RELATION OF LEARNING ON DISCRIMINATION TASKS TO ACADEMIC ACHIEVEMENT AND INTELLIGENCE

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THESIS ABSTRACT

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Currently, the literature that examines relationships between learning and memory tasks to intelligence and academic achievement are contradictory. Early findings give no support for these relationships, however more recent research does provide support for them. The present study aimed to add to this modern body of work supporting the relationship between learning and memory tasks with academic achievement and intelligence. Through the comparison of participants' scores on a specific set of discrimination tasks to GPA and SAT scores, the findings from this study provide evidence for these relationships.

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Introduction

Background Information & Literature Review

Learning, Intelligence & Academic Achievement: Historical Perspective

Traditionally, the learning and memory literature has been unable to provide consistent support for a significant relationship between various laboratory based learning and memory measures to intelligence and academic achievement. Early findings by Herbert Woodrow (1938, 1946) showed low correlations between learning on a collection of tasks measuring various factors of cognition, such as memory, (i.e., Horizontal Adding; Substitution; Spot-patterning) and intelligence test scores (Forms A and B from the Otis Advanced Intelligence Examination). Benton Underwood and his colleagues (Underwood, Boruch & Malmi, 1978) were unable to support significant relationships between people's performance on episodic memory and associative learning tasks and SAT scores, which are good stand-ins for intelligence tests (e.g., Frey & Detterman, 2004). In their study, Underwood, et al. selected their tasks with the intent of measuring specific attributes of memory to see which go together and which do not. Some of the memory and associative learning tasks they used were: Free-Recall, Paired Associates, Serial Learning, Verbal Discrimination, List Differentiation, and Memory Span (Underwood, et al., 1978). Their intelligence measures were SAT-Verbal (SATV) and SAT-Math (SATM) scores. Their analysis found that many of the measures of episodic memory and associative learning had moderate to large correlations to their counterparts (i.e. Free Recall using concrete words was correlated to free recall using abstract words at $r = .66$ and Free Recall and Paired Associates measures had moderately sized correlations at $r = .53$). However, they had very low correlations to measures of intelligence (i.e. Free

Recall tasks and SATV were correlated at r =.19, Free Recall tasks and SATM were correlated at r = .02, Paired Associates was correlated to SATM at = .21 and to SATV at r = .10). These findings were interpreted to suggest that varying measures of memory and associative learning are at best weakly related to intelligence.

Learning, Intelligence & Academic Achievement: Current Perspective

Although early research on the relationship between laboratory based learning and memory tasks to intelligence and academic achievement has struggled to find support, more recent research has begun to surface that does in fact support this relationship. For example, Williams and Pearlberg (2006) reported data showing that certain types of associative learning predicted intelligence scores on Raven's Advanced Progressive Matrices, regardless of being distinct from other measures of cognitive processing. In their study, they conducted two separate experiments to examine the relationship between associative learning and intelligence. In their first experiment, they used a three-term contingency learning measure, which is a complex associative learning task with the goal of learning the outcome of a particular response when a certain stimulus is presented (Williams & Pearlberg, 2006). For example, a stimulus word (e.g. LAB) was individually presented on the computer screen along with instructions to press a response key (e.g. the "A" key). Upon pressing the key, another word was produced (the outcome) on the computer screen (e.g. PUN). Subjects were then instructed to press a second response key (e.g. the "B" key) and another word (outcome) was produced (e.g. TRY), and then a third key (e.g. the "C" key) and another outcome was produced (e.g. EGG). Therefore, three response-outcome contingencies were learned for each stimulus. After the trial block was completed, participants went into a testing phase in which they were asked to supply the outcome word that corresponded to each stimulus-response pair (e.g. LAB & Key A). In addition to the three term contingency task, this study also measured participants' performance on two more learning measures (Free Recall and Paired Associates) as well as an intelligence score, measured by participants' performance on the Raven's Advanced Progressive Matrices. As can be seen in Figure 1, performance on the Raven's intelligence test was significantly related to performance on the three-term contingency learning measure, but not to the free recall or paired associates measures.

Spearman's rank-order correlations between tasks in Experiment I (n=98)

	Raven	Three-term	PA	FR
Raven	–	–	–	–
Three-term	0.519**	–	–	–
PA	0.125	0.430**	–	–
FR	0.147	0.313**	0.425**	–

*P<0.05.
**P<0.01.

Figure 1

In the second experiment, Williams and Pearlberg (2006) explored the relationship between intelligence and associative learning, and additionally aimed to test whether performance on these measures was related to other measures of cognitive processing. For this they added the following to their study: Paced auditory serial addition task (PASAT), Inspection Time (IT), Card sorting and the Zahlen-Verbindungen Test (ZVT). The results from this experiment can be found in Figure 2. Consistent with the findings in their first experiment, Williams and Pearlberg (2006) found a significant relationship between intelligence scores and three-term contingency scores. However, in this experiment they found that the intelligence scores also correlated to most of the other cognitive processing measures, even when those measures did not always correlate to each other or to the three-term contingency measure. These findings were interpreted to mean that intelligence can indeed be a significant predictor for varying types of learning, memory and cognitive processing measures, even when those measures are unrelated to one another.

Spearman's rank-order correlations between tasks in Experiment II ($n=60$)

	Raven	Three-term	Cardsort I	Cardsort II	ZVT	IT	
Three-term	0.586**	–	–	–	–	–	–
Cardsort I	0.239	0.053	–	–	–	–	–
Cardsort II	0.410**	0.079	0.438**	–	–	–	–
ZVT	0.419**	0.109	0.534**	0.499**	–	–	–
IT	0.392**	0.061	0.228	0.168	0.353**	–	–
PASAT	0.357**	0.153	0.280*	0.421**	0.434**	0.247	–

* $P<0.05$.
** $P<0.01$.

