# Concerns and Recommendations for Pain and Masculinity Research using Amazon Mechanical Turk: A Cautionary Tale

by

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**ABSTRACT**

The goal of research is to discover and disseminate truth. The journey toward this goal can be complex as researchers are faced with decisions throughout the research process. In the field of psychology, errors during this process are prevalent which has contributed to the concerning replication crisis and cast doubt on the credibility of psychological research. Amazon's Mechanical Turk (MTurk), a widely used online platform in psychology for collecting data, has contradictory evidence regarding its quality, which may be a significant factor in the propagation of errors. The quality of data collected through MTurk is significantly impacted by the strategies used to screen and clean data. To help researchers produce credible research, a cautionary tale is provided describing the potential consequences of adhering to the current standard of practice when collecting data through MTurk and the importance of examining data quality. The cautionary tale begins with a description of a theoretically grounded study in masculinity and pain that is argued to have compelling implications if examined effectively. The tale takes an unexpected and unfortunate turn as it is found that no matter how compelling or theoretically sound, poor research methods (e.g., data cleaning strategies) or poor-quality data can derail such a study and produce inaccurate results. The tale highlights flaws with the current standard of practice when collecting data through MTurk, analytical tools employed to identify the quality of the data as poor, the flawed results that could have been detected, and the problematic interpretations that might have been disseminated as well as recommendations for future research. The study highlights the complexity of the entire research process and the necessity for rigorous research practices to help ensure the effective discovery and dissemination of the truth in the field of psychology, particularly in masculinity and pain research using MTurk.

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# CHAPTER 1

# INTRODUCTION

The role of researchers is to discover and disseminate truths about the world around them. The journey toward truth is complex, as researchers are required to make decisions throughout the research process (e.g., how to collect data). Although accuracy is essential to discover truth, errors within this complex research process are inevitable (e.g., Bakker & Wicherts., 2011). Identifying and catching these errors are crucial, as issues such as the use of erroneous methods or poor data can affect the entire understanding of a phenomenon (Brown et al., 2018). Errors in research can not only hinder the discovery and dissemination of truth but can also cause harm. For example, in the early 1900s, a study with poor data collection strategies—including population specification error—contributed to the implementation of inappropriate radiation treatment for children to help prevent sudden infant death syndrome, which ultimately facilitated the deaths of over 10,000 children due to thyroid cancer (Ritterman, 2017). Errors in psychological research have been found to be very common (Bakker & Wicherts, 2011; John et al., 2012; Nuijten et al., 2016; Simmons et al., 2011; Stricker, J., & Günther, 2019), with some estimates that over 50% of psychological studies in published academic journals contain statistical errors that could impact their validity (e.g., Bakker & Wicherts, 2011). Nuijten and colleagues (2016) estimated that this percentage is even greater, as many of the studies they examined did not report all of their statistics. The disturbing frequency of errors in psychological research has not only caused potential harm but has contributed to the alarming replication crisis in psychology and questions as to the credibility of psychological research itself (Lilienfeld & Strother, 2020; Simmons et al., 2011; Vazire et al., 2022).

Since their advent, online crowdsourcing platforms, such as Amazon's Mechanical Turk (MTurk), have been widely used in psychological research to collect data as they allow researchers to quickly and cheaply collect large and diverse data sets (e.g., Kennedy et al., 2020). Studies estimate that over 1000 published articles a year utilize MTurk including published studies in top psychology journals, highlighting its substantial use (Bohannon, 2016; Kennedy et al., 2020; Zhou & Fishbach, 2016). MTurk's frequent use is common across psychological topics including in both masculinity and pain research fields. For example, from 2022-2023, 15-22% of published articles in *Psychology of Men & Masculinities,* a top psychology journal, collected data from MTurk (e.g., Thomas & Hart, 2023). Psychological research including in areas of masculinity or pain traditionally drew their samples from college campuses, which resulted in samples primarily comprised of White educated men (Parent et al., 2018; Roberts et al., 2020; Wong et al., 2010; Wong et al., 2017). As masculinity and pain research fields required more diverse samples to explore their research questions, researchers turned more and more to platforms such as MTurk (Alto et al., 2018; Parent et al., 2018; Strickland & Stoops, 2018).

A significant portion of literature supports MTurk's use in research, as it has been identified to provide comparable or higher quality data than that collected from more traditional collection methods (e.g., paper and pen) or compared to student samples, community samples, and some high-quality national samples (Anson, 2018; Buhrmester et al., 2011; Buhrmester et al., 2018; Follmer et al., 2017; Hauser & Schwarz, 2016; Mullinix et al., 2015; Thomas & Clifford, 2017). However, there is also contradictory evidence that draws concerns for the quality of MTurk data including indications of higher rates of inattentive responding (e.g., failing validity checks) from MTurk respondents (Aruguete et al., 2019; Burnette et al., 2022; Chmielewski & Kucker, 2020; Kennedy et al., 2020). These concerns have only increased in the past few years. Given MTurk's high usage in psychology—including in both masculinity and pain research fields—and concerns for the validity of the data collected from it, MTurk could be a large and significant factor contributing to the high publication of errors in psychology.

Most recommendations argue that concerns about collecting quality data through MTurk can be remedied through utilizing data cleaning strategies (e.g., Thomas & Clifford, 2017). These strategies include utilizing screening tools on the MTurk platform such as filtering by location (e.g., United States), paying participants, and filtering by Human Intelligence Task (HIT) approval rate $\geq$ 95% as well as utilizing data cleaning techniques such as removing participants who do not pass multiple validity checks (e.g., attention checks), block respond, and complete the survey in an unreasonably amount of time (Aruguete et al., 2019; Chmielewski & Kucker, 2020; Thomas & Clifford, 2017). The standard practice when collecting data from MTurk is to utilize at least two data cleaning strategies (Aguinis et al., 2021; Ramsey et al., 2016; Thomas & Clifford, 2017) with a majority of studies utilizing MTurk following this standard of practice.

This is true in masculinity (Levant et al., 2022), pain (Himmelstein & Sanchez, 2016), and masculinity and pain (Kolmes & Boerstler, 2020) research where studies in these three fields typically meet this minimum threshold of implementing two strategies. For example, in a study examining masculinity and gender gaps in pain, MTurk participants had to pass only two attention checks to be included in their sample (Kolmes & Boerstler, 2020). There are also more rigorous studies in masculinity research that employed an assortment of strategies (i.e., at least more than two) such as incorporating multiple attention checks, (HIT) approval rate $\geq$ 95%, CAPTCHA questions, open-ended questions, self-assessment of response accuracy, memory questions about a presented vignette, or digital programs to improve data quality through tracking geolocations (Borgogna et al., 2022; Borgogna & McDermott, 2022; Cavalhieri et al., 2022; McDermott et al., 2022; Thomas & Hart, 2023). More rigorous studies in pain research that used MTurk also utilized similar and ulterior strategies including removing participants who inconsistently reported (e.g., reported different ages) and completed their surveys too quickly or took too long (Kim et al., 2022; Mun et al., 2021; Wright & McNeil, 2021). However, some MTurk studies in masculinity (Foster et al., 2022), pain (Bartel et al., 2020), and masculinity and pain (Esiaka et al., 2019) still do not conduct or report data cleaning strategies. This draws into question these studies' findings as data cleaning strategies have been identified to be crucial in protecting against threats to data quality when using MTurk (e.g., Chmielewski & Kucker, 2020). Quality data is also essential in masculinity, pain, or masculinity and pain research where the exploration in these fields is dependent on samples that are accurately representative of specific populations, such as men with chronic pain.

Some researchers argue the standard of practice—implementing at least two data cleaning strategies—is still inadequate given the increased rising rates of poor-quality responses with MTurk (e.g., Burnette et al., 2022; Webb & Tangney, 2022). These researchers suggest that responders are finding effective ways around this standard of practice through the use of bots (i.e., digital code to automatically respond to surveys) or other measures. CAPTCHA questions (i.e., Completely Automated Public Turing Test to tell Computers and Humans Apart) have been recommended as one tool that can help improve the quality of MTurk data as CAPTCHA questions have been found to be effective in identifying and keeping out bots (Hitaj et al., 2020; Yarrish et al., 2019). In CAPTCHA questions, participants are presented with a picture of words or characters, and the respondent has to correctly type out the correct characters in order to proceed. Although most participants find this task very easy, bots have a much more difficult time and can rarely proceed past the question. Although CAPTCHA questions have been recommended and employed, there is still limited research on the quality of MTurk data when CAPTCHA questions in addition to the standard practice of data cleaning are utilized when collecting through MTurk. Most evidence for CAPTCHA's effectiveness in MTurk pertains to responders (e.g., bots) not being able to get past this question and not statistical or psychometric evidence toward the improvement of data quality.

Given the contradictory evidence on the quality of data collected through MTurk, more research is needed on the validity of data collected through MTurk and strategies, such as CAPTCHA questions, to help ensure quality data, which could help reduce the publication of errors in psychology. As masculinity and pain researchers continue to move more toward online platforms such as MTurk to collect more diverse and community samples, it is imperative to continue to examine the effectiveness of data cleaning strategies and the validity of data collected in these research contexts where accurate sample representation of specific populations is essential. To help researchers produce credible research, a cautionary tale is provided describing the potential consequences of adhering to the current standard of practice when collecting data through MTurk, as well as the importance of rigorously examining data quality. This cautionary tale is designed to reflect the research process with each step offering valuable lessons and recommendations for future research. The tale commences with a description of a theoretically grounded study in masculinity and pain, which is argued to hold significant implications if properly investigated.

**Theoretically Grounded Study on Masculine Gender Norms and Opioid Abuse among Men with Chronic Pain**

Chronic pain—pain that recurs or continues for at least three months (ICD-11; World Health Organization, 2020)—is the foremost cause of disability around the world and can lead to a cycle of persistent psychological distress, avoidance of daily activities, and disability (Fricton, 2015; Leeuw et al., 2007). Because chronic pain can have such a profound effect on an individual's life, adults with chronic pain often turn to opioids to take away their pain (e.g., Tsui et al., 2016). This draws concern for its potential abuse, as the ever-tempting desire for the alleviation of pain is reported as a leading cause of opioid abuse (Blanco et al., 2016). Research indicates that adults with chronic pain are more likely to abuse opioids (about 30% of people with chronic pain) compared to the general population (Blanco et al., 2016; Thomas et al., 2015; Tsui et al., 2016; Vowles et al., 2015).

The connection between chronic pain and opioid abuse is extremely worrying given the significant individual (e.g., associated with suicidal ideation) and societal burden (e.g., costs the American healthcare system $8 billion per year) due to opioid abuse (Argento et al., 2018; Leslie et al., 2019; Sampasa-Kanyinga et al., 2021). The problems associated with opioid abuse are only expected to worsen with its anticipated continued increase in the U.S. (Leslie et al., 2019; Florence et al., 2016). Men with chronic pain may be particularly at risk of abusing opioids as they are more likely to get opioids from non-medical sources, consume more opioids than prescribed, consume opioids longer than prescribed, overdose on opioids, and have an opioid use disorder compared to women (American Psychiatric Association, 2013; Hughes et al., 2016; Manubay et al., 2015; Wibbenmeyer et al., 2015). Given the significant personal and societal burden of both chronic pain and opioid abuse, identifying the risk of opioid abuse in men with chronic pain may help to diminish the ramifications linked with opioid abuse in this population (Akbik et al., 2006; Koyyalagunta et al., 2013; Rhodes et al., 2021).

**Social Cognitive Theory**

According to Social Cognitive Theory (SCT; Bandura, 1986), one of the most frequently used theories in the management of chronic pain (Painter et al., 2008; Tougas et al., 2015), behaviors such as the engagement in opioid abuse stem from their dynamic and reciprocal interaction with psychological and social factors (Schiavo et al., 2019). This dynamic interaction is referred to as triadic reciprocality or reciprocal determination, where one's social environment influences psychological features (e.g., thoughts and feelings) and in turn, shapes their behaviors and vice versa (Schiavo et al., 2019). For example, if an adult's family attends their doctor's appointments (i.e., social impact), the person may feel thankful for their support (i.e., psychological impact) and ultimately be more likely to adhere to medical treatments (i.e., behavioral impact) as they want to make their family proud or feel more confident given their social support.

SCT indicates that psychological and social factors can impact the engagement in opioid abuse and could therefore help inform men's risk of abusing opioids. The impact of chronic pain also highlights the importance of psychological and social factors as it is a multidimensional health concern that affects an individual's physical, psychological, and social functioning (Dekker et al., 2020; Wideman et al., 2013), thus further underscoring the need to consider these factors within the context of chronic pain and opioid abuse. Both chronic pain and opioid abuse are also unique and subjective experiences that vary greatly from person to person depending on these biopsychosocial factors (Gatchel et al., 2007; Jones et al., 2017). However, chronic pain and opioid research have historically concentrated on biological factors, while psychological and social dimensions have been comparatively overlooked (Bartley & Fillingim, 2013; Edwards et al., 2016; Hruschak & Cochran, 2018). These biologically concentrated findings are frequently mixed, and research has found psychosocial variables to be prominent factors contributing to problematic outcomes from chronic pain (Edwards et al., 2016; Keogh, 2021; Sullivan et al., 2008). The underrepresentation of psychological and social dimensions represents a significant dearth in the chronic pain literature. This has led to repeated calls by researchers and clinicians to examine psychological and social variables in chronic pain literature so experiences of people with chronic pain can be better understood and chronic pain more effectively managed such as by identifying who may be at a greater risk of abusing opioids (Crombez et al., 2012; Edwards et al., 2016; Hruschak & Cochran, 2018; Wager et al., 2020).

**Pain Self-Efficacy**

One fundamental psychological element in SCT is pain self-efficacy or one's perceived confidence in their ability to function effectively while in pain (Damush et al., 2016; Nicholas, 2007). Pain self-efficacy has continually been identified in research as a vital for toward coping with pain and influencing health behaviors (Damush et al., 2016; Jackson et al., 2002; Nicholas, 2007). Self-efficacy beliefs are argued to impact health behaviors such as opioid abuse because they can "determine how much effort people will expend and how long they will persist in the face of obstacles and aversive experiences" such as during pain (Bandura 1977, p 194). If an individual has greater confidence in their ability to function while in pain, they are more likely to engage in behaviors necessary for the treatment and management of their pain. In contrast, those who doubt their abilities to function effectively while in pain (i.e., lower pain self-efficacy) are more likely to give up or avoid engaging in necessary pain management strategies, as they expect to fail at them. Indeed, empirical evidence indicates that higher pain self-efficacy is associated with numerous preferred chronic pain outcomes including reduced pain disability, increased pain acceptance, more engagement in coping strategies, and greater overall well-being (Elander et al., 2014; Huang et al., 2021; Jalali et al., 2019; Tougas et al., 2015). Evidence from interventions targeting self-efficacy has also indicated health benefits and reductions in the engagement in unhealthy behaviors in individuals with chronic pain (Allison & Keller, 2004; Nezami et al., 2016; Tougas et al., 2015; Xu et al., 2018). Thus, according to SCT and research, pain self-efficacy is a vital psychological resource that can influence health behaviors such as men with chronic pain engaging in opioid abuse, and this association will be examined in the present study.

Research supports the potential association between pain self-efficacy and a man's risk of abusing opioids, with lower pain self-efficacy being linked with worse pain control, greater pain intensity, lower satisfaction with care, greater pain medication dependence, and increased pain medication use (Bot et al., 2014; Elander et al., 2014; Nicholas, 2007; Nota et al., 2015). These links suggest that lower pain self-efficacy would be associated with a greater risk of abusing opioids. However, the specific association between pain self-efficacy and the risk of abusing opioids has yet to be examined. Exploring this relationship may inform interventions aimed at reducing opioid abuse such as suggesting that improving pain self-efficacy could help decrease the risk of abusing opioids.

**Masculine Gender Norms and Pain Self-Efficacy**

SCT postulates that pain self-efficacy is better understood in combination with social factors, given their reciprocal relationship (Bandura, 1989). For instance, a societal expectation that men are supposed to be self-reliant may negatively impact a man's confidence toward seeking help for his pain (i.e., pain self-efficacy)—as he should be able to handle it on his own.

This in turn influences subsequent behaviors such as opioid abuse—as he feels he needs to obtain opioids from illicit sources.

According to SCT, one's gender (i.e., personal inputs) can influence their environment through social persuasion (e.g., gender norms) which are a direct source of self-efficacy beliefs (Lent et al., 2002). Social persuasion is societal messages that are comminuted, modeled, received, and adopted, which can convince individuals of their capabilities in certain situations, such as when they are in pain (Lent et al., 2002; Lent et al., 2017). A primary and extremely salient source of social persuasion (e.g., social encouragement or discouragement) for men is masculine gender norms. Masculine gender norms often attempt to persuade men to behave, think, and feel a particular way (Mahalik et al., 2003). Thus, men are confronted with social persuasion (e.g., a father saying "Men don't cry") or norms, influenced by their gender, where they learn how society wants them to behave in specific situations, which can ultimately shape their confidence in their abilities (i.e., self-efficacy) when they are in pain.

Research supports the relation between one's gender and social persuasion in numerous domains including one's career, academics, relationships, and health (Huang, 2013; Lent et al., 2002; Mansyur et al., 2016; Tokar et al., 2007; Williams & Subich, 2006). This is true in healthcare settings where empirical evidence indicates that male patients receive societal messages characterized by masculine gender norms (Griffith et al., 2016; Philbin et al., 2018). Masculine gender norms' influence on men's self-efficacy beliefs has particularly been accentuated in career-related research where men frequently report greater social persuasion toward traditionally masculine career domains (e.g., realistic, investigative, and enterprising careers; Hackett & Betz, 1981; Tokar et al., 2007; Williams & Subich, 2006), as society persuades men toward what they are supposed to do. For example, studies indicate that teachers often provide greater attention, affirmation, and opportunities to boys in traditionally male subjects (e.g., math) and men's families often discourage them from entering traditionally female-dominated professions like nursing (Bassi et al., 2018; Rochlen et al., 2009). These messages (i.e., masculine gender norms) can become adopted or internalized and consequently persuade their confidence in completing tasks (i.e., self-efficacy). This is highlighted in the literature where men are linked with greater self-efficacy surrounding traditionally masculine career domains and school subjects (Hackett & Betz, 1981; Tokar et al., 2007; Williams & Subich, 2006), as they are encouraged and fostered by society in these areas.

Although career-related literature has stressed the influence of masculine gender norms on men's self-efficacy, existing pain-related research on this subject is scarce. One study conducted by Vierhaus and colleagues (2011) found that overall adherence to traditional masculine norms was positively associated with pain self-efficacy. However, this study only examined this relation in children and adolescents in the general population. SCT and research underscore the need for the consideration of masculine gender norms in a conceptual model examining the influence of pain self-efficacy's role in the risk of men with chronic pain abusing opioids.

The relation between masculine gender norms and pain self-efficacy beliefs could also be shaped through men's learning experiences. Learning experiences mold an individual's confidence in their ability to do future tasks (i.e., self-efficacy beliefs) because they can provide evidence of one's level of ability and sculpt their expected future outcomes (Lent et al., 2002). For example, if pain interferes with a man's task at work, this may contribute to lower pain self-efficacy as they expect to be hindered from performing similar tasks in the future. Masculine gender norms have also been identified to impact men's learning experiences as gender norms can provide and hinder opportunities for learning experiences (Huang, 2013; Lent et al., 2002; Mansyur et al., 2016; Tokar et al., 2007; Williams & Subich, 2006). For instance, men with chronic pain are less likely to be referred to psychosocial treatments compared to women, as men's pain is seen as less severe or urgent, thus men may not be provided with the learning opportunities from psychosocial treatments (Bernardes & Lima, 2011; Hirsh et al., 2014).

The impact of masculine gender norms on self-efficacy may also be influenced by childhood family experiences and relationships with parents, as these environmental factors have been found to produce salient learning experiences surrounding gender norms and self-efficacy beliefs (e.g., Denollet et al., 2007). Families and parents have been found to provide pivotal roles in the instruction of appropriate gender-typed behavior (Denollet et al., 2007; Kocak et al., 2019; Kocak et al., 2022; McHale et al., 2003). This information and instruction can be impacted by the parent's gender role beliefs, as there are links between parents' gender role beliefs and their children's beliefs (Halpern & Perry-Jenkins, 2016; McHale et al., 2003). Subpar family functioning or poor relationships with parents during childhood can interfere with this process as well as one's beliefs of their capabilities (i.e., self-efficacy; McHale et al., 2003; Kocak et al., 2019). Families and parents also often reinforce and challenge gender norms which impact one's self-efficacy beliefs across domains accordingly. For example, in a society that encourages men to control their emotions, a man who consistently witnessed their family or parents punish for emotional expression may develop lower self-efficacy beliefs about their abilities to seek help or communicate, even when in pain. Thus, research suggests the impact of gender norms on self-efficacy can be influenced by the nature of childhood family experiences, and relationships with parents and examining these relations could be useful.

