Conscientiousness and General Mental Ability Predict Deviation from Optimal Resource Allocation

by

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Author's Declaration

I hereby declare that I am the sole author of this thesis. This is a true copy of the thesis, including any required final revisions, as accepted by my examiners.

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Abstract

This research speaks to developments in the conscientiousness literature regarding the consequences of being overly conscientious. Specifically, research has found that excessively conscientious individuals exhibit worse task performance than individuals with moderate levels of conscientiousness. The purpose of our study is to understand *why* and for *whom* high levels of conscientiousness may be detrimental. To this end, we incorporated resource allocation and general mental ability (GMA) to answer these questions. We conducted a laboratory study in which we manipulated the optimal level of resource allocation across multiple trials of a work simulation. Participants could maximize performance by matching actual resource allocation to the optimal level of resource allocation. This design allowed us to directly observe participants' resource allocation decisions and vary the optimal level of resource allocation from low to high. We found that individuals with high conscientiousness and low GMA deviated most from the optimal level of resource allocation. Specifically, individuals with high conscientiousness and low GMA had a tendency to *over*-allocate resources. Downstream, the *greater* the deviation from the optimal level of resource allocation the *worse* performance was. Although conscientiousness may be beneficial in some circumstances, more is not always better. We demonstrated that high levels of conscientiousness can be detrimental to performance. This reduction in performance occurs when individuals are willing to invest a great deal of resources (high conscientiousness) but unable to recognize the optimal level of resource allocation (low GMA). Past research has provided limited insight into *why* highly conscientious individuals have been found to perform worse than individuals with moderate levels of conscientiousness. Our study extends this research by using an experimental design to demonstrate that conscientiousness and GMA interact to indirectly predict performance via resource allocation.

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Table of Contents

List of Figures

List of Tables

Conscientiousness is a Big-Five personality trait characterized by organization, adherence to rules, and achievement striving (Costa & McCrae, 1992; Roberts, Jackson, Fayard, Edmonds, & Meints, 2009). Meta-analyses have shown that conscientiousness is consistently and positively correlated with performance across a variety of jobs (Barrick, Mount, & Judge, 2001; Hurtz & Donovan, 2000; Meyer, Dalal, & Bonaccio, 2009). However, some researchers argue that the relationship between conscientiousness and performance may be curvilinear. Recent evidence supports the idea that individuals with moderate levels of conscientiousness exhibit better job performance than individuals with low or high conscientiousness (Carter et al., 2014; Le et al., 2011; Wihler, Meurs, Momm, John, & Blickle, 2017). Ultimately, these studies suggest that there are situations in which higher levels of conscientiousness are not ideal. The goal of our study is to understand the conditions under which high conscientiousness may become problematic. To this end, we propose that the reductions in performance associated with high conscientiousness when compared to individuals with lower levels of conscientiousness arise from the misallocation of resources (e.g., time, effort).

Effectively managing resources is often necessary for achieving high performance. Past research has found that individuals who lack motivation have a tendency to *under*-allocate resources (allocating fewer resources than the task requires) by choosing to abandon a task or failing to allocate the resources required to achieve high performance (Bandura & Cervone, 1986; Carver & Scheier, 2001; Seo & Ilies, 2009). Similarly, problems can also emerge when highly motivated individuals *over*-allocate resources (allocating more resources than the task requires). Because performance is often multidimensional (Beck, Beatty, & Sackett, 2014), over-allocating to one facet of performance can waste resources required for other aspects of performance. For example, among professors job performance frequently consists of both research and teaching. A professor who spends too much time on teaching might do so at the expense of research. Because the multiple tasks that make up a job often compete for a shared pool of finite resources (e.g., hours in a workday) there is a need for individuals to allocate resources judiciously between competing demands. Thus, overall performance (performance across tasks that comprise an overarching job or goal) is compromised by over and under-allocation of resources. Next, we consider how high conscientiousness might promote misallocation of resources.

Conscientiousness affects performance through its impact on motivational states (Parker & Ohly, 2008) such as performance expectancies (Gellatly, 1996) and goal setting (Judge & Ilies, 2002). This leads highly conscientious employees to spend more time on-task (Biderman, Nguyen, & Sebren, 2008) and expend more effort towards work (Mount & Barrick, 1995; Yeo & Neal, 2008; Witt & Ferris, 2003) than less conscientious employees. Thus, it would seem that highly conscientious individuals are often willing to allocate a great deal of resources towards work. In general, this willingness appears beneficial as it leads conscientious workers to exert themselves and avoid under-allocating resources. However, when taken too far this practice may actually promote over-allocation. By investing heavily in one task, highly conscientious individuals may not have the resources required to achieve high performance on other tasks thereby reducing overall performance. However, we expect that there will be variance in individuals' ability to recognize situations in which allocating a great deal of resources to a given task is not necessarily beneficial. That is, although highly conscientious individuals may be *willing* to invest resources this eagerness may lead them astray if they are not *able* to determine the amount of resources required. To this end, we consider general mental ability (GMA) as a key component in the process of recognizing the need to avoid over-allocating resources.

GMA is defined as a person's ability to solve problems and perform complex information processing (Gottfredson, 1997). We propose that compared to individuals with low GMA, individuals with high GMA will more accurately judge how many resources are required to achieve high performance on a task. Over-allocation of resources may occur when there is high willingness (high conscientiousness) and low ability (low GMA). Determining *why* highly conscientious individuals might be misallocating resources is an important first step in understanding for *whom* high levels of conscientiousness might cause performance issues. Thus, we designed a laboratory study to examine the effects of conscientiousness and GMA on resource allocation.

Because we are interested in the effect that conscientiousness and GMA have on resource allocation errors (i.e., allocating too many or too few resources), we designed an experiment that allowed us to manipulate the correct or "optimal" level of resource allocation. This optimal level of resource allocation represents the point at which just enough resources are allocated to achieve the highest level of performance without wasting resources. In our study, the optimal level of resource allocation was manipulated from low (high performance requires few resources) to high (high performance requires many resources) across multiple trials of a work simulation. We predict that both conscientiousness and GMA will moderate the relationship between the optimal level of resource allocation and actual resource allocation. Specifically, we expect individuals to over-allocate the most resources when conscientiousness is high and GMA is low.

Optimal Resource Allocation

Different situations call for different levels of resource allocation. In some situations, overall performance is improved by investing a great deal of resources into the task-at-hand. In other situations, investing a great deal of resources into one task can be detrimental to overall performance if it comes at the expense of performance on other tasks. This can occur when tasks have *diminishing returns*. The concept of diminishing returns refers to the idea that, after a certain point, further input will not increase one's expected output. In other words, there exists a point after which allocating more resources to a task is unlikely to improve performance on that task. Similarly, the *costs* associated with a task (negative consequences of resource investment) also influence the optimal level of resource allocation. Next, we will unpack these two factors and discuss how they combine to create the optimal level of resource allocation.

Diminishing Returns

In many situations, as the level of resource allocation *increases* the magnitude of performance improvements may *decrease* until eventually plateauing (Norman & Bobrow, 1975). Thus, there are often *diminishing returns* associated with tasks (Fredrick & Walberg, 1980). For example, the more time a window washer spends washing a window the cleaner it will look. However, if this employee cleans for long enough he or she will eventually reach a point where the window appears to be spotless. Once this point is reached any additional time spent cleaning is time wasted (i.e., over-allocated) because further resource investment cannot noticeably improve performance. Thus, increases in resource investment may not always improve performance when there are diminishing returns. Furthermore, in many situations, there can be negative consequences associated with over-allocating resources.

