities fit perspective is that segments of the workforce with the traits needed to meet changing contextual demands will be increasingly competitive (Hesketh & Griffin, 2008; Kichuk & Wiesner, 1998; Latham & Sue- Chan, 1998) and the segments of the workplace that do not will likely be made increasingly obsolete. For instance, technology and its associated complexities have resulted in a shift in the mix of occupations, with complex, cognitively heavily jobs (i.e., computer scientist, programmer) growing rapidly, and simpler, mechanical jobs (e.g., printing press operators, telephone operators) are shrinking, and in many cases replaced by technology (e.g., Attewell, 1992; Baran, 1987; Spenner, 1995). Employment in occupations such as fabricators, laborers, production craft, and repair declined sharply between 1980 and 2015, whereas nonroutine, high-skilled occupations such as managers and professionals increased over the same time period (Sakamoto et al., 2020). Therefore, what likely began as a slow shift in organizational priorities, has propagated an immense economic issue – job polarisation. Because technology compliments high and low skills, and eliminates the need for middle-skilled work, there has been a steady decline in middle-skilled occupations and middle-class workers’ wages (Boehm, 2014).

**Future Research**

Our findings may suggest that other theories within the organizational sciences are time-bound, which begets a more general need to re-evaluate dated theories of job performance and other organizationally relevant constructs. This provides many opportunities for new research questions related to the changing nature of work. We encourage researchers to consider the role of the omnibus context, including factors such as technological advances and changes in the labor market, which shape lower-level contexts and in turn have an effect on employee attitudes and behaviors (Johns, 2006). As the modern world of work continues to change, our assumptions regarding the context of work should also change.

Future research is needed in order to understand the influence of the changing nature of work on the relationship between other individual difference variables and job performance. In selection contexts, GMA is often combined with other predictors of job performance such as personality or emotional intelligence. Given the increased importance of teamwork in the modern world of work (Mathieu et al., 2017), and the increased emphasis on nonroutine social tasks at all skill levels (Atalay, 2020), socially-relevant constructs such as emotional intelligence and agreeableness may be more related to job performance today than in years past.

**Limitations**

This study is not without limitations. As is always of concern with psychological research, we were unable to include studies that have not been published, which may result in the “file-drawer” problem. However, our large sample size alleviates this concern to a certain degree. Another limitation to this study was the relatively sparse sample of occupations. Sewing machine operators, transit dispatchers, and police recruits made up 40% of the occupations included in our sample. As more primary research becomes available, we recommend that future meta-analyses revisit this research question.

**Conclusion**

We showed that although theories predicting decreased importance of GMA for performance with accumulation of job experience were correct for their time, these theories are not applicable to the modern workplace. In fact, the opposite is true in the current work context: GMA becomes more important the longer one is on the job. This finding means that the inclusion of GMA in employee selection systems is more important now than ever. Importantly, these results suggest that failure to hire employees with high GMA will have longer-running negative impacts and increased cumulative impact on organizational effectiveness