Masculine gender norms are socially accepted standards and expectations based upon group membership that encourage and discourage behavior (Mahalik et al., 2003). These specific masculine norms are learned, taught, communicated, and observed through social interactions (Bradstreet & Parent, 2018; Mahalik et al., 2005). As a result, men learn at an early age what is socially expected of them while living their gendered lives in given situations, such as when they are in pain. Evidence from reviews of the literature and focus groups have identified several specific masculine norms that signal to men that they are supposed to be self-reliant (i.e., self-reliance), take risks (i.e., risk-taking), control their emotions (i.e., emotional control), want to win (i.e., winning), be tough and respond with violence (i.e., violence), have many non-committed sexual relationships (i.e., playboy), view that men should be in charge (i.e., power over women), present themselves as heterosexual (i.e., heterosexual self-presentation), and view work as a major focus of their life (Parent & Moradi, 2009). After men understand what society expects of them, they may choose to conform or not to conform to these specific masculine norms (Mahalik et al., 2003). Men's overall conformity to masculine norms (i.e., conformity to all masculine gender norms) is argued to be on a continuum, as men can adhere to or not adhere to different specific masculine norms. For example, a man may conform to self-reliance but not conform to risk taking. Conformity to specific masculine norms is also posited to be on a continuum as an individual may or may not conform to affective (e.g., feeling proud when conforming), behavioral (e.g., acting in ways to meet masculine gender norms), and cognitive dimensions (e.g., not believing those things that men are expected to believe) of specific masculine gender roles (Mahalik et al., 2003; Parent & Moradi, 2009; Nielson et al., 2020). Thus, one man may behave in unison with a specific masculine gender norm but not conform cognitively or affectively to it. Conformity is also not simply dichotomous (i.e., conform or not conform) as a man can conform to masculine gender norms some of the time while not conforming at other times.

The presence of many specific masculine gender norms and their conformity on a continuum represents the complexity and variability in men's conformity to gender norms. A man's conformity to masculine gender norms is also argued to be a very unique and personal experience (Mahalik, 2000). Indeed, a man's level of adherence to masculine gender norms has been found to be a core part of his identity (Mahalik et al, 2005). Yet, health research has predominately viewed and examined men's conformity to masculine norms as a unitary construct (i.e., examining total conformity) and focused on the group level, assuming that men have homogeneous levels of masculine gender norms (e.g., Gerdes & Levant, 2018). In doing so, this overlooks the variability in adherence between specific masculine norms and diminishes capturing its unique personal importance (Bradstreet & Parent, 2018; Gerdes & Levant, 2018; Levant & Wimer, 2014). Research also indicates that specific masculine gender norms can be even better predictors of psychological resources and health-related behaviors (e.g., alcohol use) compared to overall conformity to masculine gender norms, further representing the need to examine specific masculine gender norms (Bradstreet & Parent, 2018; Iwamoto et al., 2011; Parent et al., 2012; Wimer & Levant, 2013). Some research does not even support the existence of a measurable unitary conformity to masculinity construct (Hammer et al., 2018). Variability also exists between specific masculine gender norms and their relation to health-related outcomes, as conformity to some masculine norms may be problematic while conformity to others may be adaptive.

A person-centered approach could better capture the complex and deeply personal experience of a man's conformity to masculine norms by revealing meaningful subgroups of men with shared conformity to masculine norms characteristics (Muthén & Asparouhov, 2002). A person-centered approach would also follow the literature's indication that heterogeneity exists within men's conformity and different subgroups of men can be identified. This approach can help inform if men's risk of opioid abuse varies across groups of men with chronic pain and as a function of specific masculine gender norm qualities. Latent class analysis (LCA), a person-centered analytical approach, can be applied to capture within-group variation in men by clustering them into distinct groups by their unique conformity characteristics (Grant et al., 2020). Thus, the present study will utilize LCA to examine men's conformity to masculine norms so different latent groups of men with chronic pain can be identified. Once groups are identified, the relations between latent conformity to masculine gender norm groups, pain self-efficacy, and risk of opioid abuse can be examined within a model.

**Masculine Gender Norms and Risk of Abusing Opioids**

Traditional masculine norms have been found to be associated with pain-related outcomes and influence pain-related behaviors. Studies predominantly indicate that increased conformity to masculine norms is associated with negative health outcomes (Gerdes & Levant, 2018). For example, men's overall conformity to masculine norms has been found to be positively associated with the engagement in unhealthy behaviors, under reporting pain symptoms, substance use, and poorer physical health (Bradstreet & Parent, 2018; Daheim et al., 2020; Iwamoto & Smiler, 2013; Yousaf et al., 2015). Masculine norms have also been reported to be a barrier to men seeking medical help and contribute to lower rates of seeking medical care in men experiencing pain (Yousaf et al., 2015). However, there is limited research on masculine norms' association with men's risk of abusing opioids. To date, only two studies have examined and found masculine gender norms to be related with pain medication outcomes in men with chronic pain (Daheim et al., 2020; Daheim & Kim, 2023). Their findings indicated that greater endorsement of traditional domestic gender role beliefs and overall masculine norms were associated with an increased risk of abusing opioids and greater pain medication consumption. However, these studies examined masculine gender norms as a unitary construct and did not look at specific masculine norms, overlooking the person-centered approach warranted to better capture the complexity and variability within conformity to masculine norms. The present study will utilize LCA to predict meaningful subgroups of men with chronic pain based on masculine gender norms and their relation to the risk of opioid abuse.

The specific masculine gender norms of emotional control, risk-taking, self-reliance, winning, violence, playboy, power over women, heterosexual self-presentation, and primacy of work have all been found to be salient in health and substance use research with studies primarily indicating positive associations with substance use (e.g., alcohol abuse) and engagement in unhealthy behaviors (Bradstreet & Parent, 2018; Gerdes & Levant, 2018; Locke & Mahalik, 2005; Liu & Iwamoto, 2007). Mixed results are also present with some studies indicating non-significant associations (e.g., Gerdes & Levant, 2018) and contradictory findings such as links between winning and avoidance of substance use (Levant et al., 2011), emotional control and less alcohol use (Liu & Iwamoto, 2007), heterosexual self-presentation and reduced cigarette use (Sánchez-López et al., 2012), and violence and fewer overall medication consumption (Limiñana-Gras et al., 2013). Researchers have not examined these specific masculine norms in relation to opioid outcomes or a man's risk of abusing opioids. The mixed findings among these specific masculine norms, substance use tendencies, and health behaviors further indicate the importance of utilizing LCA to identify different latent conformity to masculine norm groups and their association with men's risk of abusing opioids, as groups with varying conformity (e.g., high and low to different norms) may be linked with a greater risk of opioid abuse. Following research's assertions, emotional control, risk-taking, self-reliance, winning, violence, playboy, power over women, heterosexual self-presentation, and primacy of work are specific masculine gender norms that would be useful to examine in relation to men's risk of abusing opioids within a LCA (Gerdes & Levant, 2018; Parent & Moradi, 2009).

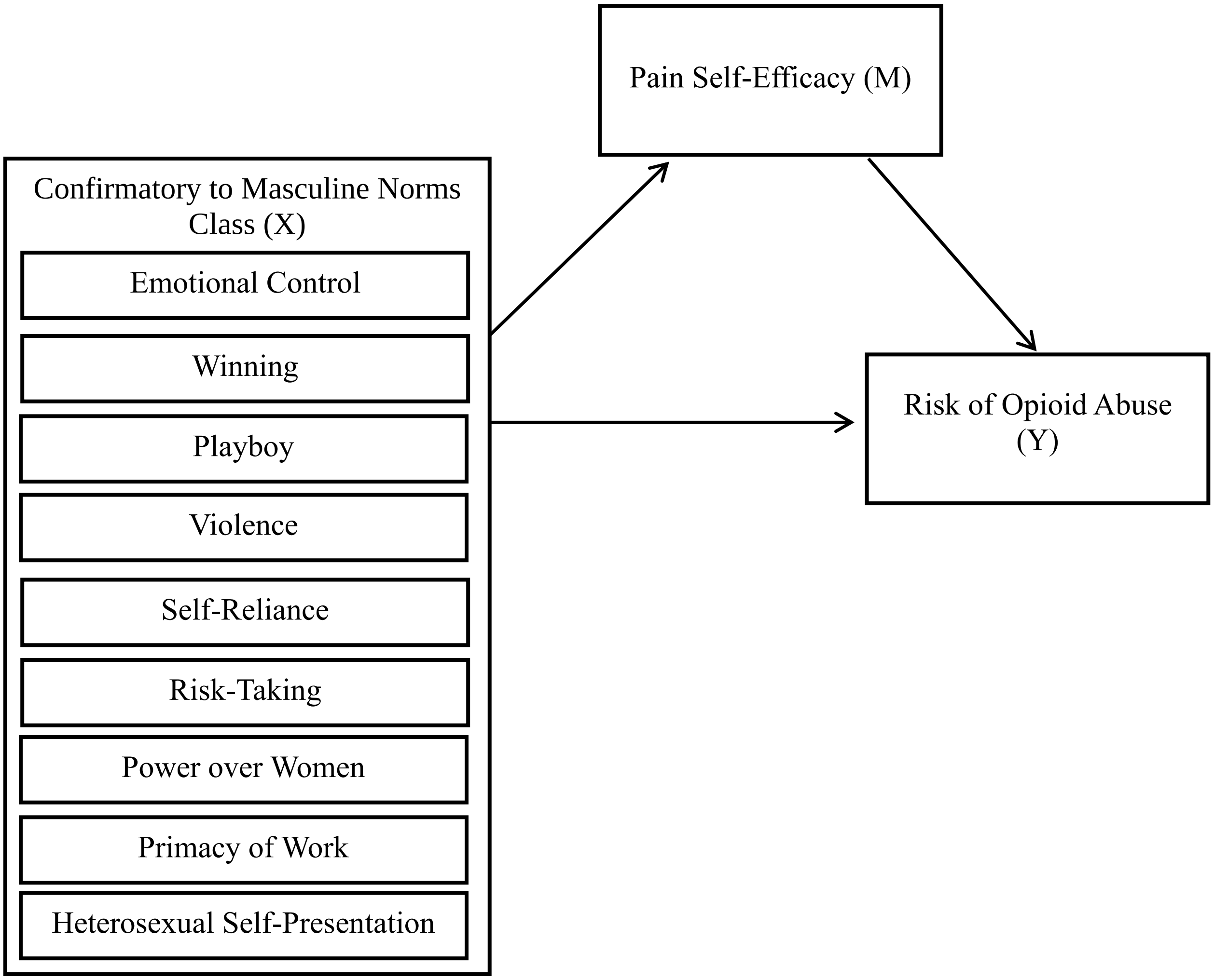
Studies utilizing LCA and latent profile analysis have identified a range of distinct masculinity groups, representing the variability in men's conformity to masculine norms (e.g., Padgett, 2017). These latent groups predominantly include groups characterized by (1) generally elevated masculinity scores, (2) mostly low masculinity scores, and (3) groups with variability between masculine norms (Casey et al., 2016; Greene & Davis, 2011; Jewkes & Morrell, 2018; McDermott & Schwartz, 2013; Padgett, 2017; Wong et al., 2012). The identified number of groups ranged from two to five, with most studies identifying three classes (e.g., Casey et al., 2016). It is expected in the present study that multiple latent conformity to masculine norm groups will exist with at least one latent group characterized by generally elevated conformity across all specific norms and another group exemplified by mostly lower conformity across all specific norms. It is noteworthy that most studies examining LCA and masculinity did not utilize commonly used masculinity measures (e.g., Adolescent Masculinity Ideology in Relationships Scale) and have not examined classes within chronic pain adults (e.g., Padgett, 2017). This signifies a notable gap within the literature as different latent conformity to masculine norm groups may exist in men with chronic pain, given pain's unique and difficult experience.

**The Study on Masculine Gender Norms and Opioid Abuse**

Given the significant personal and societal burden of both chronic pain and opioid abuse in men, the aim of the present study is to examine which men with chronic pain may be at a greater risk of abusing opioids through exploring the heterogeneity of conformity to masculine gender norms using a definite number of discrete disposition classes. Specifically, these latent conformity to masculine norm classes and pain self-efficacy will be assessed as potential predictors of the risk of opioid abuse in men with chronic pain. Men's conformity to masculine gender norms has been identified to establish early and remain relatively stable across time (Mahalik et al, 2005). Following SCT's assertions, conformity to masculine gender norms facilitates and deters learning opportunities, which are direct sources of self-efficacy beliefs (Lent et al., 2002). Then, in a model containing conformity to masculine norms, pain self-efficacy, and risk of opioid abuse, it is expected that conformity to masculine gender norms would be primal in influencing the other relations. In other words, conformity to masculine norms may influence a man's confidence in his ability to perform activities while in pain (i.e., pain self-efficacy) and subsequently his risk of engaging in abusing opioids, suggesting a mediated relation. Therefore, the present study will explore a mediation model in which pain self-efficacy mediates the relation between conformity to masculine norm classes and the risk of opioid abuse (see Figure 1). Empirical evidence suggests that age and socioeconomic status can be significant factors leading to variance in pain-related and opioid use outcomes (Daheim et al., 2020; Dahlhamer et al., 2018; Karp et al., 2013). Thus, age and socioeconomic status will be examined as covariates.

**Figure 1**

*Proposed Mediation Model with 9-Factor CMNI Class*

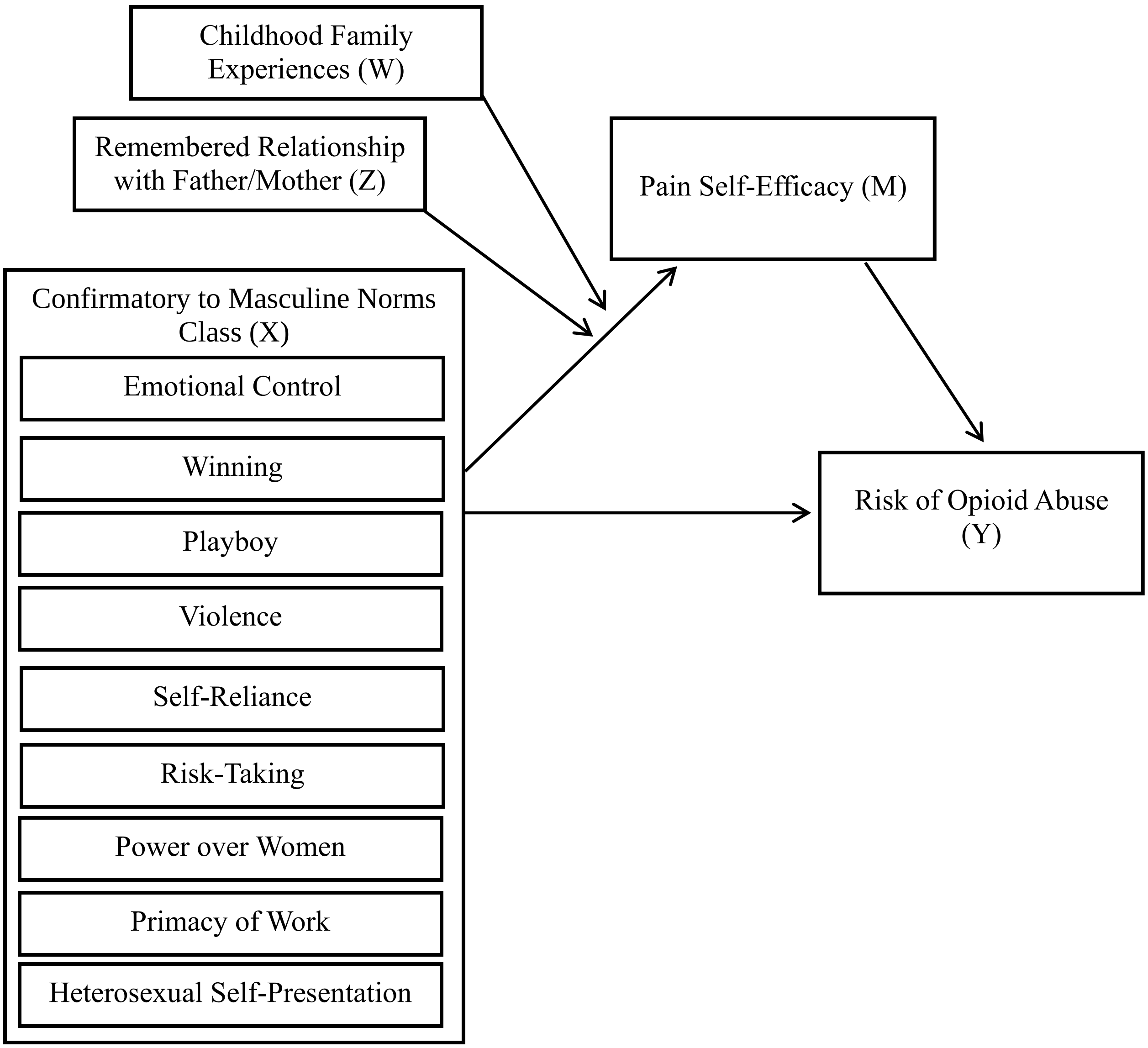



Provided that conformity to masculine gender norms is very complex, unique, and a personal experience, a person-centered approach utilizing LCA will be employed. Thus, within the proposed model, the first aim of the study is to identify different latent groups of men with chronic pain based on specific gender norms (i.e., emotional control, winning, self-reliance, risk taking, violence, playboy, power over women, heterosexual self-presentation, and primacy of work). After latent conformity to masculine norms classes are identified, the second aim of the study is to examine relations between these classes, pain self-efficacy, and risk of opioid abuse.

The third aim of the study is to conduct post hoc analyses examining the role of early childhood experiences and previous relationships with parents (e.g., mothers and fathers) in the proposed mediation model. Research indicates that the learning experience from one's family and parents during childhood may play a role in the relation between masculine gender norms and pain self-efficacy (e.g., McHale et al., 2003), demonstrating them as a noteworthy post hoc examination. Therefore, early childhood experiences and remembered relations with parents will be examined as moderators in the mediated relation (in the *a* pathway) between CMNI classes and the risk of opioid abuse through pain self-efficacy (see Figure 2).

**Figure 2**

*Moderated Mediation Model with 9-Factor CMNI Class*




## Implications

Model relations can reveal what subpopulations of men may be at a greater risk of abusing opioids. Healthcare providers can use this information to identify men who could benefit from preventive interventions for opioid abuse. Providers can tailor interventions toward at-risk men to help reduce their likelihood of abusing opioids through such intervention methods as targeting pain self-efficacy enhancement, while simultaneously minimizing unnecessary attention on men who do not require such support (Huang et al., 2021). Thus, the present study could facilitate the development of cost-effective targeted intervention strategies by distinguishing among men with chronic pain (Mangoni & Woodman, 2019). These findings could also help the implementation of person-centered care (PCC), often considered the gold standard of health-related treatment given its identified efficiency and effectiveness (Love & Pinkowitz, 2013; Yang et al., 2019). The focus of PCC is on high-quality and personalized care of the patient, where the patient's unique health needs and desires drive treatment (Santana et al., 2018). By identifying men with chronic pain into different conformity to masculine norms groups, patients' unique characteristics and subsequent needs are considered, facilitating the implementation of personalized interventions (Yang et al., 2019). Interventions could target specific masculine gender norms (e.g., self-reliance) or self-efficacy depending on an individual's group to help reduce the likelihood of them abusing opioids. Evidence-based treatments (e.g., cognitive-behavioral therapy) and social programs have proven efficacious in influencing changes in masculinity over time (Levy et al., 2020; Neilson et al., 2020; Scheinfeld et al., 2017). Identifying subgroups of men could help healthcare providers with treatment planning such as exploring alternative treatment methods besides prescribing opioids to subgroups of men who are at a greater risk of abusing opioids.

**Cautionary Tale**

The present study offers a theoretically sound study in masculinity and pain with compelling implications. It is crucial to acknowledge that even the most well-conceived studies can falter due to poor research methods or low-quality data. When left undetected, substandard data may yield inaccurate results, misguided interpretations, inappropriate recommendations, and potential harm. The following methods and results detail a cautionary tale that illustrates the process of the examination of the quality of the data in the present study, which ultimately prevented the dissemination of questionable research. By learning from this cautionary tale and incorporating recommendations derived from it, future researchers can work towards ensuring the discovery of truth and curbing the spread of flawed research.

# CHAPTER II

# METHOD

## Participants

The present study consisted of 672 men with chronic pain. Their ages ranged from 20 to 82 (*M* = 35.63, SD = 9.58). Other demographic information can be found in Table 1 and health related information in Table 2. Data was collected from Amazon's Mechanical Turk (MTurk; https://www.mturk.com), an online platform for crowdsourcing that is frequently used in the psychological sciences (e.g., Weigold & Weigold, 2021). Empirical evidence has indicated that MTurk is a valid and reliable method through which to collect data (Anson, 2018; Buhrmester et al., 2011; Buhrmester et al., 2018; Follmer et al., 2017; Mullinix et al., 2015; Thomas & Clifford, 2017).