Costs

Allocating resources towards a task can often carry potential trade-offs. If a task is unsafe (i.e., potential to cause bodily or property harm), risky (i.e., possibility of failure or loss), or competes with other tasks for resources (i.e., uses up resources required for other tasks) then higher levels of resource investment may incur greater costs. For instance, investing resources to a task that fails to improve overall performance (e.g., a window washer polishing a spotless window) is a waste of resources which could be allocated to productive tasks (e.g., washing dirty windows). Furthermore, if the task is risky then unintended negative outcomes could outweigh any potential performance gains (e.g., an athlete who trains too hard and injures themselves). In sum, the costs associated with a task can influence the optimal level of resource allocation. In some circumstances, these costs may be so exorbitant that any resource investment is a bad idea. However, in other cases, the optimal division of resources may involve taking a calculated risk.

Diminishing Returns, Costs, and Resource Allocation

The optimal level of resource allocation is a function of the benefits and costs associated with resource allocation. Specifically, diminishing returns and costs combine to create the optimal level of resource allocation. These factors determine how high (investing a large amount of resources is associated with greater overall performance) or low (investing a small amount of resources is associated with greater overall performance) the optimal level of resource allocation is. For instance, the *faster* returns diminish the *lower* the optimal level of resource allocation will be. This occurs because, if returns diminish quickly, then the point at which the benefits associated with greater resource investment plateau will also occur more quickly. For example, a window washer would be able to spend more time on an especially dirty window compared to a relatively clean window before reaching a performance plateau. Similarly, as the severity of costs associated with a task *increase* the optimal level of resource allocation will *decrease*. All things being equal, the riskier a training routine is the less time an athlete should spend training to minimize the risk of incurring an injury and hurting future performance. Thus, the optimal level of resource allocation varies across tasks as a function of diminishing returns and costs.

Because overall performance is thought to be an aggregate of multiple tasks (Beck et al., 2014) and resources are often limited (Beck & Schmidt, 2015) over-allocating resources to a task with diminishing returns can actually *decrease* overall performance by incurring undue costs. To illustrate, the more time the window washer wastes cleaning a spotless window the less time there is available to clean other windows. By wasting time on a task that fails to improve performance (i.e., washing a spotless window) the window washer may not be able to clean as many windows and overall performance will suffer. Thus, an individual who is better at matching actual resource allocation to the optimal level of resource allocation will have greater overall performance. In turn, the more an individual deviates from this optimal level of resource allocation the worse overall performance is expected to be. Issues of over-allocation may arise in individuals who are willing to allocate a high amount of resources (high conscientiousness) but unable to accurately recognize the optimal level of resource allocation (low GMA).

Conscientiousness

Researchers have often observed a positive relationship between conscientiousness and important contributors to performance such as goal setting, effort, and motivation (Barrick & Mount, 1991; Barrick, Mount, & Strauss, 1993; Gellatly, 1996; Judge & Ilies, 2002; Smillie, Yeo, Furnham, & Jackson, 2006). The general finding is that conscientious employees are achievement oriented workers who are motivated to invest a great deal of resources (e.g., effort, time, attention) into work. Furthermore, meta-analyses have observed a positive linear relationship between conscientiousness and performance (Barrick et al., 2001) across a variety of settings (Hurtz & Donovan, 2000). However, when taken to the extreme, researchers have demonstrated that the once beneficial facets of conscientiousness can become maladaptive (Samuel, Riddell, Lynam, Miller, & Widiger, 2012).

Excessively conscientious individuals have been described as compulsive perfectionists (Le et al., 2011), too meticulous (Tett, 1998), and overly detail oriented (Samuel & Widiger, 2011). Because of this, researchers have theorized that the relationship between conscientiousness and performance may weaken at high levels (Moscoso & Salgado, 2004). In support of this, researchers have found evidence of nonlinear relationships between conscientiousness and performance (e.g., Carter et al., 2014; Wihler et al., 2017). Both Le et al. (2011) and LaHuis, Martin, and Avis (2005) observed a curvilinear inverted-U relationship between conscientiousness and performance with performance being highest at moderate levels of conscientiousness. This research challenges the idea that higher levels of conscientiousness are always associated with higher levels of performance. We propose that resource allocation may help to explain why increases in conscientiousness are not always beneficial. Excessively conscientious individuals may perform worse by over-allocating resources in situations which do not warrant a high level of resource investment.

Although conscientious individuals are motivated to achieve high performance (Hart, Stasson, Mahoney, & Story, 2007) this eagerness may have unintended consequences. Perry, Hunter, Witt, and Harris (2010) argued that conscientiousness acts as a trigger which motivates individuals to expend effort towards pursuing goals. Ultimately, it seems that this general policy of investing a great deal of resources into work could be leading overly conscientious individuals awry by promoting over-allocation. An individual who allocates a high amount of resources regardless of the situation is going to perform poorly when the optimal level of resource allocation is low. Thus, simply being motivated to allocate a great deal of resources is insufficient. Achieving the highest level of overall performance requires both the *willingness* to allocate the required resources and the *ability* to recognize when it is a bad idea to allocate a high amount of resources. To this end, we suggest that GMA corresponds to one's accuracy at recognizing the optimal level of resource allocation.

General Mental Ability

Overwhelmingly, individuals with higher GMA tend to perform better across a wide variety of situations and jobs when compared to individuals with lower GMA (Hunter & Hunter, 1984; Ree, Earles, & Teachout, 1994). Researchers have also found GMA to be positively associated with problem solving skill (Burns, Lee, & Vickers, 2006; Vickers, Mayo, Heitmann, Lee, & Hughes, 2004) and information processing speed (Sheppard & Vernon, 2008). Because of these findings, we expect individuals with high GMA to be more sensitive to the optimal level of resource allocation across situations. Individuals that are more intelligent should more accurately assess the situational factors (i.e., diminishing returns and costs) that create the optimal level of resource allocation when compared to less intelligent individuals.

To accurately recognize the optimal level of resource allocation individuals must gather information from the environment and evaluate the potential costs and benefits associated with resource investment in a task. Because individuals with high GMA are naturally better at adapting to new situations (Lepine, Colquitt, & Erez, 2000), learning on the job (Hunter, 1986), and integrating information (Cokely & Kelley, 2009; Taylor & Dunnette, 1974) we predict that these individuals will be more sensitive to the optimal level of resource allocation across situations. Thus, we argue that individuals with higher GMA will more accurately recognize the optimal level of resource allocation.

Can Do vs. Will Do: Conscientiousness × GMA Interaction

To more accurately match actual resource allocation to the optimal level of resource allocation we contend that individuals need to possess both the *willingness* (conscientiousness) to allocate the required resources and the *ability* (GMA) to recognize what the optimal level of resource allocation is. When GMA is low we predict that individuals with high conscientiousness will over-allocate resources. We expect this to occur because highly conscientious individuals tend to invest great amounts of time and energy into work and low GMA individuals tend to evaluate decisions less thoroughly than individuals with high GMA (Biderman et al., 2008; Cokely & Kelley, 2009; Mount & Barrick, 1995). Past studies examining this conscientiousness × GMA interaction on performance have had mixed success. Some researchers find support for an interaction (e.g., Di Domenico & Fournier, 2015; O'Reilly & Chatman, 1994; Perry et al., 2010) whereas others only observe main effects (e.g., Mount, Barrick, & Strauss, 1999; Sackett, Gruys, & Ellingson, 1998; Van Iddekinge, Aguinis, Mackey, & DeOrtentiis, in press). Currently, it is unclear why these conflicting results exist. One explanation as to why past research has inconsistently observed this interaction may be that the joint effects of conscientiousness and GMA on performance are more nuanced than previously thought. By incorporating resource allocation, we hope to demonstrate that conscientiousness and GMA interact to indirectly predict performance via resource allocation.