Figure 2

Working Memory, Academic Achievement & Intelligence

The relationships between working memory and academic achievement, working memory and intelligence, and academic achievement and intelligence also find support through a much more consistent body of literature. Moderate correlations between these three variables are reported across studies looking at these relationships. Note that this literature involves more studies with children, which may or may not be of importance. Research shows that one's ability to temporarily store and manipulate information, or *working memory capacity* (WMC), is linked to academic achievement (Alloway, 2006; Alloway & Alloway, 2010; Coleman, 2014; Conway, Kane & Engle, 2003; Jaroslawska, Gathercole, Logie & Holmes, 2016; Khenissi, Essalmi, Jemni, Kinshuk, Chang & Chen, 2016; Klingberg, 2010; Sedek, Krejtz, Rydzewska, Kaczan & Rycielski, 2016). In a review of studies from 1989 to 2005, Alloway (2006), found that those students with poor WMC often show signs of difficulty learning in classroom settings. Another study tested

46 children (6-11 years old) with low IQ's on working memory batteries to determine whether WMC was a predictive factor for their below average academic attainment (Gathercole, Alloway, Willis & Adams, 2006). Using three tests from the Working Memory Test Battery for Children (WMTB-C), intelligence, reading comprehension, oral language, and phonological processing tests, this study found that working memory was an independent predictor for the students' below average academic performance. These examples are a few amongst many that support that WMC is related to academic achievement.

A study of 133 undergraduates using operation, reading and counting span working memory tasks and Ravens and Cattell's intelligences measures found that WMC was significantly correlated with general intelligence (Engle, Tuholski, Laughlin & Conway, 1999). Another study tested 159 sixth to eighth graders on both intelligence (Cattell Culture Fair Intelligence Test; Primary Mental Abilities-Spatial; Primary Mental Abilities-Verbal; Primary Mental Abilities-Reasoning) and academic achievement (INVALSI for both mathematics and reading literacy) tests. Their scores on these measures were compared to determine if there was a relationship between them, ultimately finding support for a strong relationship (Giofrè, Borella & Mammarella, 2017). These findings illuminate the support for the relationship between WMC and academic achievement; WMC and intelligence; and academic achievement and intelligence.

Associative Learning & Working Memory

The literature also supports the relationship between associative learning and working memory capacity. For example, recent data has found moderate correlations between participants' (n=169) scores on three-term contingency and paired associates tasks with operation span working memory tasks (Kaufman, DeYoung, Gray, Brown & Mackintosh, 2009). Another study examined the relationships between associative learning, working memory, fluid intelligence, and processing speed, and found support for the connection between associative learning measures and working memory capacity (Tamez, Myerson & Hale, 2012). Tamez, et al. measured associative learning through participants' scores on the verbal three-term contingency associative learning task from Williams & Pearlberg (2006) in addition to visual and spatial adaptations of this task. These adaptations used the same procedure as the verbal three-term contingency task, but instead of word associations, participants learned associations between radially symmetric patterns for the visual adaptation and associations between the locations of dots for the spatial adaptation (Tamez, et al., 2012). They compared participants' performance on these three associative learning tasks to participants' performance on counting span, parallel span and position span working memory tasks. They defined participants' performance on the counting span task by the number of correct letters recalled in the order they had been presented and participants' performance on the

Measure	1.	2.	3.	4.	5.
1. PS	–				
2. WM	**−.48**	–			
3. Learn	**−.26**	**.59**	–		
4. gF	**−.43**	**.55**	**.75**	–	

Note: PS = Processing Speed; WM = Working Memory; Learn = Learning (Total); *gF* = Fluid Intelligence
Correlations greater than .26 (shown in bold) are significant at the .05 level.

Figure 3

parallel and position span tasks by the total number of correctly recalled locations (Tamez, et al., 2012). Results from this study can be found in Figure 3. As can be seen below, measures of working memory significantly correlate to the associative learning measures r (80) =.59, p<.05.

The Present Study

Up until this point, the literature reviewed in this paper has supported relationships between: associative learning tasks and intelligence; WMC and intelligence; WMC and academic achievement; and academic achievement and intelligence. The final link, and perhaps the one most critical to the present study, is the relationship between associative learning discrimination tasks and WMC.

Associative Learning Discrimination Tasks & Working Memory

Recent research has found moderate correlations between associative learning discrimination tasks and working memory capacity. For example, Soreth (2016) has provided this support by exploring the relationship between four different associative learning discrimination tasks, WMC and intelligence. Associative learning tasks test one's ability to understand that different stimuli co-occur or are related to one another (Kaufman et al., 2009). In order to examine the relationship between learning, memory and intelligence, Soreth (2016) measured participants' scores on the following: Positive Patterning, Negative Patterning and Biconditional Patterning discrimination tasks; working memory updating, operation span, sentence span and spatial short-term memory working memory tasks; an arrow flankers attentional control task; and Raven's Advance Progressive Matrices intelligence task. The findings of this study confirm a moderate significant relationship between the Negative Patterning discrimination task and WMC, r (40)=.35, p<.05 which suggests that one's performance on the associative learning discrimination tasks are related to one's working memory capacity. This study's findings also replicated previous findings (Tamez, Myerson, & Hale, 2008; Tamez, et al., 2012; Unsworth, Spillers & Brewer, 2009; Unsworth & Spillers, 2010) that confirm a significant relationship between the WMC and intelligence constructs, *r* (40) =.43, *p*<.01 (Soreth, 2016).