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**Table 1**

*Studies included in the meta-analysis.*

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Authors (Year of Publication) | *N* | Employee Type | GMA Measure | Criterion | Time |
| Atwater (1992) | 82 | Midshipmen | SAT | Leadership Performance (Supervisor ratings) | 3.5 weeks |
| Bartone, Snook, & Tremble (2002) | 845 | West Point students | SA | Leadership Performance (Supervisor ratings) | 4 years |
| Bolanovich (1944) | 73 | Engineering trainees | WPT | Training Performance (GPA) | 10 months |
| Cellar, Klawsky, & Miller (1996) | 325 | Flight Attendant trainees | RC | Job Performance (Supervisor ratings) | 6 weeks |
| de Meijer, Born, Terlouw, & van der Molen (2008) | 2365 | Dutch police trainees (Ethnic Majority) | PIT | Job Performance (Supervisor ratings) | 1 year |
| de Meijer, Born, Terlouw, & van der Molen (2008) | 682 | Dutch police trainees (Ethnic Minority) | PIT | Job Performance (Supervisor ratings) | 1 year |
| Deadrick, Bennett, & Russell (1997) | 408 | Sewing machine operators | GABT | Total Production Earnings | 1 week |
| Deadrick, Bennett, & Russell (1997) | 408 | Sewing machine operators | GABT | Total Production Earnings | 6 weeks |
| Deadrick, Bennett, & Russell (1997) | 408 | Sewing machine operators | GABT | Total Production Earnings | 12 weeks |
| Deadrick, Bennett, & Russell (1997) | 408 | Sewing machine operators | GABT | Total Production Earnings | 18 weeks |
| Deadrick, Bennett, & Russell (1997) | 408 | Sewing machine operators | GABT | Total Production Earnings | 24 weeks |
| Dean, Conte, & Blankenhorn (2006) | 300 | Marine recruiter trainees | AFQT | Training Performance (Third Training Exam) | 37 days |
| Diaz, Glass, Arnkoff, & Tanofsky-Kraff (2001) | 182 | 1st-year law students | LSAT | Final Exam Grade | 4 months |
| Ferris, Witt, & Hochwarter (2001) | 106 | Software engineers | Wonderlic | Task performance | 1836 Days |
| Ferris, Witt, & Hochwarter (2001) | 106 | Software engineers | Wonderlic | Job dedication | 1836 Days |
| Ferris, Witt, & Hochwarter (2001) | 106 | Software engineers | Wonderlic | Interpersonal facilitation | 1836 Days |
| Gardner & Deadrick (2012) | 334 | Sewing machine operators | GABT | Training Performance (Trainer ratings) | 9 months |
| Gardner & Deadrick (2012) | 505 | Sewing machine operators | GABT | Training Performance (Trainer ratings) | 6 months |
| Gardner & Deadrick (2012) | 626 | Sewing machine operators | GABT | Job Performance (Supervisor ratings) | 3 months |
| Guo, Zou, He, Tan, Chen, & Feng (2020) | 70 | Transit operators - HSR dispatchers | Working Memory Task (Reaction Time) | Delay Time | 1646.2 Days |
| Guo, Zou, He, Tan, Chen, & Feng (2020) | 70 | Transit operators - HSR dispatchers | Working Memory Task (Reaction Time) | Supervisor Overall Rating | 1646.2 Days |
| Guo, Zou, He, Tan, Chen, & Feng (2020) | 70 | Transit operators - HSR dispatchers | Working Memory Task (Accuracy) | Delay Time | 1646.2 Days |
| Guo, Zou, He, Tan, Chen, & Feng (2020) | 70 | Transit operators - HSR dispatchers | Working Memory Task (Accuracy) | Supervisor Overall Rating | 1646.2 Days |