**Table 1**

*Demographic Information of Study's Sample (N = 672), 2-Factor Class 1 (n = 569), 2-Factor Class 2 (n = 103), 9-Factor Class 1 (n = 557), 9-Factor Class 2 (n = 115)*

| | % (*N*) | 2-Factor Class 1 | 2-Factor Class 2 | 9-Factor Class 1 | 9-Factor Class 2 |
|---|---|---|---|---|---|
| Ethnicity | | | | | |
| African/African American/Black | 10 (70) | 11 (63) | 7 (7) | 10 (58) | 11 (12) |
| American Indian/Native American | 3 (18) | 2 (13) | 5 (5) | 3 (16) | 2 (2) |
| Arab American/Middle Eastern | 0.1 (1) | 0 (0) | 1 (1) | 0.2 (1) | 0 (0) |
| Asian/Asian American | 1 (9) | 1 (7) | 2 (2) | 1 (6) | 3 (3) |
| Caucasian/European American/White | 79 (532) | 80 (456) | 74 (76) | 80 (447) | 77 (85) |
| Hispanic/Latina/o American | 6 (39) | 5 (28) | 11 (11) | 6 (31) | 7 (8) |
| Pacific Islander/Pacific Islander American | 0.1 (1) | 0 (0) | 1 (1) | 0 (0) | 0.9 (1) |
| Other | 0.3 (2) | 0.4 (2) | 0 (0) | 0.4 (2) | 0 (0) |
| Relationship Status | | | | | |
| Single | 10 (70) | 9 (53) | 17 (17) | 10 (55) | 14 (15) |
| Dating, casual | 6 (38) | 5 (26) | 2 (2) | 4 (23) | 5 (6) |
| Dating, long term | 4 (27) | 2 (10) | 7 (7) | 1 (6) | 10 (11) |
| Domestic (living together) partnership | 5 (31) | 3 (19) | 7 (7) | 3 (18) | 7 (8) |
| Married or Civil Union | 73 (494) | 75 (425) | 67 (69) | 76 (424) | 63 (70) |
| Polyamorous | 1.5 (6) | 0.9 (5) | 1 (1) | 0.9 (5) | 0.9 (1) |
| Other | 0.1 (1) | 0 (0) | 0 (0) | 0.2 (1) | 0 (0) |
| Education | | | | | |
| Some high school or less | 0.3 (2) | 0.2 (1) | 1 (1) | 0.2 (1) | 0.9 (1) |
| High School Diploma | 2 (12) | 2 (11) | 1 (1) | 1 (8) | 4 (4) |
| Some College | 2 (15) | 1 (6) | 9 (9) | 1 (7) | 7 (8) |
| Two year college degree (e.g., AA) | 0.9 (6) | 0.4 (2) | 4 (4) | 0.4 (2) | 4 (4) |
| Bachelor's degree (e.g., BS, BA) | 72 (483) | 74 (420) | 61 (63) | 74 (414) | 62 (69) |
| Some postgraduate work | 2 (15) | 2 (13) | 2 (2) | 2 (11) | 4 (4) |
| Postgraduate Degree (e.g., PhD) | 20 (136) | 20 (113) | 22 (23) | 20 (115) | 19 (21) |
| Employment Status | | | | | |
| Full-time | 96 (650) | 97 (551) | 96 (99) | 97 (543) | 96 (107) |
| Part-time | 2 (11) | 2 (9) | 2 (2) | 2 (9) | 2 (2) |
| Unemployed | 0.6 (4) | 0.5 (3) | 1 (1) | 0.4 (2) | 2 (2) |
| Social Class | | | | | |
| Upper Class | 8 (52) | 9 (50) | 2 (2) | 8 (47) | 5 (5) |
| Upper-Middle Class | 27 (183) | 26 (149) | 33 (34) | 26 (148) | 32 (35) |
| Middle Class | 49 (327) | 49 (278) | 48 (49) | 51 (285) | 38 (42) |
| Working Class | 15 (99) | 14 (82) | 17 (17) | 13 (73) | 23 (26) |
| Living in Poverty | 0.4 (3) | 0.4 (2) | 1 (1) | 0 (0) | 3 (3) |
| Environment | | | | | |
| Urban | 63 (425) | 63 (361) | 62 (64) | 65 (364) | 55 (61) |
| Suburban | 24 (160) | 23 (130) | 29 (30) | 22 (122) | 34 (38) |
| Rural | 11 (77) | 12 (68) | 9 (9) | 12 (65) | 111 (12) |

*Note*. Some percentages may not add up to 100%, as all participants did not answer all the demographics questions.

**Table 2**

*Health Related Information of Study's Sample (N = 672), 2-Factor Class 1 (n = 569), 2-Factor Class 2 (n = 103), 9-Factor Class 1 (n = 557), 9-Factor Class 2 (n = 115)*

| Questions & Responses | % (*n*) | 2-Factor Class 1 | 2-Factor Class 2 | 9-Factor Class 1 | 9-Factor Class 2 |
|---|---|---|---|---|---|
| Over the counter painkiller use within last month | | | | | |
| Yes | 60 (400) | 39 (221) | 50 (51) | 38 (213) | 53 (59) |
| No | 40 (272) | 61 (348) | 50 (52) | 62 (348) | 47 (52) |
| Frequency of over the counter painkiller use within last month | | | | | |
| Once or twice | 6 (39) | 6 (34) | 5 (5) | 6 (33) | 5 (6) |
| About once a week | 14 (94) | 14 (78) | 16 (16) | 14 (80) | 13 (14) |
| More than once a week | 15 (100) | 14 (81) | 18 (19) | 13 (73) | 23 (26) |
| Almost every day | 4 (28) | 4 (22) | 6 (6) | 3 (19) | 8 (9) |
| Every day | 2 (11) | 1 (6) | 5 (5) | 1 (7) | 4 (4) |
| Prescription painkiller use with last month | | | | | |
| Yes, they were prescribed | 40 (272) | 41 (232) | 39 (40) | 41 (229) | 43 (48) |
| Yes, they were obtained from another method | 6 (39) | 7 (37) | 5 (5) | 6 (36) | 3 (3) |
| No | 52 (351) | 52 (298) | 56 (58) | 52 (292) | 53 (59) |
| Frequency of prescription painkiller use within last month | | | | | |
| Once or twice | 7 (46) | 7 (38) | 8 (8) | 6 (36) | 9 (10) |
| About once a week | 16 (107) | 17 (95) | 12 (12) | 18 (99) | 7 (8) |
| More than once a week | 18 (120) | 18 (103) | 17 (17) | 17 (96) | 22 (24) |
| Almost every day | 5 (37) | 5 (31) | 6 (6) | 5 (29) | 7 (8) |
| Every day | 1.5 (10) | 1 (6) | 4 (4) | 1 (8) | 2 (2) |
| Consumed more than recommended dose of prescription painkillers | | | | | |
| Never | 4 (27) | 3 (19) | 8 (8) | 3 (17) | 9 (10) |
| Sometimes | 29 (196) | 30 (169) | 26 (27) | 30 (171) | 23 (25) |
| Usually | 10 (70) | 11 (62) | 8 (8) | 10 (56) | 13 (14) |
| Always | 4 (24) | 4 (20) | 4 (4) | 4 (21) | 3 (3) |
| Taken prescription painkillers for longer than recommended | | | | | |
| Never | 4 (28) | 3 (19) | 9 (9) | 3 (19) | 8 (9) |
| Sometimes | 24 (162) | 24 (139) | 22 (23) | 24 (136) | 23 (26) |
| Usually | 15 (100) | 16 (89) | 11 (11) | 16 (89) | 10 (11) |
| Always | 4 (28) | 4 (24) | 4 (4) | 4 (22) | 5 (6) |
| Consumption of prescription painkillers obtained from other than your physician in the last month | | | | | |
| Once or twice | 6 (41) | 5 (30) | 5 (5) | 4 (24) | 15 (17) |
| About once a week | 16 (105) | 15 (87) | 16 (16) | 16 (90) | 14 (15) |
| More than once a week | 17 (113) | 18 (103) | 12 (12) | 18 (99) | 13 (14) |
| Almost every day | 6 (41) | 7 (39) | 4 (4) | 7 (39) | 2 (2) |
| Every day | 3 (17) | 2 (13) | 4 (4) | 2 (14) | 3 (3) |
| Visited physician doctor for pain within the last month | | | | | |
| Yes | 77 (516) | 81 (458) | 56 (58) | 81 (454) | 56 (62) |
| No | 23 (153) | 19 (109) | 43 (44) | 19 (105) | 43 (48) |
| Chronic health issues | | | | | |
| Yes | 39 (261) | 39 (220) | 40 (41) | 39 (217) | 39 (44) |
| No | 61 (407) | 61 (345) | 60 (62) | 61 (340) | 60 (67) |

*Note*. All participants met chronic pain criteria which included: (1) having chronic pain, (2) having pain for four or more days per week, (3) experiencing pain beginning three or more months ago, and (4) the usual intensity of the pain in the past week being a four or greater on a scale ranging from 0 (No pain) to 10 (Worst pain possible). Percentages may not add up to 100%, as all participants did not answer all the health-related questions.

For participants to be included in the study, participants had to be 18 years of age or older, self-report as male, be from the United States, have a Human Intelligence Task (HIT) approval rate > 95%, meet chronic pain criteria, and pass several response validity indicators. To meet chronic pain criteria, participants had to report (1) having chronic pain, (2) having pain for four or more days per week, (3) experiencing pain beginning three or more months ago, and (4) the usual intensity of the pain in the past week being a four or greater on a scale ranging from 0 (*No pain*) to 10 (*Worst pain possible*). Chronic pain criteria are consistent with the definition of chronic pain in the *International Statistical Classification of Diseases and Related Health Problems* (ICD-11; World Health Organization, 2020) and derive from previous MTurk studies examining chronic pain populations (e.g., Daheim & Kim, 2021; Paulus et al., 2019).

Exceeding the standard of practice to help safeguard data quality while using MTurk (e.g., Chmielewski & Kucker, 2020), participants needed to correctly pass several response validity indicators including (1) two attention checks, (2) one marker of inconsistent reporting, (3) two CAPTCHA questions, (4) not block respond, and (5) complete the survey in an appropriate amount of time. The standard of practice recommends including at least two validity indicators (Aguinis et al., 2021; Ramsey et al., 2016; Thomas & Clifford, 2017), which was exceeded in the present study in an attempt to be rigorous in safeguarding quality data. Attention checks consisted of questions asking participants to either select a specific response (i.e., “For this item, please select "Strongly Agree"”) or not answer a question (i.e., “If you’re paying attention to this question, please do not select any answer choices and proceed to the next question.”). The marker of inconsistent reporting in the survey comprised of participants being asked to report their age on two separate occasions. Incorrectly answering attention checks and/or inconsistently reporting (e.g., reporting different ages) has been found to indicate potential inattentive responders or “bot” use (i.e., computer programs that automatically complete surveys) and can reduce the quality of the data (Chmielewski & Kucker, 2020; Lu et al., 2022). To facilitate quality data, participants who reported inconsistently (i.e., failed to consistently report their age), did not answer all attention checks correctly, did not pass CAPTCHA questions, block responded (e.g., “Strongly agree” for all items throughout the survey), or completed the survey in an unreasonable amount of time were flagged and not included in the final sample for analysis.

A total of 3029 participants were collected from MTurk. Following the above criteria, participants were removed from the final sample in the corresponding order: 707 participants were removed for reporting previously taking the MTurk study, 326 were removed for reporting any other gender besides male, 237 were removed for reporting not having chronic or persistent pain, 522 were removed for reporting pain lasting 3 months or less, 3 were removed for reporting not being 18 years of age or older, and 11 were removed for not consenting to participate. Of the remaining 1223 participants, 363 participants were removed for failing to pass one or more of the response validity indicators including (i.e., attention checks, a marker of inconsistent reporting, and CAPTCHA questions). Since the aim of the study was to explore LCA within the CMNI variable, 98 participants were removed who did not respond to any of the items on the CMNI-46. Eight participants who block responded (e.g., “Strongly agree” for all items) on the CMNI-46 were also removed. Finally, 82 participants were removed who completed the study in less than 5 minutes, a generous cutoff time given the estimated time to complete the survey (i.e., around 15-20 minutes). The final sample comprised of 672 men with chronic pain.

## Procedure

The present study was approved by the author's university's institutional review board. Participants were recruited online through MTurk. The study was listed on MTurk as a survey about how men experience chronic pain and asked for men with chronic pain to participate. Participants who voluntarily selected the study were redirected to a survey presented through Qualtrics (https://www.qualtrics.com)—an online survey software platform. Participants were first provided with an informed consent document (see Appendix A) that included information about the present study and asked if they consented to participate. Once informed consent was given by participants, inclusion criteria questions were asked (see Appendix B). Participants who met inclusion criteria were then asked to complete a battery of demographic-related questions (see Appendix C), health-related questions (see Appendix D), and the study's measures (see Appendix E-I). The study's measures were presented in a randomized order. Each participant was compensated monetarily with $1.00. Compensation is consistent with previous studies collecting data through MTurk (Ogletree & Katz, 2021; Zhou & Fishbach, 2016). MTurk facilitates compensation while maintaining anonymity for participants (Shapiro et al., 2013).

## Measures

**Demographics.** A questionnaire was utilized to collect participant's demographic information such as their gender, age, ethnicity, and socioeconomic status (see Appendix C). Age and socioeconomic status will be examined as covariates in the study's analyses. To obtain their age, participants were asked, "What is your age?". Regarding socioeconomic status, respondents were asked to respond to a question (i.e., "How would you best characterize your social class currently?") related to their socioeconomic status. Responses were scored on a five-point scale (i.e., 1 = “Upper Class”, 2 = “Upper-Middle Class”, 3 = “Middle Class”, 4 = “Working Class”, 5 = “Living in Poverty”).

**Health information**. A self-administered questionnaire was used to gather participants’ relevant health information including chronic pain data, chronic illnesses, experience of pain location, medication use (e.g., frequency), medication information (e.g., reason for use), and medical help-seeking behaviors (see Appendix D).

**Masculine norms.** The 46-item Conformity to Masculine Norms Inventory (CMNI-46; Parent & Moradi, 2009; see Appendix E) was used to assess participants’ level of adherence to masculine gender norms. Specifically, the 6-item emotional control (e.g., “I never share my feelings”), 6-item winning (e.g., “It is important for me to win”), 6-item violence (e.g., “Sometimes violent action is necessary”), 5-item self-reliance (e.g., “I hate asking for help”), 5-item risk-taking (e.g., “I take risks”), 4-item playboy (e.g., “I would feel good if I had many sexual partners”), 4-item power over women (e.g., “Things tend to be better when men are in charge”), 6-item heterosexual self-presentation (e.g., “I try to avoid being perceived as gay”), and 4-item primacy of work (“Work comes first”) subscales were utilized to assess specific masculine norms. Participants responded to items on a 4-point scale (1 = *Strongly disagree* to 4 = *Strongly agree*). Higher scores are representative of greater conformity to masculine norms (e.g., greater conformity to risk-taking). The CMNI-46 is one of the most commonly used measures of masculinity and the use of its subscales have evidenced strong psychometric support (e.g., Hammer et al., 2018). In several studies, internal consistencies of the CMNI-46 subscales have been established (e.g., Parent & Moradi, 2009). In a sample with chronic pain participants, subscales yielded the following Cronbach’s alpha: winning ($\alpha = .85$), emotional control ($\alpha = .91$), risk-taking ($\alpha = .83$), violence ($\alpha = .85$), primacy of work ($\alpha = .77$), self-reliance ($\alpha = .86$), playboy (α = .81), power over women (α = .77), heterosexual self-presentation (α = .89; Wuest et al., 2020). The CMNI-46 subscales have also demonstrated convergent and discriminant validity in several samples (e.g., Parent & Moradi, 2011). For example, subscale scores have been found to be positively associated with other masculinity measures and negatively related to impression management (Hsu & Iwamoto, 2014; Parent & Moradi, 2009, 2011; Parent & Smiler, 2012).

**Pain Self-Efficacy**. Participants' pain self-efficacy was measured using the 10-item Pain Self-Efficacy Questionnaire (PSEQ; Nicholas, 2007; see Appendix F). Participants indicated their level of confidence in their ability to perform activities despite their pain with responses on a 6-point scale ranging from "Not at all confident" to "Completely confident", with higher scores signifying great pain self-efficacy. Sample items from the PSEQ include "I can cope with my pain in most situations", "I can enjoy things, despite the pain", and "I can do some form of work, despite the pain." Empirical evidence suggests that the PSEQ is a reliable and valid tool to utilize with chronic pain samples (Mann et al., 2017; Nicholas, 2007). In the developmental study with a sample of chronic pain patients, the PSEQ items yielded an excellent internal consistency (Cronbach's $\alpha$ = .92) and a test–retest correlation of $r$ = 0.73 from baseline to 3-months (Nicholas, 2007). The PSEQ also correlated as expected (i.e., negatively) with measures of anxiety, depression, pain beliefs, and pain intensity (Nicholas, 2007). In a study conducted by Mann and colleagues (2017), the PSEQ items also evidenced excellent internal reliability (Cronbach's $\alpha$ = .92) and good convergent validity with other forms of self-efficacy beliefs in a sample with chronic pain participants.

**Risk of Opioid Abuse**. Men's risk of abusing opioids was assessed using the 14-item Screener and Opioid Assessment for Patients with Pain (SOAPP; Akbik et al., 2006; see Appendix G). The SOAPP is a tool to help identify individuals who are likely to have problems and need monitoring when on long-term opioid therapy (Akbik et al., 2006; Passik, 2008). Researchers and clinicians have used the SOAPP to inform prescription procedures and identify individuals who may need to be more closely monitored when taking opioids (Daheim & Kim, 2023; Passik & Kirsh, 2008; Yennurajalingam et al., 2021). The SOAPP is comprised of 14 items (e.g., "How often have your medications been lost or stolen?"). Participants responded to items on a 5-point scale (0 = *Never* to 4 = *Very often*), with more elevated scores indicating a greater risk of abusing opioids. The SOAPP has been evidenced to be a reliable and valid measure in research involving samples with adults with pain (Akbik et al., 2006; Elander et al., 2014). In a sample with pain, SOAPP items yielded a Cronbach's $\alpha$ of 0.81 and SOAPP scores were found to be positively associated with prescription pain reliever use, pain reliever dependence, and pain anxiety (Elander et al., 2014).

**Childhood Family Functioning.** Participants' predevelopment or childhood experiences with their family were assessed using the 12-item Childhood Family Experiences Scale (CFES; Vogt et al., 2013; see Appendix H). The CFES aims to capture participants' perceived childhood family functioning through assessing the quality of family relationships during childhood in the family of origin in terms of communication, closeness, and trust (Vogt et al., 2013). Participants responded to the 12-item CFES (e.g., "During childhood, I felt like my contributions to my family were appreciated.") using a 5-point scale (1 = *Strongly disagree* to 5 = *Strongly agree*). Higher scores are indicative of greater perceived family functioning during childhood. Literature contains strong psychometric support for the CFES's use (e.g., Vogt et al., 2013). The CFES has yielded an excellent internal consistency of $\alpha$ = 0.95 or higher (Maoz et al., 2016; Vogt et al., 2013). Scale scores have also been found to be positively associated with overall mental health and negatively associated with PTSD, anxiety, and depressive symptoms, providing evidence for convergent and discriminant validity (Maoz et al., 2016; Vogt et al., 2013).

**Remembered Relationship with Father/Mother**. Participants' perceived childhood relationships with their parents were measured using the 10-item Remembered Relationship with Parents Scale (RRPS; Denollet et al., 2007; see Appendix I). The RRPS aims to retrospectively assess the quality of an individual's perceived relationship with their father and mother when they were growing up. It contains the same 10 items concerning the participant's relationship with their father (e.g., "I was very closed toward my father") and mother (e.g., "I was very closed toward my mother"). Participants were presented with corresponding items to who they self-reported being raised by (i.e., raised by "father" = father items; "mother" = mother items; "father" and "mother" = all items). Individuals who did not report being raised by a "father" or "mother" were not requested to fill out the RRPS. The RRPS contains two 5-item subscales, which measure remembered relationships of Alienation (e.g., "My father often made me feel insecure") and Control (e.g., "My mother was overprotective"). Item responses were on a 5-point scale ranging from "False" to "True", with higher scores indicating greater perceived alienation and control in their parental relationships. The Alienation and Control subscales of the RRPS have displayed a sound factor structure, good internal consistency (Cronbach's $\alpha$ = 0.83–0.86), and convergent and discriminant validity with RRPS scores being found to be negatively associated with parental bonding and positively associated with the experience of chronic distress (Denollet et al., 2007; Van den Broek et al., 2010).

**Data Analysis**

To analyze the aims and research questions of the present study, MPlus version 8 (Muthén & Muthén, 1998-2017), SPSS Statistics 23 (IBM, 2015), the mclust package version

5.4.6 (Scrucca et al., 2016) in R version 3.5.1 (R Core Team, 2018), Hayes' (2022) PROCESS macro were employed. There was a total of 159 missing data (i.e., 0.5%) within CMNI-46 item responses. A total of 98 participants were also removed prior to analyses due to non-responses on the CMNI-46.

