# PERSONALITY AS A PREDICTOR OF DRAFT SELECTION AND PERFORMANCE IN PROFESSIONAL BASEBALL PLAYERS

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Research has demonstrated that personality factors are associated with sport performance as measured by coach ratings and objective performance outcomes, as well as factors/behaviours that are understood to be facilitative for performance, such as problem-focused coping and quality of preparation. Given the potential utility of personality assessment, professional sport organizations have integrated it into their pre-draft procedures. However, it remains unclear whether such data, particularly at the factor level, can add value to draft selection process, over and above that of past performances. The purpose of the present study was to explore if the Big-Five personality traits are related to draft order and predictive of athletes' future performance in professional baseball. Latent profile analysis revealed two distinct personality profiles amongst 2018 and 2019 draft prospects. The results of the covariate analysis were not significant; however, this was likely due to the small *n* for class 2. Thus, there might in fact still be a meaningful difference between personality profiles by draft order. The results of a series of multiple regression analyses suggested that personality factors and facets were not predictive of performance in the season following the draft, after controlling for performance in the previous season for both hitters and pitchers. Overall, the results suggest that personality assessment likely does not provide much unique and valuable information for draft selection. However, personality assessment might be valuable from a player development and support standpoint.

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# CHAPTER 1

# INTRODUCTION

Over the last few decades, sport organizations have put more resources into the processes of identifying and developing athletes, generally with the purpose of increasing their athletes' and team's potential to be successful (Abbott & Collins, 2004). This focus on talent identification would appear to be justified given the potential financial benefit, or loss, a team could experience with a successful, or unsuccessful, draft selection (e.g., Anshel & Lidor, 2012; Durand-Bush & Salmela, 2001). Not surprisingly, early applications of talent identification focused on physical assessments of athletes, such as body measurements, and/or evaluations of their current performances (Bar-Or, 1975; Gimbel, 1977). As talent identification strategies evolved, sport organizations began to expand beyond physical measures (e.g., strength, speed, aerobic capacity), to also consider cognitive abilities (e.g., WPT; executive functioning) and psychological factors (e.g., grit, confidence). Research, however, has demonstrated that predicting adult sport performance based on young athletes' motor performance tests and physiological measures (Pearson et al., 2006) or their early sport performances (e.g., Barreiros et al., 2014; Brouwers et al., 2012) is generally ineffective. Further, studies on the predictive relationships of cognitive factors, mostly between WPT scores and NFL performances, have typically produced nonsignificant results (Kuzmits & Adams, 2008; Lyons et al., 2005; Welter, 2013). When psychological characteristics have been considered, often through comparisons between athletes at varying levels (e.g., elite, professional, college, club), researchers have identified confidence, freedom from worry, goal setting and mental preparation, concentration/focus, goal setting, activation, relaxation, emotional control, and grit as associated with peak performance (e.g., Gould et al., 2002; Meyer et al., 2017). However, because of limitations in study methodologies (e.g., reliance on cross-sectional procedures) and a lack of research on the effects of personality factors (e.g., neuroticism; Aidman, 2007), the extent to which psychological characteristics, and what characteristics, actually predict athletic performance/success remains unclear.

Personality-to-performance research started within the domains of academics and work (e.g., Behling, 1998; Digman, 1989). Within academic settings, personality as represented by Conscientiousness, Openness, and Agreeableness, has been found to predict students' performances, which are often measured by course or semester grades and cumulative GPAs, at the primary, secondary, and tertiary levels (e.g., Poropat, 2009). Conscientiousness has been linked to an individual's willingness to achieve (Digman, 1989) as evidenced by sustained effort and goal setting (Barrick et al., 1993), compliance and concentration while completing homework (Trautwein et al., 2006), and time management and effort regulation (Bidjerano & Dai, 2007). Openness has been associated with being forward thinking, intelligent, and resourceful (De Raad & Schouwenburg, 1996) and with other key cognitive processes, such as learning motivation (Tempelaar et al., 2007) and critical thinking (Bidjerano & Dai, 2007), which have been associated with academic success. Agreeableness was hypothesized to predict academic performance based on higher levels of cooperation (De Raad & Schouwenburg, 1996); among university students, Agreeableness was related to higher levels of focus, effort, and adherence to teachers' instructions, all of which were thought to contribute to the academic performance (Vermetten et al., 2001). In a meta-analysis of 80 different studies on the personality–academic performance relationships where the researchers used the five-factor model, Poropat (2009) concluded that Five-Factor Model measures of personality (e.g., NEO-PI) could be useful in identifying students (from primary to tertiary levels) who were likely to underperform, which would allow teachers and other staff to proactively support them.

Similar to research on academic performance outcomes, personality has been hypothesized to predict performance in work settings as well (e.g., Barrick & Mount, 1991; Judge et al., 2013; Mount et al., 1998). For example, in their review of the extant personality-work literature, Barrick (2005) pointed out that Conscientiousness is related to an individual's willingness to follow the rules and put forth the required amount of effort to succeed. Further, an individual's level of emotional stability would likely reflect their ability to allocate and utilize their resources in order to accomplish work tasks. When considering job type, Barrick (2005) also noted that certain personality factors might be more highly desired by managers and contribute to success. For example, being sociable, assertive, and gregarious (that is, high in Extraversion) would likely contribute to success in a sales or management position. Further, when being part of a team is considered, workers who are argumentative, uncooperative, and disagreeable (that is, low in Agreeableness) may be less effective and engage in behaviours that are considered counterproductive.

Research also has supported the idea that personality is generally predictive of performance in the workplace (e.g., Barrick & Mount, 1991; Dudley et al., 2006; Hurtz & Donovan, 2000; Judge et al., 2013; Mount et al., 1998). In particular, Conscientiousness has consistently been found to predict job performance, which is often assessed using supervisor ratings (e.g., Mount et al., 1998), and been identified as the second-best predictor of job performance, only behind intelligence (Behling, 1998). Conscientiousness, as a key predictor of performance, has been supported across different types of jobs (e.g., sales, customer service, management, and skilled and semi-skilled work; Hurtz & Donovan, 2000). The relationship between Conscientiousness and job performance makes sense given that this personality factor has been associated with improved motivation in the form of performance expectations, self-efficacy, and goal setting (Hurtz & Donovan, 2000). Based on their meta-analysis of 26 studies, Hurtz and Donovan (2000) determined that the strength of relationships between other Big-Five personality factors and job performance were low to moderate. The estimated true validities for the personality factors across job types ranged from .06 to .20 and the estimate true score correlations ranged from .07 to .22. For example, lower levels of Neuroticism (e.g., calm, secure, well-adjusted, low anxiety) had consistent, but small, impacts on job performance as measured through both objective and subjective ratings, and included outcomes such as sales data, training/task performance, job knowledge, and work dedication. Similarly, higher levels of Agreeableness were found to have a small but significant relationship to job performance in positions that require interpersonal interactions, such as customer service. Further, higher levels of Extraversion were associated with improved performance in sales and Openness to Experience was related to improved performance in customer service positions. Researchers (e.g., Dudley et al., 2006) have also provided evidence for moving beyond conceptualizing personality solely at the Big-Five level; instead, there may be value in considering personality at the facet level (i.e., given that each domain covers a wide range of thoughts, feelings, and actions, personality factors have been broken down into six more specific scales within each called facets) because they represent more distinctive dimensions of personality and because such distinctions may better predict different dimensions of job performance.

Given the predictive utility of personality across academics and work, researchers began to explore sport as another performance domain (Allen et al., 2013; Poropat, 2009), applying a variety of research designs and personality assessments. For example, some studies (e.g., Piedmont et al., 1999; Teshome et al., 2015) have used the NEO-PI (Costa & McCrae, 1992), whereas others (e.g., Aidman, 2007; Gee et al., 2010) have assessed personality through The SportsPro™ (Marshall, 1979) or the 16PF (Cattell et al., 1970). The latter two measures are not based on the Five Factor Model of personality, thus making comparisons across studies challenging. Keeping this limitation in mind, the results from multiple studies do suggest that personality, such as Neuroticism, is related to different sport performance outcomes. For example, Neuroticism is negatively associated with coach ratings of female college soccer players' performance (e.g., Piedmont et al., 1999) and to collegiate athletes' ratings of their own intrinsic motivation as measured by the Behavioral Regulation in Sport Questionnaire (BRSQ; Lonsdale et al., 2008; Brinkman et al., 2016), and positively associated with athletes' avoidance coping (e.g., Allen et al., 2011; Kaiseler et al., 2019) and controlled extrinsic motivation and amotivation (Brinkman et al., 2016). Extraversion has been associated with student-athletes' (participating at a variety of levels, such as university and regional; majority male athletes; no race date provided) problem-focused coping (Allen et al., 2011; Kaiseler et al., 2019), gymnasts' distractibility (men = 63%; Woodman et al., 2010), college athletes' autonomous extrinsic motivation (women = 52%; Brinkman et al., 2016), and greater levels of commitment and relatedness in coach-athlete (mixed sample of male/female athletes and coaches) relationships at the regional level of sport (Jackson et al., 2011). Agreeableness is significantly and positively related to female college soccer players' coachability and the number of games played (Piedmont et al., 1999), male national league footballers' overall performance as rated by coaches (Teshome et al., 2015), college athletes' intrinsic motivation (Brinkman et al., 2016), relatedness in coach athlete-relationships for regional level athletes (Jackson et al., 2011), and commitment in regional all-female athlete dyads (Jackson et al., 2010). Finally, Conscientiousness has been related to female college soccer players' coachability, game performance, work ethic, and games played (Piedmont et al., 1999), football and futsal players' performance as rated by coaches (Mirzaei et al., 2013; Teshome et al., 2015), student-athletes' problem-focused coping (Allen et al., 2011; Kaiseler et al., 2019), gymnasts' quality of preparation (Woodman et al., 2010), and regional athletes' relatedness and commitment in sport relationships (Jackson et al., 2010, 2011).