| Guo, Zou, He, Tan, Chen, & Feng (2020) | 70 | Transit operators - HSR dispatchers | Multi Object Tracking (Reaction Time) | Delay Time | 1646.2 Days |
| Guo, Zou, He, Tan, Chen, & Feng (2020) | 70 | Transit operators - HSR dispatchers | Multi Object Tracking (Reaction Time) | Supervisor Overall Rating | 1646.2 Days |
| Guo, Zou, He, Tan, Chen, & Feng (2020) | 70 | Transit operators - HSR dispatchers | Multi Object Tracking (Accuracy) | Delay Time | 1646.2 Days |
| Guo, Zou, He, Tan, Chen, & Feng (2020) | 70 | Transit operators - HSR dispatchers | Multi Object Tracking (Accuracy) | Supervisor Overall Rating | 1646.2 Days |
| Hakstian, Scratchley, MacLeod, Tweed, & Siddarth (1997) | 85 | Telemarketing sales force | GMA | Job Performance (Supervisor ratings) | 3 months |
| Hall (2007) | 69 | Student teachers | ACT | Job Performance (Supervisor ratings) | 4 months |
| Hausdorf & Risavy (2015) | 147 | Transit Operators | Wonderlic | Day 5 Training Performance | 121.67 Days |
| Hausdorf & Risavy (2015) | 136 | Transit Operators | Wonderlic | Day 10 Training Performance | 121.67 Days |
| Hausdorf & Risavy (2015) | 103 | Transit Operators | Wonderlic | Day 15 Training Performance | 121.67 Days |
| Hausdorf & Risavy (2015) | 63 | Transit Operators | Wonderlic | Day 19 Training Performance | 121.67 Days |
| Hausdorf & Risavy (2015) | 127 | Transit Operators | Wonderlic | Probationary Rating | 121.67 Days |
| Hausdorf & Risavy (2015) | 185 | Transit Operators | Wonderlic | Lost time for occupational injuries | 121.67 Days |
| Hausdorf & Risavy (2015) | 185 | Transit Operators | Wonderlic | Preventable vehicle accidents | 121.67 Days |
| Hausdorf & Risavy (2015) | 184 | Transit Operators | Wonderlic | Pass-Fail Training | 121.67 Days |
| Henderson (2010) | 74 | Firefighter cadet | GMA | Training Performance (Trainer ratings) | 3 months |
| Henderson (2010) | 74 | Firefighter | GMA | Job Performance (Supervisor ratings) | 87 months |
| Henderson (2010) | 74 | Firefighter | GMA | Number of officer nominations Elite Firefighters Squad | 202 months |
| Henderson (2010) | 74 | Firefighter | GMA | Number of officer nominations Outstanding Career | 301 months |
| Kanfer (2010) | 82 | COOP | GMA | Job Performance (Supervisor ratings) | 4 months |
| Kleiman (1978) | 70 | Police recruits | OLMAT | Training Performance (Final exam) | 12 weeks |
| Lievens, Harris, Keer, & Bisqueret (2003) | 78 | European managers | VMG 1, NMG 1 | Training Performance (Trainer ratings) | 1 year |
| Lievens, Reeve, & Heggestad (2007) | 94 | Med students | GMA | Academic Performance(GPA) | 3 years |
| Lievens, Reeve, & Heggestad (2007) | 518 | Med students | GMA | Academic Performance(GPA) | 3 years |
| Lievens, Sacckett, & Buyse (2009) | 183 | Med students | GMA | Academic Performance(GPA) | 1 year |
| Lievens, Sacckett, & Buyse (2009) | 168 | Med students | GMA | Academic Performance(GPA) | 1 year |
| Lyons, Hoffman, & Michel (2009) | 762 | NFL players | WPT | NFL Performance (Statistics from sports web) | 1 year |