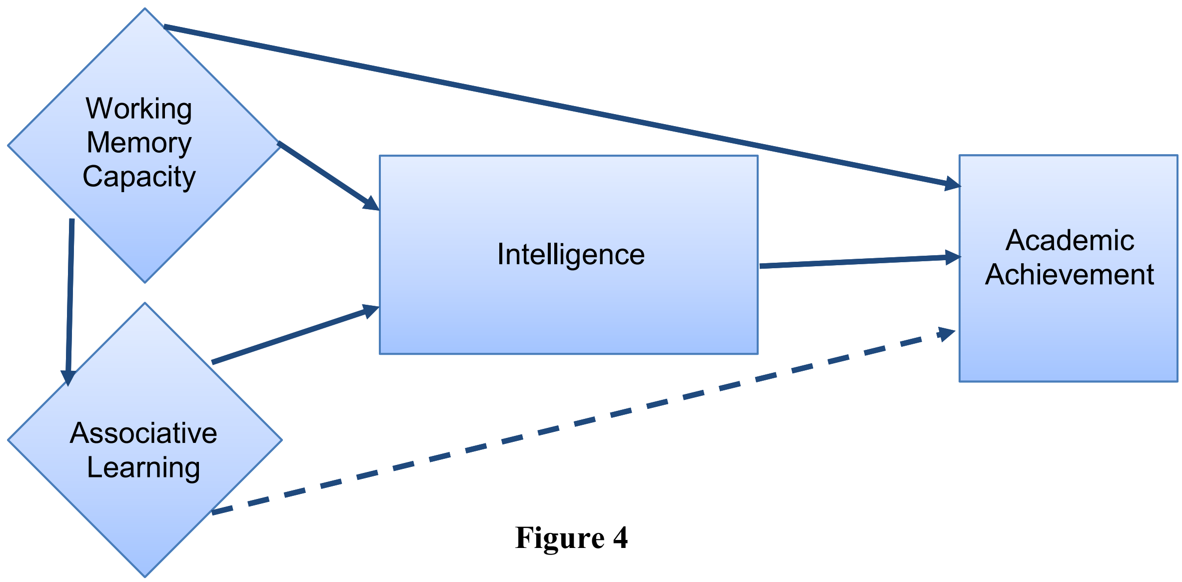

Figure 4

All of this recent research lays the groundwork for the study discussed in this paper. For a long time there was no evidence that there was a connection between associative learning tasks, working memory, intelligence and academic achievement until Williams and Pearlberg (2006). They developed an associative learning task that shows these connections and paved the way for research since then to continue adding support for their findings. As can be seen by the solid connecting lines in Figure 4, support for the following relationships has already been found: (1) discrimination tasks and working memory capacity; (2); discrimination tasks and intelligence (3) working memory capacity and intelligence; (4) WMC and academic achievement and (5) intelligence and academic achievement. However, as indicated by the dashed line in Figure 4, there has not yet been a study that examined the direct relationship between discrimination tasks and academic achievement. The present study aimed to do this by using four different types of discrimination problems (Positive Patterning, Negative Patterning, Biconditional Patterning, and Irrelevant Cues) to examine the relationships between discrimination task learning and academic achievement as measured by grade point average (GPA). This study also examined the connections between discrimination scores and intelligence, as measured by SAT scores, and intelligence and academic achievement. Based on the aforementioned literature supporting the connections between WMC and academic achievement (Alloway, 2006; Alloway & Alloway, 2010; Coleman, 2014; Conway, et al., 2003; Gathercole, et al., 2006; Jaroslawska, et al., 2016; Khenissi, et al., 2016; Klingberg, 2010; Sedek, et al., 2016) and the connections between the discrimination tasks and WMC (Soreth, 2016) the present study's hypotheses were: that (1) the discrimination tasks would directly correlate to academic achievement; (2) as well as with intelligence; (3) and that intelligence would be correlated with academic achievement.

One's working memory is reliably assessed through tasks that require the individual to process and store increasing amounts of information, to the point at which recall errors are likely to be made (Alloway, 2006). A common example of a reliable working memory task is performing a math problem without writing anything down. This act would require one to store the numbers and manipulate them in their head to compute the problem. Associative learning tasks assess one's ability to understand that different stimuli co-occur or are related to one another (Kaufman et al., 2009). These tasks can also be combined as a singular assessment that measures one's WMC via an associative learning task. For example, in Whitlow (2013) the task asked participants to process different food and wine combinations to determine, and thus infer, which would yield improved health outcomes. In this task, participants not only were learning about the different relationships between various food and wine combinations, but were also temporarily storing and manipulating that information to make a judgment about which combinations might produce improved health outcomes. Another example is a task that asked participants to process names of hypothetical actors and actresses to determine which combinations would have on-screen chemistry (Whitlow & Loatman, 2015; Soreth, 2016). Although these tasks are measures of associative learning by nature, they also allow for an accurate measure of participants' WMC because they possess the mechanism of processing information, temporarily storing that information, and then manipulating it to determine the outcome of different combinations of the originally processed material. With this, discrimination tasks were selected for the purpose of the present study because they have been successfully implemented in previous research that successfully showed that performance on the discrimination tasks related to working memory and intelligence (Soreth, 2016). Furthermore, the particular paradigm used in the present study allows for an effective measurement of one's WMC because as cue compounds and reinforcement varies, information that is not yet stored needs to be manipulated and applied in different ways to accurately determine whether there is a disruption or not.

In addition to the connection between associative learning tasks and measures of working memory, discrimination tasks have also been selected because they seem to have relationships to varying components of higher-level cognitive functions that relate to working memory (Miyake, Friedman, Emerson, Witzki, Howerter, & Wager, 2000). In the studies by Kaufman et al. (2009) and Williams and Pearlberg (2006), they used novel associative learning tasks that may require working memory to be solved, which helps to explain why there was a correlation to WMC. Discrimination tasks provide an opportunity to utilize tasks that have been used extensively in associative learning studies and seem to have connections to separate processes of working memory. Because of this, discrimination tasks provided a promising approach to be able to address a missing link in current literature, which is the question of why various learning abilities are related to intelligence and academic achievement. Discrimination tasks vary in design, which ultimately require different complex cognitive functions or processes behind different problem solving abilities, to successful solve them. For example, positive patterning, negative patterning, and biconditional discriminations require unitization, or when two previously learned stimuli are presented as a single unit (Graf & Schacter, 1989). Landy and Goldstone (2005) provide support that elements will be unitized, "when elements co-vary together and their co-occurrence predicts an important categorization," which occurs in positive, negative, and biconditional patterning. This problem solving function draws on the same processes that are thought to underlie working memory tasks because participants need to tap into temporarily stored information about which co-occurrences of stimuli pairs predict classroom disruption. As the stimuli pairs vary, it is necessary to then manipulate the temporarily stored information to continue making predictions about classroom disruption.