In addition, the ways in which researchers have assessed performance has varied, ranging from coach ratings of athletes' performances (e.g., Mirzaei et al., 2013; Teshome et al., 2015), to advancement to higher sport levels (e.g., Aidman, 2007), to objective performance metrics (e.g., goals, assists; e.g., Piedmont et al., 1999; Gee et al., 2010). Further, some studies have utilized a single-item measure of performance (e.g., Aidman, 2007), whereas others have incorporated multiple aspects/ratings, such as coachability, athletic ability, game performance, team playerness and work ethic, to create an overall measure of score (e.g., Mirzaei et al., 2013). Given these differences in how performance has been conceptualized, there is little clarity, and limited robustness, in terms of just how personality impacts performance. Finally, some studies have collected performance and personality data at the same time point (e.g., Mirzaei et al., 2013; Piedmont et al., 1999), which allows researchers to draw conclusions about associations but not on their temporal relationships with one another. Thus, the lack of longitudinal designs has been limiting and has left a gap in understanding if, and how, personality might explain future performances. In their literature review on personality and sport performance, Greenlees (2020) recommended that future studies use large samples and longitudinal designs, and carefully consider how sport performance and personality are operationalized and measured. Adopting these recommendations would allow for the determination of the temporality (and utility) of a clearly defined aspect of personality in predicting well-conceptualized measures of performance.

The purpose of my study was to determine the relationships of the Big-Five personality traits to different sport performance outcomes in a large sample of professional baseball players. Although there is some variability among baseball organizations, most used players' past performances (e.g., strikeout rate), scout ratings, athletes' responses to open ended questions about future goals and ability to cope with adversity, and personality (e.g., NEO-PI-3), to inform draft decisions. Given that organizations have been using such assessments for several years, they have extensive longitudinal data that could be used to address questions regarding whether personality predicts different aspects of baseball performance. My specific research questions were:

(1) What personality factors, as represented through the NEO-PI-3, differentiate baseball players' draft positions?

Hypothesis: I expected athletes who were drafted earlier would have scored higher on Extraversion, Agreeableness, and Conscientiousness and lower on Neuroticism than athletes who were drafted later. I did not predict significant differences on Openness based on draft order.

(2) What is the relationship of personality, as represented through the facets of the NEO-PI-3, to baseball pitchers' performances after controlling for their past performances?

Hypothesis: I expected that Assertiveness (E3), Activity (E4), Excitement-Seeking (E5), Trust (A1), Competence (C1), Achievement Striving (C4), Self-Discipline (C5), and Deliberation (C6) would be significantly and positively related to pitchers' performance. In addition, all facets of Neuroticism would be significantly and negatively related to pitchers' performance.

(3) What is the relationship of personality, as represented through the facets of the NEO-PI-3, to baseball hitters' performance after controlling for past performance?

Hypothesis: It was hypothesized that hitters' performance would be significantly and positively related to Assertiveness (E3), Activity (E4), Excitement-Seeking (E5), Trust (A1), Competence (C1), Achievement Striving (C4), Self-Discipline (C5), and Deliberation (C6), and significantly and negatively related to all facets of Neuroticism.

# CHAPTER 2

# METHOD

## Participants

Participants were 651 male athletes who were draft eligible in either 2018 (*n* = 144; 22.1%) or 2019 (*n* = 507; 77.9%) by an MLB team. Athletes' mean age at the time they were drafted was 19.46 years (*SD* = 1.57; range = 16-23); players were primarily drafted out of a four-year college (*n* = 259; 38.1%), high school (*n* = 175; 38.1%), or junior colleges (*n* = 25; 5.4%); 193 were undrafted. Of the athletes who were drafted out of a four-year college, nearly half were pitchers (*n* = 123; 51.7%) and half were hitters (*n* = 115; 48.3%). Of those who were drafted out of college/university and played in the MiLB (*n* = 249), 35.7% (*n* = 89) competed in Rookie Ball (*n* = 89), 24.5% (*n* = 61) in Low A, 1.6% (*n* = 4) in A, and 38.2% (*n* = 95) in multiple levels. Due to limitations of the data received and available online, additional demographic information (e.g., race/ethnicity) was unavailable.

## Measures

### NEO Personality Inventory-3

The NEO-PI-3 is a 240-item measure of personality used for individuals aged 12 years or older (McCrae & Costa, 2010). It assesses five domains of personality, each measured by 48 items, including: neuroticism (N), extraversion (E), openness to experience (O), agreeableness (A), and conscientiousness (C). Given that each domain covers a wide range of thoughts, feelings, and actions, the authors have identified six more specific subscales within each called facets. Each facet is composed of eight items. A benefit of the multifaceted approach is that it becomes possible to identify meaningful individual differences within each of the domains. For each item on the NEO-PI-3, individuals respond on a 5-point scale that ranges from 1, *strongly* *disagree,* to 5, *strongly agree.* On each domain or facet, online scoring software calculates *T* scores that can be categorized as: very low, low, average, very high, and high.

*Neuroticism*

The Neuroticism subscale assesses negative affect, including fear, sadness, anger, and guilt. Individuals who score high on the Neuroticism subscale are likely to have irrational ideas, be unable to control impulses, and have difficulty coping with stress. The Neuroticism subscale comprises six facets, including: anxiety (N1), angry hostility (N2), depression (N3), self-consciousness (N4), impulsiveness (N5), and vulnerability (N6). Anxiety represents tendencies to feel apprehensive, fearful, worried, nervous, and jittery. An example item is, "I rarely feel fearful or anxious." Anger hostility assesses individuals' readiness to experience anger and related emotions such as frustration and bitterness. An example item is, "Even minor annoyances can be frustrating to me." Depression represents feelings of sadness, hopelessness, and loneliness. An example item from this facet is, "Sometimes things look pretty bleak and hopeless to me." Self-consciousness assesses feeling uncomfortable around and/or inferior to others and being sensitive to ridicule. An example item from this facet is, "When I am around people, I worry that I'll make a fool of myself." The impulsiveness facet assesses individuals' ability to manage their urges and cravings. An example item is, "When I am having my favorite foods, I tend to each too much." Lastly, vulnerability is in relation to experienced stress, such as individuals' ability to cope, becoming dependent on others, or feeling panicked when in an emergency situation. An example item is, "When everything seems to be going wrong, I can still make good decisions."

*Extroversion*

Individuals who score high on Extraversion subscale are characterized as sociable, assertive, talkative, upbeat, energetic, active, optimistic, and prefer large group gatherings. The six facets within the Extraversion subscale include: warmth (E1), gregariousness (E2), assertiveness (E3), activity (E4), excitement-seeking (E5), and positive emotions (E6). Warmth assesses the degree to which individuals genuinely like people, are friendly, and form close relationships with others. An example item is, "I have strong emotional attachments to my friends." Gregariousness assesses individuals' affinity for spending time with others. An example item is, "I usually prefer to do things alone." Assertiveness assesses tendencies to be dominant and speak without hesitation. An example question is, "I have often been a leader of groups I have belonged to." Activity represents the degree to which individuals perceive themselves as fast-paced, high energy, and a desire to remain busy. An example item is, "I have a laid-back style in work and play." Excitement-seeking assesses individuals' tendency to seek excitement and loud environments. An example item from this facet is, "I like to be where the action is." Lastly, positive-emotions assess individuals' tendency to experience traditionally positive emotions such as happiness, joy, and cheerfulness. An example item from this facet is, "I'm not happy-go-lucky."

*Openness to Experience*

This domain assesses characteristics such as curiosity, imagination, and interest in novel and unconventional ideas. The facets within Openness subscale include: fantasy (O1), aesthetics (O2), feelings (O3), actions (O4), ideas (O5), and values (O6). Fantasy assesses the degree to which individuals have vivid imaginations. An example item from this facet is, "I would have difficulty just letting my mind wander without control or guidance." Aesthetics represents individuals' deep appreciation for art and beauty, though they need not have artistic talent. An example item is, "I enjoy reading poetry that emphasizes feelings and images more than story lines." The feelings facet explores individuals' receptivity to and value of their emotions as well as the depth to which they experience them. An example item is, "I find it easy to empathize – to feel myself what others are feeling." The actions facet focuses on behaviours and desires to try new things. An example item is, "I often try new and foreign foods." Ideas assesses individuals' open-mindedness and willingness to explore new ideas, though it does not necessarily coincide with intelligence. An example item is, "I often enjoy playing with theories or abstract ideas." The sixth facet is values, which refers to individuals' willingness to re-examine social, political, and religious values. An example item is, "Our ideas of right and wrong may not be right for everyone in the world."