We predict that the relationship between optimal resource allocation and actual resource allocation will be moderated by conscientiousness and GMA. Specifically, there will be a three-way interaction between the optimal level of resource allocation, conscientiousness, and GMA on actual resource allocation. We predict that individuals with high conscientiousness and low GMA will be *worst* at matching their actual resource allocation to the optimal level of resource allocation. This means that the relationship between optimal resource allocation and actual resource allocation will be *weakest* when conscientiousness is high and GMA is low. This will be manifested as a difference in slopes such that the slope will be *shallowest* when conscientiousness is high and GMA is low. Additionally, when the optimal level of resource allocation is low, we expect that individuals with high conscientiousness and low GMA will over-allocate more resources than others. This will be manifested as a difference in intercepts such that the intercept will be *highest* when conscientiousness is high and GMA is low. We expect this to occur because individuals with high conscientiousness and low GMA should be motivated to invest a great deal of resources but lack the ability to identify situations in which it is not beneficial to do so.

To test our predictions we varied the optimal level of resource allocation across multiple trials of a work simulation. Our experimental design allowed us to test the effect that both conscientiousness and GMA had on resource allocation. Because we manipulated the optimal level of resource allocation, we were able to determine with certainty how well individuals were able to match actual resource allocation decisions to the optimal level of resource allocation. The relationship between actual and optimal resource allocation represents how well individuals are able to modify their behavior to fit the situation. Under and over-allocation of resources occurs when actual resource allocation deviates from the optimal level of resource allocation. This relationship is important because the more closely an individual's actual resource allocation matches the optimal level of resource allocation the better his or her performance is expected to be.

Method

Participants

Sixty-six undergraduate psychology students from a Canadian university participated in the study. Thirteen participants were excluded from the final analysis due to incomplete data caused by technical difficulties (four cases), failure to follow instructions (eight cases), and researcher error (one case). Thus, we present the results for the 53 participants who completed the study. Each participant completed 10 trials of the task resulting in 530 observations. The final sample was 72% female, 34% Asian, 32% Caucasian, 11% East Indian, and were on average 18.94 years old (*SD* = 2.27). Participants were compensated with course credit and had the opportunity to earn cash rewards (see "Compensation Structure" section below).

Task

Participants performed a computerized work simulation adapted from Omodei and Wearing's (1995) Networked Fire Chief (NFC) program. A labeled screenshot of the task is included in Figure 1. In the task, participants decided how many *boxes* to deliver to the *storage shelves* in each trial. Participants delivered boxes by using a computer mouse to pick up the *forklift* which could carry boxes to the shelves. The forklift could only hold one box at a time meaning participants needed to make multiple trips to the storage area to deliver multiple boxes. Participants completed 10 trials of this task. In each trial, there were 10 boxes available and participants could choose to deliver as many or as few of them as they wished. Each box delivered earned participants money but also carried a risk of losing money. The full compensation structure is described in detail below.

Compensation Structure

Every box delivered to the storage shelves gained participants money. The more boxes participants delivered the more money they could potentially earn. However, if delivering boxes only gained participants money then there would be no consequences associated with over-allocation. Because our goal was to model real world resource allocation decisions, we needed variation in the optimal level of resource allocation. To this end, we incorporated diminishing returns and costs.

Diminishing returns. In general, participants could earn more money by delivering more boxes. However, the amount earned for each box diminished at an incremental rate. Specifically, each box delivered in a trial gained participants $0.05 less than the box previously delivered. Participants earned $0.50 for the first box delivered in a trial, the second box delivered was worth $0.45, the third box $0.40, and so on until the last box which only earned participants $0.05. Because there were 10 boxes available participants could potentially earn up to $2.75 ($0.50 + $0.45 + $0.40… + $0.05) in each trial and up to $27.50 across the entire experiment by delivering all boxes. Thus, although each box delivered increased the total money earned the value of delivering boxes diminished over time.

Costs. Although participants could gain money by delivering boxes, they could also lose money by causing accidents. As a simple way of modeling the potential costs of allocating resources, we added an element of risk to the task that varied across trials. Each time a box was delivered there was a chance that the delivery would cause an "accident". Every time an accident occurred participants lost $1.40 from their earnings. The total amount gained or lost in each trial carried forward and was summed to determine the amount of money each participant received at the end of the experiment. It is important to note that participants were not given performance feedback (e.g., amount of money gained or lost in each trial) on a trial-by-trial basis. This was purposefully done to ensure performance on previous trials did not influence participants' resource allocation decisions on subsequent trials. Full feedback was provided to participants upon completion of the experimental trials. Thus, participants were not aware of the number of accidents they caused until the end of the study.

Each time a box was delivered there was random chance (which varied by trial) that the delivery would cause an accident. Participants were explicitly told the odds of an accident occurring before each trial began. The odds of an accident occurring whenever a box was delivered varied between 5% – 50% (in 5% increments) by trial. Participants performed one trial of the task where the odds of causing an accident were 5%, one trial where the odds were 10%, 15%, and so on up to 50%. This means that in some trials delivering boxes was relatively safe (e.g., 5% odds of an accident occurring) whereas in others delivering boxes was risky (e.g., 50% odds of an accident occurring). The order of these trials was counterbalanced. Each time a participant completed a delivery the computer would use a random number generator to determine whether that delivery had caused an accident. Because accidents were randomly determined, each delivery had an independent chance of causing an accident (i.e., the odds of an accident occurring never varied *within* trials). This means that it was unlikely but possible for participants to earn the full $2.75 (i.e., deliver all 10 boxes and cause no accidents) even in a high risk trial. Participants completed several knowledge checks regarding the compensation structure before performing the task. We used knowledge checks to ensure participants understood the training. In order to progress in the experiment participants had to answer multiple-choice questions about costs, payment, and how to operate the task. If any question was failed participants were given a chance to review the information and retry the question until the correct answer was given.

Optimal level of resource allocation. We defined the optimal level of resource allocation as the number of boxes that a participant would have to deliver to maximize his or her *expected* payout. Expected payout refers to the amount of money a participant would be expected to earn based on his or her behavior. We derived this number by calculating how much money a participant would be expected to earn when delivering X number of boxes (0 – 10) at Y odds (5% – 50%). For example, in a trial where the odds of causing an accident was 25% delivering four boxes would gain participants $1.70 ($0.50 + $0.45 + $0.40 + $0.35 = $1.70). However, because the odds of an accident occurring are 25% (i.e., one in four) delivering four boxes would be expected to cause one accident on average (25% odds of an accident occurring multiplied by four boxes) which would lose participants $1.40. Thus, expected earnings was calculated by taking the total amount gained by delivering boxes ($1.70) and subtracting the expected number of accidents (1) multiplied by the cost of an accident ($1.40). In other words, by delivering four boxes in a trial where the level of risk is 25% the participant's expected earnings would be $0.30 ($0.50 + $0.45 + $0.40 + $0.35 - $1.40 = $0.30).

We calculated expected earnings for each combination of boxes (1 – 10) and level of risk (5% - 50%). The number of boxes associated with the highest expected earnings for each level of risk became the optimal level of resource allocation. Figure 2 shows how expected earnings for each level of resource allocation vary across a selection of low, moderate, and high risk. This figure presents three levels of risk instead of the full 10 levels to simplify interpretation of the graph. For example, in a trial where the odds of causing an accident are 50% delivering even one box is expected to, on average, lose the participant more money than would be gained. Thus, the optimal level of resource allocation for a trial where the odds of causing an accident are 50% is to deliver 0 boxes. However, when the odds of causing an accident are only 5%, delivering boxes is expected to result in a net gain up until nine boxes when there is a slight decrease in expected earnings. The optimal level of resource allocation ranged from 0 – 9 boxes depending on the level of risk. Participants were not explicitly told the optimal level of resource allocation because we were interested in whether individuals could recognize the optimal level of resource allocation.

Procedure

Participants completed the study on lab computers. After providing informed consent, participants completed the GMA, conscientiousness, and demographic measures. Participants were then trained on the task via written instructions displayed on the computer. Specifically, participants were taught how to deliver boxes and the compensation structure for the experiment. This training included several knowledge checks testing participants' understanding of the major components of the task. If at any time participants failed a knowledge check item they were given another chance to review the instructions and correct the mistake. Participants also completed several hands on trials which taught them the skills needed to perform the task. Finally, participants completed a full practice round of the task that combined everything they had previously been taught.