Negative and positive patterning also need the process of updating to be solved. Updating is the process of monitoring and coding incoming information and appropriately modifying the items being held in working memory by updating, or replacing, information that is no longer relevant with new and more relevant information (St Clair-Thompson & Gathercole, 2006). Negative patterning tasks also need the function of inhibition, which is the ability to inhibit, or stop, the execution of a behavior in response to a stimulus (Roche, Garavan, Foxe & O'Mara, 2005). This draws on the same processes that are thought to underlie working memory because participants work with the newly obtained information about student pairs to inhibit their prediction of disruption. Positive patterning tasks can also use summation to be solved (Deisig, Lachnit, Giurfa & Hellstern, 2001). Summation is when the response tendencies of individual stimuli summate, or add together, when presented as a compound (Rescorla & Wagner, 1972; Whitlow & Wagner, 1972). In these discrimination tasks, participants learned which students in the stimuli pairs are associated with disruption and no disruption in the classroom. As the stimuli pairs vary, participants needed to work with what they just learned about the individual students to continue to make predictions about how they would affect each other in the classroom. This draws on processes thought to underlie WMC because the information learned about the students is only temporarily stored in their memory, and as they begin thinking about the different student combinations, they are manipulating that temporarily stored information to continue making predictions about the outcomes of the various stimuli pairs.

Biconditional discrimination tasks also require shifting in order for them to be solved. Shifting is the process of moving back and forth "between multiple tasks, operations, or mental sets" (St Clair-Thompson & Gathercole, 2006). Shifting is needed to solve biconditional discriminations because the correct response to any particular cue depends on the specific context, or in this case, the cue with which it occurs.

Irrelevant cue discrimination tasks require stimulus selection to be solved. Stimulus selection is when cues compete with other stimuli upon presentation for the responses resulting from reinforcement (Wagner, Logan, Haberlandt & Price, 1968). Berry, Mulhern and Duncan (1975) discuss evidence that stimulus selection is shown in both children and college students who are, “sensitive to differences in stimulus element meaningfulness” or that they choose the more meaningful of two stimuli. The process of stimulus selection is necessary for irrelevant cue tasks because one of the cues presented has no effect on the elicited response (the irrelevant cue) where the other is the one that is eliciting the response, and to successfully solve these discriminations, one needs to distinguish which cue is which. This task draws on the same processes thought to underlie WMC because the various stimuli information learned is used to make decisions about which of the students in the pair are causing the disruption or no disruption outcome.

Discrimination Problem	Associated Complex Cognitive Function(s)
Positive Patterning	Unitization, Summation & Updating
Negative Patterning	Unitization, Inhibition & Updating
Biconditional Patterning	Unitization & Shifting
Irrelevant Cue	Unitization & Stimulus Selection

Table 1

Table 1 lists the different complex cognitive processes that are linked to the four discrimination problems used in this study. To summarize, this study used four discrimination tasks as a measure of learning ability because: previous research has shown moderate correlations between the four discrimination tasks and WMC (Soreth, 2016); previous research has supported the four discrimination tasks as associative learning tasks that bear a meaningful relationship WMC (Whitlow, 2013; Whitlow & Loatman, 2015; Soreth, 2016); and the various mechanisms needed to solve these four discrimination tasks draw on the same processes that are thought to underlie WMC, which provides a unique opportunity to potentially emphasize different processes of working memory.

Method

Participants

Seventy-five Rutgers University- Camden undergraduate students from Introductory Psychology and Research Methods classes participated for partial fulfillment of a course requirement. It is important to note that a majority of the participants in this sample were freshman (n=48) in Introductory Psychology. The rest of the sample (n=27) consisted of a sophomores (n=14), juniors (n=9) and seniors (n=3), with 1 participant not indicating year of study. Many of these upperclassmen were transfer students, which means they did not have freshman grades in the Rutgers University grading system. In order to reflect accurate relationships between GPA data and discrimination scores, the present study reported both overall sample correlations and freshman only correlations.

Table 2, below, provides support for this study's sample size. The first line in Table 2 provides the suggested sample size of about 29 participants to achieve a significant ($p<.05$) and large (r=.5) effect 80% of the time. The second and third lines provide the effect sizes for a sample size of 80 with significant ($p<.05$) large (r=.5) and moderate (r=.3) correlations. Based on this, the current study's sample size of 75 is close to the target of 80 in order to find significant ($p<.05$) large and moderate correlations. Furthermore, the freshman only sample of 48 is still well over the minimum sample needed to achieve a significant ($p<.05$) large (r=.5) correlation.

Statistical Test	Sample Size	Power	Correlation	Significance Level
Correlation	28.870	0.800	0.5	0.05
Correlation	80.000	0.998	0.5	0.05
Correlation	80.000	0.776	0.3	0.05

Table 2[1]

[1] Retrieved from https://www.anzmtg.org/stats/PowerCalculator/PowerCorrelation

Materials

The discrimination task battery used names[2] of 320 fictional students as stimuli. The Category Naming task (Battig and Montague, 1969) provides a cornucopia of names to use and allows for complete randomization of which names are used in each trial, and whether those names are disruptive or not. Out of the 320 fictional names, 160 were male names and 160 were female names. Names were randomly assigned for each participant to conditions. Reinforcement was operationalized as disruptive behavior, and non-reinforcement was operationalized as non-disruptive behavior. Twelve of the pairings were always followed by disruptive behavior (reinforced), and 10 of the pairings were always followed by non-disruptive (non-reinforced).