*Agreeableness*

The agreeableness domain is interpersonal in nature, assessing altruism, helpfulness, and trust of others. The Agreeableness subscale is broken down into the following facets: trust (A1), straightforwardness (A2), altruism (A3), compliance (A4), modesty (A5), and tender-mindedness (A6). Trust represents individuals' belief that others are honest and have good intentions. An example item is, "I'm suspicious when someone does something nice for me." Straightforwardness assesses honesty, sincerity, and genuineness with others. An example item from straightforwardness is, "Sometimes I trick people into doing what I want." Altruism assesses individuals' interest in others well-being and likelihood of acting on such concern. An example item from the altruism facet is, "I go out of my way to help others." Compliance represents individuals' avoidance of aggression, deference to others, and tendency to take a forgive and forget approach to conflict. An example item is, "If I don't like people, I let them know it." Modesty represents individuals' humbleness though this does not mean they are not confident. An example item is, "I'd rather not talk about myself and my achievements." Tender-mindedness assesses concern for others, representing individuals' empathy toward others' experiences. An example item from tender-mindedness is, "I have sympathy for others less fortunate than me."

### *Conscientiousness*

The fifth domain is conscientiousness which assesses individuals' level of self-control, organization, planning, and completing of tasks. The Conscientiousness subscale comprises six facets: competence (C1), order (C2), dutifulness (C3), achievement striving (C4), self-discipline (C5), and deliberation (C6). Competence represents individuals' tendencies to be sensible and prudent, confident in their abilities, and have an internal locus of control. An example item is, "I am efficient and effective at my work." Order assesses organization, neatness, and tidiness. An example item is, "I like to keep everything in its place so I know just where it is." Dutifulness assesses individuals' tendency to live in line with their values and ethical principles. An example item is, "I try to do jobs carefully, so they won't have to be done again." Achievement striving assesses the extent to which individuals are goal-oriented, have high aspirations, and are purposeful. An example item from this facet is, "I strive to achieve all I can." Self-discipline assesses individuals' ability to complete the tasks they start despite distractions or boredom. An example item is, "Once I start a project, I almost always finish it." Deliberation represents individuals' tendencies to carefully think things through before acting and are intentional. An example item from deliberation is, "I plan ahead carefully when I go on a trip."

## Other Pre-Draft Measures

Athletes entering the draft were also required to fill out four additional questionnaires through an online platform called Draft Prospect Link. The general questionnaire, medical questionnaire, and feedback questionnaire are required for all athletes entering the draft, no matter which organization is interested in them. The 59-item general questionnaire asked athletes for their advisor and coach information, marital status, children, parent/guardian information (i.e., employer, marital status, educational background, sport experience), extended family professional sport experience, educational background (i.e., names of schools, number of transfers), other sport experience, and baseball experience and goals. The 36-item medical questionnaire assessed the following: injuries sustained, treatment received, current medical conditions, management of injuries (e.g., playing through soreness/injury, leaving games due to injury), and medication use. The feedback questionnaire is 22 items and assessed players experience with the online platform, Draft Prospect Link. Finally, the organization I am working with administered their own unique questionnaire composed of 45 items. The questionnaire assessed a number of broad areas including sleep, family, alcohol consumption, baseball experience, goals, and ability, other sport involvement, academics, and experiences of adversity. For proprietary reasons, not all variables measured in this mass data collection can be identified/described and the measures cannot be included.

Performance Metrics

There are a wide variety of baseball statistics that can be used to assess a players' performance. Generally, these statistics can be broken down based into hitting and pitching performances, each with several basic and more advanced metrics. Following consultation with the director-behavioral science and the assistant general manager-research & development for a MLB team, I selected the following performance statistics (from open access resource call Fan Graphs (https://www.fangraphs.com), Baseball Reference (https://www.baseball-reference.com/), and the Baseball Cube (http://www.thebaseballcube.com/): (a) Hitting – walk rate (BB%; how often a batter walks per plate appearance [PA; BB% = BB/PA]), strikeout rate

(K%; how often a player is striking out per PA), isolated power (ISO; hitter's raw power by only taking extra-base hits, as opposed to singles, into account), batting average on balls in play (BABIP; player's batting average only including balls hit into the field of play, removing outcomes not affected by the opposing defense such as home runs and strikeouts), slugging percentage (SLG; the total number of bases a hitter records per at-bat), and on base percentage (OBP; how often a batter gets on base, specifically by getting a hit or a walk, or be being hit-by-pitch per plate appearance); and (b) Pitching - BB%, K%, strikeout-to-walk ratio (K/BB; how many strikeouts a pitcher records per walk that he allows), earned run average (ERA; the number of runs allowed by a pitcher per nine innings and is the most commonly accepted tool for evaluating pitchers), and wild pitches (WP; the number of errant pitches that are unable to be control by the catcher and results in a baserunner advancing). These statistics were collected on each player at two time points: Pre (from the season prior to the draft) and Post (from the season after the draft). However, these outcomes were collected only for athletes who competed at a four-year college due to limited availability of performance metrics at the high school and junior college level. The Pre statistics were used to control for past performances on future performances (Post).

## Procedure

During the 2018 and 2019 draft process, the MLB team collected personality data from prospects. Athletes individually completed an electronic version of the NEO-PI-3, as well as basic demographics (e.g., height, weight, date of birth, birth city, school), as part of a larger player profile; data were collected either with a scout/staff member present or virtually/away from the training facility. Data were subsequently scored using the NEO software, which produces individual personality reports for each athlete. Each report provides the *T* score and qualitative description for each domain and facet. For the present study, I will focus on athletes' scores at the facet level.

After obtaining approval through my university's IRB, the MLB team's representative provided me with athletes' NEO profiles using a secure platform. Scores were then entered into SPSS. Each athletes' performance metrics were gathered from Fan Graphs and subsequently added to the SPSS dataset. Once athletes' NEO scores and performance metrics were matched, I replaced their names with unique code numbers so as to maintain confidentiality.

## Data Analysis

To address my first research question, I used MPlus 8 (Muthen & Muthen, 1998/2017) with maximum likelihood estimation to run a latent profile analysis (LPA). This statistical technique is used to uncover latent profiles/groups of individuals who share meaningful and interpretable patterns of responses on the measures of interest (Ferguson et al., 2020). LPA was used in two ways. First, to identify latent profiles or groups of athletes who share a meaningful and interpretable pattern of personality factors, and second, to discover differences in draft order between latent groups (Ferguson et al., 2020). I worked through an iterative process to identify the best structure (i.e., diagonal class-invariant, diagonal class-varying, non-diagonal class-invariant, or non-diagonal class-varying) and the number of classes to retain. The optimal number of profiles was decided based upon lower Bayesian information criterion (BIC), sample-adjusted BIC (SABIC), Akaike's information criterion (AIC), consistent Akaike information criterion (CAIC), and approximate weight of evidence criterion (AWE). I also considered nonsignificant loglikelihood ratio tests, relative improvement in subsequent model fit, and interpretability of the model (Masyn, 2013; Moore & Little, in press). Profiles should be quantitatively and qualitatively distinct from one another and internally homogeneous. Next, the covariate, the round in which an athlete was drafted, was added in the LPA model. If an athlete was not drafted in one of the 40 rounds, they were assigned the value of 41.

To address my second and third research question, I used SPSS Version 25 and created a composite score for both hitting and pitching that represented an athlete's performance. Taking this approach was consistent with past personality and performance research (e.g., Gee et al., 2010; Mirzaei et al., 2013), and allowed me to represent performance in each area across a number of metrics (and thus not be limited by the use of any single one; e.g., Greenlees, 2020). Each final composite score was based on a combination of conceptual and statistical information. With the identified metrics within each area (see above), I ran separate principal components analyses (PCA) for both pre- and post-draft hitting and pitching data.

In order to explore the added value (i.e., incremental effect) of personality in predicting post-draft performance (hitting or pitching), I conducted a total of 12 separate hierarchical regressions; six for hitting and six for pitching. For each outcome, at Step 1, I entered the pre-draft composite performance variable; at Step 2, I entered the five personality factors. This approach allowed me to determine if personality factors accounted for a significant proportion of the variance in post-draft performance after controlling for their pre-draft statistics. I then ran five additional analyses for each performance outcome; within each analysis I again first entered the pre performance composite score, followed by the facets from each separate personality factor. For example, I entered the post-draft hitting T-score as the dependent variable and entered the pre-draft hitting T-score in step 1, and the six neuroticism facets in Step 2. I set alpha at .01 for all analyses. .

# CHAPTER 3

# RESULTS

## Pearson Correlations of Personality Domains and Performance Metrics

Table 1 presents the mean scores for the five personality factors in the present study, as well as the adolescent and adult norms.Table 3 presents the Pearson correlations for the five personality domains and the pre- and post- hitting and pitching composite scores.

Table 1

*Means and Standard Deviations for Personality Factors*

| Personality Factor | Current Sample | | Male Adult Norms | | Male Adolescent Norms | |
|---|---|---|---|---|---|---|
| | *M* | *SD* | *M* | *SD* | *M* | *SD* |
| Neuroticism | 56.99 | 17.74 | 77.2 | 20.3 | 89.3 | 20.3 |
| Extraversion | 129.12 | 16.91 | 107.4 | 19.1 | 116.5 | 18.8 |
| Openness | 109.37 | 15.96 | 103.5 | 18.8 | 112.7 | 19.4 |
| Agreeableness | 121.75 | 14.62 | 113.2 | 17.8 | 105.1 | 17.0 |
| Conscientiousness | 145.37 | 17.15 | 121.6 | 19.0 | 107.3 | 19.9 |

*Note.* Male adult and adolescent norms from professional manual (McCrae & Costa, 2010)

## Latent Profile Analysis to Define Personality Profiles

Table 2 presents classification quality.Table 4 presents the fit statistics for the LPA models. The two-profile non-diagonal class-invariant model was the best fit based on relative decreases in AIC, BIC, SABIC, CAIC, AWE, approximate correct model probability (cmP) and interpretability. The bootstrapped *p*-values were all significant.