Once training was completed participants then performed the 10 experimental trials of the task. It was made clear that performance on the experimental trials would determine the amount of money each participant would receive at the end of the study. Each experimental trial lasted two minutes. This time limit was pilot tested to ensure participants had sufficient time to deliver all 10 boxes. Participants received no feedback on money gained or lost until all 10 experimental trials were complete. Upon completion, the computer calculated the total amount of money earned by each participant and a researcher paid participants who had a positive total sum.

Participants with a negative total sum (i.e., individuals who lost more money than they earned) received no money.

Measures

GMA. A 16 item measure of GMA was adapted from Condon and Revelle's (2014) International Cognitive Ability Resource. Participants had 10 minutes to complete the items. After 10 minutes, responses on the measure were automatically recorded and participants were advanced to the next measure. The test included logic, matrix, and mental rotation problems. KR-20 for this measure was .51. Although this seems low, it is important to note that GMA is a multidimensional construct comprised of several factors (e.g., math ability, pattern recognition, mental rotation). Even though these factors all load on GMA, it is reasonable for measures of GMA to have low reliability (Brunner & SÜβ, 2005).

Conscientiousness. Conscientiousness was measured using the Unfolding Five Factor Model (UFFM-I) Conscientiousness Scale developed by Carter et al. (2014). This 20 item measure looks at the orderliness and industriousness facets of conscientiousness and uses a 6-point scale which ranges from 0 (strongly disagree) to 5 (strongly agree). The measure was designed to address the issues that Carter et al. (2014) had with how other personality tests were scored. Instead of the typical dominance model of measurement the UFFM-I Conscientiousness Scale uses an ideal point model. These two models differ in regards to how items are scored and the level of the trait that items are designed to assess. Dominance models use sum-scoring and assume that greater endorsement of items is associated with higher levels of the trait. However, this assumption precludes the possibility that individuals may disagree with an item because it suggests more *or less* of the variable than the person possesses (Carter, Dalal, Guan, LoPilato, & Withrow, 2017; Kang & Waller, 2005). Thus, it may be incorrect to assume that greater endorsement of items is always associated with higher levels of a trait. Ideal point models do not carry this assumption as they account for the difficulty or extremity (i.e., how high on the trait an individual would need to be to fully endorse the item) of each item when scoring. For a more in depth review of the advantages of using an ideal point model see Carter et al. (2017).

Participant responses on the UFFM-I Conscientiousness Scale are scored using a modified version of the GUMSCORE SPSS macro developed by Carter and LoPilato (2014). This macro uses item characteristic information (e.g., how "extreme" each item is) to calculate each participant's trait conscientiousness score and then transforms those scores into standard deviations. Thus, a score of -1 on the UFFM-I Conscientiousness Scale would be interpreted as one standard deviation *below* the trait conscientiousness mean. Sample items include "I always go above and beyond what is expected" and "I wouldn't describe myself as messy or clean; my organization is average".

Optimal level of resource allocation. The optimal level of resource allocation was the number of boxes in each trial associated with the highest expected payout. We calculated this value using the formula described above in the "Optimal strategy" section of "Compensation structure". Essentially, this formula calculates the expected gains and expected losses associated with each number of boxes delivered given the odds of an accident occurring. This value ranged from 0 – 9.

Goals. A single item measure of resource allocation intentions was included to assess whether participants experienced any difficulties allocating resources during the task (e.g., running out of time, not understanding how to deliver boxes). Before each of the 10 experimental trials participants were asked "During the UPCOMING TRIAL my goal is to deliver __ number of boxes". Participants then used a dropdown menu to indicate the number of boxes they intended to deliver during the next trial. This value ranged from 0 – 10.

Results

Table 1 displays the descriptive statistics including means, standard deviations, and intercorrelations. Because observations were nested within individuals, we implemented multilevel modeling (MLM; e.g., Raudenbush & Bryk, 2002) using SAS Proc Mixed (Singer, 1998). We used MLM because using single-level regression techniques on nested data can downwardly bias standard errors.

Before conducting our analyses, we first tested to ensure that participants were able to allocate the amount of resources they intended to allocate during the experimental trials. Because participants worked under a time limit (i.e., each experimental trial automatically ended after two minutes), we wanted to rule out the possibility that participants did not have sufficient time to allocate all of the resources they intended to allocate. We verified this by comparing participants' resource allocation goal for each trial (i.e., the number of boxes they intended to deliver) to the amount of resources actually allocated within the trial (i.e., the number of boxes actually delivered). We observed a strong positive relationship between the resource allocation goals participants set and actual resource allocation ($r = .91$, $p < .001$). This strong correlation suggests that participants' were in control of their resource allocation decisions during the experimental trials.

Next, we tested to see if the optimal level of resource allocation was influencing participants' resource allocation decisions. If participants were able to recognize the optimal level of resource allocation then we would expect participants to modify the actual amount of resources they allocated as the optimal level of resource allocation varied from trial to trial. There was a significant and positive relationship between optimal resource allocation and actual resource allocation ($r = .56$, $p < .001$). It seems that participants were sensitive to the optimal level of resource allocation. In general, participants allocated more resources in trials where the optimal level of resource allocation was high and fewer resources in trials where the optimal level of resource allocation was low.

Hypotheses Testing

We predicted that conscientiousness and GMA would moderate the relationship between the optimal level of resource allocation and actual resource allocation. Specifically, we predicted that individuals with high conscientiousness and low GMA would perform the worst at matching actual resource allocation to the optimal level of resource allocation. As shown in Step 3 of Table 2, there was a significant three-way interaction between the optimal level of resource allocation, conscientiousness, and GMA on actual resource allocation. This interaction is plotted in Figure 3. This figure provides initial support for our contention that individuals with high conscientiousness and low GMA would be the worst at matching their actual resource allocation to the optimal level of resource allocation. The graph shows that the relationship between optimal and actual resource allocation appears to be weakest for individuals with high conscientiousness and low GMA. Additionally, when the optimal level of resource allocation is zero (i.e., optimal strategy is to allocate no resources), individuals with high conscientiousness and low GMA also seem to be over-allocating more resources than other individuals.

To determine if the differences in slopes observed were meaningful we tested whether the slope for individuals with high conscientiousness and low GMA was significantly different from the other slopes. In line with our predictions, individuals with high conscientiousness and low GMA had the weakest slope between optimal resource allocation and actual resource allocation (γ = .24, 95% CI [.15, .34]). The slope for individuals with high conscientiousness and low GMA was significantly lower than individuals with low conscientiousness and low GMA (γ

= .48, 95% CI [.40, .56]), individuals with low conscientiousness and high GMA (γ = .62, 95% CI [.52, .71]), and individuals with high conscientiousness and high GMA (γ = .63, 95% CI [.55, .70]). Thus, we found support for our prediction that individuals with high conscientiousness and low GMA were worst at matching their actual resource allocation to the optimal level of resource allocation. A display of the slopes and confidence intervals can be found in Figure 4.

Similarly, we also predicted that individuals with high conscientiousness and low GMA would over-allocate resources more than other individuals. We tested this prediction by examining whether there were significant differences among the intercepts at both the low (optimal level of resource allocation is zero) and high (optimal level of resource allocation is nine) levels. When the optimal level of resource allocation was low individuals with high conscientiousness and low GMA had the highest intercept (B_0 = 4.83, 95% CI [3.73, 5.93]). The intercept for individuals with high conscientiousness and low GMA was significantly higher than individuals with low conscientiousness and low GMA (B_0 = 3.65, 95% CI [2.79, 4.52]), individuals with low conscientiousness and high GMA (B_0 = 2.93, 95% CI [1.83, 4.02]), and individuals with high conscientiousness and high GMA (B_0 = 2.2, 95% CI [1.32, 3.08]). This means that individuals with high conscientiousness and low GMA allocated significantly more resources than other individuals when the optimal level of resource allocation was low. Additionally, we conducted the same analysis to see if there were any differences in intercepts when the optimal level of resource allocation was high. However, no significant differences were observed. This means that participants did not significantly differ in their resource allocation decisions when the optimal level of resource allocation was high. A graph displaying the intercepts and confidence intervals when the optimal level of resource allocation is low and when the optimal level of resource allocation is high can be found in Figure 5 and Figure 6 respectively.