Consistent with previous research (Matsunaga, 2010; Padgett, 2017), a confirmatory factor analysis (CFA) of the CMNI-46 was examined first, to observe if the CMNI-46 factor structure fit our data well. Parent and Moradi (2009) proposed the CMNI-46 to have a nine-factor model structure with latent factors of winning, emotional control, risk-taking, violence, primacy of work, self-reliance, playboy, power over women, and heterosexual self-presentation. Several studies have supported this nine-factor structure in several different samples including men in the community, college men, White American men, Asian American men, and women (Hammer et al., 2018; Hsu & Iwamoto, 2014; Parent & Moradi, 2009, 2011; Parent & Smiler, 2012). However, the factor structure of the CMNI-46 has yet to be examined in the chronic pain population. Thus, the CFA was conducted to examine the nine-factor model structure of the CMNI-46 in our sample of men with chronic pain, to see if the factor structure fit the data well. Consistent with similar work (e.g., Stevens et al., 2018), the CFA was conducted in MPlus 7.11 software (Muthén & Muthén, 1998-2017). Given the nominal nature of the CMNI's scale responses, delta parameterization was used to handle its categorical nature (Muthen & Satorra, 1995). Model fit for CFA was evaluated using the Comparative Fit Index (CFI) and Root Mean Square Error of Approximation (RMSEA). According to Hu and Bentler (1998), CFI values of .90 or greater represent "good" fit, and values of .95 or greater represent "excellent" fit. RMSEA values of .80 and .10 or less represent acceptable and marginal fit. Lai and Green (2016) argued that when inconsistency in result cutoffs occur between RMSEA and CFI, CFI should be interpreted with priority given RMSEA is sensitive to degrees of freedom and sample size. RMSEA’s cutoffs are also argued to be subjective (Lai & Green, 2016).

The first aim of the study was to identify latent conformity to masculine norm groups within the sample. Finite mixture models were used to identify these groups based on similar response patterns on nine indicators including emotional control, risk-taking, self-reliance, winning, violence, playboy, power over women, heterosexual self-presentation, and primacy of work. Indicators derive from subscales from the CMNI-46. Finite mixture modeling was performed using the mclust package (Scrucca et al., 2016) in R (R Core Team, 2018). Mclust identified the best fitting solutions through utilizing Gaussian finite mixture analysis based on differential parameterization of the covariance matrix (Scrucca et al., 2016). Specifically, latent groups were estimated through comparing 1-9 different classes using 14 variance/covariance structures. Thus, 126 models were examined. Then, to determine the best class solutions from the resulting classes and variance/covariance structures, the Bayesian Information Criteria (BIC), integrated complete data likelihood (ICL), and entropy scores were examined (Scrucca et al., 2016).

BIC is a criterion for model section, with lower BIC preferred (Schwarz, 1978). When mclust results were examined, decreases in BIC from model extraction indicated better model fit (Scrucca et al., 2016). ICL is another criterion in helping to determine the best fitting model with lower ICL scores indicating better model fit (Biernacki et al., 2000). ICL is argued to account for some of the limitations of BIC (e.g., BIC can overestimate the correct size if the correct model is not in the considered models; Biernacki et al., 2000). Therefore, a model with lower values of BIC and ICL signified a better model fit. Once the best fitting model was identified using BIC and ICL, entropy—how likely each participant is a member of a given class—and the size of each class was examined. Entropy scores nearer to 1 indicated clearer delineation of classes (Celeux & Soromenho, 1996). These procedures are largely consistent with previous research (e.g., Cadigan et al., 2015; Shi et al., 2020; Talley et al., 2012). Several researchers also argue that utilizing mclust for finite mixture model analyses is the superior method to alternative approaches, as mclust approximates the best model from varying clusters and covariant structures (Haughton et al., 2009). Examination of descriptive statistics (e.g., means and standard deviations) across classes was conducted to facilitate a better understanding of the differences in relations between masculine norm classes, self-efficacy, and risk of opioid abuse.

With the established classes, Hayes' (2022) PROCESS macro for SPSS was used to examine the proposed mediation and post hoc moderated mediation models. In PROCESS macro, estimates model parameters derive through the use of ordinary least squares (OLS) regression and predefined models to test mediation and moderated mediation models. As two classes were identified, reference cell coding was utilized to create a dichotomous categorical variable for the independent variable in the models (i.e., CMNI classes). PROCESS Model 4 tests mediation models and was used to examine the proposed mediation model. PROCESS Model 9 tests moderated mediation models and was used to examine the post hoc analysis. Covariates of age and socioeconomic status were included in all models. Models were both examined using the classes derived from the 2-factor CMNI structure and the 9-factor CMNI structure. The bias-corrected 95% confidence interval (CI) was calculated using 5000 bootstrapping re-samples to examine the significance and nature of each mediation and moderated mediation model. If the 95% CI does not include zero, it is concluded that the interaction effect, conditional direct effect, indirect effects, and overall models are statistically significant ($p < .05$).

**Power Analysis**

Finite mixture modeling is largely exploratory as groups are extracted from the provided data (Nylund-Gibson & Choi, 2018). In Latent Class Analysis (LCA), it is often unclear the characteristics or number of classes that will be delineated (Dziak et al., 2014; Muthén & Muthén, 1998-2017). Thus, conducting power analyses and estimating desired sample sizes are difficult and are typically not conducted a-priori (Tekle et al., 2016). The difficulty estimating power and a desired sample size is argued not to be a huge limitation of finite mixture modeling, as research indicates that the sample size has minimal influence on the capability to identify the best mixture solution (Tein et al., 2013). Research also signals that sample size has a marginal impact on power, with samples with larger sizes seemingly to have little to no impact on power (Tein et al., 2013). There is also a weak relation in determining accurate classes and sample size in finite mixture modeling (Henson et al., 2007; Steinley & Brusco, 2011). Therefore, an a-priori power analysis was not conducted for the LCA, a practice consistent with research utilizing finite mixture modeling (e.g., Wong et al., 2012).

Although sample size does not impact the capability to distinguish the best mixture solution, analyses involving class comparisons could be impacted by the number of participants in each class. Therefore, a power analysis was conducted to help determine a desired sample size for the study's proposed mediation model after CMNI classes were identified. A power analysis helps estimate the smallest sample size needed for an analysis given a statistical power (i.e., "probability of selecting the true model"), thus supporting results as genuine and not due to chance (Tein et al., 2013). Using G*Power (Erdfelder et al., 1996; Faul et al., 2007), an a-priori power analysis indicated a sample size of 92 participants would be needed to detect a medium effect ($f^2$ = .15) for a multiple regression F test ($\alpha$ = .05, $\eta^2$ = .80) or the analysis for the study's proposed mediation model. Regarding the post hoc analysis of a moderated mediation model, a power analysis indicated that a sample size of 103 participants would be needed to detect a medium effect ($f^2 = .15$, $\alpha = .05$, $\eta^2 = .80$). Within the LCA, classes with at least 103 participants were recommended to facilitate adequate power (power = 0.80) to detect medium effect sizes for the mediation and moderated mediation analyses.

# CHAPTER III

# RESULTS

## Nine-Factor Confirmatory Factor Analyses

A confirmatory factor analysis (CFA) was conducted to examine the nine-factor structure of the CMNI-46 as suggested by Parent and Moradi (2009). Multiple studies found the correlated nine-factor to be a better fitting model compared to second order and bifactor structures in community and college samples (e.g., Hammer et al., 2018). However, the factor structure has yet to be examined in a chronic pain sample. The nine-factor model exhibited adequate fit based on $\chi 2$ (953) = 3084.557, $p < .001$, RMSEA = 0.058; CFI = 0.897. Although the model represented adequate fit statistics, correlations between latent variables were alarming high (see Table 3) with Heywood cases present (e.g., correlations out of model parameters). Output syntax also reported warning labels of the latent variable covariance matrix as being not positive definite, which could be caused by correlations greater than or equal to one between variables. These highly correlated latent variables are in contrast to the literature which predominantly has found small to medium correlations (i.e., $r \geq .50$) between subscales (e.g., Parent & Moradi, 2009). These results suggest the CMNI-46 may lack configural invariance (i.e., the number of factors and pattern of loadings is the same across groups) between our men with chronic pain sample and samples in which the CMNI-46 factor structure has been examined in including men in the community, college men, White American men, Asian American men, and women (Hammer et al., 2018; Hsu & Iwamoto, 2014; Parent & Moradi, 2009, 2011; Parent & Smiler, 2012).

**Table 3**

*Correlations Between Latent CMNI-46 Subscales from 9-factor Confirmatory Factor Analysis*

| Subscales | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 |
|---|---|---|---|---|---|---|---|---|---|
| 1. Emotional Control | ----- | | | | | | | | |
| 2. Winning | -.998 | ----- | | | | | | | |
| 3. Playboy | .961 | -.778 | ----- | | | | | | |
| 4. Violence | -1.008 | .976 | -.862 | ----- | | | | | |
| 5. Self-reliance | 1.049 | -.938 | .927 | -.990 | ----- | | | | |
| 6. Risk-taking | .967 | -.879 | .963 | -.907 | .933 | ----- | | | |
| 7. Power over Women | .923 | -.799 | 1.025 | -.842 | .860 | .926 | ----- | | |
| 8. Primacy of Work | .881 | -.929 | .651 | -.846 | .767 | .797 | .714 | ----- | |
| 9. Heterosexual Self-presentation | .936 | -.905 | .840 | -.930 | .928 | .873 | .863 | .721 | ----- |

*Note*. Some correlations were out of model parameters (e.g., greater than 1)

## Exploratory Factor Analysis

Given that the CFA suggests that the nine-factor structure does not fit the data well, an exploratory factor analysis (EFA) was conducted (see Table 4). An EFA is a multivariate statistical method that helps identify the smallest number of latent constructs that can parsimoniously explain the covariation observed among a set of measured variables (Hayton et al., 2004). In other words, it can help explore the best fitting factor structure of the CMNI-46 within the present data. The Scree test argues that the best factor structure should be determined by where there is a distinct elbow in the visualization of the eigenvalues (Luo & Li, 2016). In accordance with the eigenvalue criteria and the Scree test, the two-factor model is the best factor structure for the data. The two-factor structure also designated appropriate model fit statistics (i.e., $\chi2$ (944) = 2365.913, $p < .001$, RMSEA = 0.047; CFI = 0.931). The correlation between the two factors was -.618, rectifying the concern for the high correlations from the nine-factor CFA.

**Table 4**
*Exploratory Factor Analysis Summary Fit Statistics*

| Factor Structure | *df* | $\chi 2$ | *p* | CFI | RMSEA | Eigenvalue |
|---|---|---|---|---|---|---|
| One | 989 | 3249.713 | < .001 | .890 | .058 | 15.102 |
| Two | 944 | 2365.913 | < .001 | .931 | .047 | 2.908 |
| Three | 900 | 1926.349 | < .001 | .950 | .041 | 2.258 |
| Four | 857 | 1591.528 | < .001 | .964 | .036 | 1.716 |
| Five | 815 | 1415.102 | < .001 | .971 | .033 | 1.339 |
| Six | 774 | 1288.665 | < .001 | .975 | .031 | 1.173 |
| Seven | 734 | 1184.879 | < .001 | .978 | .030 | 1.078 |
| Eight | 695 | 1094.986 | < .001 | .981 | .029 | 1.057 |
| Nine | 657 | 1005.715 | < .001 | .983 | .028 | 0.991 |

*Note*. $N = 672$.

**Parallel Analysis**

To explore other potential factor structures of the CMNI-46 with the study's data, a parallel analysis was also conducted (see Table 5). A parallel analysis is argued to be one of the most accurate factor retention methods (Hayton et al., 2004). Caution with interpretation of results is recommended; as although the present data indicates categorical examination, a parallel analysis requires variables to be considered continuous as maximum likelihood estimation is used (Hayton et al., 2004; Timmerman & Lorenzo-Seva, 2011). A parallel analysis helps determine the optimum number of factors in an exploratory factor analysis (Hayton et al., 2004). It is a method that uses random data with the same number of observations and variables as the original data. The correlation matrix of the random data is used to compute eigenvalues. These eigenvalues are compared to the eigenvalues of the original data. The optimum number of factors is the number of the original data eigenvalues that are larger than the random data eigenvalues (i.e., 95 percentile eigenvalues from parallel analysis; Timmerman & Lorenzo-Seva, 2011). According to this criterion, the ideal number of factors is four given its eigenvalue (i.e., eigenvalue = 1.649) is the last one greater than its 95th percentile eigenvalue from the parallel analysis (i.e., eigenvalue = 1.441). Fit statistics of $\chi 2$ (857) = 1992.881, $p < .001$, RMSEA =

0.044; CFI = 0.894 also indicate that the four factor structure fits the data well. However, when examined closer, factor loadings suggest that all items load onto two factors (i.e., the highest loading for each item fell only two factors). This result posits that the four-factor structure may not be appropriate, as it cannot be said with confidence that CMNI-46 items appropriately delineate on all four factors. The two-factor structure still seems appropriate given its eigenvalue (i.e., eigenvalue = 2.498) was greater than its 95th percentile eigenvalue from parallel analysis (i.e., eigenvalue = 1.523). Cross-loadings also better reflect a delineation of all of the factors (i.e., two).

**Table 5**

*Parallel Analysis for Exploratory Factor Analysis Eigenvalue Summary*

| Factor Structure | Eigenvalues for Sample | 95% Eigenvalues |
|---|---|---|
| One | 13.150 | 1.595 |
| Two | 2.498 | 1.523 |
| Three | 2.047 | 1.484 |
| Four | 1.649 | 1.441 |
| Five | 1.272 | 1.404 |
| Six | 1.150 | 1.379 |
| Seven | 1.066 | 1.345 |
| Eight | 1.038 | 1.319 |
| Nine | 0.982 | 1.306 |

*Note*. $N$ = 672. To run a parallel analysis, data must be considered continuous.

**Two-Factor Confirmatory Factor Analysis**

EFA and parallel analysis posit that a two-factor structure may fit the data the best. To confirm this assertion, a CFA was conducted to examine the two-factor structure. Items were assigned to each factor based on (1) the factor loadings from the EFA (i.e., higher item loading on a given factor suggests it loads onto or is more related to the given factor) and (2) the relevancy/association with the potential factor construct. Factor loading can be viewed in Table 6. Based on these criteria, items 1, 3, 5, 7, 9, 11, 13, 15, 17, 19, 21, 23, 25, 27, 29, 31, 33, 35, 37, 38, 39, 41, 43, and 45 were included in one factor and labeled as "Efficiency and Self-Preservation Driven" given item content. Items 2, 4, 6, 8, 10, 12, 14, 16, 18, 20, 22, 24, 26, 28, 30, 32, 34, 36, 40, 42, 44, and 46 were included the other factor and labeled "Power and Risk Driven." The two-factor model exhibited adequate fit based on $\chi 2$ (988) = 2463.580, $p < .001$, RMSEA = 0.047; CFI = 0.928. The correlation between the Efficiency and Self-Preservation Driven and Power and Risk Driven factors was also .763.

**Table 6**
*Cross Loading from the 2-Factor Exploratory Factor Analysis*

| Item | Factor 1 | Factor 2 |
|---|---|---|
| 1 | -0.374* | 0.126* |
| 2 | -0.103* | 0.593* |
| 3 | -0.514* | -0.001 |
| 4R | 0.031 | -0.540* |
| 5R | 0.508* | -0.004 |
| 6R | 0.295* | -0.345* |
| 7R | 0.537 | -0.050 |
| 8 | -0.021 | 0.597* |
| 9R | 0.700* | 0.047 |
| 10R | -0.081 | -0.663* |
| 11 | -0.381* | 0.088 |
| 12R | -0.091 | -0.625* |
| 13R | 0.385* | -0.144* |
| 14 | -0.135* | 0.586* |
| 15R | 0.679* | 0.038 |
| 16 | -0.053 | 0.565* |
| 17R | 0.793* | 0.139* |
| 18 | -0.201* | 0.529* |
| 19 | -0.558* | 0.076 |
| 20 | 0.007 | 0.705* |
| 21 | -0.385* | 0.257* |
| 22 | 0.103 | 0.655* |
| 23R | 0.596* | 0.062 |
| 24 | -0.168 | 0.588* |
| 25R | 0.510* | -0.101 |
| 26 | -0.281* | 0.476* |
| 27R | 0.598* | -0.044 |
| 28 | -0.120* | 0.553* |
| 29 | -0.401* | 0.265* |
| 30 | -0.039 | 0.582* |
| 31 | -0.345* | 0.197* |
| 32 | 0.011 | 0.601* |
| 33R | 0.632* | -0.024 |
| 34R | 0.067 | -0.572* |
| 35 | -0.456* | 0.233* |
| 36 | 0.004 | 0.655* |
| 37 | -0.489* | 0.210* |
| 38R | 0.379* | -0.297* |
| 39 | -0.252* | 0.225* |
| 40R | 0.097* | -0.540* |
| 41R | 0.713* | 0.051 |
| 42 | 0.033 | 0.734* |
| 43 | -0.459* | 0.139* |
| 44 | 0.086* | 0.747* |
| 45 | -0.545* | 0.079 |
| 46 | -0.173* | 0.530* |

*Note*. * significant at 5%. R indicates reversed scored items.

Although fit statistics indicate this new two-factor model fit the study's data well, concerning trends arose during the CFA process. When examining factor loadings (see Table 6), a large number of items exhibited significant cross loadings (i.e., significant factor loadings on both factors). An intriguing pattern also emerged in which higher factor loadings indicated that most odd items fell onto one factor and even items onto the other. When examining significant loadings, a meaningful construct connection was difficult to identify that linked the items within a factor. Despite this, labeling the factors was attempted (i.e., Efficiency and Self-Preservation Driven, Power and Risk Driven). These results, in addition to the 9-factor CFA results, further drew into question the quality (e.g., reliability and validity) of the present study's data. Thus, further analyses were conducted to examine the quality of the data.

**Further Data Quality Checks**

Data cleaning procedures (e.g., inclusion criteria, response validity indicators were checked again, and reverse coding) were again checked for accuracy and it was determined that procedures were followed appropriately.

Cronbach's alphas, a measure of internal consistency, were conducted for all of the study's scales (see Table 7). Alpha's greater than or equal to .7, .8, and .9 are argued to indicate acceptable, good, and excellent internal consistency respectively. In the present study, all scales demonstrated at least good internal consistency (i.e., Cronbach's $\alpha \geq .8$) except for the CMNI-46 (i.e., Cronbach's $\alpha = .61$). Most CMNI-46 subscales also represented unacceptable internal consistency with Cronbach's alphas ranging from .04 to .73. These results are considerably different from previous research using the CMNI-46 (Parent & Moradi, 2009, 2011; Wuest et al., 2020). The CMNI-46 was the only scale in the present study with reversed scored items and could be linked with these poor results. When internal consistency was examined without reverse scoring items, Cronbach's alphas dramatically improved (see Table 7). This suggests the study's respondents may not have provided quality responses, as block responding or other inattentive responding patterns could have been utilized. Examining correlations between CMNI-46 items further supports this assertion, as several correlations between items were counterintuitive (e.g., a positive correlation when a negative correlation was expected). For example, items "I never share my feelings" and "I like to talk about my feelings" were positively associated without reverse coding ($r = .17$, $p > .01$). Another example, without reverse scoring, items "It is important for me to win" and "Winning is not important to me" were positively correlated ($r = .17$, $p > .01$).

**Table 7**
*Cronbach's Alphas for Study's Overall Sample*

| | Cronbach's α | Cronbach's *α* *(excluding reverse coded items)* |
|---|---|---|
| CMNI-46 | .61 | .94 |
| Emotional Control | .15 | .65 |
| Risk-taking | .43 | .69 |
| Self-reliance | .04 | .65 |
| Winning | .38 | .67 |
| Violence | .19 | .69 |
| Playboy | .43 | .64 |
| Power over Women | .73 | --- |
| Heterosexual self-presentation | .38 | .76 |
| Primacy of Work | .18 | .52 |
| PSEQ | .90 | --- |
| SOAPP | .94 | --- |
| CFES | .87 | --- |
| RRPS-F | .86 | --- |
| RRPS-M | .86 | --- |

Note. "Cronbach's α" column indicates alphas for scales scored as intended with reverse coded items included. "Cronbach's α (excluding reverse coded items)" column indicates alphas derived from scales items that were not reverse coded.

Further examination of the data (e.g., Cronbach's alphas) provides additional evidence that the present study's data is questionable at best. The results are consistent with questions as to the validity of the data drawn from previous analyses (e.g., Confirmatory Factor Analysis). Results indicate that the data could not be used in analyses to effectively explore or answer the present study's research questions and thus should not be examined. The examination of bad data can affect the entirety of the knowledge of a phenomenon and cause harm (Brown et al., 2018).

Although it was determined that the present study's data is flawed and should not be analyzed, the study's aims were still analyzed to provide further context and depth to the discussion session. Many studies and articles do not do as thorough of an analysis, which helped identify that the data was flawed. Analyses were still conducted to demonstrate what results could have been erroneously determined and what interpretations of these results could have inaccurately been posited, thus tangibly representing the potential harm of not following more rigorous recommendations. Hence, analyses were conducted from the perspectives of both the research-supported 9-factor CMNI structure and the newly identified 2-factor CMNI structure from the study's EFA and parallel analysis. Both perspectives were run as other researchers could have argued to run their analyses based upon either factor structure depending on their approach to their analyses. These analyses can suggest recommendations for future studies to help recognize problematic data, but they also demonstrate the ramifications of not following these recommendations and potentially articulating flawed interpretations and impact statements. This dialogue can be viewed in the discussion section.