Table 2

*Classification Quality of Final Enumerated 2-Class Non-Diagonal, Class-Invariant Model (*n = *651)*

| Class k | Model Estimated Class Prop. | | mcaP | AvePP | OCC |
|---|---|---|---|---|---|
| | Mean | 90% C.I. | | | |
| Class 1 | 96% | .916, .987 | 96.5% | 0.947 | 0.80 |
| Class 2 | 4% | .013, .084 | 3.5% | 0.842 | 118.60 |

*Note*. mcaP (modal class assignment proportion); AvePP (average posterior probabilities); OCC (odds of correct classification) which is odds of model estimated class assignment relative to random assignment by class proportion; OCC > 5 supporting adequate class separation and precision.

Table 3

*Pearson Correlations of Personality Domains and Performance Measures*

| Variable | | Neuroticism | Extraversion | Openness | Agreeableness | Consciousness | Pre-Draft Hitting | Post-Draft Hitting | Pre-Draft Pitching | Post-Draft Pitching |
|---|---|---|---|---|---|---|---|---|---|---|
| Neuroticism | Pearson Corr. | 1 | | | | | | | | |
| | Sig. | | | | | | | | | |
| Extraversion | Pearson Corr. | -.325** | 1 | | | | | | | |
| | Sig. | 0.000 | | | | | | | | |
| Openness | Pearson Corr. | -.203** | .425** | 1 | | | | | | |
| | Sig. | 0.000 | 0.000 | | | | | | | |
| Agreeableness | Pearson Corr. | -.464** | .209** | .224** | 1 | | | | | |
| | Sig. | 0.000 | 0.000 | 0.000 | | | | | | |
| Consciousness | Pearson Corr. | -.699** | .376** | .216** | .391** | 1 | | | | |
| | Sig. | 0.000 | 0.000 | 0.000 | 0.000 | | | | | |
| Pre-Draft Hitting | Pearson Corr. | -.255** | 0.024 | -0.037 | 0.108 | 0.126 | 1 | | | |
| | Sig. | 0.006 | 0.799 | 0.699 | 0.255 | 0.180 | | | | |
| Post-Draft Hitting | Pearson Corr. | -0.048 | 0.068 | -0.081 | 0.034 | -0.036 | 0.155 | 1 | | |
| | Sig. | 0.612 | 0.471 | 0.389 | 0.716 | 0.705 | 0.099 | | | |
| Pre-Draft Pitching | Pearson Corr. | .177* | 0.048 | -0.015 | -.181* | -.183* | .[c] | .[c] | 1 | |
| | Sig. | 0.049 | 0.594 | 0.865 | 0.044 | 0.042 | | | | |
| Post-Draft Pitching | Pearson Corr. | 0.128 | 0.017 | 0.042 | -0.144 | -.184* | .[c] | .[c] | .247** | 1 |
| | Sig. | 0.146 | 0.852 | 0.633 | 0.102 | 0.036 | | | 0.007 | |

*Note*. **. Correlation is significant at the 0.01 level (2-tailed). *; Correlation is significant at the 0.05 level (2-tailed); c. Cannot be computed because at least one of the variables is constant; Personality factors *n* = 651; Hitting performance metrics *n* = 114; Pitching performance metrics *n* = 124.

Table 4

*Fit Statistics for Latent Profile Analysis (*n *= 651)*

| Var-Cov Structure | Model (K-class) | LL | npar | Scaling Factor | AIC | BIC | SABIC | CAIC | AWE | $RI_{K, K+1}$ vs Ref = K2, K1 | H0: K classes; H1: K+1 classes | | within class | across classes |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | | | | | | | LRTS | Adj LMR p-value | cmP (K) | cmP(K) |
| Diagonal, Class-Invariant | 1-class | -13728.608 | 10 | 1.141 | 27477.216 | 27522.00 | 27490.25 | 27532.00 | 27616.79 | | | | 0.000 | |
| | 2-class | -13458.404 | 21 | 1.2725 | 26958.808 | 27052.86 | 26986.18 | 27073.86 | 27251.91 | | 540.40 | <0.001 | 0.000 | |
| | 3-class | -13382.534 | 22 | 1.3455 | 26809.068 | 26907.60 | 26837.75 | 26929.60 | 27116.12 | 0.28 | 188.475 | <0.001 | 1.000 | 0.000 |
| | 6-Class | -13298.051 | 40 | 1.6285 | 26676.102 | 26855.24 | 26728.24 | 26895.24 | 27234.38 | | 54.194 | 0.5063 | | |
| Diagonal, Class-Varying | 1-class | -13728.608 | 10 | 1.141 | 27477.216 | 27522.00 | 27490.25 | 27532.00 | 27616.79 | | | | 0.000 | |
| | 2-class | -13458.404 | 21 | 1.2725 | 26958.808 | 27052.86 | 26986.18 | 27073.86 | 27251.91 | | 540.407 | <0.001 | 0.000 | |
| | 3-class | -13353.056 | 32 | 1.493 | 26770.112 | 26913.42 | 26811.82 | 26945.42 | 27216.74 | 0.39 | 210.697 | 0.1935 | 0.000 | |
| | 4-class | -13297.859 | 43 | 1.2404 | 26681.718 | 26874.29 | 26737.77 | 26917.29 | 27281.87 | 0.20 | 110.394 | 0.0430 | 0.071 | |
| | 5-class | -13259.929 | 54 | 1.1973 | 26627.858 | 26869.70 | 26698.25 | 26923.70 | 27381.54 | 0.14 | 54.194 | 0.5005 | 0.707 | 0.000 |
| | 6-class | -13225.455 | 65 | 1.1342 | 26580.910 | 26872.01 | 26665.64 | 26937.01 | 27488.12 | 0.13 | 68.929 | 0.0718 | 0.222 | |
| | 7-class | -13200.508 | 76 | 1.1271 | 26553.016 | 26893.38 | 26652.08 | 26969.38 | 27613.75 | 0.09 | 49.896 | 0.1302 | 0.000 | |
| Non-Diagonal, Class-Invariant | 1-class | -13301.95 | 20 | 1.1801 | 26643.900 | 26733.47 | 26669.97 | 26753.47 | 27616.79 | | | | 0.000 | |
| | 2-class | -13271.475 | 26 | 1.216 | 26594.950 | 26711.39 | 26628.84 | 26737.39 | 26957.83 | | 60.949 | 0.028 | 1.000 | 0.998 |
| Non-Diagonal, Class-Varying | 1-class | -13301.95 | 20 | 1.1801 | 26643.900 | 26733.47 | 26669.97 | 26753.47 | 26923.04 | | | | 0.000 | |
| | 2-class | -13229.38 | 41 | 1.2433 | 26540.760 | 26724.38 | 26594.20 | 26765.38 | 27113.00 | | 145.139 | 0.0975 | 0.000 | 0.002 |

*Note.* Model log likelihood value; npar = number of free parameters; AIC = Akaike's information criterion; BIC = Bayesian Information Criterion; SABIC = sample-adjusted BIC; CAIC = Consistent Akaike Information Criterion; AWE = Approximate Weight of Evidence Criterion; RI = Relative Improvement; LRTS = loglikelihood ratio test statistic; cmP = Approximate Correct Model Probability. Selected model highlighted in green.

The entropy for the two-profile model was .751 and the profiles were distinct from one another for at least one indicator based on the Cohen's *d* (see Tables 5 and 6).

Table 5

*Class Descriptive Statistics (*n *= 651)*

| Class | Variable | Mean | SD | Correlations | | | | Class Homog. |
|---|---|---|---|---|---|---|---|---|
| Class 1: (96%) | Neuroticism | 56.45 | 17.54 | 1.00 | | | | 0.98 |
| | Extraversion | 128.64 | 16.74 | -0.20 | 1.00 | | | 0.98 |
| | Openness | 109.24 | 15.94 | 0.09 | 0.27 | 1.00 | | 1.00 |
| | Agreeableness | 123.04 | 13.26 | -0.39 | 0.11 | 0.05 | 1.00 | 0.83 |
| | Conscientiousness | 145.06 | 17.07 | -0.68 | 0.32 | 0.08 | 0.34 | 0.99 |
| Class 2: (4%) | Neuroticism | 69.07 | 17.54 | 1.00 | | | | 0.98 |
| | Extraversion | 139.80 | 16.74 | -0.20 | 1.00 | | | 0.98 |
| | Openness | 112.25 | 15.94 | 0.09 | 0.27 | 1.00 | | 1.00 |
| | Agreeableness | 92.80 | 13.26 | -0.39 | 0.11 | 0.05 | 1.00 | 0.83 |
| | Conscientiousness | 152.37 | 17.07 | -0.68 | 0.32 | 0.08 | 0.34 | 0.99 |