Overall, the nature of the three-way interaction between the optimal level of resource allocation, conscientiousness, and GMA on actual resource allocation was as predicted. The pattern of results supported our general hypothesis that individuals with high conscientiousness and low GMA performed worst at matching their actual resource allocation to the optimal level of resource allocation. The relationship between optimal and actual resource allocation was weakest for individuals with high conscientiousness and low GMA. Additionally, we also found that individuals with high conscientiousness and low GMA over-allocated resources significantly more than other individuals in situations where the optimal level of resource allocation was low.

Auxiliary Analyses

We operationalized performance in our study as the amount of money participants earned on the task. Based on how we designed the task, individuals who were better at matching their actual resource allocation to optimal resource allocation *should* have the greatest performance and earn more money than individuals who did a poorer job of matching actual resource allocation to optimal resource allocation. To verify this, we calculated the slope of the relationship between actual and optimal resource allocation for each participant. If the slope was positive, then the stronger the slope the better the participant was at matching actual resource allocation to the optimal level of resource allocation. A negative or weak slope reflects a poor match between actual and optimal resource allocation. Next, we ran a regression with slope predicting performance on the task. As predicted, we found a positive relationship between slope and performance on the task (b = 888.14, SE = 181.23, p < .001). This supports our argument that we were able to design a task in which allocating resources optimally resulted in greater performance.

Additionally, we also tested the above prediction using intercepts instead of slopes. When the optimal level of resource allocation is zero any amount of resource allocation would result in over-allocation. We predicted that the *higher* a participants' intercept when the optimal level of resource allocation is low (i.e., zero) the *lower* performance should be. We ran a regression using each participant's intercept at zero to predict performance on the task. As predicted, we found that there was a negative relationship between intercept and performance on the task ($b = -124.57$, $SE = 19.90$, $p < .001$). This provides further support that achieving high performance on the task requires a match between actual resource allocation and optimal resource allocation.

To determine whether slope or intercept was the better predictor of performance we conducted one final regression with both slope and intercept predicting performance. When analyzed together only intercept ($b = -107.77$, $SE = 32.61$, $p = .002$) and not slope ($b = 177.59$, $SE = 272.23$, $p = .517$) was a significant predictor of performance. This suggests that intercept better predicts performance in our study. In sum, these auxiliary analyses demonstrate that the experimental task we designed was able to model the relationship between resource allocation and performance that we sought to model. As intended, achieving high performance on the task required participants to match actual resource allocation to the optimal level of resource allocation.

Discussion

Recent research has found that higher levels of conscientiousness may not always be beneficial for performance (e.g., Carter et al., 2014; LaHuis et al., 2005). Although this research established that there are can be downsides to extreme conscientiousness, it provided little insight into why this might be. To address this limitation, we designed a study to test the conditions under which high levels of conscientiousness can become problematic. Our results support previous research which finds that higher levels of conscientiousness do not always improve performance. However, we also provide new insights into understanding this effect. We demonstrated that high conscientiousness promoted deviation from the optimal level of resource allocation for individuals with low GMA. Specifically, individuals with high conscientiousness and low GMA were most likely to over-allocate resources during a work simulation. We found that individuals with high conscientiousness and low GMA had the weakest slope between actual and optimal resource allocation when compared to others. Additionally, we demonstrated that this weak slope was a function of over-allocation as individuals with high conscientiousness and low GMA allocated significantly more resources than others did when the optimal level of resource allocation was low. In turn, over-allocating resources had a downstream negative effect on performance. Thus, our findings suggest that individuals who are highly motivated but unable to recognize the optimal level of resource allocation perform worse than others do because of their tendency to over-allocate resources. This is an important finding as it advances research on the negative effects of conscientiousness (e.g., Carter et al., 2014; Le et al., 2011) by providing context for *whom* high levels of conscientiousness may be detrimental to performance and *how* this effect can occur.

Theoretical Implications

Previous theorizing on the relationship between conscientiousness and performance generally agreed that increases in conscientiousness improve performance across a variety of domains (Barrick et al., 2001). However, some researchers challenged this position by arguing that conscientiousness may not always be beneficial to performance (Carter et al., 2014; Samuel et al., 2012). We lend further support to this view by replicating the finding that high levels of conscientiousness can be detrimental to performance. Additionally, we extend this research by identifying one potential mechanism for how these negative effects can occur. An important contribution we make to this literature is to demonstrate that, for individuals with low GMA, high levels of conscientiousness can be detrimental to performance by promoting over-allocation of resources. This finding provides a theoretical base for future research to build upon when studying the relationship between conscientiousness and performance.

Another contribution we make is in connecting research on conscientiousness and GMA with the resource allocation literature. Although there has been some initial research on the role conscientiousness plays in resource allocation (e.g., Sun, Chen, & Song, 2016) no study has considered the combined effects of conscientiousness and GMA on resource allocation. Our study demonstrates that both of these factors have important implications for how individuals make resource allocation decisions. Incorporating conscientiousness and GMA into the literature on resource allocation provides a more complete picture of the process individuals use when allocating resources. Thus, by considering the joint effects that conscientiousness and GMA have on resource allocation we advance theory by identifying an important determinant of resource allocation. Both GMA and conscientiousness interact to influence the resource allocation decisions individuals make.

Our results also speak to the debate over the relationship between conscientiousness, GMA, and performance. Past research has suggested that conscientiousness and GMA should interact to predict performance (Sackett et al., 1998; Vroom, 1959). The logic of this hypothesized relationship is that how well an individual performs depends on the joint effects of ability (GMA) and motivation (conscientiousness). An individual can only achieve high performance if he or she possesses both the motivation to expend effort and the ability to perform well. However, empirical support for this relationship has been inconsistent (e.g., Mount et al., 1999; Perry et al., 2010; Van Iddekinge et al., in press). In the current study, we observed that conscientiousness and GMA interact to indirectly predict performance via resource allocation. This element of resource allocation may help to explain the inconsistent findings from previous research. Although not definitive, the current study provides initial support for the idea that the hypothesized conscientiousness by GMA interaction on performance may be more nuanced than previously thought. Further research is required to unpack the role resource allocation plays in this relationship and to determine whether our results can generalize to the workplace contexts previously studied (e.g., Sackett et al., 1998).

Practical Implications

The results of this study have practical implications for managers, teachers, and anyone in a supervisory role. Individuals who must manage subordinates should be mindful of the negative effect that high levels of conscientiousness and low levels of GMA can have on resource allocation and performance. Using the results of our study to identify which employees are most likely to over-allocate resources could help supervisors diagnose and address performance issues. By identifying which subordinates are most likely to over-allocate resources, supervisors could tailor their management strategies to address this issue for these individuals.

Understanding how individuals tend to allocate resources could affect the goals, feedback, or norms a supervisor communicates to his or her subordinates. In more extreme cases, supervisors may seek to curtail this issue of over-allocation by having subordinates form implementation intentions related to resource use or by limiting the autonomy that high risk groups (i.e., individuals with high conscientiousness and low GMA) have in making resource allocation decisions. In general, we expect that a greater understanding of which individuals are most likely to over-allocate resources would help supervisors to better manage their subordinates. More research is required to understand how supervisors might implement interventions (e.g., feedback, goal setting) to reduce the over-allocation of resources across a variety of settings.

