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A Multi-Method Investigation of Officer Decision-Making and Force Used or Avoided in Arrest Situations: Tulsa, Oklahoma and Cincinnati, Ohio Police Use of Force Narrative Data Analysis Report

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EXECUTIVE SUMMARY

The overarching goal of this project was to provide a deeper and more contextualized understanding of how and why police use or avoid the use of force and to identify policy, training, or other ways that law enforcement agencies can reduce the need for force, lower the rate of injuries or deaths to civilians, and reduce police victimization when interacting with members of the public under stressful or uncertain conditions.[1] To conduct this work, the *IACP / UC Center for Police Research and Policy,* sponsored by the Laura and John Arnold Foundation (LJAF), partnered with a research team from the University of Texas at San Antonio (UTSA). The research team partnered with police executives from the Tulsa Police Department (TPD) and the Cincinnati Police Department (CPD) to review arrest and use of force encounters over a multiyear period within each community.

This second report supplements a previously issued report - *A Multi-Method Investigation of Officer Decision-Making and Force Used or Avoided in Arrest Situations: Tulsa, Oklahoma Police Department Administrative Data Analysis Report* – and details findings from an analysis of officer use of force narratives in both cities, Tulsa and Cincinnati.

The overall study used various data sources and a series of convergent analytic approaches to address the following research questions:

- How and why do some arrests turn violent while most do not?
- What factors or combination of factors contribute to injuries to civilians and the victimization of police officers during arrests?
- How can law enforcement agencies minimize conflict to reduce force, lower injuries and victimizations, and improve outcomes during arrests and similar encounters with civilians?

The "Administrative Data Analysis Report" delivered in December 2019 offered partial answers to these questions, but this report extends the inquiry to specifically examine the data drawn from officer narrative accounts of use of force incidents. The examination of these data, including all data coding and analytic decisions, was driven by interest in answering the following specific research questions (key *independent variables are italicized,* and the <u>dependent variables are underlined</u>):

1. Do the *total number of actions* in an exchange predict the <u>maximum level of force</u> within an exchange while controlling for other relevant factors?
2. Do the *total number of actions* in an exchange predict the <u>maximum level of resistance</u> within an exchange while controlling for other relevant factors?
3. Do the *total number of actions* in an exchange predict the <u>force factor</u> within an exchange while controlling for other relevant factors?

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[1] The analyses and findings presented in this report are empirical and data-driven. They do not represent a legal analysis, and the authors offer no opinions on the legality of the actions undertaken by officers in individual cases represented in the data analyzed for this report.

4. Does the *initial level of force* predict the maximum level of force within an exchange while controlling for other relevant factors?
5. Does the *initial level of resistance* predict the maximum level of resistance within an exchange while controlling for other relevant factors?
6. Does the *initial level of force or resistance* predict the force factor within an exchange while controlling for other relevant factors?

The results from the narrative analyses reported here cover a 30-month period (Jan 1, 2016 – Jun 30, 2018) and include 1,180 narrative accounts of use of force incidents written by police officers or supervisors across both agencies. The narratives were carefully coded by trained research assistants from the University of Texas at San Antonio and the University of Cincinnati. The incidents, as described by the officers, were de-constructed and coded action-by-action to produce a detailed accounting of the actions officers and suspects took as the events described in the narratives unfolded. Altogether, the data yielded 1,743 exchanges (the sequence of interactions) between officers and suspects across the 1,180 incidents.

The actions taken by officers initially were coded on a 10-item force scale that ranged from consensual conversation through the use of a weapon or canine. Suspect resistance was similarly coded on an 11-item scale and ranged from compliant/no resistance up to the use of a weapon against an officer. Within these scales, weapon or canine use was captured as (1) draw/display, (2) point or threaten, and (3) actual use. The types of less lethal weapons or firearms displayed, threatened, or used also were captured in the coding schema. The initial 10 and 11 item force and resistance scales were subsequently collapsed into corresponding 6 category scales of force and resistance for the purposes of the analyses reported here.

The primary analytic approach to addressing the research questions involved multivariate modeling. Linear regression models were estimated to understand the maximum level of force used in an encounter and the maximum level of resistance present in a situation. These models used the unique and thorough coding of each action in an encounter to explore specific factors related to these actions. Additionally, analyses explored single officer, single suspect encounters and included officer, suspect, and contextual variables to assess potential relationships with maximum force and maximum resistance.

Findings

Across all of the data, Level 5 force (hard hand control, pepper spray/ball, TASER, canine) was the most frequently employed maximum level of force used by the police (68%), while Level 1 force (verbal commands) was the most frequent *starting* level of force (55%). On the resistance side, suspects most frequently engaged in Level 3 resistance (defensive resistance, attempting to flee) as both their maximum and starting levels of resistance. The mean number of actions taken was 8 across all incidents. When officers used weapons, their weapon of choice was most often the TASER (42%); suspects most frequently employed knives (3.2%) and handguns (2.3%) when using a weapon to resist arrest.

In Tulsa, canines were used more frequently than TASERs (25% v. 22%), and together pepper spray and pepper balls represented nearly 20% of actions involving weapons. In Cincinnati, TASERs dominated weapon usage (67%) followed by canines (3%) in a distant second place. In Tulsa, police displayed, threatened, or used handguns more than twice as often (5.8%) as officers in Cincinnati (2.6%).

Across all actions modeled, the *total number* of actions was positively associated with the maximum level of force used by the police. Not surprisingly, higher *starting* levels of force also were positively associated with higher *maximum* levels of force used; when police began an encounter using force at higher levels, they ended up using higher levels of force altogether.

Although s*tarting* levels of resistance were not associated with higher levels of maximum force, one of the most surprising findings in the overall maximum force model was the contribution of *maximum* resistance to maximum force. As suspect resistance increased along the continuum, the maximum force used by officers slightly decreased, a finding that was particularly pronounced in Cincinnati.

Like the force model, the overall maximum resistance model also showed a positive relationship between the number of actions taken and maximum resistance by suspects. Likewise, higher levels of starting resistance were associated with higher levels of maximum resistance. Maximum force used by the police was weakly and negatively correlated with maximum resistance. The maximum force and maximum resistance findings in the overall model were largely mirrored in the agency-specific models.

The overall Force Factor[2] model and the one for Tulsa showed no relationship between the number of actions taken and the Force Factor – measured as the relative difference between maximum force and maximum resistance. In Cincinnati, the total number of actions was weakly but positively associated with the Force Factor, indicating that more complex encounters with a greater number of actions taken resulted in slightly higher levels of force relative to resistance.

The single officer, single suspect incident models showed similar patterns with respect to the influence of total actions on maximum force and resistance. However, these models also allowed for the introduction of some contextual variables (weekday and daytime) and officer and suspect-level variables, most of which were non-significant. Daytime incidents were weakly and positively associated with higher levels of maximum force, but officer race/ethnicity, gender, rank, and years of service were not. Likewise, with the exception of actions involving male suspects, which were positively correlated with higher levels of maximum force, suspect race/ethnicity and age were unrelated to force. In particular, Black and Hispanic suspects were

[2] The Force Factor is a measurement of force relative to resistance. With the six-category force and resistance scales utilized here, the Force Factor can range from 5 to -5. Positive values indicate that police used higher levels of force relative to resistance, while negative values indicate less force compared to resistance. The Force Factor is a well-known and longstanding analytic tool for examining force and resistance. Positive values in individual cases should not be interpreted as evidence of excessive force by the police. Police are permitted to use reasonable force to *overcome* suspect resistance depending upon the facts and circumstances of each case, including factors such as the severity of the crime, the threat posed by the suspect, and whether the suspect was actively resisting arrest or attempting to flee (*Graham v. Connor,* 1989).

no more likely than White suspects to have higher levels of force used against them in the overall model or in either city individually.