**Latent Class Analysis**

The first aim of the present study was to identify different latent groups of men with chronic pain based on conformity to specific masculine gender norms. Thus, a Latent Class

Analysis (LCA) was conducted utilizing the CMNI 9-factor structure identified in previous research and the CMNI 2-factor structure identified in the present study. LCA was performed using the mclust package in R. Lower fit indices of Bayesian Information Criteria (BIC) and integrated complete data likelihood (ICL) indicated better fitting solutions (Scrucca et al., 2016). Mclust identified a 2-class solution for both the 9-factor (*BIC* = -5108.378, *ICL* = -5172.081) and 2-factor (*BIC* = 316.466, *ICL* = 145.121) structures of the CMNI. For the 9-factor CMNI structure, 557 participants fell within the first class and 115 participants in the second class. The means and standard deviations of the two classes for the 9-factor structure of CMNI can be found in Table 8. The two identified classes were largely based on consistent levels of endorsement (e.g., high vs. low). The first class (*n* = 557; 83%) was characterized by the endorsement of *HIGH masculine norms and LOW winning and violence*. The second class (*n* = 115, 17%) in contrast was characterized by an endorsement of *LOW masculine norms and HIGH violence and winning*. For the 2-factor CMNI structure, 569 participants were included in the first class and 103 in the second class. Table 9 includes the means and standard deviations of the two classes from the 2-factor structure of CMNI. The first class (*n* = 569; 85%) was characterized by *LOW drive for efficiency and self-preservation and HIGH drive for power and risk*. The second class (*n* = 103, 15%) was characterized by *HIGH drive for efficiency and self-preservation and LOW drive for power and risk*. Descriptors represent class membership in comparison to the other class in the mixture based on mean differences.

**Table 8**

*Means and Standard Deviations for 9-factor CMNI by Class*

| | Class 1 (*SD*, *n* = 557) | Class 2 (*SD*, *n* = 115) |
|---|---|---|
| Emotional Control | 2.52 (.25) | 2.34 (.51) |
| Winning | 2.36 (.30) | 2.67 (.62) |
| Playboy | 2.82 (.40) | 2.25 (.78) |
| Violence | 2.31 (.25) | 2.46 (.52) |
| Self-Reliance | 2.59 (.28) | 2.41 (.59) |
| Risk-taking | 2.92 (.32) | 2.50 (.67) |
| Power over Women | 3.12 (.50) | 2.33 (.95) |
| Primacy of Work | 2.91 (.35) | 2.89 (.72) |
| Heterosexual Self-Preservation | 2.74 (.30) | 2.39 (.62) |

*Note*. Items included: Emotional Control 13, 18, 25, 32, 40, & 45; Winning 1, 7, 15, 22, 27, 33; Playboy 2, 12, 21, 36; Violence 4, 9, 19, 30, 34, 41; Self-Reliance 3, 10, 26, 38, 43; Risk-Taking 6, 8, 16, 28, 35; Power Over Women 20, 29, 42, 44; Primacy of Work 11, 23, 31, 39; Heterosexual Self-Presentation 5, 14, 17, 24, 37, 46; Class 1 = HIGH masculine norms and LOW winning and violence, Class 2 = LOW masculine norms and HIGH violence and winning.

**Table 9**

*Means and Standard Deviations for 2-factor CMNI by Class*

| Factor | Class 1 (SD, *n* = 569) | Class 2 (SD, *n* = 103) |
|---|---|---|
| Efficiency and Self-Preservation Driven | 2.52 (.12) | 2.55 (.31) |
| Power and Risk Driven | 2.78 (.23) | 2.42 (.33) |

*Note*. Items 1, 3, 5, 7, 9, 11, 13, 15, 17, 19, 21, 23, 25, 27, 29, 31, 33, 35, 37, 38, 39, 41, 43, 45 included in Efficiency and Self-Preservation Driven (F1), Items 2, 4, 6, 8, 10, 12, 14, 16, 18, 20, 22, 24, 26, 28, 30, 32, 34, 36, 40, 42, 44, 46 included in Power and Risk Driven (F2); Class 1 = LOW drive for efficiency and self-preservation and HIGH drive for power and risk, Class 2 = HIGH drive for efficiency and self-preservation and LOW drive for power and risk.

Means and standard deviations across all study variables in the overall sample and classes can be found in Table 10. When comparing the two classes identified from the 2-factor CMNI structure, class 1 (*LOW drive for efficiency and self-preservation and HIGH drive for power and risk*) was younger and generally in a lower socioeconomic status. Class 1 also endorsed greater levels of overall conformity to masculine norms and pain self-efficacy. When comparing the two classes identified from the 9-factor CMNI structure, class 1 (*HIGH masculine norms and LOW winning and violence*) endorsed higher levels of overall conformity to masculine norms, pain self-efficacy, and risk of opioid abuse. This class was also younger and generally in a lower socioeconomic status.

**Table 10**
*Means (SDs) for Overall Sample and Classes Across Variables*

| | Overall Sample | 2-Factor Class 1 | 2-Factor Class 2 | 9-Factor Class 1 | 9-Factor Class 2 |
|---|---|---|---|---|---|
| Age | 35.62 (9.58) | 35.42 (9.46) | 36.74 (10.18) | 35.31 (9.35) | 37.23 (10.58) |
| SS | 2.73 (.83) | 2.71 (.84) | 2.82 (.76) | 2.69 (.81) | 2.88 (.91) |
| CMNI-46 | 2.66 (.20) | 2.69 (.13) | 2.47 (.33) | 2.69 (.15) | 2.47 (.28) |
| PSEQ | 5.41 (.91) | 5.50 (.83) | 4.93 (1.16) | 5.53 (.79) | 4.85 (1.19) |
| SOAPP | 3.50 (.84) | 3.65 (.70) | 2.66 (1.03) | 3.67 (.69) | 2.63 (.97) |
| CFES | 3.94 (.54) | 3.97 (.50) | 3.75 (.68) | 3.97 (.48) | 3.76 (.74) |
| RRPS-M | 3.64 (.71) | 3.79 (.57) | 2.87 (.83) | 3.81 (.55) | 2.87 (.82) |
| RRPS-F | 3.65 (.70) | 3.78 (.58) | 2.91 (.85) | 3.80 (.56) | 2.81 (.79) |

*Note*. SS = socioeconomic status, CMNI = Conformity to Masculine Norms Inventory-46, PSEQ = Pain Self-Efficacy Questionnaire, SOAPP = Screener and Opioid Assessment for Patients with Pain, CFES = Childhood Family Experiences Scale, RRPS-M = Remembered Relationship with Mother; RRPS-F = Remembered Relationship with Father; 2-factor Class 1 = LOW drive for efficiency and self-preservation and HIGH drive for power and risk, 2-factor Class 2 = HIGH drive for efficiency and self-preservation and LOW drive for power and risk, 9-factor Class 1 = HIGH masculine norms and LOW winning and violence, 9-factor Class 2 = LOW masculine norms and HIGH violence and winning.

Correlations between all study variables in the overall sample and identified classes can be found in Table 11. Of note, both class 1 (*LOW drive for efficiency and self-preservation and HIGH drive for power and risk*) and class 1 (*HIGH masculine norms and LOW winning and violence*) from the 2-factor and 9-factor CMNI structures exhibited significant and positive correlations between pain self-efficacy and conformity to masculine norms and pain self-efficacy and risk of opioid abuse. Class 2 from the 2-factor CMNI structure (*HIGH drive for efficiency and self-preservation and LOW drive for power and risk*) and class 2 from the 9-factor CMNI structure (*LOW masculine norms and HIGH violence and winning*) did not exhibit significant correlations between these variables.

**Table 11**

*Correlations Among Overall Sample Variables (N = 672)*

| Overall Sample | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 |
|---|---|---|---|---|---|---|---|---|
| 1. Age | --- | | | | | | | |
| 2. SS | .05 | --- | | | | | | |
| 3. CMNI-46 | -.07 | -.10* | --- | | | | | |
| 4. PSEQ | -.04 | -.09* | .34** | --- | | | | |
| 5. SOAPP | -.05 | -.16** | .57** | .52** | --- | | | |
| 6. CFES | .01 | -.11* | .28** | .54** | .40** | --- | | |
| 7. RRPS-F | -.09* | -.09* | .54** | .50** | .75** | .38** | --- | |
| 8. RRPS-M | -.07 | -.12** | .51** | .49** | .71** | .32** | .87** | --- |

*Correlations Among 2-Factor CMNI Class 1 (n = 569) and Class 2 (n = 103)*

| 2-Factor Class 1 | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 2-Factor Class 2 |
|---|---|---|---|---|---|---|---|---|---|
| 1. Age | --- | .16 | -.21* | -.18 | -.10 | .06 | -.20 | -.17 | Age .1 |
| 2. SS | .03 | --- | -.15 | .19 | -.09 | .01 | -.02 | -.31** | SS .2 |
| 3. CMNI-46 | .01 | -.07 | --- | .08 | .49** | -.09 | .33** | .30** | CMNI-46 .3 |
| 4. PSEQ | .01 | -.15** | .42** | --- | .08 | .29* | .16 | .25* | PSEQ .4 |
| 5. SOAPP | -.01 | -.17** | .49** | .63** | --- | -.12 | .65** | .54** | SOAPP .5 |
| 6. CFES | .01 | -.12** | .46** | .60** | .54** | --- | -.08 | -.21 | CFES .6 |
| 7. RRPS-F | -.02 | -.07 | .51** | .58** | .70** | .51** | --- | .75** | RRPS-F .7 |
| 8. RRPS-M | -.01 | -.07 | .45** | .55** | .65** | .50** | .86** | --- | RRPS-M .8 |

*Correlations Among 9-Factor SMNI Class 1 (n = 557) and Class (n = 115)*

| 9-Factor Class 1 | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9-Factor Class 2 |
|---|---|---|---|---|---|---|---|---|---|
| 1. Age | --- | .11 | -.14 | -.11 | .01 | -.01 | -.20 | -.11 | Age .1 |
| 2. SS | .31 | --- | -.16 | .18 | -.26* | -.16 | -.06 | -.06 | SS .2 |
| 3. CMNI-46 | -.01 | -.04 | --- | .07 | .45* | -.02 | .22* | .29** | CMNI-46 .3 |
| 4. PSEQ | .01 | -.16** | .36** | --- | .08 | .30** | .06 | .07 | PSEQ .4 |
| 5. SOAPP | -.02 | -.10** | .48** | .60** | --- | .02 | .57** | .54** | SOAPP .5 |
| 6. CFES | .03 | -.07 | .38** | .65** | .52** | --- | -.21 | -.10 | CFES .6 |
| 7. RRPS-F | -.01 | -.06 | .48** | .59** | .72** | .58** | --- | .81** | RRPS-F .7 |
| 8. RRPS-M | -.02 | -.11* | .41** | .63** | .66** | .53** | .82** | --- | RRPS-M .8 |

*Note*. *p < .01, **p < .01. SS = socioeconomic status, CMNI = Conformity to Masculine Norms Inventory-46, PSEQ = Pain Self-Efficacy Questionnaire, SOAPP = Screener and Opioid Assessment for Patients with Pain, CFES = Childhood Family Experiences Scale, RRPS-M = Remembered Relationship with Mother; RRPS-F = Remembered Relationship with Father; 2-factor Class 1 = LOW drive for efficiency and self-preservation and HIGH drive for power and risk, 2-factor Class 2 = HIGH drive for efficiency and self-preservation and LOW drive for power and risk, 9-factor Class 1 = HIGH masculine norms and LOW winning and violence, 9-factor Class 2 = LOW masculine norms and HIGH violence and winning.

## Mediation Models

The second aim of the study was to examine a mediation model in which pain self-efficacy mediated the relation between conformity to masculine norm (CMNI) classes and the risk of opioid abuse (see Figure 1 and Figure 3). Results for the 2-factor and 9-factor mediation models that include CMNI classes derived from the LCA can be viewed in Table 12. Age and socioeconomic status were examined as covariates within the models. Participants were dummy coded to create a CMNI class variable, where participants were coded by their class membership (i.e., 1 or 2). Thus, classes could be compared within the mediation model as there were only two classes identified from the LCA. It is important to note, that running multiple models within the same sample may increase Type I error (Cafri et al., 2010). Given analyses were exploratory in nature, corrections (e.g., Bonferroni) were not conducted as results can provide suggestions for future research and examination.

**Figure 3**

*Proposed Mediation Model with 2-Factor CMNI Class*

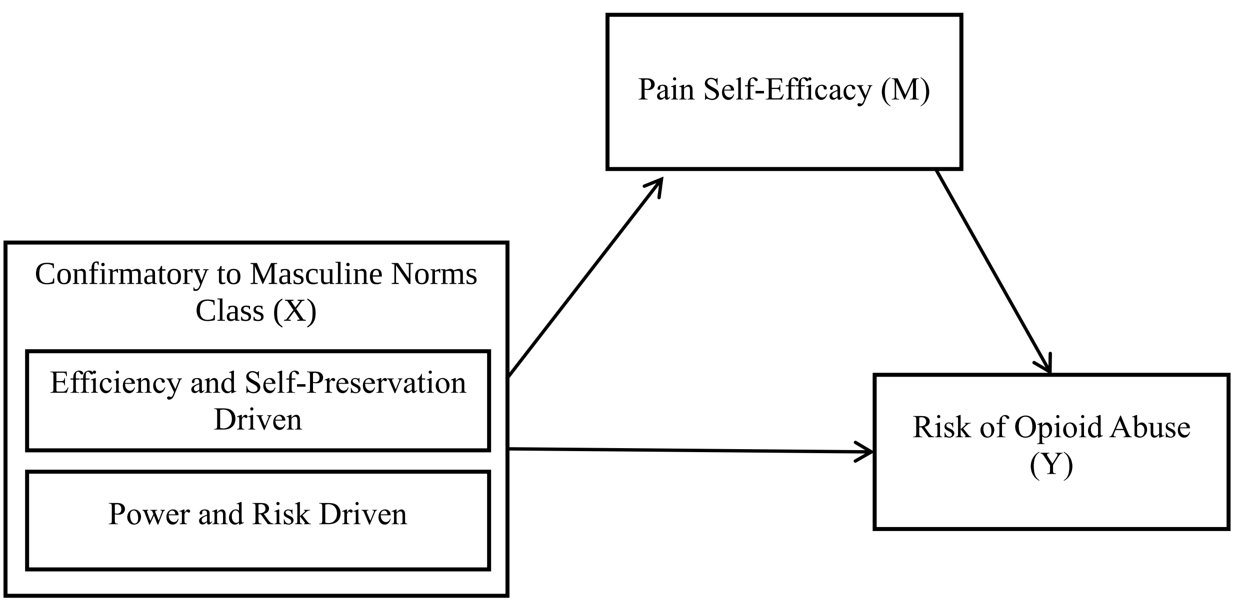


**Table 12**
*Standardized PROCESS Macro Mediation Model with Classes; CMNI-C (X), PSEQ (M), and SOAPP (Y).*

| Mediation Model with CMNI Classes from 2-factor Structure | | | | | |
|---|---|---|---|---|---|
| | *B* | *SE* | *p* | *LLCI* | *ULCI* |
| CMNI-C to PSEQ | -.556 | .118 | < .001*** | -.786 | -.324 |
| PSEQ to SOAPP | .388 | .034 | < .001*** | .322 | .454 |
| Direct Effect of CMNI-C to SOAPP | -.838 | .088 | < .001*** | -1.010 | -.666 |
| Indirect Effect of CMNI-C to SOAPP | -.215 | .064 | < .05* | -.351 | -.099 |
| Medication Model with CMNI Classes from 9-factor Structure | | | | | |
| | *B* | *SE* | *p* | *LLCI* | *ULCI* |
| CMNI-C to PSEQ | -.729 | .109 | < .001*** | 6.122 | 6.997 |
| PSEQ to SOAPP | .363 | .034 | < .001*** | .295 | .430 |
| Direct Effect of CMNI-C to SOAPP | -.789 | .085 | < .001*** | -.957 | -.622 |
| Indirect Effect of CMNI-C to SOAPP | -.264 | .063 | < .05* | -.401 | -.157 |

*Note*. Age and socioeconomic status were held constant. CMNI-C = Conformity to Masculine Norms Inventory Class, PSEQ = Pain Self-Efficacy Questionnaire, SOAPP = Screener and Opioid Assessment for Patients with Pain, LLCI = lower level confidence interval 95%, ULCI = upper level confidence interval 95%. *p < .05, **p < .01, ***p < .001.

**Mediation Model with CMNI Classes from 2-factor Structure**. For the mediation model that derived from the 2-factor CMNI structure, the CMNI class variable included class 1 (i.e., dummy coded as 1 = class *LOW drive for efficiency and self-preservation and HIGH drive for power and risk*) and class 2 (i.e., dummy coded as 2 = class *HIGH drive for efficiency and self-preservation and LOW drive for power and risk*). Within the model, pain self-efficacy significantly mediated the relation between CMNI class and risk of opioid abuse ($F$ = 78.918, $p$ < .001, $R^2$ = 0.400). There was a significant difference between CMNI classes in pain self-efficacy, with class 1 (*LOW drive for efficiency and self-preservation and HIGH drive for power and risk*) class being associated with greater pain self-efficacy (*Path a*: $B$ = -.556, < $p$ = .001, 95% *CI* [-.786, -.324]). Greater pain self-efficacy was associated with a greater risk of opioid abuse (*Path b*: $B$ = .388, $p$ < .001, 95% *CI* [.322, .454]). In turn, a significant indirect effect of CMNI class on the risk of opioid abuse through pain self-efficacy (*Effect* = -.215, 95% *CI* [-.351, -.099]) was found. CMNI class was found to be significantly related to one's risk of opioid abuse (*Path c'*: $B$ = -.838, < $p$ = .001, 95% *CI* [-1.010, -.666]), with class 2 (*HIGH drive for efficiency and self-preservation and LOW drive for power and risk*) being significantly associated with a reduced risk of opioid abuse. These results indicate pain self-efficacy partially mediates the relation between CMNI class and risk of opioid abuse.

**Mediation Model with CMNI Classes from 9-factor Structure**. For the mediation model that derived from the 9-factor CMNI structure, the CMNI class variable included class 1 (i.e., dummy coded as 1 = class *HIGH masculine norms and LOW winning and violence*) and class 2 (i.e., dummy coded as 2 = class *LOW masculine norms and HIGH violence and winning*). Within the mediation model results, CMNI class and the risk of opioid abuse were significantly mediated by pain self-efficacy ($F$ = 76.836, $p$ < .001, $R^2$ = 0.394). CMNI class was significantly associated with pain self-efficacy, with class 1 (*HIGH masculine norms and LOW winning and violence*) being associated with greater pain self-efficacy (*Path a*: $B$ = -.729, < $p$ = .001, 95% *CI* [-.943, -.515]). Greater pain self-efficacy was significantly related with a greater risk of opioid abuse (*Path b*: $B$ = .363, $p$ < .001, 95% *CI* [.295, .430]). In turn, a significant indirect effect of CMNI class on the risk of opioid abuse through pain self-efficacy (*Effect* = -.264, 95% *CI* [-.401, -.157]) was found. CMNI class was also found to be significantly associated to one's risk of opioid abuse (*Path c'*: $B$ = -.779, < $p$ = .001, 95% *CI* [-.957, -.622]), with class 2 (*LOW masculine norms and HIGH violence and winning*) being significantly related with a lesser risk of abusing opioids. Results provide evidence for a partial mediation relation between CMNI class and the risk of opioid abuse through pain self-efficacy.

**Post Hoc Examination of Moderated Mediation Models**

The third aim of the study was to conduct post hoc analyses examining the role of early childhood experiences and previous relationships with parents (e.g., mothers and fathers) in the study's proposed model relations. Guided by research, moderated mediation models were examined with early childhood experiences and remembered relations with parents moderating the mediation relation (in the *a* pathway) between CMNI classes and risk of opioid abuse through pain self-efficacy (see Figure 2 and Figure 4). Results for the 2-factor and 9-factor moderated mediation models can be viewed in Table 13. Participants were still dummy coded by class (i.e., 1 or 2) to create a CMNI class variable. Age and socioeconomic status were still examined as covariates within the models. Moderated mediation models were examined with both remembered relationship with mother and remembered relationship with father as moderators.