[2] Names are used for this task because in the real world, people regularly need to determine the impact people have on each other in social situations. Whether it is a casting director trying to determine chemistry for his or her lead actors, couples arranging which people should be at which tables for their wedding, or a teacher determining which students will work well together for a group project. This type of real life discrimination happens every day.

Measures

Type of Discrimination	Pairs
Positive Patterning	AW-, BX-, AB+
Negative Patterning	CY+, DZ+, CD-
Biconditional Patterning	EF+, GH+, EG-, FH-
Irrelevant Cue	IK+, IL+, JK-, JL-

Table 3

Associative Learning Task/Working Memory Capacity was measured as participants' performance on four types of discrimination tasks. Discrimination performance was defined as accuracy, or percent of correct discriminations, on the four types of tasks. The discrimination tasks asked participants, presented with various pairs of names of hypothetical students, to judge for each pair whether those students would cause a disruption in the classroom or would be able to work together and not cause a disruption. Participants received feedback after each choice to either confirm or disconfirm their prediction.

Table 3 consists of the four types of discrimination problems that were used in this experiment. The first discrimination problem in Table 3 is a positive patterning discrimination task. For positive patterning, four students were presented to create three separate pairings. Two students resulted in a disruption in the classroom when paired together, but not when they were paired with anyone else (i.e. AlexanderWilma-, BethXavier-, AlexanderBeth+)[3]. The second discrimination problem in Table 3 is a negative patterning task. Similar to the positive patterning, the negative patterning task presented four students to create three separate pairings. However, in this discrimination

[3] Plus signs indicate a disruptive pair, and minus signs indicate no disruption.

two students caused a disruption in the classroom when paired with any other student, except when they were paired with each other (i.e. ChristopherYael+, DeniseZachary+, ChristopherDenise-). The third discrimination problem was biconditional patterning. For this task, four students were presented to create four separate pairings. In these combinations, two student pairings caused a disruption in the classroom, but when they are switched they did not (i.e. EthanFran+, GrettaHank+, EthanGretta-, FranHank-). The final discrimination problem in this study was an irrelevant cue task. For the irrelevant cue discrimination problem, two students were presented with two constant students (irrelevant cues) to create four separate pairings. In this task, the two students that were presented with the constant students were the ones that determined whether there was a disruption caused by the combination, making the constant students irrelevant (i.e. IsaacKelly+, IsaacLisa+, JohnKelly-, JohnLisa-).

The program used for this experiment was written in GWBASIC under MSDOS. The program consisted of 15 trial blocks. In any one trial block, the program took participants through a series of 22 trials, which showed the student pairings, one at a time, on the computer screen. Participants used the "1" and "2" keys to indicate whether they believed the pair was disruptive or not. Pressing "1" indicated that the participant believed the pair would have very disruptive chemistry and pressing "2" indicated that the participant believed the pair would have no problems working together.

Academic Achievement was measured using participants' grade point average (GPA) from the fall 2017 semester. Participants' provided their consent for the researcher to obtain their fall 2017 GPA through the Rutgers University grading system once the semester concluded.

Intelligence was measured using participants' SAT R, SAT W (if applicable), and SAT M scores. Participants were notified upon registering for this study that these scores were needed for their participation. They provided these scores at the start of the experiment. Note: The request for SAT scores was voluntary and not all participants complied. Their compliance did not affect their participation in the study. Once all the SAT scores were obtained, the research team used the College Board official SAT conversion tool to convert the old SAT scores into one total SAT score that matched with the newer scoring structure. This allowed for all SAT scores to be on the same scoring plane, for purpose of analysis consistency.

Procedure

Participants were greeted upon their arrival to the lab on the Rutgers University-Camden campus. They signed in in order to receive credit towards their course requirement. At the outset of the experiment, each participant was asked to read a 3-page instruction packet (see appendix) that outlined the scenario for the task. The scenario asked participants to assume the role of a teacher who must evaluate the chemistry of students working together in their classroom. The goal is to distinguish between pairs of students who are disruptive from pairs of students who can work together without causing a disruption. Once they read through the instructions, the researcher asked the participants if they had any questions about the activity. Upon receiving verbal confirmation that the participant understood their instructions, they were asked to complete an informed consent form (see appendix) and asked to answer the following 3 questions on a sheet of paper:

1. Please indicate if you are a: Freshman, Sophomore, Junior, or Senior
2. Please indicate which class participation in this study is for: (i.e. Intro to Psych, Research Methods, etc.)
3. Please indicate your SAT scores:

    SAT Math:

    SAT Reading:

    SAT Writing:

After both the participant and the researcher signed the form, the participant was instructed to hit the “enter” key on their keyboard to initiate the task. The task took an average of 50-60 minutes to complete. The participants completed 15 blocks of learning about the student pairs. At the conclusion of the experiment, participants were thanked for their time and asked if they had any questions about what they just did. They were informed that at the end of the semester, a summary of the research findings and aims would be disseminated to their classes so they could see what we were testing for in this study.