The findings from the maximum resistance models involving one officer and one suspect largely tracked with those from the all cases models. In the combined model (both cities), none of the contextual or officer-levels variables were significant. On the suspect side, Hispanic suspects were more likely than White suspects to evidence higher levels of maximum resistance, while Blacks suspects were *less likely* than Whites to demonstrate higher levels of resistance. Suspect gender was a non-significant predictor of resistance in the combined single officer, single suspect model.

In Tulsa, male suspects were less likely than female suspects to show higher levels of maximum resistance while the opposite was true in Cincinnati. And in Cincinnati, Hispanic suspects (but not Black suspects) were more likely than White suspects to demonstrate higher levels of resistance. None of the contextual variables, officer-level variables, or the remaining suspect variables were significant in either city.

Finally, the combined city single officer, single suspect Force Factor model showed a slightly negative association between the total number of actions taken and the Force Factor. The only contextual, officer, or suspect-level variable to show a relationship with the Force Factor in the single officer, single suspect combined city model was the Black suspect variable, which showed a statistically significant, but substantively weak, positive correlation with the Force Factor. When each city was examined separately, however, the findings show that Black suspects were no more likely than White suspects to experience higher levels of force relative to their resistance. Thus, the race of the suspect did not predict the level of force officers used in relation to the resistance they were shown in either Cincinnati or Tulsa. Finally, male suspects were more likely than female suspects to experience higher levels of force compared to resistance in Tulsa, but not in Cincinnati.

Implications

Expeditious control of suspects with minimum requisite force

A primary question of interest in this research was whether longer and/or more complex use of force incidents (those with greater numbers of exchanges) were associated with higher levels of force or resistance. For the most part, this proved to be the case, although the relationship was not particularly strong. This suggests that a marginal reduction in the severity of force used may be achievable with a more expeditious resolution of physical conflict situations, which may escalate to higher levels of force as events drag out. Training and tactical approaches that emphasize verbal de-escalation techniques followed by skillful applications of appropriate force relative to resistance have the best chance at minimizing overall force and resistance levels.

Paradigmatic changes in the use of force may be occurring

An unexpected finding from this research was the weak and negative correlation between resistance and force found in the combined city model examining predictors of maximum force.

In the individual city models, resistance and force also were negatively correlated in Cincinnati, and they were unrelated in Tulsa. Because these findings run counter to much of the extant research on use of force, which finds a consistent and positive relationship between resistance and force, they suggest the possibility of a paradigmatic shift in how police in Tulsa and Cincinnati are employing physical force in response to resistance encountered from civilians. Rather than escalating force in response to resistance, the data show that officers are doing the opposite, and this represents a significant shift from what we thought we knew about police use of force behavior.

While the jury is still out on the effectiveness of de-escalation training at reducing the need for force, efforts are currently underway to study its effectiveness. In addition, testing whether the results reported here from Tulsa and Cincinnati hold true for other cities represents an important next step for researchers studying the use of force by police in the post-Ferguson era.

Future research must develop new data sources, coding mechanisms, and analytic approaches

Body-worn camera footage arguably offers a more objective and accurate perspective on use of force encounters than the officer narratives relied upon as a primary data source for this report. With the widespread proliferation and use of body worn cameras in American police forces, camera footage represents an enormous pool of potential data for studying and better understanding the complex dynamics of conflict between police and civilians. However, given the current time and labor constraints involved in making use of these data for research purposes, future social science researchers would be well-served to partner with colleagues from disciplines such as computer science, data analytics, and data visualization to identify new methods for using artificial intelligence and/or machine learning to automate the manual coding and analytic processes that currently dominate the research space. If researchers could identify reliable machine-driven techniques for coding and/or analyzing body worn camera footage, they could more fully realize the potential of the data to dramatically expand our ability to learn from violent police-civilian encounters, improve police training, and reduce harm.

I. INTRODUCTION

With the August 2014 shooting death of Michael Brown by Officer Darren Wilson in Ferguson, Missouri and additional publicized incidents of deadly force, protests and concerns about police use of force erupted into the Black Lives Matter movement and evoked memories of the 1960s Civil Rights Movement. Spurred by the recent deaths of young minority individuals at the hands of the police, the national discussions of use of force have been dominated by the argument that racial minorities are disproportionately subject to police actions (Donner et al., 2017; Fridell, 2017; Stroshine & Brandl, 2019). Furthermore, police use of force can have devastating consequences in terms of injuries to both officers and civilians and can lead to broader societal unrest (Alpert & Dunham, 2010). As a result, use of force by the police arguably poses the greatest threat to police and community relationships (Smith, 1995). At this critical juncture in policing, it is imperative to better understand what factors influence use of force decisions and what characteristics of encounters are related to increased injuries to officers and civilians.

The overarching goal of this research study is to provide a deeper and more contextualized understanding of how and why police use or desist from the use of force. The findings reported below offer a new window into the study of police use of force post-Ferguson. The study is built upon a solid foundation of previous research, while making improvements to the research methods, data sources, and analytic tools necessary to properly address how and why some arrests turn violent, or even lethal, while most do not. In particular, the focus of this report on written use of force narratives as a primary data source has both strengths and weaknesses. On one hand, police narratives offer detailed, contemporaneous accounts of the events described and are routinely written to document the use of force in police-civilian encounters. They reflect eyewitness accounts and are usually written shortly after the events take place and while memories are still fresh. On the other hand, these narratives offer only a single lens through which the events can be seen and are open to the criticism of being potentially self-serving.

In Tulsa, the narratives were written by the officers themselves who were involved in the events. In Cincinnati, use of force narratives are written by first-line supervisors who typically respond to the scene where force was used, conduct a preliminary investigation of the event and its circumstances, and then write a descriptive narrative of their initial findings. The research design employs quantitative methodologies to analyze a large sample of use of force narratives (n=1,180) from two jurisdictions, Tulsa, Oklahoma and Cincinnati, Ohio, that were coded by trained research assistants on an action-by-action basis to provide a highly detailed accounting of the force and resistance actions undertaken by officers and civilians involved in the encounters. This study's data and findings address important gaps in our knowledge of police decision-making during critical events and provide a detailed picture of the multi-level interactions between a number of situational, civilian, and officer characteristics associated with the decisions by officers to use or desist from the use of force.

To conduct this work, the *IACP / UC Center for Police Research and Policy,* sponsored by the Laura and John Arnold Foundation (LJAF), partnered with a research team from the University of Texas at San Antonio (UTSA). This research team, in turn, partnered with police executives from the Tulsa Police Department (TPD) and the Cincinnati Police Department (CPD) to review arrest and use of force encounters over a multiyear period within each community and in the case of this report, to code and analyze almost 2,000 use of force narratives.