Our study also has several implications for employee selection. GMA and conscientiousness are two indicators of performance commonly used in employee selection and assessment (Behling, 1998). However, some practitioners have advocated *against* using measures of GMA when hiring (Briner & Rousseau, 2011) with the majority believing conscientiousness to be a better single indicator of performance (Rynes, Brown, & Colbert, 2002). Our results demonstrate that the joint effects of conscientiousness *and* GMA matter when predicting performance. Issues may arise when organizations seek to hire highly conscientious employees but disregard GMA. Organizations that use this strategy run the risk of hiring highly conscientious individuals with low GMA who will over-allocate resources and not perform as effectively as their high GMA counterparts perform. Although researchers have advocated that organizations should measure GMA from a validity standpoint (Rynes et al., 2002), we bolster this argument by demonstrating that there are unique problems associated with excluding measures of GMA. Because of the indirect effect that conscientiousness and GMA have on performance via resource allocation, it may be detrimental for organizations to maximize conscientiousness in employees without considering GMA.

Strengths, Limitations, and Future Directions

The laboratory approach used in the current study has several strengths over other designs. Using a laboratory paradigm allowed us to unobtrusively measure the resource allocation decisions made by participants. The ability to directly observe these behaviors in a controlled environment is a strength of our study. Additionally, our use of an experimental design granted us a level of control that would be difficult to achieve using a non-experimental design. With this high level of control, we were able to vary the optimal level of resource allocation from low to high. Because of this, we could make stronger inferences regarding causality than could be made using other designs. Thus, we were able to demonstrate that conscientiousness, GMA, and the optimal level of resource allocation *can* affect actual resource allocation. However, the extent to which this effect *will* generalize to applied settings requires further research.

Next, we recognize several limitations of the current study that provide opportunities for future research to address. First, although our use of a work simulation provided a high level of control it comes at the cost of ecological validity. One could make the argument that several aspects of the task do not match the experience of employees in the workplace. For instance, we operationalized "costs" in the current study as the money participants could lose during the task. However, the costs associated with under or over-allocating resources at work are not always monetary. An employee who misallocates resources could face a variety of negative outcomes which range in severity including poor performance reviews, demotion, or termination. Although the current study does not capture the full range of costs as they exist in the workplace, we would argue that varying the type or severity of costs should not change the underlying effect we observed. The effect of costs on behavior occurs through the optimal level of resource allocation. Thus, varying costs should only affect behavior insofar as it influences the optimal level of resource allocation. Similarly, in the current study we manipulated the optimal level of resource allocation by varying costs and holding diminishing returns constant. Theoretically, there is no reason why varying diminishing returns as opposed to costs would change the results we obtained but it is a question that should be answered empirically. We invite future research to address these concerns by replicating our findings using other types of costs and varying diminishing returns.

A second limitation of our study design is related to how we communicated information about the optimal level of resource allocation to participants. Given that our intention was to control the optimal level of resource allocation we simplified costs and diminishing returns to their most basic elements. This allowed us to easily communicate information about the optimal level of resource allocation to participants but may not reflect how individuals receive this information in the workplace. In the current study, we explicitly gave participants absolute knowledge about the costs and benefits associated with their behavior. We provided this information to ensure internal validity of our optimal level of resource allocation manipulation. However, in the workplace it is unlikely that an employee would receive such absolute information about the costs and benefits associated with resource allocation. Thus, the current study may not fully capture the ambiguity involved in making resource allocation decisions in the workplace. Future research should examine how uncertainty surrounding the optimal level of resource allocation influences the resource allocation decisions that individuals make.

Conclusion

The current study provides insight into the effects of conscientiousness and GMA on resource allocation. In general, conscientiousness can be beneficial as it promotes a high level of motivation, effort, and leads individuals to invest a great deal of resources into work (Barrick et al., 1993; Gellatly, 1996; Judge & Ilies, 2002). However, this strategy of investing a great deal of resources can become problematic when broadly applied to situations in which a high level of resource investment is unnecessary or unwarranted. Specifically, individuals with low GMA may fail to consider the optimal level of resource allocation when making resource allocation decisions. Thus, highly conscientious individuals with low GMA may end up over-allocating resources. This occurs because these individuals are motivated to invest a great deal of resources but unable to recognize the optimal level of resource allocation. Ultimately, we find that this over-allocation of resources has a negative downstream effect on performance.

The results of our study expand upon previous work to highlight the circumstances under which high levels of conscientiousness can become detrimental to performance. It is our hope that these findings will provide researchers with new ways to understand the relationship between conscientiousness and performance. Additionally, supervisors could utilize the insights into conscientiousness, resource allocation, and performance that the current study provides to better identify potential resource allocation issues in subordinates. These findings could allow managers, teachers, and anyone in a leadership role to more effectively manage their subordinates by tailoring supervisory strategies to mitigate the misallocation of resources.

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Table 1

Means, Standard Deviations, and Intercorrelations of All Study Variables

Variable	*M*	*SD*	*1*	*2*	*3*	*4*
1. Optimal	3.45	3.23	1.00			
2. Conscientiousness	−.25	.53	.00	1.00		
3. General Mental Ability	5.83	1.82	.00	.22	1.00	
4. Actual	5.04	2.91	.56	−.06	−.14	1.00

Note: Optimal = optimal level of resource allocation, Actual = actual level of resource allocation. n = 530 observations nested within N = 53 individuals.

Table 2

Interaction of Optimal Resource Allocation, Conscientiousness, and GMA on Actual Resource Allocation

	γ	SEγ	p	R^2	ΔR^2
Step 1: Main Effects				.33	–
Opt	.51	.02	<.001		
Consc	−.15	.47	.742		
GMA	−.21	.14	.124		
Step 2: Two Way Interactions				.36	.03
Opt	.07	.08	.394		
Consc	1.85	1.54	.236		
GMA	−.53	.16	.001		
Opt × Consc	−.11	.04	.011		
Opt × GMA	.07	.01	<.001		
Consc × GMA	−.28	.25	.272		
Step 3: Three Way Interaction				.37	.01
Opt	−.05	.09	.569		
Consc	3.15	1.61	.056		
GMA	−.59	.16	<.001		
Opt × Consc	−.49	.14	<.001		
Opt × GMA	.09	.01	<.001		
Consc × GMA	−.5	.26	.063		
Opt × Consc × GMA	.06	.02	.005		

Note: Opt = optimal level of resource allocation, Consc = conscientiousness, and GMA = general mental ability. Because a true value for R^2 could not be calculated we estimated R^2 using the squared correlation between the predicted and observed outcomes (Northcraft, Schmidt, & Ashford, 2011). n = 530 observations nested within N = 53 individuals.