Results

The focus of this experiment was on the correlations between accuracy on the discrimination tasks and the measures of academic achievement, on the one hand, and of intelligence, on the other. Since the present study examined relationships between two continuous variables, the correlation coefficient, *r*, was used to determine the degree of the relationship between the pairs of variables (i.e. Discrimination Accuracy/Intelligence, Discrimination Accuracy/Academic Achievement, etc.). Participants' discrimination accuracy scores were calculated as the percentage of times they correctly identified a pairing as leading to disruption minus the percentage of times they incorrectly identified a pairing as leading to disruption when there in fact was not one (% accuracy). Discrimination accuracy was calculated for each of the 15 trial blocks, and then averaged for a total discrimination accuracy score. We used the total discrimination accuracy here to have the best chance of finding a relation to GPA. Follow up work with larger samples can be used to determine whether specific discrimination tasks are more or less informative. Participant's GPA was obtained via the Rutgers University grading system for the fall 2017 semester. Participant's self-reported SATM, SATR, and total SAT scores were provided at the time of participation in the experiment. The SAT scores provided were a mix of scores from the old SAT and new SAT. In order to allow for consistency across the intelligence measure, College Board official conversion concordance tables[4] were used to convert any old SAT scores to their equivalent on the new SAT scoring structure.

[4] https://collegereadiness.collegeboard.org/educators/higher-ed/scoring/concordance

Table 4 shows the results from this research study. A Pearson's correlation coefficient was computed for the following variable relationships: discrimination score and GPA; discrimination score and SAT score; and SAT score and GPA. Consistent with previous research, this study found large positive correlations between SAT scores and GPA for both the total sample [*r*=.43, n=75, p<.01] and the freshman only sample [*r*=.54, n=48, p=.01]. The typical correlation found between SAT scores and first year college GPA is *r*=.53 [n=2,050] (Shaw, Marini, Beard, Shmueli, Young & Ng, 2016).

The results also showed a moderate positive correlation between participants' discrimination accuracy and GPA. However, this was only significant in the freshman only sample [*r*=.38, n=48, p=.05]. SPSS was used to compute partial correlations for both variables' relationships with GPA, while controlling for the other (i.e. for discrimination score and GPA, while holding SAT constant). The first analysis showed that discrimination scores were significantly correlated with GPA (*r*=.35, n=39[5], p<.05) while controlling for SAT scores. The second analysis showed that the opposite is also significant in that SAT scores are correlated to GPA (*r*=.48, n=39, p<.01) while holding discrimination scores constant. The standardized beta weights were .30 for discrimination accuracy and .45 for SAT scores, indicating that both were strong effects.

SPSS was also used to compute stepwise linear regressions for discrimination score and GPA and SAT score and GPA. When discrimination score was the first variable in the analysis, it has a moderate correlation to GPA [*r*=.43] accounting for about 19% of the variance of GPA. When SAT scores are then added into the analysis, the correlation increased to *r*=.61, accounting for 37% of the variance of GPA. When this

[5] This n represents the total number of participants who provided SAT scores from the freshman only sample.

analysis was reversed and SAT scores were correlated to GPA, there was again a moderate correlation [*r*=.53] that accounted for 29% of the variance of GPA. When the discrimination scores were added the correlation increased [*r*=.61], indicating a significant increase in the proportion of variance accounted for, $F(1,36) = 4.86$, $p < .05$. These findings support the hypotheses that there would be a significant relationship between discrimination scores and GPA and SAT scores and GPA.

The data from this study also found moderate positive correlations between participants' discrimination score and SAT score for both the total sample [*r*=.25, n=75, p=.05] and the freshman only sample [*r*=.29, n=48, p=.05]. These findings support the hypothesis that there would be significant relationships between these variables.

Correlations (*r*) for Relationships between Discrimination Score, GPA, and SAT Scores		
Variables	Total Sample (n=75)	Freshman Only Data (n=48)
Discrimination Score & GPA	*r*= .21	*r*= .38**
Discrimination Score & SAT	*r*= .25*	*r*= .29*
SAT & GPA	*r*= .43**	*r*=.54**

Table 4: *are significant at the p=.05 level; ** are significant at the p=.01 level

Discussion

The findings from the present study echo those from the literature supporting the relationships between: Discrimination Accuracy & Academic Achievement; Discrimination Accuracy & Intelligence; and Intelligence and Academic Achievement. Multiple regression analyses show that both discrimination accuracy and SAT scores influence freshman GPA independent of one another. Stepwise linear regression analyses show that when adding SAT scores to the relationship between discrimination accuracy and GPA, SAT scores increase the strength of the relationship. This is also the case when the analysis is reversed and discrimination accuracy is added to the relationship between SAT score and GPA, suggesting that both discrimination accuracy and SAT scores influence different aspects of GPA. Furthermore, these analyses show that discrimination accuracy has an effect on GPA separate from that of SAT scores. These results indicate that discrimination accuracy can serve as an indicator of cognitive ability.

The current findings have an interesting implication regarding the differences, and overlap, between cognitive ability, academic achievement and intelligence. The data shows that discrimination scores relate to GPA in a similar capacity as SAT scores do. What makes this finding so interesting is that multiple regression analysis shows that this relationship accounts for similar functions. In other words, the discrimination score and the SAT scores predict GPA in equal capacities, suggesting that discrimination scores can be used in a similar way to predict students' ability to perform in a college setting.

The literature around SAT scores has been very concerned with the social implications and is continuing to grapple with the issue of score gaps between various ethnic and racial groups (Toldson & McGee, 2014; Hannon, 2012; Kobrin, Sathy, &

Shaw, 2007; Halpern, Benbow, Geary, Gur, Shibley Hyde & Gensbacher, 2007; Zwick, 2007). For example, in a study using data from the Texas Schools Microdata Panel, the score gap on the writing component of the SAT showed that the average white student performed better that the average minority student (Thomas, 2004). This SAT score gap can also be seen in the mean scores on SAT-M and SAT-V tests for various racial/ ethnic groups between the years 1987-2006 (Kobrin, et al., 2007). With the exception of SAT-M scores for the Asian American/Pacific Islander cohort, students who identify themselves as White, consistently outscore their counterparts in other racial/ethnic groups (Kobrin, et al., 2007).