This report provides the results from the narrative analyses for both cities and discusses the implications of those results for policing and the future study of use of force. This report is organized into five sections. In Section II, previous studies of police use of force are reviewed to describe the major trends in how researchers have measured and analyzed use of force, and the primary factors that are significantly associated with use of force. In Section III, the current study's research sites, methodology, data, and analytical plan are described. Section IV presents the findings from the statistical analyses of the quantitative data for CPD and TPD. Section V of the report summarizes the findings and discusses their implications for policing, use of force data collection, and future research on the use of force by the police.

II. PREVIOUS RESEARCH

Police use of force is action taken by police that threatens, attempts, or employs physical force to compel compliance from an unwilling subject (Garner et al., 1995; Henriquez, 1999). Most studies find that it is a rare occurrence, with approximately 1-5% of police-civilian encounters resulting in force (Davis et al., 2018; Friedrich, 1980; Garner et al., 2018). The prevalence of police use of force, however, depends upon how it is measured (Terrill, 2003). Unfortunately, most use of force studies do not clearly define the concept of force and vary in its measurement; similarly, reporting requirements differ across police agencies (Garner et al., 2002, 2018; Hickman et al., 2008; Pate et al., 1993; Terrill et al., 2018).[3] Some actions are nearly always conceptualized and documented as force: weaponless physical force, physical restraints, chemical spray, control tactics and nonlethal weapons (TASER), and firearm threat or use (Klahm et al., 2014). Whether verbal commands and handcuffing should be included as force is debated (Fridell, 2017; Klahm et al., 2014; Klinger, 1995; Terrill, 2003) and other scholars note that verbal force is frequently not reported by police agencies (Willits & Makin, 2018; Wolf et al., 2009). These differences in how force is measured are critical to understand because the characteristics that predict police use of force frequently vary by how it is measured (Garner et al., 2002). The prevalence of force also depends on whether the sample is all police-civilian encounters or just encounters resulting in arrest; with a higher rate of force and more serious force for those arrested (Davis et al., 2018; Garner et al., 1995; Hickman et al., 2008). Recent data from the Police Public Contact Survey indicate that less than 2% of all police-civilian contacts result in force compared to 20% of arrests (Davis et al., 2018; Hickman et al., 2008).

Studies note that when force does occur, it most commonly involves low levels of hands-on force only (Bayley & Garofalo, 1989; Garner et al., 1995, 2018; Klinger, 1995; Terrill, 2003; Torres, 2018). For example, a recent study found that use of force incidents involved “physical force only” 75% of the time, and physical force in combination with other types of force (e.g. weapon use) in another 12% of incidents (Stroshine & Brandl, 2019). Despite weaponless physical force being the most commonly used type of force, it is also the least studied, which is problematic for several reasons. First, it has been argued that force on the lower end of a force continuum has the most potential for abuse due to the greater discretion and lower visibility of these incidents (Lawton, 2007). Second, physical force is associated with a higher likelihood of both officer and civilian injury in comparison to other types of force (Stroshine & Brandl, 2019; Alpert & Smith, 1999). Finally, there is empirical evidence that the factors that influence the frequency and severity of force are different; this highlights the importance of capturing the dependent variable in multiple ways to better understand the complexities of these encounters (Lautenschlager & Omori, 2019).

The study of police use of force has evolved considerably since the early studies of Westley (1953, 1970). Historically, force was measured as a simple dichotomous variable (e.g., force/no

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[3] For a comprehensive review summarizing how police use of force has been conceptualized and measured, as well as the methodological limitations of previous research, see Hollis (2018). For a review of the strengths and weaknesses of various use of force data sources, see Garner et al. (2002).

force, deadly force/non-deadly force), which makes no distinctions based on severity of force (Crawford & Burns, 1998; Garner et al., 1995, 2002). Studies then began to measure and analyze force as a continuum, which better captures the policy, training and legal requirements for officers to use only the force that is proportionate to what is used against them or which is necessary to obtain compliance. Most studies of this type still only capture the most severe type of force used, and they usually do not capture multiple types of force occurring in the same encounter (Alpert & Dunham, 1999; Garner et al., 1995; Terrill & Paoline, 2012; Terrill et al., 2018).

In order to better disentangle the micro-level interactions between officers and civilians, a number of researchers explored content-rich data sources like observations, report narratives, body-worn camera footage, and interviews with officers and civilians to examine the "force factor" (i.e., the level of civilian resistance subtracted from the officer level of force), and other measures like time to force use and duration of force (Alpert & Dunham, 1999; Rojek et al., 2012; Terrill, 2005; Willits & Makin, 2018). The last several decades of use of force research are characterized by increased empirical attention to advanced statistical techniques, varied study designs, and greater focus on the sequential actions and reactions between officers and civilians during these encounters. The current study builds upon these advancements to continue to better understand police use of force.

Predicting the Use and Severity of Force

In order to interpret rates of police use of force, the percent of various racial/ethnic groups who experience force are often compared to the same groups' representation in population statistics; known as a "benchmark," the comparison group data is supposed to represent similarly situated people at risk of experiencing force assuming no bias exists (Engel & Calnon, 2004; Tillyer et al., 2010). The difficulty with this type of comparison is that Census data do not measure the types of characteristics that research shows put individuals at risk of experiencing force, including a number of legal and extra-legal characteristics but especially *civilians' legally relevant behaviors* such as, civilian resistance, presence of a weapon, and criminal behavior during the encounter. Simply stated, aggregate level comparisons of coercive police outcomes (e.g., stops, arrests, use of force) to Census population figures by racial/ethnic group do not consider the complexity of police-civilian interactions and should not be used (Engel et al., 2002; Nix et al., 2017). Rather, a rigorous and methodologically sound study of use of force provides a stronger mechanism to examine and control for context at the police-civilian encounter level.

An extensive body of scholarly research has also emerged that seeks to identify and measure the influence of situational, civilian, officer, organizational, and community characteristics on the likelihood of police use of force, the severity of the force used, and both civilians and officers' resulting injuries (for review, see previous report). Nevertheless, the available evidence leaves many questions unanswered. Several comprehensive reviews of police use of force studies conducted in the last two decades have noted that this body of research is marked by a number of methodological concerns that may explain the inconsistent and even contradictory estimates of both the frequency of the use of force and the reported effects of relevant predictor variables like civilian race (Garner et al., 2002; Hollis, 2018; Hollis & Jennings, 2018; Klahm et al., 2014; Klahm & Tillyer, 2010). As Fridell (2017) notes, "variation in findings could reflect variation in the actual phenomenon across agencies and/or geographic areas or could reflect different methods used to study the same phenomenon" (p.511).