**Figure 4**

*Post Hoc Moderated Mediation Model with 2-Factor CMNI Class*

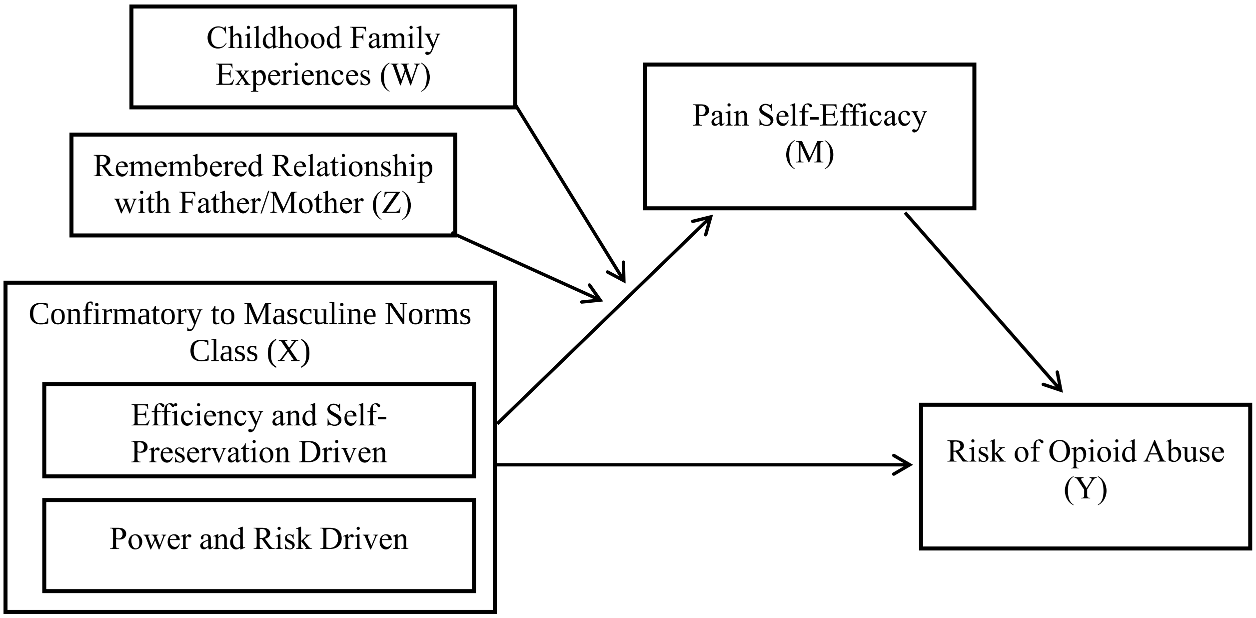


**Table 13**

*Standardized PROCESS Macro Moderated Mediation Models with Classes; CMNI-C (X), PSEQ (M), SOAPP (Y), CFES (W), and RRPS (Z).*

| Moderated Mediation Model with Classes from 2-factor Structure and Father Relation | | | | | |
|---|---|---|---|---|---|
| | *B* | *SE* | *p* | *LLCI* | *ULCI* |
| CMNI-C to PSEQ | .982 | .949 | .302 | -.887 | 2.850 |
| CMNI-C × CFES to PSEQ | -.284 | .292 | .194 | -.714 | .146 |
| CMNI-C × RRPS-F to PSEQ | .013 | .172 | .941 | -.326 | .352 |
| Direct Effect of CMNI-C to SOAPP | -.939 | .108 | $< .001^{***}$ | -1.150 | -.727 |
| PSEQ to SOAPP | .402 | .036 | $< .001^{***}$ | .331 | .474 |
| Index of CFES Moderated Mediation | -.114 | .121 | > .05 | -.328 | .145 |
| Index of RRPS-F Moderated Mediation | .005 | .128 | > .05 | -.267 | .240 |
| **Moderated Mediation Model with Classes from 2-factor Structure and Mother Relation** | | | | | |
| | *B* | *SE* | *p* | *LLCI* | *ULCI* |
| CMNI-C to PSEQ | .117 | .967 | .821 | -1.786 | 2.021 |
| CMNI-C × CFES to PSEQ | -.242 | .221 | .275 | -.677 | .193 |
| CMNI-C × RRPS-M to PSEQ | .223 | .193 | .250 | -.158 | .604 |
| Direct Effect of CMNI-C to SOAPP | -.726 | .113 | $< .001^{***}$ | -.948 | -.503 |
| PSEQ to SOAPP | .432 | .041 | $< .001^{***}$ | .351 | .513 |
| Index of CFES Moderated Mediation | -.105 | .117 | > .05 | -.312 | .153 |
| Index of RRPS-M Moderated Mediation | .096 | .142 | > .05 | -.179 | .366 |
| **Moderated Mediation Model with Classes from 9-factor Structure and Father Relation** | | | | | |
| | *B* | *SE* | *p* | *LLCI* | *ULCI* |
| CMNI-C to PSEQ | 1.490 | .884 | .093 | -.250 | 3.230 |
| CMNI-C × CFES to PSEQ | -.141 | .199 | .479 | -.533 | .251 |
| CMNI-C × RRPS-F to PSEQ | -.398 | .169 | $.020^{*}$ | -.731 | -.064 |
| Direct Effect of CMNI-C to SOAPP | -.847 | .103 | $< .001^{***}$ | -1.051 | -.644 |
| PSEQ to SOAPP | .378 | .038 | $< .001^{***}$ | .303 | .452 |
| Index of CFES Moderated Mediation | -.053 | .109 | > .05 | -.267 | .170 |
| Index of RRPS-F Moderated Mediation | -.150 | .124 | > .05 | -.420 | .071 |
| **Moderated Mediation Model with Classes from 9-factor Structure and Mother Relation** | | | | | |
| | *B* | *SE* | *p* | *LLCI* | *ULCI* |
| CMNI-C to PSEQ | 2.445 | .858 | $.004^{**}$ | .755 | 4.133 |
| CMNI-C × CFES to PSEQ | -.314 | .204 | .126 | -.716 | .089 |
| CMNI-C × RRPS-M to PSEQ | -.427 | .172 | $.014^{*}$ | -.767 | -.088 |
| Direct Effect of CMNI-C to SOAPP | -.758 | .099 | $< .001^{***}$ | -.952 | -.563 |
| PSEQ to SOAPP | .415 | .040 | $< .001^{***}$ | .336 | .494 |
| Index of CFES Moderated Mediation | -.130 | .104 | > .05 | -.349 | .065 |
| Index of RRPS-M Moderated Mediation | -.177 | .112 | > .05 | -.398 | .033 |

*Note*. Age and socioeconomic status were held constant. CMNI-C = Conformity to Masculine Norms Inventory Class, PSEQ = Pain Self-Efficacy Questionnaire, SOAPP = Screener and Opioid Assessment for Patients with Pain, CFES = Childhood Family Experiences Scale, RRPS-M = Remembered Relationship with Mother; RRPS-F = Remembered Relationship with Father, LLCI = lower level confidence interval 95%, ULCI = upper level confidence interval 95%. *p < .05, **p < .01, ***p < .001.

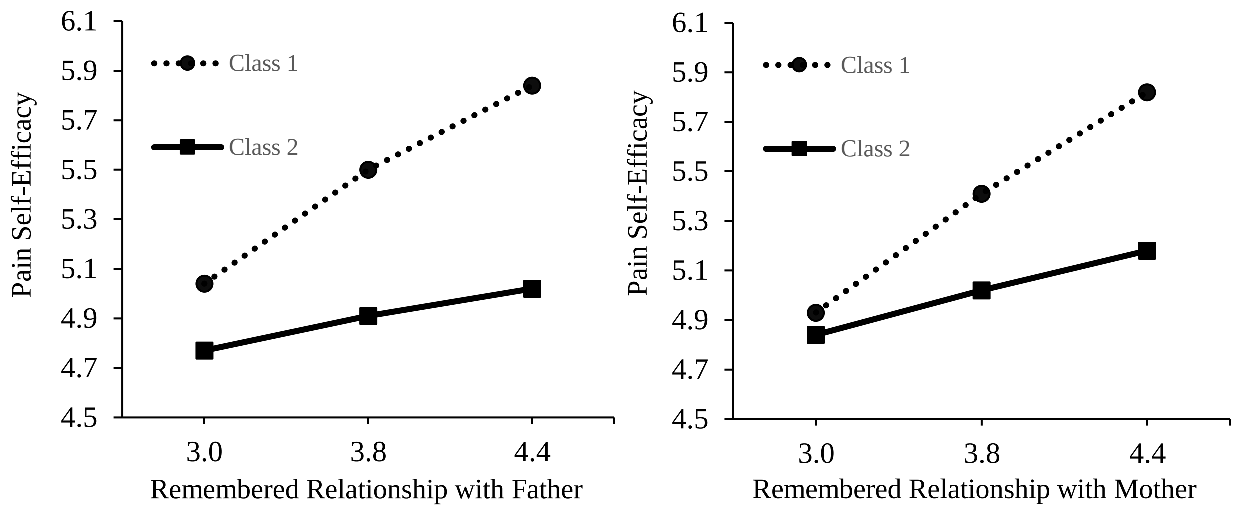
**Moderated Mediation Model with CMNI Classes from 2-factor Structure and Father Relation**. The results indicated that not all model pathways were significant, with CMNI class not being significantly associated with risk of opioid abuse (*Path a*: $B$ = .982; 95% CI [-.887, 2.850]; $p$ = .302). This does not demonstrate a mediated relation between CMNI class and risk of opioid abuse through pain self-efficacy. Childhood family experiences ($B$ = -.284; 95% CI [-.714, .146]; $p$ = .194) and remembered relationship with father ($B$ = .013; 95% CI [-.326, .352]; $p$ = .941) were also not significant moderators of the relation between CMNI class and pain self-efficacy. Childhood family experiences (*index* = -.114; 95% CI [-.328, .145]; $p$ > .05) and remembered relationship with father (*index* = .005; 95% CI [-.267, .240]; $p$ > .05) also did not significantly moderate the mediated relation between CMNI class to risk of opioid abuse through pain self-efficacy. Thus, the family experiences during childhood and the remembered relationship with one's father did not influence the magnitude of indirect effects of CMNI class on men's risk of opioid abuse through pain self-efficacy.

**Moderated Mediation Model with CMNI Classes from 2-factor Structure and Mother Relation**. Results for the moderated mediated model with remembered relation with mother were consistent with the moderated mediated model with remembered relation with father. Remembered relationship with mother was found to not be a significant moderator of the relation between CMNI class and pain self-efficacy ($B$ = .223; 95% CI [-.158, .604]; $p$ = .250). Remembered relationship with mother also did not significantly moderate the relation between CMNI class and risk of opioid abuse through pain self-efficacy (*index* = .096; 95% CI [-.179, .366]; $p$ > .05). Hence, the moderated meditated model with both remembered relationship with father and mother were not appropriate in predicting men's risk of abusing opioids with chronic pain.

**Moderated Mediation Model with CMNI Classes from 9-factor Structure and Father Relation**. Results indicated that CMNI class and pain self-efficacy were not significantly correlated (*Path a*: $B = 1.490$; 95% CI [-.250, 3.230]; $p = .093$). A non-significant *a* pathway in a mediation relation implies that pain self-efficacy does not partially or fully mediate the relation between CMNI class and risk of opioid abuse. Childhood family experiences also did not significantly moderate the *a* pathway ($B = -.141$; 95% CI [-.533, .251]; $p = .479$) or the mediated relation between CMNI class to risk of opioid abuse through pain self-efficacy (*index* = -.053; 95% CI [-.167, .170]; $p > .05$). However, there was a significant interaction effect in the *a* pathway with remembered relationship with father being a significant moderator of the relation between CMNI class and pain self-efficacy ($B = -.398$; 95% CI [-.731, -.064]; $p = .02$). Visualization of interaction effect (see Figure 5) indicates that as perceptions of alienation and control from father (i.e., remembered relationship with father) increases from low to high levels, risk of opioid abuse increases in both class 1 (i.e., HIGH masculine norms and LOW winning and violence) and class 2 (i.e., LOW masculine norms and HIGH violence and winning). Compared to class 2, class 1 had a greater magnitude of a positive relation between perceptions of alienation and control from father and risk of opioid abuse.

**Figure 5**

*Significant Interaction Effects of Remembered Relationship with Father and Mother*




*Note*. Relation between CMNI class and pain self-efficacy at Low (-1 *SD*), Moderate (*Mean*), and High (+1 *SD*) levels of perceived alienation and control from father (i.e., remembered relationship with father) and mother (i.e., remembered relationship with mother), controlling for age, socioeconomic status, and childhood family experiences, risk of opioid abuse. Class 1 = HIGH masculine norms and LOW winning and violence and Class 2 = LOW masculine norms and HIGH violence and winning.

Although remembered relationship with father was a significant moderator in the *a* pathway, it did not significantly moderate the mediated relation between CMNI class to risk of opioid abuse through pain self-efficacy (*index* = -.150; 95% CI [-.420, .071]; $p > .05$). Therefore, overall model results indicate that childhood family experiences and the remembered relationship with one's father does not influence the magnitude of indirect effects of CMNI class on risk of opioid abuse through pain self-efficacy in men with chronic pain.

**Moderated Mediation Model with CMNI Classes from 9-factor Structure and Mother Relation**. Results for the moderated mediated model with remembered relation with mother indicated significant relations between all mediation pathways including a positive association between CMNI class and pain self-efficacy (*Path a*: *B* = 2.445; 95% CI [.755, 4.134];

*p* = .004), positive relation between pain self-efficacy and risk of opioid abuse (*Path b*: *B* = .415; 95% CI [.336, .494]; $p \leq .001$), and negative correlation between CMNI class and risk of opioid abuse (*Path c'*: *B* = -.758; 95% CI [-.952, -.563]; $p \leq .001$). Significant pathways imply that pain self-efficacy partially mediates the relation between CMNI class and risk of opioid abuse.

While childhood family experiences did not demonstrate as a significant moderator (*B* = -.314; 95% CI [-.716, .089]; *p* = .126), remembered relationship with mother was a significant moderator of the relation between CMNI class and pain self-efficacy (*B* = -.427; 95% CI [-.767, -.088]; *p* = .014). Visualization of interaction effect (see Figure 5) signifies that as perceptions of alienation and control from mother (i.e., remembered relationship with mother) increases from low to high levels, risk of opioid abuse increases in both class 1 (i.e., HIGH masculine norms and LOW winning and violence) and class 2 (i.e., LOW masculine norms and HIGH violence and winning). Class 1 had a greater magnitude of a positive association between perceptions of alienation and control from mother and risk of opioid abuse compared to class 2.

Although remembered relationship with mother was a significant moderator in the relation between CMNI class and pain self-efficacy, results did not indicate either childhood family experiences (*index* = -.130; 95% CI [-.349, .065]; $p > .05$) or remembered relationship with mother (*index* = -.177; 95% CI [-.398, .033]; $p > .05$) alone as a significant moderator in the mediated relation between CMNI class and risk of opioid abuse through pain self-efficacy. Yet, taken together, the conditional indirect effect of CMNI class on the risk of opioid abuse through pain self-efficacy was significant at the mean of childhood family experiences and the mean of remembered relationship with mother (*Effect* = -.163; $p < .05$; 95% CI [-.325, -.001]), mean of childhood family experiences and one *SD* above remembered relationship with mother (*Effect* = -.269; $p < .05$; 95% CI [-.521, -.017]), one *SD* above childhood family experiences and the mean of remembered relationship with mother (*Effect* = -.228; $p < .05$; 95% CI [-.458, -.015]), and one *SD* above childhood family experiences and one *SD* above remembered relationship with mother (*Effect* = -.334; $p < .05$; 95% CI [-.637, -.045]). Thus, the overall moderated mediation model was significant at the mean and one *SD* above both remembered relationship with mother and childhood family experiences. The magnitude of the negative conditional indirect effect of CMNI class on the risk of opioid abuse through pain self-efficacy increased as both remembered relationship with mother (i.e., perceived alienation and control from mother) and childhood family experiences (i.e., greater family functioning) rose from moderate to high levels.

# CHAPTER IV

# DISCUSSION

Although the goal of researchers is to discover and disseminate truth, errors in the research process are inevitable and unfortunately fairly common in the field of psychology (e.g., Brown et al., 2018). These errors can have a profound impact on the field of psychology, as they can affect the entirety of the knowledge of a phenomenon and cause harm (Brown et al., 2018). Amazon's Mechanical Turk (MTurk) is a widely used online crowdsourcing platform in psychology to collect data including in both pain and masculinity research. Concerns have been raised as to the quality of the data collected from MTurk, which could be a large and significant factor contributing to the high publication of errors in psychology. To illuminate and rectify these concerns, there have been repeated calls in the literature (e.g., Mehler et al., 2019) for more rigorous recommendations for research practices when collecting data from MTurk and to highlight and normalize examples of non-significant findings. To help researchers produce credible research, a cautionary tale is detailed about the importance of rigorously examining data quality and the potential consequences of adhering to the current standard of practice when collecting data through MTurk. Each step through this cautionary tale offers valuable lessons and recommendations for future research, particularly in the context of masculinity and pain research.

## Examination of Data Quality

The cautionary tale began with a description of a theoretically sound study in pain and masculinity that highlighted the need for its examination and the potentially compelling implications that could have been derived from its examination. Results from the study indicated that the quality of the study's data was poor, which highlighted the crucial lesson that even the most well-conceived study can get derailed due to poor research methods or low-quality data. Specifically, findings suggested that a significant portion of the study's sample may have inattentively responded to the study's survey and enough of these participants were not able to be accurately identified to be removed from the data set. This occurred in spite of exceeding the current standard of practice from literature—utilizing at least two data cleaning strategies—when collecting data through MTurk (e.g., Chmielewski & Kucker, 2020) including surpassing strategies used by recent studies in masculinity, pain, or masculinity and pain that followed this practice of incorporating two (Kolmes & Boerstler, 2020; Himmelstein & Sanchez, 2016; Levant et al., 2022). The present study utilized the following data cleaning strategies: multiple attention checks, markers of inconsistent reporting, CAPTCHA questions, block responses, and completion time. This cautionary tale highlights that simply following or even exceeding the current standard of practice from literature when collecting data through MTurk can be insufficient in ensuring quality data. It is essential that regardless of what data cleaning strategies are utilized when collecting data through MTurk, researchers must statistically examine the quality of their data. The process used in the present study to examine the quality of data can provide a useful model and lessons for future research as the process ultimately provided evidence and clues to the poor quality of the data.

First, the Confirmatory Factor Analysis (CFA) of the research posited (e.g., Parent & Moradi, 2009) nine-factor structure of the Confirmatory to Masculine Norms Inventory-46 (CMNI-46) revealed that the nine-factor structure did not fit the data well. Specifically, within the CFA, correlations between the nine latent variables were alarmingly high, with some correlations being out of model parameters (e.g., greater than 1). Although the nine-factor structure not fitting the data was contrary to previous research (e.g., Parent & Moradi, 2009), the psychometric properties of the CMNI-46 had yet to be examined in a sample of men with chronic pain. These results could be argued to indicate that the nine-factor model structure of the CMNI-46 may lack configural invariance (i.e., the number of factors and pattern of loadings is the same across groups) in men with chronic pain and a different factor structure may be more appropriate. This was the first clue that the study's data quality was poor.

Second, results from the exploratory factor analysis (EFA) and parallel analysis (PA) revealed concerns regarding significant cross loadings, higher factor loadings from odd items falling on one factor and even items onto another, and difficulty identifying potential meaningful links or constructs between items. Although the CFA for the newly identified 2-factor structure indicated acceptable fit, the results from the EFA and PA revealed the second clue as to concerns to the present study's data validity. Thus, further data quality checks were conducted.

Third, further data quality checks uncovered unacceptable internal consistency within the CMNI-46 and its subscales and correlations between CMNI items that were blatantly counterintuitive (e.g., a positive correlation when a negative correlation was expected). When examined without reverse scoring, which is necessary with the measures used, the concerns with internal consistency and item correlations were rectified (e.g., acceptable or better internal consistency), highlighting the third clue. This suggests the study's respondents may not have provided quality responses, as block responding or other inattentive responding patterns could have been utilized. These issues were identified despite following and double-checking data cleaning procedures recommended by the literature to help collect quality data when utilizing MTurk (e.g., Chmielewski & Kucker, 2020).

CFA, EFA, PA, internal reliability, and item-level correlations in unison drew significant concerns as to the validity of the data and signified that the data could not be used in analyses to effectively explore or answer the present study's research questions. Each one of these statistical analyses was key in providing evidence for the quality of the data and could be used by future researchers to examine the quality of the data. However, many researchers do not utilize these strategies or rigorously examine the quality of their data which, as a result, they could unknowingly be using substandard data that yields inaccurate results, misguided interpretations, inappropriate recommendations, and potential harm (e.g., Brown et al., 2018) which is illustrated in the present cautionary tale.

**Importance of Rigorously Examining Data Quality**

Utilizing a CFA was one fundamental tool that helped to illuminate the problems with the present study's data. CFA is one of the first fundamental steps in Structural Equation Modeling. Results from a CFA can help demonstrate that a model or factor structure (i.e., specified relations between latent factors and observed indicator variables) is not appropriate to measure or represent a construct, as the specified structure does not fit the data well. Utilizing a model with poor fit draws concerns as to whether the results really represent what the model is argued to measure, clouding and diluting the knowledge of the phenomenon. Although a CFA can indicate that a factor structure is not appropriate to represent a construct, this indication is reliant on the quality of the data and that it accurately represents the desired population. Thus, CFAs can not only indicate model structure but also provide evidence toward the quality of the data itself (e.g., Carle, 2010). The present study highlighted how a CFA can also provide clues about the quality of the data.