Table 6

*Profile Separation Characteristics (*n *= 651)*

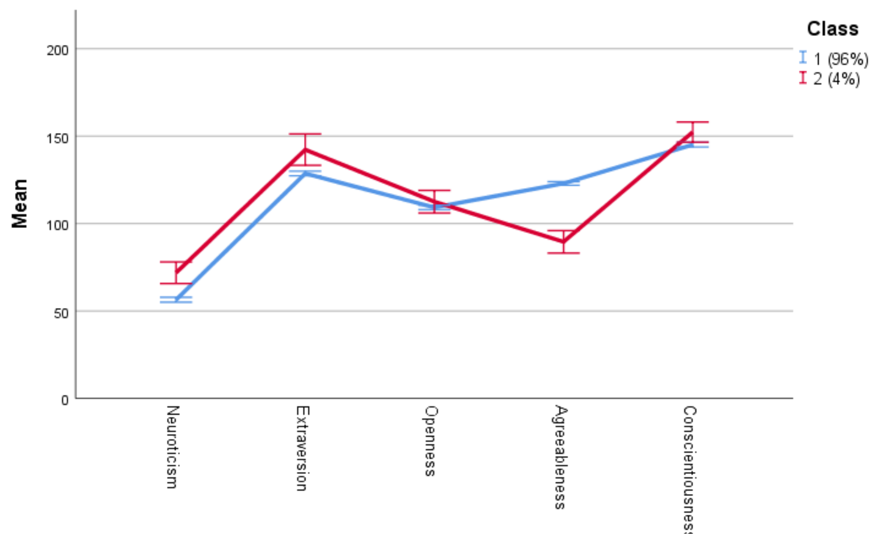
| Variable | Class 1 vs Class 2 |
|---|---|
| Neuroticism | -0.72 |
| Extraversion | -0.67 |
| Openness | -0.19 |
| Agreeableness | **2.28** |
| Conscientiousness | -0.43 |

Note. Cohen's d values of 2 or greater bolded to highlight class separation.

Profile 1 represented 96% (*n* = 628) of the sample and was named *Higher Agreeableness Athletes* because the biggest point of distinction between classes was on that personality factor, and the athletes in Class 1 had higher scores on Agreeableness. Profile 2 represented 4% (*n* = 23) of the sample and was named *Lower Agreeableness Athletes* because those athletes scored lower on that personality factor. Although there were some noticeable differences in Neuroticism and Extraversion, namely Class 2 athletes scored higher on both, the Cohen's *d* value suggest these differences are not very meaningful. See Figure 1.

Figure 1

*Indicator Means for the Two-Class Personality Profile Solution*




*Note*. Error Bars: 95% CI. Class 1 is Higher Agreeableness Athletes ($n$ = 628; 95%); Class 2 is Lower Agreeableness athletes ($n$ = 23; 4%).

Personality profile membership did not significantly predict athletes' draft order ($p$ = .247). However, based on the means for the ranks, it is possible that there is in fact a meaningful difference that was undetected due to the small $n$ of Class 2.

## Performance Composite Scores

### Hitting

In both the pre- and post-draft PCA's, KK% and ISO demonstrated low factor loadings (< .40) and thus were removed. In the PCA with the remaining metrics (BB%, BABIP, OBP, and SLG), BB% loaded poorly so it was removed. In the final PCA, I entered BABIP, OBP, and

SLG. For pre-draft performance, the Kaiser-Meyer-Olkin measure verified the sampling adequacy for the analysis (KMO = .680, $p < .001$). Bartlett's test of sphericity $\chi^2$ (3) = 144.62, $p < .001$, indicated that correlation structure is adequate for factor analyses. The total variance explained was 75.59% and all factor loadings were above .80. For post-draft performance, the KMO = .672, $p < .001$ and Bartlett's test of sphericity was $\chi^2$ (3) = 94.52, $p < .001$. The total variance explained was 68.60% and all factor loadings were above .75. As such, the composite score to assess hitting performance would was composed of BABIP, OBP, and SLG.

### Pitching

In the pre- and post-draft pitching PCA's, K% and WP loaded poorly on the factor and were removed for subsequent analyses. In the final EFA for pitching, I entered B%, K/BB, and ERA. For pre-draft performance, the KMO measure verified the sampling adequacy for the analysis (.549, $p < .001$). Bartlett's test of sphericity $\chi^2$ (3) = 71.86, $p < .001$, indicated that correlation structure is adequate for factor analyses. The total variance explained was 61.37% and all factor loadings were above .60. For post-draft performance, the KMO = .529, $p < .001$ and Bartlett's test of sphericity was $\chi^2$ (3) = 54.15, $p < .001$. The total variance explained was 56.17% and all factor loadings were above .60. As such, the composite score to assess pitching performance would was composed of B%, K/BB, and ERA.

For each composite, I transformed the saved standardized score into a T-score so that all measures were on the same scale. This results in four performance scores: pre-draft hitting, post-draft hitting, pre-draft pitching, and post-draft pitching.

## Regression Analyses

### Hitting

Step 1, which included the pre-draft hitting composite, was not significant, adjusted $R^2$ =

.02, $F(1, 112) = 2.69$, $p = .104$, accounting for just under 2% of the athletes' post-draft hitting performance (Step 1 is consistent for the remaining five regression analyses for hitting so will not be repeated in each subsequent section). The inclusion of the Big-Five personality variables at Step 2, also was not significant, $\Delta R^2 = .04$, $F(5, 107) = .83$, $p = .531$. Overall, the full model was not significant, $F(6, 113) = 1.14$, $p = .347$, and none of the predictors were significant either. See Table 7.

Table 7

*Hierarchical Regression Analysis Predicting Post-Draft Hitting Performance using the Big-Five Personality Factors (*n *= 115)*

| Step/Predictor | Adj $R^2$ | $\Delta R^2$ | $\Delta F$ | *B* | *SE B* | β | *t* |
|---|---|---|---|---|---|---|---|
| Step 1 | .015 | .023 | 2.685 | | | | |
| Pre-Draft Hitting | | | | .154 | .094 | .153 | 1.639 |
| Step 2 | .007 | .036 | .83 | | | | |
| Pre-Draft Hitting | | | | 0.137 | 0.089 | 0.136 | 1.396 |
| Neuroticism | | | | -0.062 | 0.082 | -0.114 | -.753 |
| Extraversion | | | | 0.121 | 0.079 | 0.178 | 1.537 |
| Openness | | | | -0.101 | 0.069 | -0.158 | -1.464 |
| Agreeableness | | | | 0.024 | 0.077 | 0.039 | .308 |
| Conscientiousness | | | | -0.123 | 0.088 | -0.206 | -1.391 |
| Full Model $R^2 = .060$, Overall $F\ (6, 113) = 1.14$ | | | | | | | |

*Note*: The $\Delta F$-test is for that step of the model and the Overall $F$-test is for the final step of the model when all variables had been entered. Degrees of freedom corresponding to $\Delta F$ are 6, 113. Pre-draft hitting performance was measured by creating a composite score that included hitters' BABIP, OBP, and SLG statistics from the season prior to their draft year. Post-draft hitting performance was assessed using a composite score that included hitters' BABIP, OBP, and SLG statistics from the MiLB season following the draft. Personality was measured using the NEO-PI-3 (McCrae & Costa, 2010).

In the second regression, the addition of the six facets at Step 2 was also not significant, $\Delta R^2 = .035$, $F(6, 106) = .66$, $p = .685$. The full model was not significant, $F(7, 113) = .94$, $p = .480$, and none of the predictors were either. See Table 8.

Table 8

*Hierarchical Regression Analysis Predicting Post-Draft Hitting Performance using Neuroticism Facets (*n *= 115)*

| Step/Predictor | Adj $R^2$ | $\Delta R^2$ | $\Delta F$ | *B* | *SE B* | β | *t* |
|---|---|---|---|---|---|---|---|
| Step 1 | .015 | .023 | 2.685 | | | | |
| Pre-Draft Hitting | | | | .154 | .094 | .153 | 1.639 |
| Step 2 | -.004 | .035 | 0.656 | | | | |
| Pre-Draft Hitting | | | | 0.179 | 0.103 | 0.178 | 1.737 |
| Anxiety (N1) | | | | 0.140 | 0.311 | 0.064 | 0.451 |
| Angry Hostility (N2) | | | | -0.481 | 0.294 | -0.198 | -1.636 |
| Depression (N3) | | | | -0.285 | 0.413 | -0.102 | -0.690 |
| Consciousness (N4) | | | | 0.389 | 0.406 | 0.149 | 0.958 |
| Impulsiveness (N5) | | | | 0.129 | 0.333 | 0.048 | 0.387 |
| Vulnerability (N6) | | | | 0.063 | 0.495 | 0.022 | 0.128 |
| Full Model $R^2$ = .058, Overall $F$ (7, 113) = .939 | | | | | | | |

*Note*: The $\Delta F$-test is for that step of the model and the Overall $F$-test is for the final step of the model when all variables had been entered. Degrees of freedom corresponding to $\Delta F$ are 7, 113. Pre-draft hitting performance was measured by creating a composite score that included hitters' BABIP, OBP, and SLG statistics from the season prior to their draft year. Post-draft hitting performance was assessed using a composite score that included hitters' BABIP, OBP, and SLG statistics from the MiLB season following the draft. Personality was measured using the NEO-PI-3 (McCrae & Costa, 2010).

In the third regression, the inclusion of the six Extraversion facets at Step 2, also was not significant, $\Delta R^2 = .04$, $F(6, 106) = .38$, $p = .891$. Although the full model was not significant, $F(7, 113) = .70$, $p = .676$. See Table 9.