| Lyons, Hoffman, & Michel (2009) | 762 | NFL players | WPT | NFL Performance (Statistics from sports web) | 2 years |
| Lyons, Hoffman, & Michel (2009) | 762 | NFL players | WPT | NFL Performance (Statistics from sports web) | 3 years |
| Marcus, Goffin, Johnston, & Rothstein (2007) | 119 | Midlevel management candidates | EAS | Job Performance (Supervisor ratings) | 1 year |
| Neel & Dunn (1960) | 32 | Supervisor trainees | WPT | Training Performance (GPA) | 6 weeks |
| Neuman & Wright (1999) | 316 | Full-time human resource representatives | TMA | Task Performance (Peer rating) | 3 years |
| Ng, Ang, & Chan (2008) | 303 | Military recruits | GMA | Leadership Performance (Superiors ratings) | 2 years |
| Ono, Sachau, Deal, Englert, & Taylor (2011) | 131 | US federal crime investigator trainees | SILS | Training Performance (Trainer ratings) | 17 weeks |
| Ono, Sachau, Deal, Englert, & Taylor (2011) | 38 | New US federal criminal investigators | SILS | Training Performance (Trainer ratings) | 1 year |
| Plag, & Goffman (1967) | 1541 | Naval enlistees | AFQT | Job Performance (Supervisor ratings) | 2 years |
| Plag, & Goffman (1967) | 1776 | Naval enlistees | AFQT | Job Performance (Supervisor ratings) | 4 years |
| Ree, Carretta, & Teachout (1995) | 3428 | Pilot trainees | AFOQT | Final flight check (Instructor ratings) | 53 weeks |
| Rothstein, Paunonen, Rushm, & King (1994) | 450 | MBA students | GMAT | Academic Performance (Faculty ratings) | 1 year |
| Scarfo (2002) | 152 | Police recruits | CSE | Training Performance (Trainer ratings) | 24 weeks |
| Spain (2010) | 178 | Police recruits | WPT | Training Performance (Trainer ratings) | 3 weeks |
| Spain (2010) | 178 | Police recruits | WPT | Training Performance (Trainer ratings) | 6 weeks |
| Spain (2010) | 178 | Police recruits | WPT | Training Performance (Trainer ratings) | 9 weeks |
| Spain (2010) | 178 | Police recruits | WPT | Training Performance (Trainer ratings) | 12 weeks |
| Srikanth (2019) | 140 | Working HR professionals | Wesman Personnel Classification Test / Watson–Glaser Critical Thinking Appraisal Form A | HR competencies | 730 Days |
| Surrette (2003) | 129 | Recently hired police officers | SILS | Job Performance (Supervisor ratings) | 1 year |
| Tracey, Sturman, & Tews (2007) | 241 | Frontline hospitality employees | Wonderlic | Technical and interpersonal performance dimensions (e.g. product knowledge, guest relations, sales expertise, helping others, and adhering to health and safety standards) | 755.55 Days |
| Vasilopoulos, Cucina, & Hunter (2007) | 1010 | Trainees at a police training academy | LBM | Training Performance (Law/ops avg) | 18 weeks |
| Weekly & Ployhart (2005) | 271 | Loss prevention managers | Proprietary measure | Task Performance | 1660.8 Days |
| Zhao, Li, Harris, Rosen, & Zhang (2020) | 95 | Tech company employees | Raven's Progressive Matrices | Core member rating | 803 Days |
| Zhao, Li, Harris, Rosen, & Zhang (2020) | 95 | Tech company employees | Raven's Progressive Matrices | Peripheral member rating | 803 Days |