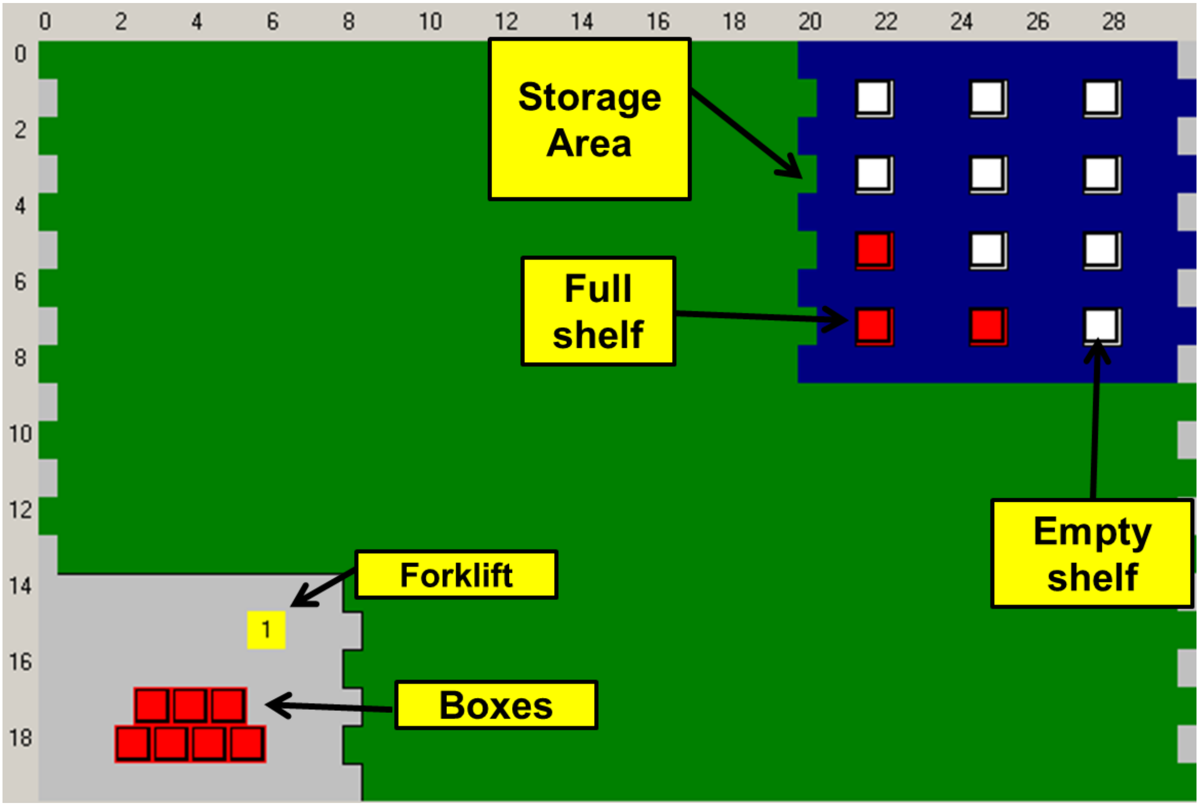

Figure 1. Labeled screenshot of experimental task shown to participants.

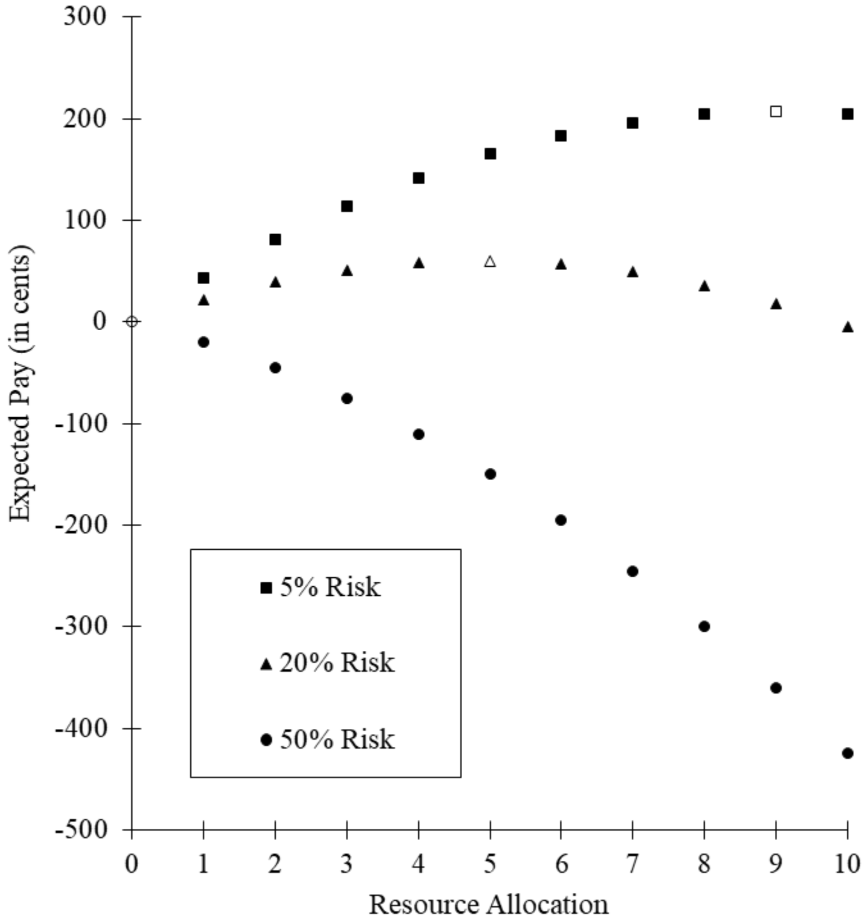

Figure 2. Graphical depiction of how gains, diminishing returns, and costs create the optimal level of resource allocation. Unfilled markers indicate the optimal level of resource allocation. At the 5% Risk the optimal level of resource allocation is nine boxes and expected pay is $2.07. At the 20% Risk the optimal level of resource allocation is five boxes and expected pay is $0.60. At the 50% Risk the optimal level of resource allocation is zero boxes and expected pay is $0.00.

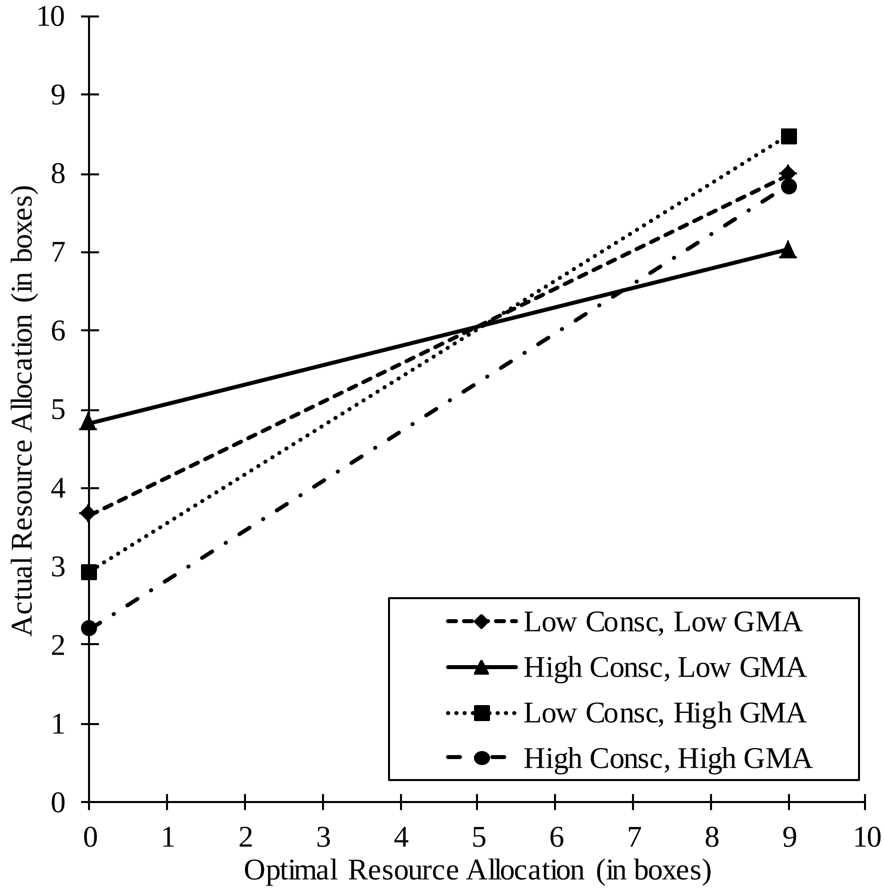

Figure 3. Interaction between optimal level of resource allocation, conscientiousness, and GMA on actual resource allocation. High = +1 SD, Low = −1 SD.