Table 9

*Hierarchical Regression Analysis Predicting Post-Draft Hitting Performance using Extraversion Facets (*n *= 115)*

| Step/Predictor | Adj $R^2$ | $\Delta R^2$ | $\Delta F$ | *B* | *SE B* | β | *t* |
|---|---|---|---|---|---|---|---|
| Step 1 | .015 | .023 | 2.685 | | | | |
| Pre-Draft Hitting | | | | .154 | .094 | .153 | 1.639 |
| Step 2 | -.019 | .020 | .379 | | | | |
| Pre-Draft Hitting | | | | 0.165 | 0.089 | 0.165 | 1.687 |

*(table continues)*

| Step/Predictor | Adj $R^2$ | $\Delta R^2$ | $\Delta F$ | *B* | *SE B* | β | *t* |
|---|---|---|---|---|---|---|---|
| Warmth (E1) | | | | -0.051 | 0.422 | -0.017 | -0.121 |
| Gregariousness (E2) | | | | 0.143 | 0.258 | 0.61 | 0.555 |
| Assertiveness (E3) | | | | -0.185 | 0.294 | -0.070 | -0.629 |
| Activity (E4) | | | | 0.417 | 0.405 | 0.121 | 1.031 |
| Excitement Seeking (E5) | | | | 0.021 | 0.291 | 0.008 | 0.071 |
| Positive Emotions (E6) | | | | -0.029 | 0.327 | -0.011 | -0.089 |
| Full Model $R^2$ = .044, Overall *F* (7, 113) = .695 | | | | | | | |

*Note*: The $\Delta F$-test is for that step of the model and the Overall *F*-test is for the final step of the model when all variables had been entered. Degrees of freedom corresponding to $\Delta F$ are 7, 113. Pre-draft hitting performance was measured by creating a composite score that included hitters' BABIP, OBP, and SLG statistics from the season prior to their draft year. Post-draft hitting performance was assessed using a composite score that included hitters' BABIP, OBP, and SLG statistics from the MiLB season following the draft. Personality was measured using the NEO-PI-3 (McCrae & Costa, 2010).

In the fourth regression, I entered the six Openness facets in Step 2 and they were not significant, $\Delta R^2$ = .019, $F(6, 106)$ = .35, $p$ = .910. The full model was not significant, $F(7, 113)$ = .67, $p$ = .699. See Table 10.

Table 10

*Hierarchical Regression Analysis Predicting Post-Draft Hitting Performance using Openness Facets (*n *= 115)*

| Step/Predictor | Adj $R^2$ | $\Delta R^2$ | $\Delta F$ | *B* | *SE B* | β | *t* |
|---|---|---|---|---|---|---|---|
| Step 1 | .015 | .023 | 2.685 | | | | |
| Pre-Draft Hitting | | | | .154 | .094 | .153 | 1.639 |
| Step 2 | -.021 | .019 | .347 | | | | |
| Pre-Draft Hitting | | | | 0.142 | 0.097 | 0.141 | 1.464 |
| Fantasy (O1) | | | | -0.105 | 0.276 | -0.043 | -0.381 |
| Aesthetics (O2) | | | | -0.079 | 0.240 | -0.039 | -0.330 |
| Feelings (O3) | | | | -0.154 | 0.271 | -0.063 | -0.570 |
| Actions (O4) | | | | 0.199 | 0.339 | 0.067 | 0.588 |
| Ideas (O5) | | | | 0.124 | 0.272 | 0.057 | 0.454 |
| Values (O6) | | | | -0.394 | 0.365 | -0.122 | -1.079 |
| Full Model $R^2$ = .042, Overall *F* (7, 113) = .667 | | | | | | | |

*Note*: The $\Delta F$-test is for that step of the model and the Overall *F*-test is for the final step of the model when all variables had been entered. Degrees of freedom corresponding to Δ*F* are 7, 113. Pre-draft hitting performance was measured by creating a composite score that included hitters' BABIP, OBP, and SLG statistics from the season prior to their draft year. Post-draft hitting performance was assessed using a composite score that included hitters' BABIP, OBP, and SLG statistics from the MiLB season following the draft. Personality was measured using the NEO-PI-3 (McCrae & Costa, 2010).

In the fifth regression, the inclusion of the six Agreeableness facets at Step 2, also was not significant, $\Delta R^2 = .04$, $F(6, 106) = 1.05$, $p = .400$. The full model was not significant, $F(7, 113) = 1.28$, $p = .266$. See Table 11.

Table 11

*Hierarchical Regression Analysis Predicting Post-Draft Hitting Performance using Agreeableness Facets (*n *= 115)*

| Step/Predictor | Adj $R^2$ | $\Delta R^2$ | $\Delta F$ | *B* | *SE B* | β | *t* |
|---|---|---|---|---|---|---|---|
| Step 1 | .015 | .023 | 2.685 | | | | |
| Pre-Draft Hitting | | | | .154 | .094 | .153 | 1.639 |
| Step 2 | .017 | .055 | 1.047 | | | | |
| Pre-Draft Hitting | | | | 0.137 | 0.096 | 0.136 | 1.423 |
| Trust (A1) | | | | 0.376 | 0.306 | 0.132 | 1.228 |
| Straight Forwardness (A2) | | | | -0.261 | 0.282 | -0.102 | -0.925 |
| Altruism (A3) | | | | 0.589 | 0.356 | 0.190 | 1.657 |
| Compliance (A4) | | | | 0.116 | 0.267 | 0.046 | 0.436 |
| Modesty (A5) | | | | -0.083 | 0.243 | -0.036 | -0.342 |
| Tender Mindedness (A6) | | | | -0.510 | 0.338 | -0.174 | -1.507 |
| Full Model $R^2 = .078$, Overall $F$ (7, 113) = 1.282 | | | | | | | |

*Note*: The Δ*F*-test is for that step of the model and the Overall *F*-test is for the final step of the model when all variables had been entered. Degrees of freedom corresponding to Δ*F* are 7, 113. Pre-draft hitting performance was measured by creating a composite score that included hitters' BABIP, OBP, and SLG statistics from the season prior to their draft year. Post-draft hitting performance was assessed using a composite score that included hitters' BABIP, OBP, and SLG statistics from the MiLB season following the draft. Personality was measured using the NEO-PI-3 (McCrae & Costa, 2010).

In the sixth hitting regression, the addition of the six Conscientiousness facets at Step 2 was not significant, $\Delta R^2 = .035$, $F(6, 106) = .66$, $p = .679$. The full model was not significant, $F(7, 113) = .95$, $p = .475$. See Table 12.

Table 12

*Hierarchical Regression Analysis Predicting Post-Draft Hitting Performance using Conscientiousness Facets (*n *= 115)*

| Step/Predictor | Adj $R^2$ | $\Delta R^2$ | $\Delta F$ | *B* | *SE B* | β | *t* |
|---|---|---|---|---|---|---|---|
| Step 1 | .015 | .023 | 2.685 | | | | |
| Pre-Draft Hitting | | | | .154 | .094 | .153 | 1.639 |
| Step 2 | -.003 | .035 | .664 | | | | |
| Pre-Draft Hitting | | | | 0.148 | 0.096 | 0.147 | 1.532 |
| Competence (C1) | | | | 0.528 | 0.499 | 0.159 | 1.059 |
| Order (C2) | | | | -0.406 | 0.303 | -0.173 | -1.341 |
| Dutifulness (C3) | | | | 0.157 | 0.426 | 0.056 | 0.369 |
| Achievement Striving (C4) | | | | -0.456 | 0.451 | -0.135 | -1.012 |
| Self-Discipline (C5) | | | | 0.093 | 0.511 | 0.033 | 0.182 |
| Deliberation (C6) | | | | -0.093 | 0.322 | -0.036 | -0.288 |
| Full Model $R^2$ = .059, Overall F (7, 113) = .946 | | | | | | | |

*Note*: The $\Delta F$-test is for that step of the model and the Overall *F*-test is for the final step of the model when all variables had been entered. Degrees of freedom corresponding to $\Delta F$ are 7, 113. Pre-draft hitting performance was measured by creating a composite score that included hitters' BABIP, OBP, and SLG statistics from the season prior to their draft year. Post-draft hitting performance was assessed using a composite score that included hitters' BABIP, OBP, and SLG statistics from the MiLB season following the draft. Personality was measured using the NEO-PI-3 (McCrae & Costa, 2010).

Overall, personality at the factor and facet levels did not account for a significant proportion of the variance in post-draft hitting performance after controlling for the pre-draft performance.

## Pitching

In the seventh regression, Step 1, which included the pre-draft pitching composite, was significant, $R^2 = .06$, $F(1, 117) = 7.59$, $p = .007$, accounting for just under 6% of the athletes' post-draft pitching performance (Step 1 is consistent for the remaining five regression analyses for pitching). The inclusion of the Big-Five personality variables at Step 2, was not significant,

$\Delta R^2 = .02$, $F(5, 112) = .83$, $p = .793$. The full model was not significant, $F(6, 118) = 1.64$, $p = .347$. See Table 13.