Although its utility, conducting a CFA is not a widespread practice as several studies utilizing latent class analysis (LCA) or latent profile analysis (LPA) to explore masculinity groups did not conduct a CFA or examine the factor structures of their measures (Casey et al., 2016; Greene & Davis, 2011; McDermott & Schwartz, 2013; McDermott et al., 2022). Without a CFA, other researchers could have used the research posited 9-factor model structure of the CMNI-46 for the Latent Class Analysis and subsequent mediation analyses. This would have made it difficult for researchers to identify the flaws of not only the poor fit of the 9-factor with the data but the poor quality of the data itself in the present study. Without utilizing a CFA, other researchers could have erroneously interpreted results utilizing the 9-factor structure as valid. Conducting a CFA can help future researchers avoid this mistake and its subsequent consequences, further supporting the validity of their research.

Even if other researchers conducted a CFA and a questionable fit was determined, other researchers could have stopped after conducting an EFA or PA. For example, in the present study, the EFA identified a new 2-factor structure of the CMNI-46, which results indicated appropriate fit for the data. Other researchers could have moved forward with examining the study's research aims through utilizing this newly identified 2-factor structure. However, results derived from these analyses would be based on poor-quality data and could produce questionable or inaccurate results and interpretations. Thus, examining the internal consistency of scales (i.e., Cronbach's alphas) and item-level correlations were the second and third fundamental analytical tools that helped to illuminate the problems with the present study's data. Specifically examining the internal consistency and item-level correlations with reverse scored items was enlightening, as these indicated concerns for participants' response patterns (e.g., inattentive responding patterns).

Future research that incorporates measures utilizing reverse scored items could benefit from examining internal consistency and item-level correlations as it could provide further validity to their study. However, measures of internal consistency, such as Cronbach's alphas, should be interpreted with caution, as Cronbach's alpha denotes how closely related a set of items are as a group and the number of items in a measure can impact this score (Alkhadim, 2022). For example, if the CMNI-46 contained fewer reverse scored items instead of its 18, the present study's Cronbach's alpha for the CMNI-46 could have exhibited an acceptable or greater internal consistency and not provided evidence for participants' inattentive or block response patterns. Examining item-level correlations between non and reverse scored items is more resilient to this concern. If the internal consistency and item-level correlations were examined earlier in the present study, it would have saved time and is recommended for future researchers utilizing reverse scored items.

In the present study, examining a CFA, the internal consistency, and item-level correlations were three instrumental statistical tools in identifying the poor quality of the data. These three analytic tools are often overlooked by many researchers (e.g., Casey et al., 2016), and if not used in the present study, might have led to flawed results. The cautionary tale displays what flawed results could have been identified by other researchers if they moved forward with the 9-factor (i.e., no CFA examined) or 2-factor (i.e., stopping after EFA) structure of the CMNI-46. Researchers could have found and highlighted notable yet flawed results including: (1) the 9-factor structure of the CMNI-46 not fitting a sample of men with chronic pain, (2) a newly identified 2-factor structure of the CMNI-46 fitting the better data better, (3) two identified conformity to masculine norm classes characterized by high and low levels of endorsement (derived from both the 9-factor and 2-factor structures of the CMNI-46), (4) *HIGH masculine norms and LOW winning and violence* class was younger and generally in a lower socioeconomic status as well as endorsed higher levels of overall conformity to masculine norms, pain self-efficacy, and risk of opioid abuse, (5) *LOW drive for efficiency and self-*

*preservation and HIGH drive for power and risk* class endorsed higher levels of overall conformity to masculine norms and pain self-efficacy and was younger and generally in a lower socioeconomic status, (6) a significant partial mediation between CMNI class to risk of opioid abuse through pain self-efficacy with the significant and negative indirect effect indicating less risk of opioid abuse in the *LOW masculine norms and HIGH violence and winning* class (9-factor CMNI-46 structure) and the *HIGH drive for efficiency and self-preservation and LOW drive for power and risk* class (2-factor CMNI-46 structure), (7) once moderators of childhood family experiences and remembered relation with father were added to the model, the mediation relation was no longer significant, (8) a significant moderated mediation relation between CMNI class (9-factor CMNI-46 structure) to risk of opioid abuse through pain self-efficacy with childhood family experiences and remembered relation with mother as moderators, (9) within the significant moderated mediation relation, the magnitude of the negative conditional indirect effect of CMNI class (i.e., class 1 to class 2) on risk of opioid abuse through pain self-efficacy increased as both remembered relationship with mother (i.e., perceived alienation and control from mother) and childhood family experiences (i.e., greater family functioning) rose from moderate to high levels , (10) remembered relation with mother as a significant moderator in the relation between CMNI class and pain self-efficacy with as perceptions of alienation and control from mother (i.e., remembered relationship with mother) increases from low to high levels, risk of opioid abuse increases in both *HIGH masculine norms and LOW winning and violence* class and *LOW masculine norms and HIGH violence and winning class*.

As described above, there could have been several noteworthy and ultimately flawed results that could have been identified through the present study if appropriate steps were not taken to determine that the quality of the data was poor. Problematic interpretations and recommendations could have been drawn from these flawed results, which could have had far-reaching consequences. For example, from the results, researchers could have highlighted that men with chronic pain characterized by high conformity to masculine norms and low conformity to winning and violence are at a greater risk of abusing opioids. This is supported by previous research that has linked masculine norms with increased engagement in unhealthy behaviors, under-reporting pain symptoms, greater substance use, help-seeking avoidance, and increased pain medication consumption (Bradstreet & Parent, 2018; Daheim et al., 2020; Iwamoto & Smiler, 2013; Yousaf et al., 2015). However, these response patterns as a group and the low conformity to winning and violence are novel findings and could be argued to provide greater context to men's opioid use behaviors.

From this group response pattern finding, researchers could suggest the importance of identifying men within this group and tailoring interventions toward them to help reduce the likelihood of them abusing opioids. This could minimize unnecessary attention toward men who do not require such support, such as men with low conformity to masculine norms and high conformity to winning and violence, providing cost-effective and person-centered interventions. These interventions could include referring at-risk men with chronic pain to evidence-based interventions proven to help influence changes in conformity to masculine norms (e.g., Levy et al., 2020). Cognitive-behavioral therapy is one such evidence-based intervention and could target changes in specific masculine norms such as lowering conformity to self-reliance or increasing conformity to winning to help reduce men's risk of abusing opioids in this group of men. Researchers could also argue from this finding that healthcare providers could explore alternative treatment methods to prescribing opioids to men with high conformity to masculine norms and low conformity to winning and violence, as they are at a greater risk of abusing opioids.

However, these interpretations and recommendations are based upon flawed results and if followed could cause harm. First, these results and interpretations would dilute the knowledge and understanding of the overall phenomenon of men's medication use behaviors. This could impact future research as it could guide future research studies and inaccuracy support or contradict future findings. Second, if the above interpretations and recommendations are followed, men could be receiving flawed interventions, or men in need of interventions could be overlooked leading to negative biopsychosocial outcomes. These are just a few examples of ultimately flawed interpretations and recommendations that could have been highlighted. These flawed results and subsequent problematic interpretations and recommendations could have had far-reaching consequences, representing the importance of rigorously examining data quality such as through conducting a CFA, assessing internal consistency, and examining item-level correlations.

**Recommendations**

The cautionary tale provides valuable lessons and recommendations for future research. In the present study, the data was proven to have poor quality despite exceeding the current standard of practice from literature (e.g., Aguinis et al., 2021) when collecting data from MTurk. The data cleaning strategies that were utilized included using screening tools on the MTurk platform such as filtering by location (e.g., United States), paying participants, and filtering by Human Intelligence Task (HIT) approval rate > 95% approval as well as employing data cleaning techniques such as removing participants who did pass multiple attention checks, inconsistently reported, did not get past CAPTCHA questions, block responded, and responded too quickly. The standard practice when collecting data through MTurk advises utilizing at least two data cleaning strategies (e.g., Aguinis et al., 2021), which was exceeded in the present study in an attempt to be rigorous in safeguarding quality data. However, exceeding this standard of practice from the literature was inadequate. This is largely consistent with more recent research that has argued the standard of practice is insufficient when collecting data with MTurk given the increased rising rates of poor-quality responses (e.g., Burnette et al., 2022; Webb & Tangney, 2022). Utilizing CAPTCHA questions were also not effective in eliminating poor responses, a more recent recommendation from literature to eliminate bots (Hitaj et al., 2020; Yarrish et al., 2019). The present study provides evidence that including CAPTCHA questions is not the sole solution to ensuring quality responses and suggests that bots may not be the primary concern when collecting data with MTurk.

This indication that following or even exceeding the standard of practice from literature (e.g., Chmielewski & Kucker, 2020) is insufficient in ensuring quality data calls into question the results of recently published articles in masculinity (Borgogna et al., 2022; Borgogna & McDermott, 2022; Cavalhieri et al., 2022; McDermott et al., 2022; Thomas & Hart, 2023), pain (Kim et al., 2022; Mun et al., 2021; Wright & McNeil, 2021), or masculinity and pain (Kolmes & Boerstler, 2020) that used MTurk as they have all largely followed or exceeded—similarly to the present study—this standard of practice. For example, in a study examining the stability of masculinity ideology over time, researchers used multiple attention checks and a self-report question assessing response accuracy to help clean their data (Borgogna & McDermott, 2022). Several studies in masculinity (Foster et al., 2022), pain (Bartel et al., 2020), and masculinity and pain (Esiaka et al., 2019) still do not conduct or report data cleaning strategies. Collecting valid data is important in each of these three research areas, as researchers often are trying to examine a specific and unique population—such as men with chronic pain—where participants must meet certain criteria (e.g., self-report as male; pain for four or more days per week). If quality research is not collected, it draws concerns for whether samples from MTurk are truly representative of the target population (e.g., men with chronic pain) as responders not of the intended population can pass validity checks through misrepresentation or inattention. Thus, caution and more rigorous strategies are needed with MTurk in general but also particularly in masculinity, pain, and masculinity and pain research.

Data cleaning strategies employed by other masculinity or pain studies provide additional strategies that could be utilized to increase rigor toward protecting against threats to data validity when collecting through MTurk. Ulterior strategies used by these researchers include incorporating self-assessment of response accuracy, open-ended questions, programs to track IP addresses origin, and memory questions about a presented vignette (Borgogna et al., 2022; Borgogna & McDermott, 2022; Cavalhieri et al., 2022; McDermott et al., 2022; Thomas & Hart, 2023).

Recent research also supports the specific use of employing qualitative responses and examining IP addresses when collecting data with MTurk (e.g., Dennis et al., 2020). In a study examining data collection strategies on MTurk, Kennedy and colleagues (2020) found that participants utilizing Virtual Private Servers (VPS) or IP addresses from outside of the United States failed to pass validity checks at a significantly higher rate than other participants, and once removed, improved the quality of data. Another study highlighted an alarming number of participants who attempted to conceal their IP addresses (e.g., using VPS) and circumvented screening methods and provided low quality responses (Dennis et al., 2020). However, there are limitations with attempting to collect and remove participants by IP addresses, which include getting permission from IRBs and inadequate tools/programs to track the origination of IP addresses or the use of VPS.

Qualitative questions such as open-ended questions have also been suggested as a useful tool when collecting data through MTuck (Aguinis et al., 2021; Burnette et al., 2022; Webb & Tangney, 2022). Removing participants who respond unusually to these questions, such as words that do not make sense to the question (e.g., “Who are you?” = “Soon”), has proven to help identify inattentive respondents (Webb & Tangney, 2022). Thus, incorporating qualitative responses and/or examining IP addresses in addition to the strategies utilized in the present study including attention checks, markers of inconsistent reporting, CAPTCHA questions, block responding, and completion time cutoffs may be useful in cleaning data collected from MTurk. The strategies used in the present study were effective in identifying problematic respondents, but not effective enough as proven by statistical examination. This evidence indicates that the current standard of practice from research (e.g., Aguinis et al., 2021) of incorporating at least two validity indicators are effective in identifying potentially problematic respondents but insufficient in ensuring quality data (i.e., failed to identify the majority of likely invalid responses). It is recommended, evidenced by the present study, that researchers should utilize more rigorous data cleaning strategies such as including multiple strategies, as many as feasible, to clean their data when using MTurk including incorporating qualitative responses and/or examining IP addresses to help protect quality data. Table 14 provides a list of data cleaning strategies that could help address validity threats in collecting data from MTurk with each being identified to help recognize potentially problematic respondents. These data cleaning strategies are also not exclusive to MTurk, and can be effectively applied in other online data collection platforms to help ensure the integrity and reliability of the data collected in psychology across online platforms, as data quality concerns are not exclusive to MTruk.

**Table 14**

*Data Cleaning Strategies to Help Address Validity Threats in Collecting data from MTurk*

| Platform | Strategy | Description/Note |
|---|---|---|
| MTurk (pre-screening) | • Filtering by location (e.g., only participants from the United States) if appropriate | ▪ U.S. participants have been identified to have lower rates of inattentive responding |
| | • Human Intelligence Task (HIT) approval rate > 95% approval | ▪ Represents the proportion of completed tasks that are approved by Requesters; > 95% approval is argued to be indicative of more attentive responders as their work has previously been approved |
| | • Paying participants U.S. minimum wage when drawing on U.S. samples | ▪ Shown to help reduce perceived researcher unfairness and greater participant incentive/buy in to provide quality responses |
| Validity Check Indicators (data cleaning strategy) | • Including multiple attention checks – the more the better but at least more than two | ▪ Examples include: instructed items that direct participants to complete or abstain from a particular action, bogus items that ask participants to answer obvious or ridiculous questions |
| | • Markers of inconsistent reporting | ▪ Repeating questions or content questions that can assess if participants inconsistently report (e.g., reporting different ages through the survey) |
| | • Incorporating at least two CAPTCHA questions, with one at the begging | ▪ CAPTCHA questions have been found to be effective in identifying and keeping out bots |
| | • Block responding | ▪ Removing participants who block respond (e.g., answer "strongly agree" to all items) – determining appropriateness is necessary as block responding could be genuine responses; measures with reverse scoring items could warrant block responding removal |
| | • Completion time cut offs for inclusion | ▪ Removing participants who complete the survey in an appropriate amount of time (i.e., complete too quickly or too long) |
| | • Qualitative open-ended question | ▪ Removing participants who respond unusually to open-ended questions, such as words that do not make sense to the question (e.g., "who are you?" = "soon"), have proven to help identify inattentive respondents |
| | • Examining IP addresses | ▪ Tracking IP addresses can enable researchers to remove participants who attempt to conceal their IP addresses or participate when they don't meet criteria (e.g., from outside of U.S. when U.S. participants are needed); Research has found participants who utilize Virtual Private Servers (VPS) or IP addresses from outside of the United States to fail to pass validity checks at a significantly higher rate than other participants |
| | • Self-assessment of response accuracy or effort | ▪ Include a question asking participants if they considered their responses to be accurate or the degree of effort they put into testing. Studies have found that some MTurk respondents will report low accuracy or effort, indicating truthful or inattentive responding. |
| | • Memory questions about a presented vignette | ▪ Researchers can present a short video or written vignette and ask questions pertaining to its content. However, researchers should be cautious of time commitment of completing the survey for participants. |

*Note*. Strategies have been identified in the present study and literature to help identity potentially problematic responders (e.g., inattentive responding); Present study's recommendation is to include multiple data cleaning strategies, as many as feasible, when using MTurk including incorporating qualitative responses and/or examining IP addresses to help protect quality data; The more strategies used the better.

As the present study highlighted, simplifying following the data cleaning recommendations above does not ensure quality data when collected from MTurk or through another platform. Researchers must rigorously examine their data to provide statistical evidence of their data's quality, as participants simply passing data cleaning procedures is insufficient. This practice of statistical examination of the quality of data is largely absent or not reported in the masculinity, pain, or masculinity and pain research fields (e.g., Thomas & Hart, 2023), even when MTurk is used. The absence of statical examination can result in the publication and dissemination of inaccurate results, misguided interpretations, and inappropriate recommendations as illustrated in the present cautionary tale. Thus, the absence of specifically examining the quality of their data further draws into question masculinity and pain research that has used MTurk and did not adopt this practice.

Masculinity as well as pain research that has specifically examined the quality of their data from MTurk utilized analytic tools to assess analysis assumptions (e.g., normality), internal consistency, and model factor structures such as CFAs (Borgogna & McDermott, 2022; Cavalhieri et al., 2022; Foster et al., 2022). These studies are largely outliers, highlighting the worrying absence of examining data quality in the research. Examining CFAs, internal consistency, and item-level correlations were three instrumental statistical tools in identifying the poor quality of the present study's data (Borgogna & McDermott, 2022; Foster et al., 2022). However, the statistical examination of the quality of data including these analytic tools is often overlooked by many researchers (e.g., Casey et al., 2016) and the lack of examination of data quality could be a contributing factor leading to questions as to the credibility of research in the field of psychology and the data collected from MTurk (Lilienfeld & Strother, 2020; Simmons et al., 2011; Vazire et al., 2022). It is recommended, no necessary, that researchers provide statistical evidence for the quality of their data—especially in masculinity or pain research—when using MTurk, with CFAs, internal consistency, and item-level correlations as three potentially useful analytical tools.

It is also recommended that researchers specifically describe their data screening process and examination of data quality when using MTurk to help others assess the integrity of their data and aid in the reproducibility of their research. This practice of reporting is alarmingly often not included in studies utilizing MTurk (Burnette et al., 2022) such as in masculinity (Foster et al., 2022), pain (Bartel et al., 2020), or masculinity and pain research (Esiaka et al., 2019). Specifically reporting data cleaning procedures and statistical evidence regarding data quality is in line with the open science movement in psychology. Open science is a set of practices designed to make scientific processes and results more transparent, credible, reproducible, and accessible (Hesse, 2018). Specifically exploring and describing the data cleaning strategies utilized and the process of the examination of the quality of the data were notable strengths of the present study and in line with this open science movement. Employing this open science approach, the present study took a transparent and much deeper dive into the data which provided valuable lessons and recommendations for future researchers. The present study offers several recommendations for best practices to help protect against threats to data quality when utilizing MTurk. Table 15 summarizes these recommendations derived from the present study in unison with recommendations from the literature to help researchers improve research practices. While some of these best practices may also apply to studies that do not utilize MTurk, recommendations specifically focus on how to help ensure quality data collected from this platform and in the context of masculinity and pain research. Following these recommendations could ultimately help the replication crisis in psychology and the credibility of psychological research, as more reliable research is distributed.

**Table 15**

*Recommendations for Best Practices to Help Protect Against Threats to Data Quality When Utilizing MTurk*

| Recommendation | Implementation |
|---|---|
| 1.) Evaluate appropriateness of utilizing MTurk to collect data | • Acknowledge and articulate specific characteristics desired in sample to effectively assess study's hypotheses or research questions<br>• Assess potential alignment between desired target population and that which could be collected through MTurk<br>• Review recent and up to date research on sampling characteristics and strategies to collect data from MTurk |
| 2.) Develop procedures to collect data with MTurk in alignment with recent research | • Paying U.S. minimum wage when drawing from U.S. participants<br>• Decide what criteria (if any) will be used to decline payment to MTurk participants<br>• Identify and specify procedure of removing participants from the final sample – *should pass as many as feasible* |
| 3.) Implement data cleaning strategies in survey, as many as feasible, to help address validity threats in collecting data | • Begin survey with informed consent document that includes details on compensation rules (e.g., codes of conduct, monitoring procedures, and penalties for fraudulent or untruthful reporting)<br>• Pair a CAPTCHA verification with informed consent to help prevent bots at the beginning of the survey<br>• Include items to detect characteristics needed for the required sample (e.g., age, gender, chronic pain criteria)<br>• Implement MTurk pre-screening strategies (see Table 14 – it is recommended to include all strategies)<br>• Embed validity check indicators for data cleaning once study is completed (see Table 14); The more validity indicators the better; Should include as many as feasible or more indicators; Incorporating open-ended questions and tracking IP addresses should be given priority |
| 4.) Determine desired sample size | • Conduct power analysis to determine necessary sample size for study's analyses<br>• Plan to collect and compensate more participants than desired sample size as participants will be removed through data cleaning procedures and attrition. Aguinis and colleagues (2021) advised that at least an additional 30% of the desired sample should be expected to be collected. |
| 5.) Screen and clean MTurk data | • Screen data and pay participants in a timely manner in accordance with a-priori criteria<br>• Respond promptly to any questions raised by participants<br>• Monitor participant MTurk IDs to check for potential multiple completion of the study by the same participant<br>• Collect more MTurk batches or participants until desired sample size is reached after data cleaning |
| 6.) Provide statistical evidence for the quality of the data, regardless of what data cleaning strategies utilized | • Conduct and report analysis to examine quality of the data. If appropriate and in line with study, analyses could include:<br>o Confirmatory Factor Analysis (CFA)<br>o Internal consistency<br>o Item-level correlations (may be particulate useful with reverse scored items) |
| 7.) Specifically report data screening procedures and examination of data quality process | • Aim to be transparent, credible, reproducible, and accessible in line with open science movement<br>• Report information regarding all procedures followed during each stage of the research process<br>• Provide necessary data if requested for examination or replication by other researchers<br>• Report significant and non-significant findings |

*Note*. Recommendations derive from lessons learned from the present study's cautionary tale and suggestions from literature in combination.