**Table 2**

*Model comparisons*

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Model | AIC | LRT | *df* | *p* | IVE |
| Null Model | -31.74 |  |  |  | . |
| Main Effects (Year, Job Tenure, Criterion Type) | -29.64 | 3.91 | 3 | .272 | 7.30 |
| Year × Criterion Type;  Job Tenure × Criterion Type | -28.93 | 3.28 | 2 | .194 | 3.80 |
| **Year × Job Tenure** | **-30.32** | **3.39** | **1** | **.065** | **12.60** |
| Year × Job Tenure × Criterion Type | -28.77 | 0.44 | 1 | .505 | 1.60 |

*Note*. Best-fitting model in bold; AIC=Akaike Information Criterion; LRT=Likelihood Ratio Test; Difference in -2 times the log likelihood of models; Δ*df=*Difference in the number of model parameter estimates; IVE=Incremental Variance Explained as indicated by the marginal R2.

**Table 3**

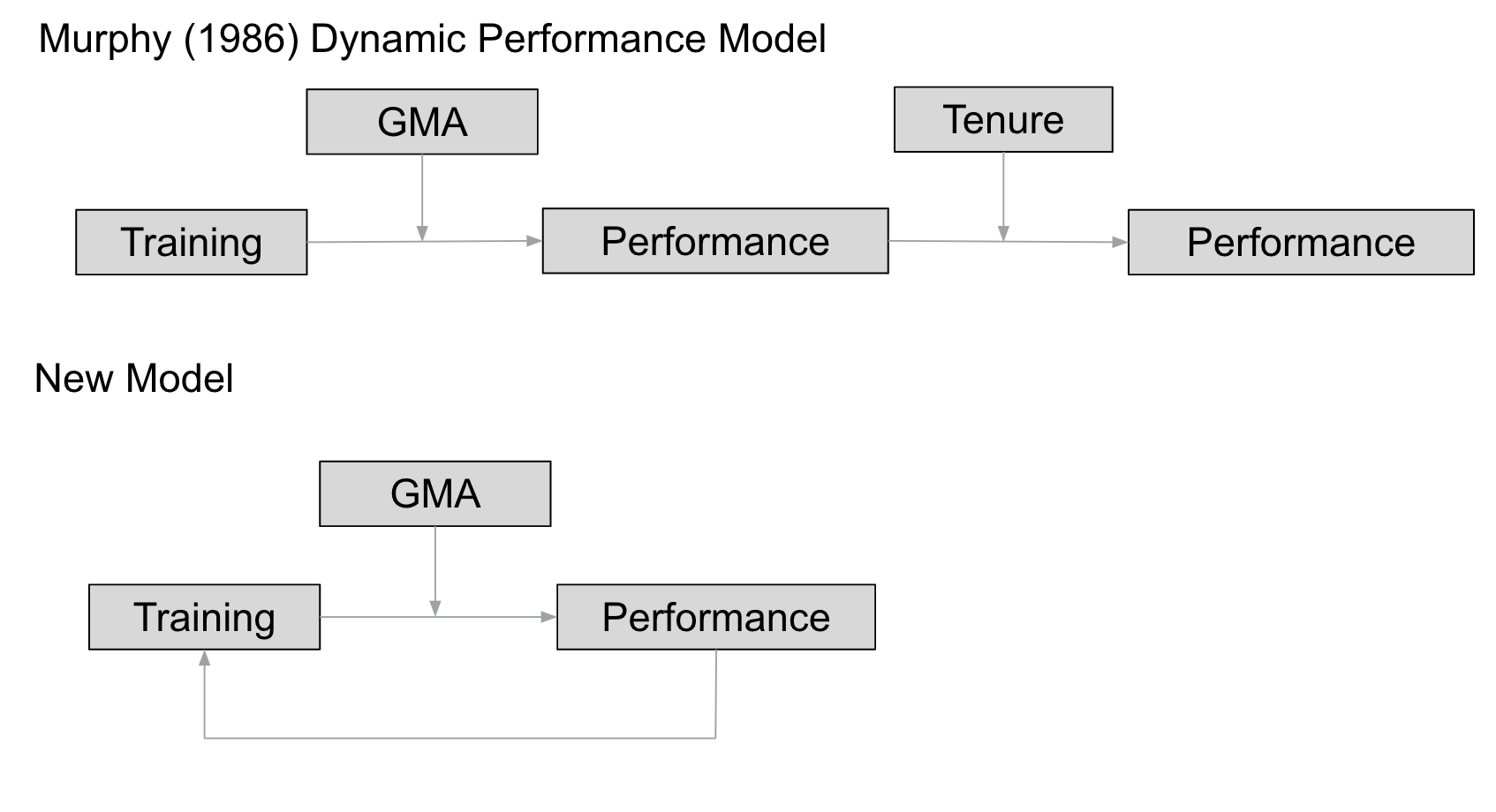
*Parameter estimates and significance tests for the best-fitting model and a model controlling for job complexity.*

|  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  |  | **Best-Fitting Model** | | | | |  | **Two-Way Interaction Controlling for Job Complexity** | | | | | |
| Factor | β | *d* | *SE* | *df* | *t* | *p* | Factor |  | β | *SE* | *df* | *t* | *p* |
| (Intercept) | **.161** | **.892** | **.052** | **38** | **3.10** | **.001** | (Intercept) |  | .208 | .119 | 29 | 1.75 | .090 |
| Criterion Type | .033 | **.134** | .051 | 42 | .642 | .524 | Job Complexity |  | -.006 | .020 | 27 | -.30 | .766 |
| Year | .024 | -.464 | .053 | 47 | .453 | .652 | Year |  | .034 | .048 | 38 | .70 | .488 |
| Tenure | -.083 | .181 | .098 | 45 | -.861 | .394 | **Tenure** |  | **-.089** | **.037** | **50** | **-2.37** | **.022** |
| Year × Criterion Type | .002 | .110 | .034 | 35 | .589 | .560 | **Year × Tenure** |  | **.232** | **.106** | **44** | **2.20** | **.033** |
| Tenure × Criterion Type | -0.00 | -.016 | .100 | 44 | -.028 | .978 | . |  | . | . | . | . | . |
| Year × Tenure | **.200** | **1.089** | **.112** | **51** | **1.764** | **.042** | . |  | . | . | . | . | . |