Of importance to the current study, situational factors (i.e., the details and characteristics of the situation involving the use of force), include both legal and extralegal considerations regarding the immediate context of police-civilian encounters. The body of evidence that has accumulated on officer decisions to use force has consistently found that several situational and legal factors are the strongest predictors of officers' decisions to use force and the severity of the force used. In particular, across varied study designs and measures of officer use of force, civilians' resistance is the single most important factor explaining whether force is used and the severity of that force (e.g., Fridell & Lim, 2016; Gau et al., 2010; Lawton, 2007; Stroshine & Brandl, 2019; Terrill & Mastrofski, 2002). For example, Rossler and Terrill (2017) found that civilians who were non-resistant or simply failed to comply experienced significantly lower levels of force compared to civilians who were defensively resistant (physically struggling to avoid arrest); likewise, civilians who displayed aggressive physical resistance or deadly resistance were significantly more likely to experience even more serious levels of force than those who were engaged in defensive resistance alone. In short, the vast majority of studies find that officers' use and severity of force is directly correlated with civilians' resistance during encounters with police. These findings are not surprising given that officers are trained to escalate or de-escalate force in response to resistance, and the Supreme Court has interpreted the Fourth Amendment to permit police to use only the amount of force that is reasonable under the circumstances (*Graham v. Connor*, 1989). Some studies further report that the size and statistical significance of the effects of other variables, including civilian race, change once resistance is controlled (Garner et al., 2002).

Beyond these legal and situational considerations, researchers have also explored the influence of non-legal predictors of the use of force by police, including both civilian and officer characteristics. The body of evidence for these characteristics is generally mixed, with some civilian and officer characteristics showing consistent relationships with use of force, but most showing inconsistent findings across studies (Crawford & Burns, 1998; Klahm & Tillyer, 2010; McElvain & Kposowa, 2008; Schuck & Rabe-Hemp, 2007). For example, most research finds that civilian demeanor is a strong predictor of officers' use of force; civilians who are more disrespectful are more likely to experience force and more severe force (Engel et al., 2000; Engel et al., 2012; James et al., 2018; Sun & Payne, 2004; c.f. Terrill & Mastrofski, 2002). For example, Crawford and Burns (1998) found that suspects who had an angry or aggressive demeanor were more than nine times as likely to have chemical agents used against them and almost six times as likely to have physical control tactics or nonlethal weapons employed against them. Nix and colleagues (2017b) found that officers perceive disrespectful suspects as a greater threat to them. It is important to note, however, that civilian demeanor is one of the most difficult characteristics to reliably measure. Some research highlights that civilian demeanor often changes during the course of an officer-civilian interaction and may do so in response to officer demeanor or behavior (Dunham & Alpert, 2009; Reisig et al., 2004). Other research finds that measures of demeanor almost exclusively rely on observers' perceptions of disrespect, rather than the officers' (Donovan et al., 2018). Engel and colleagues (2012), however, found that officer perceptions of demeanor varied by their race as well as civilian race. Therefore, it is unknown if studies that failed to find a significant effect of demeanor are due to measurement issues associated with this variable or whether the impact of demeanor may be significant for some types of force but not others (Klahm & Tillyer, 2010).

Sequencing of Police-Civilian Encounters

Early researchers considering police use of force also recognized the importance of understanding the exchange process between officers and civilians. Clearly officers' use of force does not happen in a vacuum and understanding the role that civilian behaviors play during these encounters is of critical importance. For example, when describing the "violent police-civilian encounter," Binder and Scharf (1980) noted the encounter is "considered a developmental process in which successive decisions and behaviors by either police officer or civilian, or both, make a violent outcome more or less likely" and further that "the emphasis upon mutual contributions in the encounter carries policy implications that have not always been carefully considered in the past" (p.111). By documenting four phases of police-civilian encounters (anticipation, entry, information exchange, and final decision), these scholars highlighted the complexity of violent encounters between the police and the public.

The importance of measuring the sequencing of actions during police-civilian encounters found further support in early research conducted by Sykes and Brent (1980) that sought to determine the factors related to officers "taking charge" of police-civilian interactions. Prior to this work, no research had attempted to systematically study the verbal or physical exchanges between officers and civilians during their interactions. Using the Midwest City data, collected through systematic social observation of officers from 1970-1973, Sykes and Brent (1980) analyzed each coded "utterance" between police and suspects collected across 95 separate encounters. As noted, "since the utterances of officers and civilians were coded as they occurred, this permitted the analysis of the sequence of responses, specifically, the officer's response to the civilian's disturbance" (Sykes & Brent, 1980, p.189). Through this early research, the importance of documenting the process of police-civilian interactions was established.

Force Factor

Given the importance of civilians' resistance in predicting police use of force, additional research effort has been placed on measuring resistance as it relates directly to use of force. Prior to the late 1990s, researchers examined the highest level of force used by police during an encounter, without directly accounting for the civilian's level of resistance (Alpert & Dunham, 1999). Out of concern that previous use of force research was not providing a thorough understanding of the police-civilian encounter, Alpert and Dunham (1997) proposed the creation of a "force factor" that compares the civilian's amount of resistance displayed to the amount and severity of force used by officers. Specifically, to create a force factor measure, the officer's *level* of force and civilian's *level* of resistance need to be similarly measured and scaled (Alpert & Dunham, 1999). These levels are determined based on their position on a continuum. As noted by Terrill (2005), two concepts are inherent within police use of force continuum structures: proportionality and incrementalism. First, the amount of officer force should be *proportional* to the type of civilian resistance displayed. Second, increases or decreases in the use of force should be *incremental,* based on changes in the level of civilian resistance experienced.

Using the concept of measuring force on a continuum, the force factor is calculated by subtracting the level of civilian resistance from the level of officer force. If the force factor is zero, it indicates a level of force commensurate with a level of resistance. A positive force factor indicates that the level of force used by police was higher than the level of civilian resistance, and a negative force factor indicates that the level of force used by police was lower than the level of resistance displayed by civilians.

Alpert and Dunham (1997) developed and used the force factor by comparing the highest level of officer force used during an encounter, to the highest level of civilian resistance displayed during an encounter. In this manner, they were able to assess the consistency of the officer's force to civilian's resistance. Using official data from police departments in Miami, Florida and Eugene, Oregon, Alpert and Dunham (1997) examined differences in force factors based on certain contextual, officer, and civilian characteristics (e.g., in Miami, female police officers used significantly less force than male officers for a given level of resistance). Alpert and Dunham (1999) noted that if the level of force is higher than the level of resistance, it does not necessarily indicate that the officer used excessive or improper force. It is possible that the officer needed to use more force to gain control of the incident. Beyond its research application, the force factor can be applied within departments to assess differences across units.

Following the force factor method outlined by Alpert and Dunham (1997, 1999), other researchers have used the force factor to determine differences in officers' responses to civilian resistance using weighted force factors, examine differences in the relative level of force across different types of calls for service, and assess the value of weighted force factors as an early intervention program indicator (Bazley et al., 2007, 2009; MacDonald et al., 2003). For example, Bazley and colleagues (2007) calculated a weighted force factor for each officer that was a composite of the number, differential, and direction for each officer's individual report history. Their results indicated that female and male officers responded differently to civilian resistance. MacDonald and colleagues (2003) found that there were mostly no differences in the relative level of force (i.e., highest level of force minus highest level of resistance) amongst different calls for service; however, officers used more force as compared to civilian resistance on calls related to property offenses than domestic disturbances.