Race/Ethnicity	SAT-M	SAT-V
African American	423	431
American Indian/Alaskan Native	477	477
Asian American/Pacific Islander	559	495
Hispanic	459	456
White	524	525
Other	505	498

Table 5: Mean SAT M and SAT V scores from the 20-year period of 1987-2006

Some researchers explain this score gap as the result of inherent cultural bias within the standardized test content (Fisher, 2005; Helms, 2006; Landau, Greenberg, & Rothschild, 2009). Fleming (2000) defines cultural bias in SAT tests as question framing that favors the majority (i.e. European American, middle to upper class students) because the questions reflect values and norms of the majority culture.

The cultural bias of test content can impact test performance because it places increased and differential demands on cognitive processing resources and working memory capacity (Landau, et al., 2009; Gigerenzer & Hug, 1992; Wason, 1969). This point is illustrated by the research of Hamdi, Knirk and Michael (1982) who tested 33 American children and 30 Arabic children on pictorial depth perception test problems. These researchers used two variations of a structurally parallel test, one that reflected scenes typically encountered in American culture, and the other reflecting scenes typically encountered in Arab culture. They found that:

1) The American children scored higher on the test with American scenes than did the Arab children;
2) The Arab children scored higher on the test with Arab scenes than did the American children;
3) The American children scored higher on the American version of the test than they did on the Arabic version; and
4) the Arabic children scored higher on the Arabic test than they did on the American version (Hamdi, et al., 1982).

These results suggest that differences in the participants' cultural backgrounds affect their familiarity of the test content, thus contributing to the significant difference in their performance on the two tests.

Discrimination problems have the potential to serve as a non-culturally loaded test that has predictive ability for college GPA. Research supports that adults perform poorly on test problems rooted in abstract terms and conditions, but when the problems reflect culturally familiar experiences their performance improves drastically (Landau, et al., 2009). By employing a paradigm that uses the common social situation of grouping people together, it allows for universal applications free of cultural bias. Furthermore, the use of names is easily adapted to various cultures to ensure names are common and familiar to the test taker's background. As depicted in Hamdi, et al. (1982), when reducing non-familiar cultural context from test content, students perform better on the test. Because of this, the test content would require less demand on the participant's cognitive processing and working memory ability, and allow them to perform in a way that is more representative of their intellectual ability (Landau, et al., 2009; Gigerenzer & Hug, 1992; Wason, 1969). Future research should continue to examine and compare scores on SAT tests and discrimination problems for various racial/ethnic backgrounds in order to confirm the elimination of a score gap between cultural backgrounds.

In addition to cultural bias of test content, other research explains the SAT score gap as a result of varying socioeconomic statuses/parental resources (Toldson & McGee, 2014; Kobrin, et al., 2007). Toldson & McGee (2014) further describe the effects of socioeconomic status as the ability or inability to partake in the necessary preparation practices to sufficiently train students to perform well on the SAT's. Since prep course cost up to $6,600, more affluent families are able to pay for their children to participate, which commonly involves a mix of some content training and mostly test taking strategies often not taught in schools (Toldson & McGee, 2014). Due to the costliness of SAT prep courses and materials, less affluent students systematically eliminated from accessing the SAT test-taking training, suggesting the racial/ethnic performance gap is more an indicator of their lack of training to take the SAT well rather than an indicator of their intellectual ability. This relationship between socioeconomic status and SAT score gaps is depicted in a national study of the 2003 cohort of college-bound high school seniors who took the SAT during their junior or senior year of high school and identified as either Black (n=121,722) or White (n=659,715) (Dixon-Román, Everson & McArdle, 2013). The findings from this study (see Table 6) confirm the SAT score gap between Black and White test-takers and provide support that the more affluent the family, the better the student performs on the SAT exam (Dixon-Román, et al., 2013). Furthermore, the findings from this study, support that as affluence increases for *both* Black and White test-takers, so does the student's performance on the SAT.

	Black Test-takers		White Test-takers		Total Sample	
Family Income	Math Score	Verbal Score	Math Score	Verbal Score	Math Score	Verbal Score
Less than $10,000	382	381	478	480	418	418
$10,000 to $15,000	395	398	478	481	435	439
$15,000 to $20,000	400	405	485	488	446	450
$20,000 to $25,000	409	413	493	495	460	463
$25,000 to $30,000	411	419	495	497	466	470
$30,000 to $35,000	419	426	502	504	479	482
$35,000 to $40,000	422	430	504	505	484	487
$40,000 to $50,000	431	438	510	510	496	498
$50,000 to $60,000	441	450	516	514	507	506
$60,000 to $70,000	440	450	521	519	512	512
$70,000 to $80,000	448	457	528	524	521	518
$80,000 to $100,000	461	468	539	534	533	529
More than $100,000	490	495	568	557	564	555

Table 6: Mean SAT M and SAT V scores by family income for the 2003 college bound cohort.

Discrimination problems would also address this explanation to the SAT performance gap. In addition to providing culture free test content, discrimination problems offer a way to contribute to the reduction of this racial/ethnic SAT performance gap because it is a test that requires no preparation. Its design is about learning as the test is happening, thus training and measuring participants' ability simultaneously. This eliminates the potential for gaps based on issues of affordability and access to prep courses and/or materials. Further research should continue to build on this by comparing performance on SAT's and discrimination problems by socioeconomic status and race. As we approach an era of increasing diversity and awareness of cultural differences in our country, it is important we begin to think about ways to measure college readiness and intelligence in a way that is adaptable and fair across racial/ethnic backgrounds and socioeconomic statuses. The findings from the current study provide a potential tool to achieve this necessary adjustment to our assessment practices.

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Appendices

A1: Acknowledgment of Informed Consent

INFORMED CONSENT FORM

You are invited to participate in a research study that is being conducted by Nicole Ferris, who is a graduate student in the Psychology Department at Rutgers University. The purpose of this research is to look at perception, memory, judgment, or some combination of these three processes.