Table 13

*Hierarchical Regression Analysis Predicting Post-Draft Pitching Performance using the Big-Five Personality Factors (*n *= 123)*

| Step/Predictor | Adj $R^2$ | $\Delta R^2$ | $\Delta F$ | $B$ | $SE\ B$ | β | $t$ |
|---|---|---|---|---|---|---|---|
| Step 1 | .053 | .061 | 7.594 | | | | |
| Pre-Draft Pitching | | | | .268 | .097 | .247 | 2.756* |
| Step 2 | .031 | .020 | .477 | | | | |
| Pre-Draft Pitching | | | | 0.226 | 0.104 | 0.209 | 2.182 |
| Neuroticism | | | | -0.028 | 0.077 | -0.047 | -.366 |
| Extraversion | | | | 0.005 | 0.059 | 0.085 | 0.933 |
| Openness | | | | 0.018 | 0.067 | 0.027 | 0.269 |
| Agreeableness | | | | -0.054 | 0.076 | -0.079 | -0.708 |
| Conscientiousness | | | | -0.078 | 0.076 | -0.127 | -1.025 |
| Full Model $R^2 = .081$, Overall F (6, 118) = 1.635 | | | | | | | |

*Note*: The $\Delta F$-test is for that step of the model and the Overall $F$-test is for the final step of the model when all variables had been entered. Degrees of freedom corresponding to $\Delta F$ are 6, 118. Pre-draft pitching performance was measured by creating a composite score that included pitchers' BB%, K/BB, and ERA statistics from the season prior to their draft year. Post-draft pitching performance was assessed using a composite score that included pitchers' BB%, K/BB, and ERA statistics from the MiLB season following the draft. Personality was measured using the NEO-PI-3 (McCrae & Costa, 2010). * $p < .05$

In the eighth hierarchical regression, the addition of the six Neuroticism facets at Step 2 was not significant, $\Delta R^2 = .08$, $F(6, 111) = 1.68$, $p = .132$. The full model was not significant, $F(7, 118) = 2.56$, $p = .017$. See Table 14

Table 14

*Hierarchical Regression Analysis Predicting Post-Draft Pitching Performance using Neuroticism Facets (*n *= 123)*

| Step/Predictor | Adj $R^2$ | $\Delta R^2$ | $\Delta F$ | $B$ | $SE\ B$ | β | $t$ |
|---|---|---|---|---|---|---|---|
| Step 1 | .053 | .061 | 7.594 | | | | |
| Pre-Draft Pitching | | | | .268 | .097 | .247 | 2.756* |

*(table continues)*

| Step/Predictor | Adj $R^2$ | $\Delta R^2$ | $\Delta F$ | *B* | *SE B* | β | *t* |
|---|---|---|---|---|---|---|---|
| Step 2 | .085 | .08 | 1.68 | | | | |
| Pre-Draft Pitching | | | | 0.284 | 0.102 | 0.262 | 2.783 |
| Anxiety (N1) | | | | -0.581 | 0.305 | -0.241 | -1.905 |
| Angry Hostility (N2) | | | | 0.516 | 0.308 | 0.203 | 1.672 |
| Depression (N3) | | | | 0.506 | 0.329 | 0.177 | 1.537 |
| Consciousness (N4) | | | | -0.064 | 0.334 | -0.024 | -0.192 |
| Impulsiveness (N5) | | | | -0.391 | 0.316 | -0.156 | -1.237 |
| Vulnerability (N6) | | | | 0.442 | 0.397 | 0.137 | 1.115 |
| Full Model $R^2$ = .139, Overall *F* (7, 118) = 2.564 | | | | | | | |

*Note*: The $\Delta F$-test is for that step of the model and the Overall *F*-test is for the final step of the model when all variables had been entered. Degrees of freedom corresponding to $\Delta F$ are 7, 118. Pre-draft pitching performance was measured by creating a composite score that included pitchers' BB%, K/BB, and ERA statistics from the season prior to their draft year. Post-draft pitching performance was assessed using a composite score that included pitchers' BB%, K/BB, and ERA statistics from the MiLB season following the draft. Personality was measured using the NEO-PI-3 (McCrae & Costa, 2010). * $p < .05$

In the ninth regression, the addition of the six Extraversion facets at Step 2 was not significant, $\Delta R^2 = .018$, $F(6, 111) = .362$, $p = .902$. The full model was not significant, $F(7, 118) = 1.36$, $p = .230$. See Table 15.

Table 15

*Hierarchical Regression Analysis Predicting Post-Draft Pitching Performance using Extraversion Facets (*n *= 123)*

| Step/Predictor | Adj $R^2$ | $\Delta R^2$ | $\Delta F$ | *B* | *SE B* | β | *t* |
|---|---|---|---|---|---|---|---|
| Step 1 | .053 | .061 | 7.594 | | | | |
| Pre-Draft Pitching | | | | .268 | .097 | .247 | 2.756* |
| Step 2 | .021 | .02 | .362 | | | | |
| Pre-Draft Pitching | | | | 0.251 | 0.101 | 0.232 | 2.486 |
| Warmth (E1) | | | | -0.266 | 0.377 | -0.105 | -0.706 |
| Gregariousness (E2) | | | | 0.027 | 0.250 | 0.014 | 0.107 |
| Assertiveness (E3) | | | | -0.237 | 0.282 | -0.100 | -0.841 |
| Activity (E4) | | | | 0.378 | 0.334 | 0.136 | 1.132 |
| Excitement Seeking (E5) | | | | 0.109 | 0.306 | 0.040 | 0.356 |

*(table continues)*

| Step/Predictor | Adj $R^2$ | $\Delta R^2$ | $\Delta F$ | *B* | *SE B* | β | *t* |
|---|---|---|---|---|---|---|---|
| Positive Emotions (E6) | | | | 0.022 | 0.348 | 0.008 | 0.063 |
| Full Model R² = .079, Overall F (7, 118) = 1.359 | | | | | | | |

*Note*: The $\Delta F$-test is for that step of the model and the Overall $F$-test is for the final step of the model when all variables had been entered. Degrees of freedom corresponding to $\Delta F$ are 7, 118. Pre-draft pitching performance was measured by creating a composite score that included pitchers' BB%, K/BB, and ERA statistics from the season prior to their draft year. Post-draft pitching performance was assessed using a composite score that included pitchers' BB%, K/BB, and ERA statistics from the MiLB season following the draft. Personality was measured using the NEO-PI-3 (McCrae & Costa, 2010). * $p < .05$

In the tenth regression, the inclusion of the six Openness facets at Step 2 was not significant, $\Delta R^2 = .060$, $F(6, 111) = 1.27$, $p = .277$. The full model was not significant, $F(7, 118) = 2.19$, $p = .041$. See Table 16.

Table 16

*Hierarchical Regression Analysis Predicting Post-Draft Pitching Performance using Openness Facets (*n *= 123)*

| Step/Predictor | Adj $R^2$ | $\Delta R^2$ | $\Delta F$ | *B* | *SE B* | β | *t* |
|---|---|---|---|---|---|---|---|
| Step 1 | .053 | .061 | 7.594 | | | | |
| Pre-Draft Pitching | | | | .268 | .097 | .247 | 2.756* |
| Step 2 | .066 | .06 | 1.270 | | | | |
| Pre-Draft Pitching | | | | 0.230 | 0.099 | 0.212 | 2.326 |
| Fantasy (O1) | | | | 0.100 | 0.249 | 0.040 | 0.402 |
| Aesthetics (O2) | | | | 0.493 | 0.256 | 0.211 | 1.922 |
| Feelings (O3) | | | | 0.105 | 0.263 | 0.039 | 0.400 |
| Actions (O4) | | | | 0.194 | 0.291 | 0.065 | 0.666 |
| Ideas (O5) | | | | -0.346 | 0.251 | -0.164 | -1.378 |
| Values (O6) | | | | -0.554 | 0.304 | -0.180 | -1.823 |
| Full Model $R^2$ = .121, Overall $F$ (7, 118) = 2.188 | | | | | | | |

*Note*: The $\Delta F$-test is for that step of the model and the Overall $F$-test is for the final step of the model when all variables had been entered. Degrees of freedom corresponding to $\Delta F$ are 7, 118. Pre-draft pitching performance was measured by creating a composite score that included pitchers' BB%, K/BB, and ERA statistics from the season prior to their draft year. Post-draft pitching performance was assessed using a composite score that included pitchers' BB%, K/BB, and ERA statistics from the MiLB season following the draft. Personality was measured using the NEO-PI-3 (McCrae & Costa, 2010). * $p < .05$

In the eleventh regression, the addition of the six Agreeableness facets in Step 2 was not significant, $\Delta R^2 = .011$, $F(6, 111) = .23$, $p = .968$). The full model was not significant, $F(7, 118) = 1.23$, $p = .290$. See Table 17.

Table 17

*Hierarchical Regression Analysis Predicting Post-Draft Pitching Performance using Agreeableness Facets (*n *= 123)*

| Step/Predictor | Adj $R^2$ | $\Delta R^2$ | $\Delta F$ | *B* | *SE B* | β | *t* |
|---|---|---|---|---|---|---|---|
| Step 1 | .053 | .061 | 7.594 | | | | |
| Pre-Draft Pitching | | | | .268 | .097 | .247 | 2.756* |
| Step 2 | .014 | .01 | .23 | | | | |
| Pre-Draft Pitching | | | | 0.237 | 0.105 | 0.219 | 2.251 |
| Trust (A1) | | | | -0.032 | 0.286 | -0.013 | -0.112 |
| Straight Forwardness (A2) | | | | -0.044 | 0.260 | -0.018 | -0.169 |
| Altruism (A3) | | | | -0.133 | 0.395 | -0.041 | -0.337 |
| Compliance (A4) | | | | -0.140 | 0.257 | -0.056 | -0.544 |
| Modesty (A5) | | | | -0.033 | 0.220 | -0.015 | -0.149 |
| Tender Mindedness (A6) | | | | -0.053 | 0.308 | -0.019 | -0.172 |
| Full Model $R^2 = .072$, Overall F (7, 118) = 1.234 | | | | | | | |

*Note*: The $\Delta F$-test is for that step of the model and the Overall $F$-test is for the final step of the model when all variables had been entered. Degrees of freedom corresponding to $\Delta F$ are 7, 118. Pre-draft pitching performance was measured by creating a composite score that included pitchers' BB%, K/BB, and ERA statistics from the season prior to their draft year. Post-draft pitching performance was assessed using a composite score that included pitchers' BB%, K/BB, and ERA statistics from the MiLB season following the draft. Personality was measured using the NEO-PI-3 (McCrae & Costa, 2010). * $p < .05$

In the twelfth and final regression, the inclusion of the six Conscientiousness facets at Step 2 was not significant, $\Delta R^2 = .023$, $F(6, 111) = .47$, $p = .829$. The final model was not significant, $F(7, 118) = 1.46$, $p = .189$. See Table 18.