Since Alpert and Dunham's (1997) pioneering work, researchers have expanded creation and use of force factors to assess more than just the highest levels of force and resistance used in an incident, including all of the individual interactions or exchanges within a single police-civilian encounter. For instance, Terrill (2001) proposed comparing an individual force factor score to a continuum of force called the Resistance Force Comparative Scale (RFCS), which linked each instance of resistance to the comparable level of force within a sequence (also see Terrill, 2005; Terrill et al., 2003). Within an individual incident, there can be multiple sequences of officer force and civilian resistance (e.g., in a study from the Project on Policing Neighborhoods data, there were on average 1.8 sequences per encounter; Terrill, 2005). Terrill's (2001, 2005) approach was to determine if the force continuum was followed for each sequence, and then if the continuum was followed as a whole. An advantage of the RFCS approach is the consideration of multiple levels of force and resistance in an encounter as opposed to just the highest levels to determine the extent that the officer is responding proportionally and incrementally to the civilian's resistance (Terrill, 2005; Terrill et al., 2003).

Using the force factor method and the RFCS approach in Queensland, Hine and colleagues (2018b) coded each sequence interaction (i.e., civilian resistance followed by officer action) in a use of force report to create an overall incident relative level of force—commensurate (all interactions at similar levels), higher (officer used higher force than civilian resistance or a mix of higher and commensurate), lower (officer used lower force than civilian resistance or a mix of lower and commensurate), and mixed (encounter involved both higher and lower relative force). Most incidents involved one or two sequence interactions and were considered to be commensurate force (Hine et al., 2018b). Officers tended to use lower relative force when encountering female and young suspects and were less likely to use higher relative force when encountering suspects with a weapon or who were physically aggressive.

Others have moved beyond the original force factor method of using the highest level of force and resistance (e.g., static force factor) to coding multiple dynamic force factors in use of force incidents, averaging the level of force applied across dyadic interactions and comparing it to civilian resistance (e.g., to measure dominant and accommodating force; Alpert et al., 2004), and creating a cumulative force factor (e.g., see Albert & Dunham, 2004; Alpert et al., 2004; Hickman et al., 2015; Wolf et al., 2008, 2009). For example, Hickman and colleagues (2015) coded up to ten dyadic action and reaction sequences in official use of force reports from the Seattle Police Department in order to capture the dynamic nature of incident from the first action to the end of the incident. Wolf and colleagues (2009) created a cumulative force factor by combining force factors from each iteration (i.e., an officer's use of force and a civilian's use of resistance) in an event. From their cumulative force factor research, officers tended to operate at a force deficit, and after multiple iterations, there was a greater likelihood for increased officer and civilian injury (Wolf et al., 2009). Over half of the confrontations (55.5%) ended after the first iteration and no cases extended beyond three iterations (Wolf et al., 2008, 2009). In addition, Kahn and colleagues (2017) demonstrated that breaking down police-civilian interactions into "discrete sequences" provides a better opportunity to examine the potential impact of factors other than civilian resistance (e.g., civilians' race, gender, etc.) on police use of force.

Several researchers have used the original conceptualization of the force factor by Alpert and Dunham (1997) as a way of moving beyond measuring only the officer's level of force (e.g., Bazley et al., 2007; MacDonald et al., 2003). Others have extended the idea of the force factor to capture the dynamic nature of police-civilian interactions (e.g., creating a cumulative force factor, coding multiple iterations of officer force and civilian resistance, and comparing force factor scores to the force continuum to assess deviations from the continuum (RFCS method); (see Albert & Dunham, 2004; Alpert et al., 2004; Hickman et al., 2015; Terrill, 2001, 2003, 2005; Terrill et al., 2003; Wolf et al., 2008, 2009). In comparison to the large literature base on police use of force, there have been relatively few studies that have used the force factor method and RFCS extension (Hine et al., 2018b). Overall, the force factor has shown promise in its practical utility for police executives and the method's reliability in use of force research (Hickman et al., 2015).

Limitations

As noted by Atherley and Hickman (2014), coding use of force narratives to measure police use of force comes with limitations. Statements written by police officers or their supervisors serve not only the purpose of documenting their actions, but possibly also "justifying their actions," and therefore "cannot be considered strictly objective accounts" (p.127). This limitation applies to some degree to all official data used throughout the criminal justice system (Coleman & Moynihan, 1996). Interestingly, research has documented that officers' accounts regarding their highest levels of force used during encounters is consistent with civilians' accounts; however, descriptions of the highest levels of resistance displayed by civilians varied dramatically across officers and civilians' accounts of the same incidents (Rojek et al., 2012).

As an alternative, some research relies on systematic social observation (SSO) as a method of data collection. Using this method, researchers observe officers during their regular shift, and record information about police-civilian encounters. Officers are selected for observation through a form of random sampling, and a predetermined, structured protocol is used to code each observation allowing researchers to focus on specific attributes of police work (Worden & McLean, 2014).

Use of force data collected from SSO are considered, in some ways, superior to official use of force narratives or various forms of civilians accounts because the narratives gathered through SSO are written by trained observers witnessing police-civilian encounters, rather than from the perspective of police officials or civilians themselves (Rojek et al., 2012). More recently, researchers are exploring the use of body-worn camera (BWC) footage to create use of force databases that rely on coding police-civilian interactions using a standardized data collection form (e.g., see Willits & Makin, 2018). The coding of BWC footage in one police agency has further supported the classic finding that suspect resistance predicts how quickly force is used during an encounter (time to force), how long the force is used (duration of force), and severity of force (Willits & Makin, 2018). These data may also be limited, however, particularly when actions are not fully captured on the bodycam footage (e.g., due to the angle of the camera, equipment malfunction, etc.)

Summary

In summary, the body of evidence examining the predictors of police use of force, and injuries to both officers and civilians, directly follows the pattern identified by Terrill et al. (2008, p.57): "The most powerful predictor of force is the presence and level of suspect resistance presented to officers." Despite variation across studies in the measurement of use of force (e.g., the inclusion or exclusion of verbal commands and handcuffing) and other methodological differences, civilian resistance remains the most consistent and most important factor in predicting the use of force and the severity of force (e.g., Fridell & Lim, 2016; Gau et al., 2010; Lawton, 2007; Stroshine & Brandl, 2019; Terrill & Mastrofski, 2002). Furthermore, civilian physical resistance increases the likelihood of civilian and officer injury, and during encounters when officers use less force than civilian resistance, the likelihood of officer injuries increased (Castillo et al., 2012; Hine et al., 2018a; Jetelina et al., 2018; Lin & Jones, 2010; Morabito & Socia, 2015; Paoline et al., 2012; Wolf et al., 2009).

Variations in methods, data sources, and measurement have profound implications for research findings and partially explains the inconsistent—and at times contradictory—findings in the literature related to significant predictors of force (e.g., the impact of civilian race on the use of force; Garner et al., 2002; Hollis, 2018; Hollis & Jennings, 2018; Klahm et al., 2014; Klahm & Tillyer, 2010). Research has considerably evolved over the past several decades from simply measuring force as a dichotomous variable, to measuring force on a continuum but only capturing the highest level of force used, to directly comparing officer force to civilian resistance (i.e., through a force factor), and to capturing the sequences of actions during incidents (e.g., Alpert & Dunham, 1997; Hine et al., 2018b; Kahn et al., 2017; Terrill, 2001, 2005; Wolf et al., 2008, 2009). In order to better understand police-civilian encounters, it is imperative to capture the interactions between civilians and officers throughout the incident. When considering each action and reaction, a more complete picture of the inherent dynamic process becomes evident and this consideration better allows researchers to assess the impact of various factors (e.g., civilian race) on the use of force.