Approximately 100 subjects will participate in the study, and each individual's participation will last approximately 1 hour.

Participation in this study will involve studying lists of names of hypothetical students. You will be asked to assume the role of a teacher to make judgments about the students' compatibility in the classroom.

This research is confidential. Confidential means that the research records will include some information about you and this information will be stored in such a manner that some linkage between your identity and the response in the research exists. Some of the information collected about you includes your name, your gender, your date of participation and your GPA. Please note that we will keep this information confidential by limiting individual's access to the research data and keeping it in a secure location in encrypted files on password protected computers that only the PI and faculty advisor have access to.

The research team and the Institutional Review Board at Rutgers University are the only parties that will be allowed to see the data, except as may be required by law. If a report of this study is published, or the results are presented at a professional conference, only group results will be stated. All study data will be retained indefinitely.

There are no foreseeable risks to participation in this study.

You have been told that the benefits of taking part in this study are to advance general understanding of psychological processes and to help me understand the nature of psychological research. However, you may receive no direct benefit from taking part in this study. You will receive partial credit towards a course requirement for completing the entire study.

Participation in this study is voluntary. You may choose not to participate, and you may withdraw at any time during the study procedures without any penalty to you. In addition, you may choose not to answer any questions with which you are not comfortable.

If you have any questions about the study or study procedures, you may contact myself at 311. N. Fifth Street, Camden, NJ 08102, by email at ndf17@scarletmail.rutgers.edu, and/or by phone at (856) 225-6334. You may also contact my faculty advisor Dr. J.W. Whitlow Jr. at 311. N. Fifth Street, Camden, NJ 08102, by email at bwhitlow@camden.rutgers.edu, and/or by phone at (856) 225-6334.

If you have any questions about your rights as a research subject, please contact an IRB Administrator at the Rutgers University, Arts and Sciences IRB:

Institutional Review Board

Rutgers University, the State University of New Jersey

Liberty Plaza / Suite 3200

335 George Street, 3rd Floor

New Brunswick, NJ 08901

Phone: 732-235-2866

Email: humansubjects@orsp.rutgers.edu

You will be given a copy of this consent form for your records.

Sign below if you agree to participate in this research study:

Subject (Print) ____

Subject Signature ____________________________ Date ______________________

Principal Investigator Signature _____________________ Date __________________

A2: Instructions

Social Judgment Studies-Classroom Management (CAUSAL 740)

Dear Participant:

This experiment is part of a research project that seeks to understand how we learn about the impact one or more people have on other people. Obviously, deciding how people will affect other is a complicated social judgment, because many different factors affect the influence that one person or several people will have on others. Nonetheless, despite its difficulty, the problem is one we encounter frequently, whether we consider our families, our friends, our coworkers, or simply a group of people at a gathering.

Because we are social creatures, we presumably know how to make social judgments successfully, at least much of the time. However, the details of how people make this kind of judgment and the factors that make such judgments easier or harder are not well understood. This research is designed to help us understand the process better.

We appreciate your participation in this study.

Instructions

1. In this experiment you will be playing the role of a teacher who must evaluate the chemistry of students working together in your classroom. It is important to differentiate pairs of students who are disruptive from students who can work together without causing problems in order to provide the best experience for all students. As you become more familiar with your students you will learn who tends to be disruptive and who does not to avoid any problems and increase productivity in the classroom.

2. You will be presented with a series of names of hypothetical students who are seated together, and your task is to predict whether they will be disruptive or not. Thus you will see a pair of names and be asked to predict whether a table with those two individuals is like to be *very disruptive*. After your prediction, you will get feedback about the pairing.

    If the two students tend to be disruptive, you will see a message "Outcome of pairing was VERY DISRUPTIVE CLASSROOM!"

    If the two students work together without creating disruptions, you will see the message "Outcome of pairing was no classroom disruption."

Your goal is to learn to predict the classroom chemistry resulting from various pairings of students. In some cases, one particular student may be disruptive when placed with any other student; in some cases, two students may be disruptive when they are together but may work well with other students. Conversely, come students may be disruptive with every other student but not when they are put together.

3. You will be tested at various points as you go through the examples. These tests are intended to provide us with information about what you have learned, and it is important that you provide this information as accurately as you can.

4. You will be asked to predict the classroom chemistry for a pairing of two particular students. For this judgment, respond with "1" to indicate "very disruptive chemistry" and "2" to indicate "no problems working together"

Note that at the outset of the experiment, you will have to guess what the classroom chemistry of the pairings will be, because you won't know. As you get more experience, you will start to learn about the classroom chemistry of various students and will not need to guess.

Another type of judgment you will be asked to make is about the strength of the association of an individual student or a pair of students together with disruptive classroom chemistry. For these questions, use a scale of 0 to 100, as shown at the bottom of the page.

Use the number to express your sense of the strength of the association to disruptive classroom chemistry, where *+100* means that there is *very disruptive chemistry* and *0* means there is no major problem with the students.

For example, if your sense was that a particular student or pair of students had moderately disruptive classroom chemistry, you might enter '+65'; whereas if your sense was that the individual or the pair was not very disruptive, you might enter '15'.

Note that for this task you have to think back over all the pairings you saw earlier.

5. Please use the *number keys* at the top of the keyboard to enter your responses to each question type. Use the *backspace key* if you make a mistake or accidentally enter a number you did not intend.

6. At the end of the experiment, you will see a message stating

This experiment is over. Thank you.

7. Please contact the experimenter, who will ask you some questions about your experience during this task. The experimenter will also be happy to answer any questions you may have.

8. Strength of Classroom Disruptiveness Scale

100	80	60	40	20	0
Very Disruptive	Strongly Disruptive	Moderately Disruptive	Sort of Disruptive	Weakly Disruptive	Not Disruptive