*Note*. Coefficients in bold if *p*<.05; *df* are approximate degrees of freedom using the Satterthwaite approach. The Year x Tenure interaction effect was examined using a one-sided hypothesis test, thus the obtained *p-*value was divided by two. The effect size of the fixed effects, *d*, was computed as

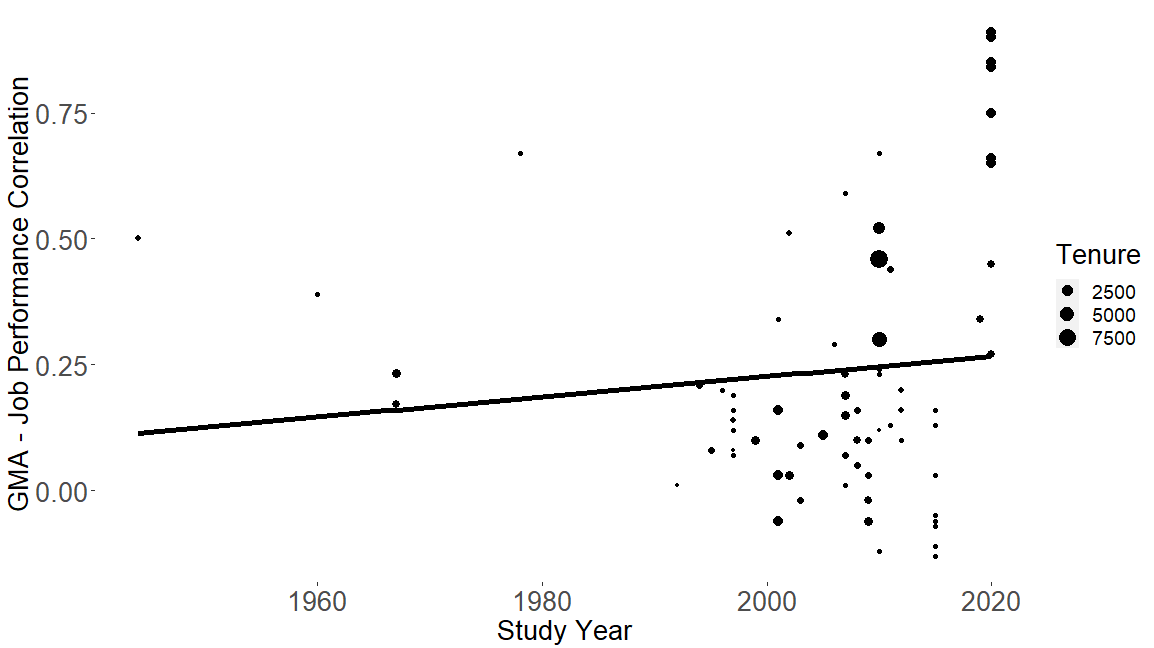
**Figure 1**

*A Comparison of the Theoretical Model Proposed in Murphy (1989) to the Theoretical Model Proposed in the Present Study.*



**Figure 2**

*The correlation of GMA and Job Performance plotted as a function of both time and the tenure of primary studies*



**Appendix:**

**Sensitivity Analysis**

Due to the substantial range of GMA-Job Performance correlations observed in prior work, we sought to ensure our findings were robust to the exclusion of potentially highly influential observations. Thus, we re-evaluated the model in our main analyses with two sets of robustness checks. For our first robustness check, we removed individual correlations in the top or bottom 2.5% and 5% of the sample, resulting in a 5% and 10% reduction of correlation coefficients examined compared to the original full sample (i.e. 69 and 65 correlations from 36 primary studies). For our second robustness check, we completely excluding primary studies with any correlation falling in the top or bottom 2.5% and 5% of our original sample, resulting in samples containing 52 correlation coefficients nested within 33 primary studies and 44 correlation coefficients nested within 29 primary studies, respectively. Results from our first robustness check removing individual, potentially influential, correlation coefficients were nearly identical in regard to estimates and were in complete agreement with the findings from our main analysis (i.e., perfect agreement of statistical tests and significant Year x Job Tenure interaction effect, see Table A1). While results from the removal of primary studies indicated non-significant Tenure x Study Year interaction effects (see Table A2), we conclude that this can be attributed to the substantial loss of statistical power resulting from the removal of nearly 30% and 40% of our original sample size. In sum, we believe the results of these sensitivity analyses lend strong support to the robustness of our model and corresponding conclusions in this article.