Furthermore, researchers have used varied data sources, including systematic social observations, official records, civilian interviews, and most recently, body-worn camera footage to address the inherent challenges with each data source (e.g., MacDonald et al., 2003; Rojek et al., 2012; Terrill, 2005; Willits & Makin, 2018). Although the extensive literature base on use of force is both varied in measurement and methodology, and has systematically explored the influence of situational, civilian, officer, organizational, and community characterizes on use of force, there are many questions left unanswered. Use of force research and policy discussions will benefit from a more nuanced understanding of the dynamic nature of a use of force encounter by considering the evolution of actions and reactions throughout the incident.

III. METHODOLOGY

Data on all use of force incidents were obtained for incidents occurring between January 1, 2016 and June 30, 2018 from the Tulsa Police Department and the Cincinnati Police Department. These data were used to address the following broad research questions:

- How and why do some arrests turn violent while most do not?
- What factors or combination of factors contribute to injuries to civilians and the victimization of police officers during arrests?
- How can law enforcement agencies minimize conflict to reduce force, lower injuries and victimizations, and improve outcomes during arrests and similar encounters with civilians?

The "Administrative Data Analysis Report" delivered in December 2019 offered partial answers to these questions, but this report extends the inquiry to specifically examine the data drawn from officer narrative accounts of use of force incidents. The examination of these data, including all data coding and analytic decisions, was driven by interest in answering the following specific research questions (key *independent variables are italicized,* and the <u>dependent variables are underlined</u>):

7. Do the *total number of actions* in an exchange predict the <u>maximum level of force</u> within an exchange while controlling for other relevant factors?
8. Do the *total number of actions* in an exchange predict the <u>maximum level of resistance</u> within an exchange while controlling for other relevant factors?
9. Do the *total number of actions* in an exchange predict the <u>force factor</u> within an exchange while controlling for other relevant factors?
10. Does the *initial level of force* predict the <u>maximum level of force</u> within an exchange while controlling for other relevant factors?
11. Does the *initial level of resistance* predict the <u>maximum level of resistance</u> within an exchange while controlling for other relevant factors?
12. Does the *initial level of force or resistance* predict the <u>force factor</u> within an exchange while controlling for other relevant factors?

Data Coding

In both research sites, officer narrative descriptions of use of force incidents were recorded. In Tulsa, the narratives are written by the officer who engaged in the use of force, while in Cincinnati, the supervising officer recorded the narrative. Every available use of force narrative was reviewed and coded based on a pre-defined coding structure developed by the research team. This coding structure was loosely based on prior research by Hickman and colleagues (2015) and recently employed by the U.S. Department of Justice, Office of Community Oriented Policing Services research team in the San Francisco Police Department Collaborative Reform analysis.

The key and substantive contribution of the current study that differs from most previous studies is the ability to trace the incident through a series of time-ordered actions in order to understand the nature of how these incidents unfolded and how actions changed during the course of the interaction. Such an approach is unique and offers an ability to dissect the incident into its component parts and understand the sequential processes (i.e., action-reaction) that occurred between civilians and officers. Key variables of interest include the types of force used by the officer(s), the levels of resistance offered by the civilian(s), and the sequencing of these actions.

Initially, a small number of narratives (e.g., 10) were used as a pilot test to specify the processes used to code the narratives. This involved several independent assessments of the test narratives to refine and finalize the coding structure. Once the coding instrument was finalized, each narrative was coded based on the actions of the officer, civilian, or canine. Each action taken was attributed to a specific target, and actions were coded in the order they occurred as described in the narrative. If actions occurred simultaneously by more than one officer or civilian at different levels of force or resistance or if an officer and civilian engaged in actions simultaneously, the actions were coded sequentially in the order in which they were described in the narrative. Importantly, if multiple levels of resistance were offered by the same civilian at the same time, only the highest level of resistance offered by that civilian was coded. Similarly, if multiple levels of force were used by the same officer at the same time, only the highest level of force by that officer was coded. Weapon use by officers or civilians was also coded to indicate the specific type of weapon (e.g., a firearm, TASER, etc.). In addition, the number of times the weapon was used/deployed/fired was coded. If a range was provided (fired 6-10 rounds), the highest number in the range was coded. Finally, the effectiveness of a police canine or police weapon was coded on a three-level ordinal scale ranging from ineffective (i.e., weapon had little to no effect on resistance or compliance by civilian), to partially effective (i.e., weapon produced noticeable reduction in resistance by civilian but did not end resistance and/or resulted in only partial compliance), to completely effective (i.e., weapon ended all resistance and/or produced total or nearly total compliance by civilian).

After the pilot test, all available narratives were coded using these coding rules. Initially, all actions were coded using the 10-point force scale and the 11-point resistance scale as shown the in "Administrative Data Analysis Report". After initial examination of the distribution of cases, combined with associated requirements for analysis, these actions were re-coded into six-point scales for force and resistance (see Table 1 below). The only substantive difference between the original coding and the six-point scale used was the inclusion of canine actions into the force scale. While canine actions were initially coded separately, they were re-assigned as officer actions to better reflect the reality that canines are used as a tool by officers under the direction of an officer. Thus, their actions are part of the use of force continuum and should be reflected as such. Therefore, all canine actions were assigned to the first officer in each incident.[4] All narratives were analyzed using this coding structure.

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[4] One limitation to the approach adopted to modify the data from incidents to exchanges involves situations in which the narrative described multiple officers or multiple suspects across actions, but at no time was a single officer or suspect mentioned. This was a rare occurrence, but these actions were not included in the analyses. Including them would have required an assumption that all five officers and all five suspects engaged all the actions, which is a tenuous assumption.

Table 1: Force and Resistance Coding

Civilian Resistance	Officer Force	Force Factor	
		Resist	Force
Non-compliance: verbal resistance without threats; subject ignores officer or refuses to comply	Issuance of lawful announcements, warnings, orders, or commands	1	1
Passive physical resistance (e.g. "dead weight")	Physical touch not exceeding a firm grip	2	2
Moved away from officer; fleeing or attempting to flee; Defensive resistance	Physical control tactics; pain compliance techniques; hair pulling; joint locks and come-alongs; open-handed strikes; take-downs	3	3
Verbal or physical threats (e.g. fighting stance, reaching for possible weapon, other furtive movements) from officers' perspective	Display/threat of less lethal weapon (pepper spray/ball, TASER, baton, canine, firearm)	4	4
Unarmed assaultive physical resistance; subject strikes or attempts to strike officer with hands, feet, elbows, knees or other body parts; includes kicking at officer to avoid control or handcuffing; **no apparent attempt to kill or seriously injure officers**	Hard hand control; Use of pepper spray/ball[5], TASER, baton, canine, LVNR	5	5
Use of hands, fists, feet, etc. **with apparent attempt to cause death or serious bodily injury to officer**	Deadly force; use of firearm	6	6
Display or threat of weapon **with apparent attempt to cause death or serious bodily injury to officer**	Deadly force; use of firearm	6	6
Use of weapon **with apparent attempt to cause death or serious bodily injury to officer**	Deadly force; use of firearm	6	6

Unit of Analysis

The coding of all officer narratives reflected actions undertaken within an incident. An incident is defined as an interaction involving at least one officer and one suspect in which force was

[5] The placement of pepper spray on police use of force continua varies widely across agencies (Smith & Alpert, 2000; Terrill & Paoline, 2012). For the purposes of the analyses shown below, pepper spray was grouped with other less lethal weapons or tactics shown at Level 5. However, the Tulsa Police Department's policy on use of force places pepper spray in a lower category of force than the TASER, baton, canine bite, and LVNR on its use of force continuum (TPD Procedure 31-101A, 2018).

applied by the officer. In its simplest form, an incident involves a single officer and a single suspect. In many incidents, however, more than one officer and/or suspect were present and engaged in actions. This presented both a conceptual and analytic challenge as the goal was to understand the force-resistance dynamics of individual exchanges between officers and civilians. To meet this goal, the interaction between each officer and suspect had to be specified. This necessitated the creation of exchanges as a second unit of analysis.