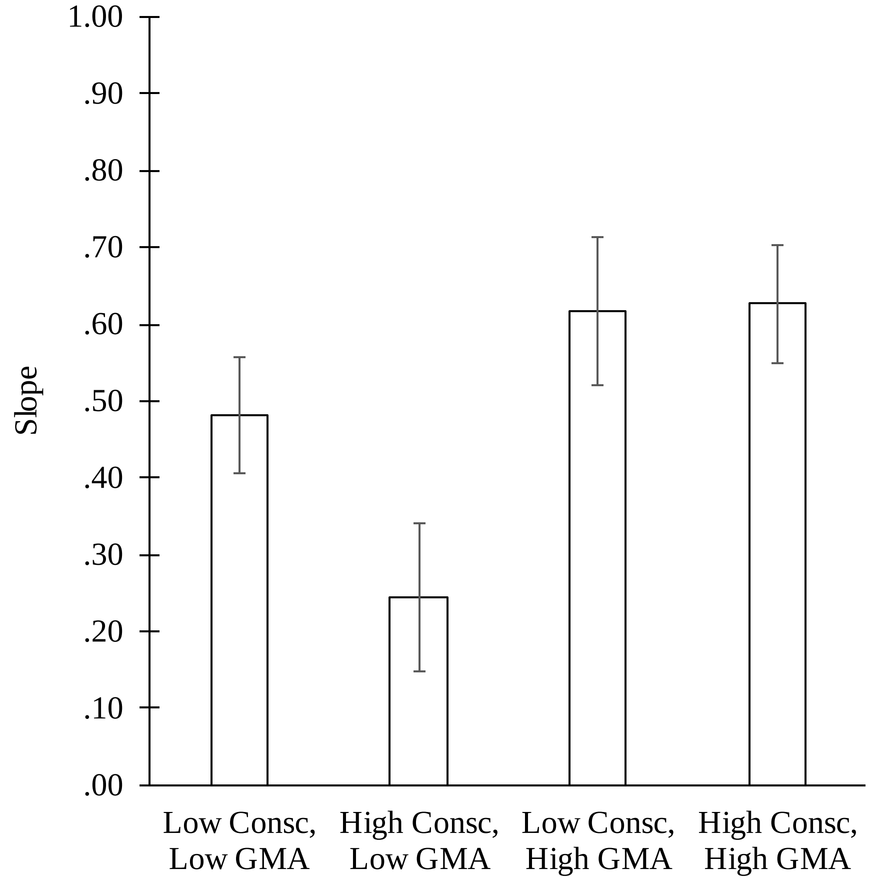

Figure 4. Slopes with 95% confidence intervals. Error bars represent standard errors. High = +1 SD, Low = −1 SD. n = 530 observations nested within N = 53 individuals.

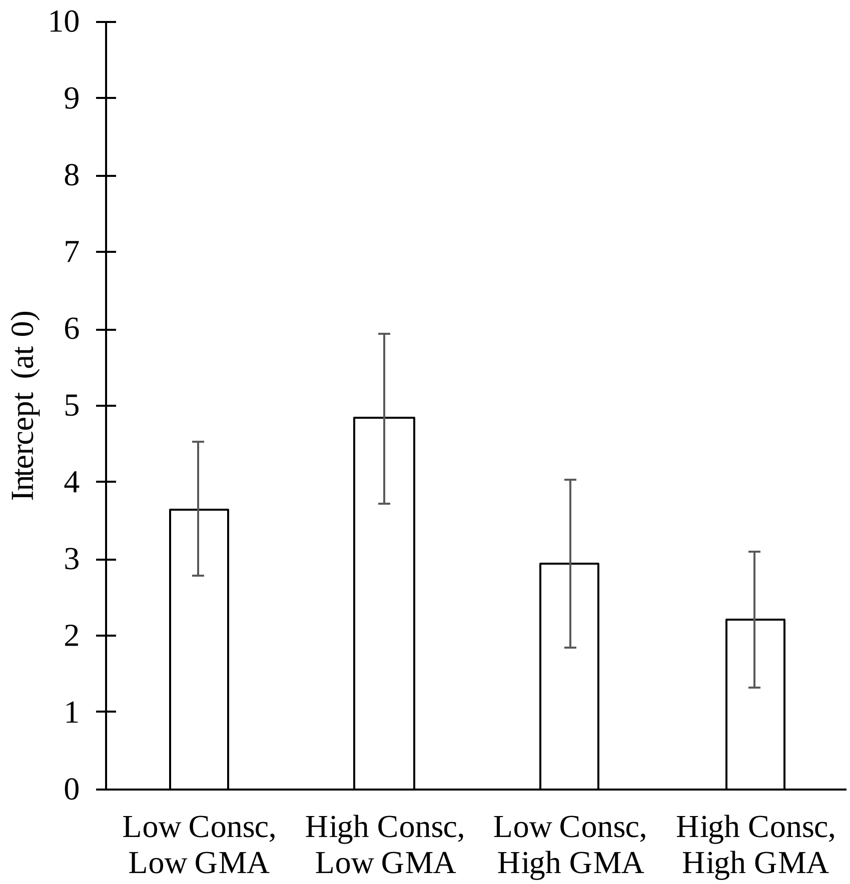

Figure 5. Intercepts at lowest optimal level of resource allocation (0) with 95% confidence intervals. Error bars represent standard errors. High = +1 SD, Low = −1 SD. N = 53.

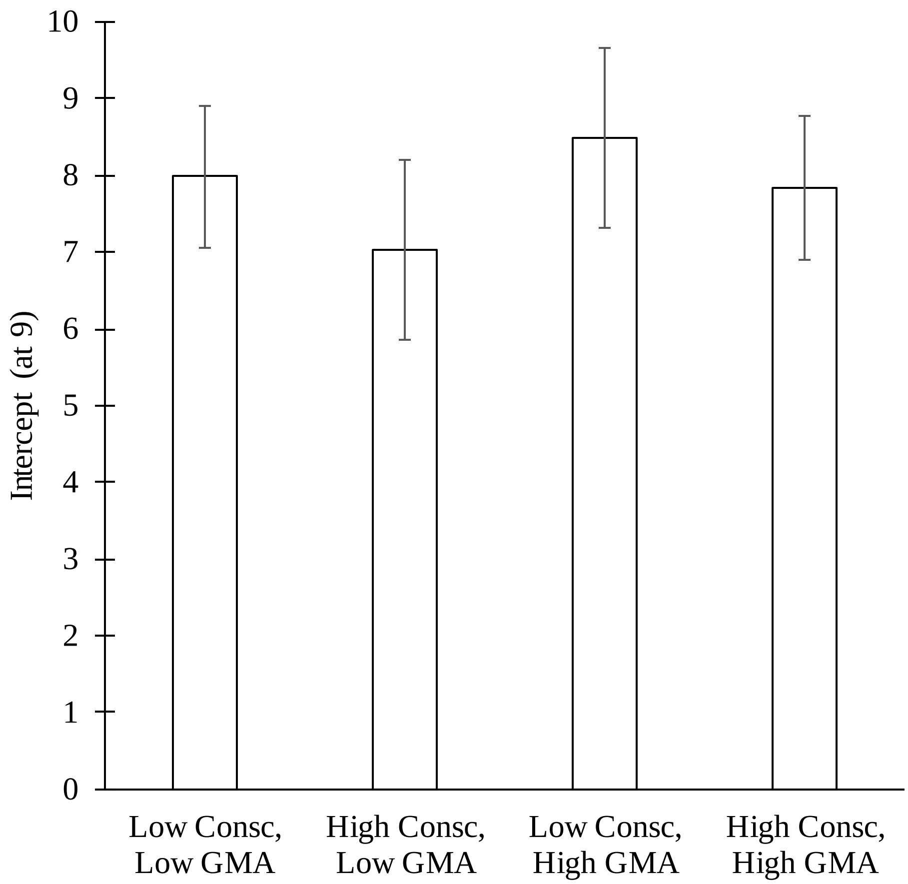

Figure 6. Plot of intercepts at highest optimal level of resource allocation (9) with 95% confidence intervals. Error bars represent standard errors. High = +1 SD, Low = −1 SD. N = 53.