**Table A1**

*Parameter estimates and significance tests for the best-fitting model after removal of potential influential correlations..*

|  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  |  | **(5% of Correlations Removed)** | | | | | | **(10% of Correlations Removed)** | | | | | |
| Factor | β | *SE* | *df* | *t* | *p* |  | β | | *SE* | *df* | *t* | *p* |
| **(Intercept)** | **0.171** | **0.050** | **36** | **3.393** | **0.002** |  | **0.172** | | **0.049** | **36** | **3.486** | **0.001** |
| Criterion Type | 0.040 | 0.049 | 40 | 0.802 | 0.427 |  | 0.040 | | 0.048 | 39 | 0.819 | 0.418 |
| Year | 0.032 | 0.052 | 44 | 0.621 | 0.538 |  | 0.031 | | 0.051 | 43 | 0.612 | 0.544 |
| Tenure | -0.090 | 0.094 | 43 | -0.957 | 0.344 |  | -0.093 | | 0.092 | 42 | -1.006 | 0.320 |
| Year × Criterion Type | 0.019 | 0.032 | 33 | 0.580 | 0.566 |  | 0.018 | | 0.032 | 33 | 0.558 | 0.580 |
| Tenure × Criterion Type | 0.001 | 0.097 | 41 | 0.013 | 0.989 |  | 0.006 | | 0.095 | 41 | 0.063 | 0.950 |
| **Year × Tenure** | **0.202** | **0.109** | **47** | **1.865** | **0.034** |  | **0.196** | | **0.106** | **47** | **1.844** | **0.036** |

*Note*. Coefficients in bold if *p*<.05; *df* are approximate degrees of freedom using the Satterthwaite approach. The Year x Tenure interaction effect was examined using a one-sided hypothesis test, thus the obtained *p-*value was divided by two.

**Table A2**

*Parameter estimates and significance tests for the best-fitting model after removal of potential influential primary studies.*

|  |  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  |  | **(5% of Primary Studies Removed)** | | | | | | **(10% of Primary Studies Removed)** | | | | |
| Factor | β | *SE* | *df* | *t* | *p* |  | β | | *SE* | *df* | *t* | *p* |
| **(Intercept)** | **0.160** | **0.046** | **27** | **3.498** | **0.002** |  | **0.179** | | **0.045** | **22** | **4.029** | **0.001** |
| Criterion Type | 0.043 | 0.044 | 31 | 0.986 | 0.332 |  | 0.071 | | 0.042 | 27 | 1.678 | 0.105 |
| Year | -0.033 | 0.058 | 45 | -0.563 | 0.577 |  | -0.015 | | 0.054 | 37 | -0.280 | 0.781 |
| Tenure | -0.016 | 0.106 | 29 | -0.150 | 0.882 |  | 0.063 | | 0.110 | 22 | 0.579 | 0.568 |
| Year × Criterion Type | 0.040 | 0.031 | 34 | 1.270 | 0.213 |  | 0.027 | | 0.030 | 27 | 0.890 | 0.381 |
| Tenure × Criterion Type | -0.015 | 0.097 | 34 | -0.157 | 0.876 |  | 0.025 | | 0.100 | 28 | 0.251 | 0.804 |
| Year × Tenure | 0.106 | 0.131 | 45 | 0.807 | 0.424 |  | 0.119 | | 0.119 | 37 | 1.003 | 0.322 |

*Note*. Coefficients in bold if *p*<.05; *df* are approximate degrees of freedom using the Satterthwaite approach. The Year x Tenure interaction effect was examined using a one-sided hypothesis test, thus the obtained *p-*value was divided by two.