An exchange (i.e., an officer-civilian dyad) is defined **as the sequence of interactions between one officer and one suspect.** As mentioned, many incidents involved multiple officers and/or suspects, resulting in a larger number of cases (i.e., exchanges) than the original number of incidents. For example, an incident in which two officers and a single suspect take actions against each other would result in two different exchanges. Exchange 1 would reflect the actions of Officer 1 and Suspect 1, while Exchange 2 would contain the actions of Officer 2 and Suspect 1. More complicated scenarios existed, and this methodology was applied in each case. Below are some examples of how a single incident was modified into multiple exchanges:

- Officer 1 interacts with Suspect 1 = 1 exchange
- Officer 1 interacts with Suspect 1 & Suspect 2 = 2 exchanges
- Officer 1 interacts with Suspect 1; Officer 2 interacts with Suspect 2 = 2 exchanges
- Officer 1 interacts with Suspect 1 & 2; Officer 2 interacts with Suspect 1 = 3 exchanges
- Officer 1 interacts with Suspect 1; Officer 1 interacts with Suspect 2; Officer 2 interacts with Suspect 1; Officer 2 interacts with Suspect 2 = 4 exchanges

The coding structure contained the potential for up to five officers and five suspects to take actions within any single incident. Thus, there was a possibility of up to 25 exchanges within any single incident (combination of five officers interacting with five suspects; 5x5=25). After this adjustment, the narratives were represented in two forms: at the incident level and at the exchange level. When involving a single officer and a single suspect, the incident and exchange coding was identical, whereas in more complicated incidents, there were more exchanges than incidents.

Cases

As a result of the coding structure and different units of analysis, the narrative data were arrayed in various forms for analysis. Table 2 summarizes three distinct representations of the data at (1) the incident level, (2) the exchange level, and (3) incidents/exchanges involving only a single officer and a single suspect (i.e., one-to-one exchange). At the incident level, there were originally a total of 1,344 cases (726 in Tulsa and 618 in Cincinnati) received from each research site. Initial assessment of these data resulted in removal of 164 cases[6] due to duplicate unique

[6] These cases were removed for the following reasons: 143 duplicate incidents, 18 reliability tests, and three missing unique identifiers. It is not clear why there were duplicate incidents, but they were manually evaluated, and a single

identifiers, cases removed due to reliability checks, and missing data. This resulted in 1,180 use of force incidents across the two research sites (626 in Tulsa and 554 in Cincinnati). Following the exchange coding described in the previous section, 2,084 exchanges were identified (1,150 in Tulsa and 934 in Cincinnati). These exchanges were evaluated for data quality, and 341 cases[7] were removed to allow full and complete analysis. Thus, 1,743 exchanges were analyzable (979 in Tulsa and 764 in Cincinnati). Finally, additional data fields were available to be appended to the one-to-one incidents (discussed in detail below), and so those cases were identified and separately assessed for data analysis. Originally, 495 cases were available but after assessing relevant variables, 41 cases[8] were removed leaving 454 one-to-one exchanges (211 in Tulsa and 243 in Cincinnati) for analysis.

Table 2: Summary of Cases

		Tulsa	Cincinnati	All Data
Incidents	Original Incidents	726	618	1,344
	Cases Removed	100	64	164
	Incident Sub-Total	626	554	1,180
Exchanges	Original Exchanges	1,150	934	2,084
	Cases Removed	171	170	341
	Exchange Total	979	764	1,743
One-to-one Exchange	Original One-to-one Exchanges	238	257	495
	Cases Removed	27	14	41
	One-to-one Exchanges Total	211	243	454

Variables

For all incidents, exchanges, and one-to-one situations, a series of variables were created to answer the research questions. These variables were created to take advantage of the unique

copy of the incident was maintained for analysis. The reliability tests were undertaken by the research team to ensure that narratives were being coded consistently and produced a duplicate copy of the incident.

[7] These cases were removed because they did not contain a measure of maximum force and/or maximum resistance. There are several reasons why an exchange may not contain these measures: 1) the exchange may not contain any action by one of the parties (i.e., officers or suspects). For example, an exchange may be identified in which an officer takes an action against a suspect, but the suspect does not respond directly against that officer (based on the narrative). Such an exchange would be coded as officer action (and associated maximum force) and no suspect resistance. 2) Re-coding from a larger scale to a six-point scale – This re-coding eliminated the lowest level of force (no actions taken; consensual conversation) and resistance (no resistance; suspect is compliant), and so any exchange involving those actions as the highest level of force or resistance were now coded as missing. Thus, while these exchanges appear in the Original Exchange count, they reflect exchanges that were not able to be analyzed.

[8] These cases were removed because they did not contain information on one of the following fields of interest: time of day; day of week; Officer characteristics: maximum force, gender, race/ethnicity, years of service, or rank; or Suspect characteristics: maximum resistance, gender, race/ethnicity, age.

coding methodology undertaken in this study to properly understand the sequential nature of how incidents/exchanges unfold over time. For each case (regardless of the level), up to 25 total actions undertaken by either an officer or suspect were coded using the aforementioned coding structure. The sequential nature of this coding allowed for the creation of variables that have not previously been examined in the reported literature. The subsequent discussion of variables applies to the incident, exchange, and one-to-one situations.

Three key dependent variables were created to answer the research questions: maximum force, maximum resistance, and a "Force Factor" (Alpert & Dunham, 1997, 1999). *Maximum force* is a measure of the highest level of force used in the incident/exchange by an officer across all 25 actions, and it is measured on the six-point scale. *Maximum resistance* is a measure of the highest level of resistance used in the incident/exchange by a suspect across all 25 actions, and it is measured on the six-point scale. A *Force Factor* is a measure of the difference between the highest level of force used and the highest level of resistance encountered. Force Factors derived from a six-point force/resistance scale will range from a low of -5 to a high of +5. This range calculated by subtracting suspect resistance from officer force. A positive value indicates that the officer used a higher level of force than the suspect's level of resistance, whereas a negative value represents a situation in which the suspect's resistance was higher than the officer's level of force.