Overall, personality at the factor and facet levels did not account for a significant proportion of the variance in post-draft pitching performance after controlling for the pre-draft performance.

Table 18

*Hierarchical Regression Analysis Predicting Post-Draft Pitching Performance using Conscientiousness Facets (*n *= 123)*

| Step/Predictor | Adj $R^2$ | $\Delta R^2$ | $\Delta F$ | *B* | *SE B* | β | *t* |
|---|---|---|---|---|---|---|---|
| Step 1 | .053 | .061 | 7.594 | | | | |
| Pre-Draft Pitching | | | | .268 | .097 | .247 | 2.756* |
| Step 2 | .026 | .02 | .02 | | | | |
| Pre-Draft Pitchng | | | | 0.260 | 0.108 | 0.240 | 2.407 |
| Competence (C1) | | | | 0.072 | 0.534 | 0.022 | 0.135 |
| Order (C2) | | | | -0.191 | 0.264 | -0.080 | -0.723 |
| Dutifulness (C3) | | | | 0.135 | 0.554 | 0.040 | 0.244 |
| Achievement Striving (C4) | | | | -0.253 | 0.486 | -0.071 | -0.520 |
| Self-Discipline (C5) | | | | -0.255 | 0.507 | -0.089 | -0.502 |
| Deliberation (C6) | | | | 0.057 | 0.277 | 0.025 | 0.208 |
| Full Model $R^2$ = .084, Overall $F$ (7, 118) = 1.459 | | | | | | | |

*Note*: The $\Delta F$-test is for that step of the model and the Overall $F$-test is for the final step of the model when all variables had been entered. Degrees of freedom corresponding to $\Delta F$ are 7, 118. Pre-draft pitching performance was measured by creating a composite score that included pitchers' BB%, K/BB, and ERA statistics from the season prior to their draft year. Post-draft pitching performance was assessed using a composite score that included pitchers' BB%, K/BB, and ERA statistics from the MiLB season following the draft. Personality was measured using the NEO-PI-3 (McCrae & Costa, 2010).* $p < .05$

## CHAPTER 4

## DISCUSSION

Regarding the athletes' personalities, two distinct profiles emerged in which the main difference was found on their levels of Agreeableness. However, the results of the covariate analysis did not reach significance, which is likely due to Class 2 being so small ($n$ = 23) and thus having larger standard error. After reviewing the estimates of draft round for each profile, the athletes who were higher in Agreeableness tended to get drafted across earlier rounds (round 21.36) than the athletes who were lower in Agreeableness (round 25.92); support for this conclusion comes from looking at Class 1 to Class 2, but not when looking at Class 2 to Class 1. It is possible that with a larger sample, Class 2 would also have been larger, and the confidence interval would have narrowed enough to get support from both sides to distinguish between the two classes. The idea that athletes higher in Agreeableness (i.e., altruism, helpfulness, and trust of others) would get drafted earlier is consistent with findings from past research (e.g., Brinkman et al., 2016; Jackson et al., 2011; Piedmont et al., 1999; Teshome et al., 2015). For example, Teshome et al. (2015) found that male athletes who scored higher on Agreeableness were rated by their coaches as having better overall performance (as measured by a mean score of five player dimensions: coachability, athletic ability, game performance, team playerness, and work ethics). Further, Agreeableness has been found to be significantly and positively correlated to male and female college athletes' intrinsic motivation (Brinkman et al., 2016) and female college soccer players' coachability (Piedmont et al., 1999). Taken together, coaches, and even scouts, appear to develop better impressions of "agreeable" athletes that, in turn, may influence positively their intentions to draft or recruit them on their teams.

In terms of predicting the baseball players' performance, in either hitting or pitching, there was no support for personality as a significant predictor. Whether represented at the factor or facet level by the NEO-PI, personality was not related to baseball pitchers' or hitters' subsequent performance after controlling for their past performances. Previous research findings have been equivocal with respect to how personality relates to athletic performances (e.g., Elumaro, 2016; Mirzaei et al., 2013; Teshome et al., 2015). For example, in a study of club level and college level athletes (59% male), Elumaro (2016) found that grit could differentiate between sport performance/achievement whereas the Big Five personality factors (as measured by the BFI-10; Rammstedt & John, 2007) could not. On the other hand, Mirzaei et al. (2019) demonstrated that conscientiousness was significantly and positively correlated with non-elite football and futsal players' season-long sport performance. There are many reasons, ranging from methodological to measurement, to explain these varied findings, some of which apply in my study.

A strength of the present study was the longitudinal design, where I obtained both personality and performance data prior to the players' first MiLB season. This longitudinal design, particularly with controlling for baseline performance, allowed me to test whether personality was a predictor of objective sport performance. Past research that has used cross-sectional designs (e.g., Mirzaei et al., 2013; Piedmont et al., 1999; Teshome et al., 2015), and collected personality and performance data at the end of the season, generally have shown that personality relates to performance, such as Agreeableness being significantly and positively related to women's NCAA Division I soccer players' coachability and the number of games played (Piedmont et al., 1999). Another strength of my study, and key difference with past research (e.g., Mirzaei et al., 2013; Piedmont et al., 1999; Teshome et al., 2015), was how I measured performance. In my study, I used common, objective baseball metrics, creating a composite score given that no one metric fully represents either hitters' or pitchers' performances. In past research where relationships have been found between personality and performance, the performance outcome measures often are subjective reports, such as coach assessments/ratings of athletes' performances (Mirzaei et al., 2013; Piedmont et al., 1999; Teshome et al., 2015). Thus, it may be that past associations between personality and sport performance have been artifacts of cross-sectional designs and subjective ratings; if so, then my results may represent more the reality of personality's place in determining performance. However, it also may be that personality's influences on performance, particularly in the transitionary time as athletes move into the professional/elite ranks, emerges over a longer period of time which has been empirically supported (e.g., Aidman, 2007; Gee et al., 2010). From a conceptual standpoint, personality factors have been significantly correlated to sport behaviours such as coping, motivation, and preparation quality (Allen et al., 2011; Brinkman et al., 2016; Kaiseler et al., 2012), all of which could contribute to an athlete's long-term success. Future research should continue to explore whether personality factors are significant predictors of performance across multiple years.

Despite the methodological strengths of my study, there are several limitations that warrant discussion. First, my sample included only baseball players and thus my findings are limited to that sport and level of athletes. It may be that in sports where teams are smaller, such as basketball, personality has more influence on performance, perhaps through team dynamics. Research is needed to examine this question. Second, I examined the players during a specific time in their sport careers, when they were transitioning from college to the minor leagues of professional baseball. Thus, I do not know if the effects of personality may have been present, but only emerge later in a player's career. That is, although personality may not be predictive of performance within the first year of being in the league, it may predict other outcomes, such as longevity. Third, my data represented only athletes in which a specific MLB team was interested, not all the players who had been eligible for the draft in those years. This sampling bias may have reduced the variability in the personality and skill measures, and thus attenuated what otherwise might have been significant findings. Even so, my sample was sufficiently large, and powered, to address my research questions. In addition, as an outcome, draft order does not perfectly reflect athletes' abilities or likelihood of success in the league. At times, MLB teams will opt to draft one player over a more desirable player because of what they would otherwise have to pay the more desirable player in the way of a signing bonus. Further, given the variety of positions within a baseball team, draft selection (and thus overall order) is highly influenced by organizational need. For example, a team in need of left-handed pitching might opt to draft a lower-rated player of that position over a superior player in another position. Lastly, I utilized well established, psychometrically sound measure of personality, I conceptualized personality as a trait. There have been recent calls in personality research to integrate both the trait and state perspectives given their unique and valuable explanations of behavior (e.g., Baumert et al., 2017; Fleeson, 2017; Judge et al., 2014; Sosnowska et al., 2020). For example, Sosnowska et al. (2020) proposed the Personality Dynamics model that integrates the dynamic systems principles and moves towards conceptualizing personality as a system. Future research could utilize this approach to better understand the stable and dynamic elements of personality in relation to sport performance.

In my longitudinal examination of the influence of personality on objective performance, after controlling for prior ability, I found that personality (no matter how it was represented) did not predict baseball players' hitting or their pitching performances. As my study is one of the first to use such a design and way of measuring performance, it is unclear if my findings represent a true lack of predictive validity for sport performance when so measured. Additional research is needed, using similar designs and objective performance outcomes, to delineate how personality may be related to performance. Such research should be conducted across different sports, lengths of time, and sport levels (e.g., high school, college, professional). Given the potential financial benefit and performance-related outcomes (i.e., winning seasons) of being able to identify athletes who will be successful, and psychological and personality factors likely play a role, sport organizations may want to continue to invest in such research as the payoff may be high.

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