**Limitations and Future Directions**

Although the present cautionary tale provides valuable lessons and recommendations for future researchers, limitations should be noted. First, the cautionary tale presented derives from a specific research process taken during the examination of a study on men with chronic pain, conformity to masculine norms, and risk of opioid abuse. It is important to consider that the lessons learned from this cautionary tale may not be directly applicable to other research contexts or studies with different populations, representing a limitation of the generalizability of the cautionary tale. Second, the cautionary tale highlights three analytical tools including CFAs, internal consistency, and item-level correlations that were instrumental in helping to identify the data as poor and recommended as potential tools for future researchers to do the same. While these methods can be useful for identifying issues with data quality, they may not be relevant or applicable to other studies. Future research could disseminate a manuscript that specifically describes various strategies researchers could employ to provide statistical evidence to the quality of their data when using MTurk, given the importance of doing so as identified in the present cautionary tale. Third, the cautionary tale focuses on issues related to data quality and data cleaning procedures in the context of MTurk. There are many other factors that can contribute to errors in psychological research, such as research design, biases in sampling, measurement errors, and analytical choices. Unique and different challenges may also be present when collecting data through other sources besides MTurk. The cautionary tale did not address all these potential sources of errors and focused on the context of MTurk. Future discussions of cautionary tales in psychological research should aim to provide more comprehensive and specific guidance on best practices in research design, data collection, and analysis, as well as consider a wider range of potential sources of errors and challenges that researchers may face to address the present study’s limitations.

Another area for future research is examining the present study's proposed model which entailed examining which men with chronic pain may be at a greater risk of abusing opioids through exploring the heterogeneity of conformity to masculine gender norms using a definite number of discrete disposition classes. The study articulated an important need (e.g., significant personal and societal burden of both chronic pain and opioid abuse in men) for this research and notable gaps (e.g., the absence of examination of different latent masculine norms groups in men with chronic pain) it could fill in the research. Incorporating recommendations from the present study (e.g., incorporating qualitative responses for data cleaning with MTurk) could help future researchers collect quality responses to be able to effectively examine the proposed model. If future research is to examine masculine gender norms and opioid abuse, it is important to examine how other factors such as race, ethnicity, or other social identities intersect with men's conformity to gender norms to shape their health outcomes.

**Cautionary Tale Synopsis**

MTurk is a widely used platform in psychology to collect data and there is evidence that if not screened or cleaned effectively, data collected can be poor and significantly contribute to the dissemination of errors. The present cautionary tale indicates that the current standard of practice to clean data collected from MTurk is insufficient to ensure quality data and that more rigorous data cleaning procedures are needed. Incorporating multiple (i.e., as many as feasible) strategies to clean data including incorporating qualitative responses and/or examining IP addresses may be the more rigorous practices needed to help protect quality data. Continued research in this area is needed such as through comparing and examining the psychometric properties of measures between groups using different data cleaning strategies (e.g., cleaning by IP addresses vs. attention checks). The present cautionary tale highlights that no matter how theoretically sound a study is or what data cleaning strategies are used, researchers using MTurk should provide statistical evidence for the quality of their data. Examining CFAs, internal consistency, and item-level correlations are three statistical tools that could provide support for the quality of one's data. Researchers should also report their process of data screening and examination of data quality when using MTurk in line with the open science movement to help facilitate more transparent, credible, reproducible, and accessible research in psychology. These recommendations impose minimal costs on authors, readers, and reviewers and could most importantly help further ensure the finding and dissemination of truth. It is hoped that researchers—especially masculinity or pain researchers—will embrace these recommendations as if the credibility of the field of psychology depends on it, as in a way it truly does.

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# APPENDICES

## Appendix A

## Information Sheet MTURK

**What is this project studying?**
The main purpose of this study is to learn how individuals perceive and respond to physical discomfort.

**What would I do if I participate?**
All eligible participants will complete an online study consisting of varying questions and psychological measures. The survey will take about 15 minutes to complete. Upon completion all participants will receive $1.00 to their MTurk account.

**Potential risks and benefits of participating.**
There are no anticipated physical, psychological, social, legal, or economic risks associated with this project. There are also no direct benefits from participating in this study.

**Can I quit if I become uncomfortable?**
Yes. You can stop your participation at any time without penalty or skip any questions. ***If you do not wish to participate in this study, click on the "No" button below.***

**How are you protecting privacy?**
Your identity will be kept confidential to the extent provided by law. Upon signing up to the study, participants are provided a unique identification code provided by Qualtrics. This unique code, rather than your name, is associated with your data. As such, at no point will we be able to associate your name with any of your responses, so all participants' information will be anonymous. All data files will only be accessible to the principal investigator and their research assistants. Your name will not be used in any report based on this study.

There is a minimal risk that security of any online data may be breached, because Qualtrics uses Transport Layer Security (TLS) encryption (also known as SSLv3.1) for all transmitted data. It is unlikely that a security breach of the online data will result in any adverse consequence for participants. For more information on Qualtrics's privacy and security statement, participants may visit http://www.qualtrics.com/privacy-statement/ or contact security@qualtrics.com

**Important point**
Please note that as you click "next" at the bottom of each survey page, your responses to that page are saved and you cannot go back and change them.

**I have some questions about this study. Who can I ask?**
The study is being run by Dr. Shin Ye Kim (shinye.kim@ttu.edu) and Jacob Daheim (jacob.daheim@ttu.edu). They will answer any questions you have about the study. TTU also has a board that protects the rights of people who participate in research. You can ask them questions at 806-742-2064. You can also email (hrpp@ttu.edu) or mail your questions to the Human

Research Protection Program, Office of the Vice President for Research, Texas Tech University, Lubbock Texas 79409.

**Who can participate?**
Any adult who self identifies as a male, being over age 18, and currently has chronic pain is eligible to participate.

***Are you 18 and older?*** Yes OR No (select one)

**Do you wish to participate?** Yes OR No (select one)

# Appendix B

## Screening Questions

To be included in the study, participants must be 18-years of age or older, self-identify as male, and meet chronic pain criteria. The following questions were used as screening questions to help determine if participants meet inclusion criteria:

1.) What is your age?

2.) What is your gender?
  a) Male
  b) Female
  c) Transgender, Male-to-Female (MTF)
  d) Transgender, Female-to-Male (FTM)
  e) Genderqueer
  f) Gender not list. Please specify: ________

3.) Do you experience persistent or chronic pain?
  a) Yes
  b) No

4.) How long ago did your current pain episode begin?
  a) Less than 3 months
  b) Three or more months ago

*Note*. To meet chronic pain criteria, participants must "Yes" #3 and "Three or more months ago" to #4.

## Appendix C

## Demographic Related Questions

1.) What is your age?

2.) What is your race/ethnicity?
- a) African/African America/Black
- b) American Indian/Native American
- c) Arab American/Middle Eastern
- d) Asian/Asian American
- e) Caucasian/European American/White
- f) Hispanic/Latina/o American
- g) Pacific Islander/Pacific Islander American
- h) Biracial/Multiracial
- i) Race/ethnicity not listed. Please specify: ____________

3.) How do you identify your sexual orientation?
- a) Exclusively lesbian or gay
- b) Mostly lesbian or gay
- c) Bisexual
- d) Mostly Heterosexual
- e) Exclusively Heterosexual
- f) Queer
- g) Asexual
- h) Sexual orientation not listed. Please specify: ___________

4.) What is your relationship status? Select all that apply.
- a) Single
- b) Dating, casual
- c) Dating, long term
- d) Domestic (living together) partnership
- e) Married or Civil Union
- f) Polyamorous
- g) Relationship status(es) not listed. Please specify: ____________

5.) What is the highest level of education you have completed?
- a) Some high school or less
- b) High School Diploma
- c) Some college
- d) Two year college degree (e.g., AA)
- e) Bachelor’s degree (e.g., BS, BA)
- f) Some postgraduate work
- g) Postgraduate Degree (e.g., MA, MS, PhD, MD)

6.) What is your current employment status?
a) Full-time
b) Part-time
c) Unemployed
d) Retired

7.) What is your annual household income?
a) 0-20,000
b) 20,001-40,000
c) 40,001-60,000
d) 60,001-80,000
e) 80,001-100,00
f) 100,000-150,000
g) 150,000 and above

8.) How would you best characterize your family's social class during grade school?
a) Upper Class
b) Upper-Middle Class
c) Middle Class
d) Working Class
e) Living in Poverty

9.) How would you best characterize your family's social class during high school?
a) Upper Class
b) Upper-Middle Class
c) Middle Class
d) Working Class
e) Living in Poverty

10.) How would you best characterize your social class currently?
a) Upper Class
b) Upper-Middle Class
c) Middle Class
d) Working Class
e) Living in Poverty

11.) In what environment did you primarily reside during grade school?
a) Urban
b) Suburban
c) Rural

12.) In what environment did you primarily reside during high school?
a) Urban
b) Suburban
c) Rural

13.) In what environment do you currently reside?
  a) Urban
  b) Suburban
  c) Rural

14.) What was your family's religious affiliation when you were in grade school?
  a) Christianity
  b) Islam
  c) Hinduism
  d) Buddhism
  e) Judaism
  f) Other: (please specify) _________
  g) No religious affiliation
  h) Don't know

15.) What was your family's religious affiliation when you were in high school?
  a) Christianity
  b) Islam
  c) Hinduism
  d) Buddhism
  e) Judaism
  f) Other: (please specify) _________
  g) No religious affiliation
  h) Don't know

16.) What is your current religious affiliation?
  a) Christianity
  b) Islam
  c) Hinduism
  d) Buddhism
  e) Judaism
  f) Other: (please specify) _________
  g) No religious affiliation
  h) Don't know

17.) What best describes the political ideology of your family when you were in grade school?
  a) Liberal
  b) Moderate
  c) Conservative
  d) Other: (please specify) ___________
  e) None
  f) Don't know

18.) What best describes the political ideology of your family when you were in high school?
  a) Liberal
  b) Moderate

c) Conservative
d) Other: (please specify) ___________
e) None
f) Don't know

19.) What best describes your current political ideology?
a) Liberal
b) Moderate
c) Conservative
d) Other: (please specify) ___________
e) None
f) Don't know

20.) Who were you raised by growing up? (click all that apply)
a) Father
b) Mother
c) Grandmother
d) Grandfather
e) Other: (please specify) ___________

## Appendix D

## Health Related Questions

1.) What is the cause of your chronic pain?

2.) How often do you experience your pain?
   a) 4 or more days per week
   b) 1-3 days per week
   c) Less than 1 day per week

3.) What was the **USUAL** intensity of your pain in the **past week**?

| | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| No Pain | ☐ **0** | ☐ **1** | ☐ **2** | ☐ **3** | ☐ **4** | ☐ **5** | ☐ **6** | ☐ **7** | ☐ **8** | ☐ **9** | ☐ **10** | Worst Pain Possible |

4.) Have you used over the counter painkillers within the last month?
   a) Yes. (for what reason/s?)
   b) No

5.) How often have you consumed over the counter painkillers in the last month?
   a) Once or twice
   b) About once a week
   c) More than once a week
   d) Almost every day
   e) Every day

6.) Have you consumed prescription painkillers within the last month? (select as many as apply)
   a) Yes, they were prescribed. (Why were they prescribed?) ___________
   b) Yes, they were obtained from another method. (What source did you obtain them from?) _________
   c) No

7.) How often have you consumed prescription painkillers in the last month?
   a) Once or twice
   b) About once a week
   c) More than once a week
   d) Almost every day
   e) Every day

8.) Within the last month, how often have you consumed more than the recommended dose of prescription painkillers?
   a) Never
   b) Sometimes
   c) Usually
   d) Always

9.) Within the last month, how often have you take prescription painkillers for longer than was recommended?
a) Never
b) Sometimes
c) Usually
d) Always

10.) Within the last month, how often have you consumed prescription painkillers obtained from other than your physician?
a) Once or twice
b) About once a week
c) More than once a week
d) Almost every day
e) Every day

11.) Name any prescription painkillers you have used within the past month. (common examples: Fentanyl (Actiq, Duragesic, Fentora), Hydrocodone (Hysingla, Zohydro, Lorcet, Lortab, Norco, Vicodin), Hydromorphone (Dilaudid, Exalgo), Meperidine (Demerol), Methadone (Dolophine, Methadose), Morphine (Astramorph, Avinza, Kadian, MS Contin, Ora-Morph SR), Oxycodone (OxyContin, Oxecta, Roxicodone, Percocet, Endocet, Roxicet, Targiniq ER))

12.) Have you visited a physician or doctor for issues related to pain or a physical injury within the last month?
a) Yes
b) No

13.) When you are prescribed medications, do you take them as prescribed?
a) Never
b) Sometimes
c) Usually
d) Always

14.) When you are prescribed medications, do you frequently have extra left?
a) Yes
b) No

15.) Do you ever use medications not prescribed to you?
a) Yes
b) No

16.) Do you have any chronic health issues?
a) Yes. (please specify) ________
b) No

## Appendix E

### The Conformity to Masculine Norm Inventory-46 (CMNI-46; Parent & Moradi, 2009)

Instructions:
Thinking about your own actions, feelings and beliefs, please indicate how much you personally agree or disagree with each statement. There are no right or wrong responses to the statements. You should give the responses that most accurately describe your personal actions, feelings and beliefs. It is best if you respond with your first impression when answering.

Response options:
1 = Strongly Disagree
2 = Disagree
3 = Agree
4 = Strongly Agree

Items:
1. In general, I will do anything to win
2. If I could, I would frequently change sexual partners
3. I hate asking for help
4. I believe that violence is never justified
5. Being thought of as gay is not a bad thing
6. In general, I do not like risky situations
7. Winning is not my first priority
8. I enjoy taking risks
9. I am disgusted by any kind of violence
10. I ask for help when I need it
11. My work is the most important part of my life
12. I would only have sex if I was in a committed relationship
13. I bring up my feelings when talking to others
14. I would be furious if someone thought I was gay
15. I don’t mind losing
16. I take risks
17. It would not bother me at all if someone thought I was gay
18. I never share my feelings
19. Sometimes violent action is necessary
20. In general, I control the women in my life
21. I would feel good if I had many sexual partners
22. It is important for me to win.
23. I don't like giving all my attention to work.
24. It would be awful if people thought I was gay
25. I like to talk about my feelings
26. I never ask for help
27. More often than not, losing does not bother me
28. I frequently put myself in risky situations
29. Women should be subservient to men

30. I am willing to get into a physical fight if necessary
31. I feel good when work is my first priority
32. I tend to keep my feelings to myself
33. Winning is not important to me
34. Violence is almost never justified
35. I am happiest when I'm risking danger
36. It would be enjoyable to date more than one person at a time
37. I would feel uncomfortable if someone thought I was gay
38. I am not ashamed to ask for help
39. Work comes first
40. I tend to share my feelings
41. No matter what the situation I would never act violently.
42. Things tend to be better when men are in charge
43. It bothers me when I have to ask for help
44. I love it when men are in charge of women
45. I hate it when people ask me to talk about my feelings
46. I try to avoid being perceived as gay

Subscales:
*Emotional Control* 13, 18, 25, 32, 40, & 45; *Winning* 1, 7, 15, 22, 27, 33; *Playboy* 2, 12, 21, 36; *Violence* 4, 9, 19, 30, 34, 41; *Self-Reliance* 3, 10, 26, 38, 43; *Risk-Taking* 6, 8, 16, 28, 35; *Power Over Women* 20, 29, 42, 44; *Primacy of Work* 11, 23, 31, 39; *Heterosexual Self-Presentation* 5, 14, 17, 24, 37, 46.

Scoring:
Items 4, 5, 6, 7, 9, 10, 12, 13, 15, 17, 23, 25, 27, 33, 34, 38, 40, & 41 are reverse scored. Higher scores indicating greater conformity to masculine norms.

## Appendix F

### Pain Self-Efficacy Questionnaire (PSEQ; Nicholas, 2007)

Instructions: Please rate how confident you are that you can do the following things at present, despite the pain. To answer, circle one of the numbers on the scale under each item, where 0 = "Not at all confident" and 6 = "Completely confident".

Remember, this questionnaire is not asking whether or not you have been doing these things, but rather how confident you are that you can do them at present, despite the pain.

Response options:

**0__________1__________2__________3__________4__________5__________6**

Not at all Confident Completely Confident

Items:

1. I can enjoy things, despite the pain.
2. I can do most of the household chores (eg. tidying-up, washing dishes, etc.) despite the pain.
3. I can socialize with my friends or family members as often as I used to do, despite the pain.
4. I can cope with my pain in most situations.
5. I can do some form of work, despite the pain ("work” includes housework, paid and unpaid work).
6. I can still do many of the things I enjoy doing, such as hobbies or leisure activities, despite the pain.
7. I can cope with my pain without medication.
8. I can still accomplish most of my goals in life, despite the pain.
9. I can live a normal lifestyle, despite the pain.
10. I can gradually become more active, despite the pain.

Scoring:

Higher scores indicating greater pain self-efficacy.

## Appendix G

### Screener and Opioid Assessment for Patients with Pain (SOAPP; Akbik et al., 2006)

Instructions:
Please answer the questions below using the following scale:

Response options:
0 = Never
1 = Seldom
2 = Sometimes
3 = Often
4 = Very often

Items:

1. How often do you have mood swings?
2. How often do you smoke a cigarette within an hour after you wake up?
3. How often have any of your family members, including parents and grandparents, had a problem with alcohol or drugs?
4. How often have any of your close friends had a problem with alcohol or drugs?
5. How often have others suggested that you have a drug or alcohol problem?
6. How often have you attended an Alcoholics Anonymous or Narcotics Anonymous meeting?
7. How often have you taken medication other than the way that it was prescribed?
8. How often have you been treated for an alcohol or drug problem?
9. How often have your medications been lost or stolen?
10. How often have others expressed concern over your use of medication?
11. How often have you felt a craving for medication?
12. How often have you been asked to give a urine screen for substance abuse?
13. How often have you used illegal drugs (e.g., marijuana, cocaine) in the past 5 years?
14. How often, in your lifetime, have you had legal problems or been arrested?

Scoring:
Higher scores indicate a greater risk of abusing opioids.

## Appendix H

## Childhood Family Experiences Scale (CFES; Vogt et al., 2013)

Instructions:
The sentences below refer to your relationship with your family WHEN YOU WERE GROWING UP. Please describe how much you agree or disagree with each statement by marking the response that best fits your choice. If you spent time in more than one family setting, please answer these questions about the family in which you spent the greatest part of your childhood.

Response Options:
1 = Strongly disagree
2 = Somewhat disagree
3 = Neither agree nor disagree
4 = Somewhat agree
5 = Strongly agree

Items:
1. During childhood, I get along well with my family members.
2. During childhood, I felt like I fit in with my family.
3. During childhood, family members knew what I thought and how I felt about things.
4. During childhood, I felt like my contributions to my family were appreciated.
5. During childhood, I shared many common interests and activities with family members.
6. During childhood, my opinions were valued by other members.
7. During childhood, I was affectionate with family members.
8. During childhood, I played an important role in my family.
9. During childhood, I spent as much of my free time with family members as possible.
10. During childhood, family members told me when they were having a problem.
11. During childhood, I could be myself around family members.
12. During childhood, my input was sought on important family decisions.

Scoring:
Higher scores indicated greater family functioning

# Appendix I

Remembered Relationship with Parents Scale (RRPS; Denollet et al., 2007)

Instructions:
Below are a number of statements that people often use to describe their relationship with their parents **while growing up**. Read each statement and click the appropriate response next to that statement to indicate how you remember your relationship with your **father** and **mother while growing up**. There are no right or wrong answers; the only thing that matters is **your own impression**.

Responses:
0 = False
1 = Mostly false
2 = Neutral
3 = Mostly true
4 = True

Items:
Father:
1. I was very closed towards my father
2. I kept my troubles to myself (towards father)
3. I wished my father would worry less about me
4. My father often made me feel insecure
5. My father's anxiety that something might happen to me was exaggerated
6. My father worried that I couldn't take care of myself
7. My father often made me feel guilty
8. I often felt that my father did not understand me
9. My father sheltered me too much from difficulties
10. My father was overprotective

Mother:
1. I was very closed towards my mother
2. I kept my troubles to myself (towards mother)
3. I wished my mother would worry less about me
4. My mother often made me feel insecure
5. My mother's anxiety that something might happen to me was exaggerated
6. My mother worried that I couldn't take care of myself
7. My mother often made me feel guilty
8. I often felt that my mother did not understand me
9. My mother sheltered me too much from difficulties
10. My mother was overprotective

Subscales:
*Alienation*: 1, 2, 4, 7, 8; *Control*: 3, 5, 6, 9, 10

Scoring:
Higher scores are indicative of recollections of poorer relationships with parents. The interpretation does not differ by mother or father.

*Note*: Only participants who reported being raised by a “mother” and/or “father” where displayed the RRPS. For example, participants who only endorsed being raised by a mother where only displayed the RRPS mother items. For participants who endorsed being raised by a mother and a father, RRPS mother and father items were shown. For participants who reported being raised by a figure other than a mother or father, the RRPS was not displayed.