A series of independent variables were also created in an effort to understand how these concepts may be related to the dependent variables. *Total actions* includes all actions taken within the incident/exchange by either an officer or suspect. Conceptually, this variable could range from 2 to 25. *Starting force* is a measure of the initial force action within the incident/exchange and allows for an assessment of the force level where the situation began, which frequently differs from the measure of maximum force. This variable is measured on the six-point force scale. *Starting resistance* is a measure of the initial resistance within the incident/exchanges and allows for an assessment of the initial resistance encountered when the situation began, and which also frequently differs from the measure of maximum resistance. This variable is likewise measured on the six-point resistance scale. For descriptive purposes, measures of officer and suspect weapons also were created. Each of the following variables is measured as a dichotomy; in other words, either the incident/exchange included this weapon, or it did not. Variables for police weapons include: canine, pepper spray, pepper ball, TASER, baton, handgun, rifle, and "other weapons" not specified. Suspect weapon variables include: knife, blunt object, projectile (e.g. rock or bottle), handgun, rifle, and "other weapons" not specified.

Additional independent variables were also created for the one-to-one exchanges. These included officer, suspect, and contextual/environmental characteristics. This information was unavailable to be added to cases involving multiple officers and/or suspects because the data links to individual persons. For example, an incident involving two officers did not have a unique identifier for each officer in the narrative that could be linked back to the data containing all officers' characteristics. In other words, the narrative might identify the officers by name, but there was no reliable method to link those officers to a badge number (or other identifier) contained in the officer characteristics data base. Thus, the following variables were only created for the one-to-one subset of cases:

- *Officer age* is a continuous measure of the individual's age in years
- *Officer gender* was coded as a simple dichotomy indicating male or female
- *Officer race/ethnicity* similarly is a dichotomy categorizing individuals as White, Black, Hispanic, or Other (Asian, Native American, Pacific Islander, or other)
- *Officer length of service* is a continuous measure of the number of years an individual has been a sworn officer with the department
- *Rank* (police officer) was created to identify non-supervisory officers as compared to all other sworn officers at any other higher rank

Suspect variables were created using an identical methodology for suspect age, suspect gender, and suspect race/ethnicity. *Suspect age* is a continuous variable reflecting age in years. *Suspect male* is a dichotomous variable indicating whether the suspect is male. *Suspect race/ethnicity* is coded as a series of dichotomous variables for White, Black, Hispanic, and persons of Other (Asian, Native American, Pacific Islander, and other) races/ethnicities. Contextual variables were only available for Tulsa and included calls for service (i.e., priority level), a measure of concentrated disadvantage, and the percent of the population between the ages of 18 and 24 years of age. Please refer to the "Administrative Data Analysis Report" for a full discussion of these measures.

Analysis Plan

As described previously, three sets of data were derived from the narrative descriptions of use of force events: incidents, exchanges, and one-to-one situations. Given the interest in the individual, sequential actions taken by each officer and suspect, *exchanges* were the primary focus of the analytic strategy. Thereafter, the *one-to-one* situations were explored to assess if these conditions exhibited different patterns and if any officer, suspect, or contextual/environmental characteristics might be related to the dependent variable of interest. Finally, *incidents* also were analyzed to inform the research questions. However, after examining the incident-level models, the results were not substantively different from the exchange-level models; thus, we did not include them in the report. Incident-level findings are available from the authors upon request.

Descriptive statistics were initially calculated for all variables of interest, which included percentages (i.e., how many cases possessed the characteristic of interest), means (i.e., the average level of the variable across all cases), and standard deviations (i.e., the average difference between cases on the characteristic of interest) for each variable. These summary statistics offer important contextual information about the data and informed the subsequent multivariate analyses.

Thereafter, multivariate modeling was used as the primary analytic tool to address the research questions. Multivariate analysis is a key technique for observing the effects of each independent variable by identifying the impact of a single variable on a dependent variable while considering the effect of all other variables simultaneously (Hanushek & Jackson, 1977). For all dependent variables, linear regression models were estimated to identify the impact of each independent variable. These models produce a coefficient, a standard error, a beta weight, and identify statistical significance. Statistical significance is flagged with an asterisk on any coefficient that demonstrates a likely relationship between the independent and dependent variables while controlling for other independent variables and within a pre-defined level of confidence that the result is not due to chance. For example, a single asterisk attached to a coefficient indicates that the independent variable exerts an influence on the dependent variable that is likely to be true and accurate 95% of the time (if the model were to be re-estimated 100 times). Two asterisks reflect a 99% percent confidence level, and three asterisks indicate a 99.9% chance that the relationship is not due to chance. The coefficient is used to reflect the relative impact of the variable, and the beta weight suggests a standardized effect on the dependent variable. In short, asterisks identify independent variables related to and exerting an influence on the dependent variable of interest. All results and interpretation of the descriptive and multivariate models are provided in the next section.

IV. FINDINGS

Use of force narratives were analyzed using the strategy detailed in Section III that began with calculating descriptive statistics for all measured variables at the exchange level. Tables 3-5 report the minimum and maximum levels of each variable, the percentage of cases in each category, and the average (mean) and standard deviation for all continuous variables. These tables are organized to report the dependent variables followed by the independent variables.

Exchange Descriptives

Data from Tulsa and Cincinnati combined to produce 1,743 cases that ranged in maximum force and maximum resistance from one to six (see Table 3). Level 5 was the most common maximum level of force applied (68.0%), while Level 3 was the most frequently occurring maximum level of resistance (57.2%). Across all cases the average level of maximum force was 4.3, and the maximum level of resistance was 3.4. This difference is best exemplified by the average Force Factor (0.9) that indicates a slightly higher average level of maximum force relative to the maximum level of resistance.

The total number of actions ranged from two to 25 with an average of slightly more than eight actions per exchange (8.4). The most common starting point of force was Level 1 (55.0%), while the most common starting point of resistance was Level 3 (54.7%). The most common weapon used by officers was a TASER (41.7%) followed by the use of a canine (15.4%). Suspects most frequently used a knife (3.2%) or a handgun (2.3%).

In Tulsa, the average maximum level of force was 4.4 with Level 5 the most commonly appearing (69.9%) (see Table 4). Maximum resistance was most frequently at Level 3 (49.3%) with an average of 3.6. The average Force Factor was 0.8 indicating a slightly higher maximum level of force compared to the maximum level of resistance. The total number of actions averaged 8.8 across all cases with force most frequently starting at Level 1 (51.5%), and resistance most frequently starting at Level 3 (55.4%). Canine (25.2%) and TASER (22.2%) usage are most common, but represented roughly only a quarter of all use. The use of pepper ball (10.7%), pepper spray (6.2%), and handguns (5.8%) were also noticeable. Suspect weapon use was most frequently a knife (5.4%) or handgun (3.2%).

In Cincinnati, the maximum level of force was most frequently Level 5 (65.6%) with the average maximum level of force slightly more than 4 (4.2) (see Table 5). Maximum resistance was most common at Level 3 (67.3%) with a similar average - 3.1. The average Force Factor was 1.1 indicating a higher ratio of force to resistance across all exchanges. On average, total actions were slightly less than 8 per exchange (7.9) with most exchanges starting at force of Level 1 (59.6%) and Level 3 on the resistance scale (53.9%). Officers in Cincinnati predominately used TASERs (66.6%), while suspects most frequently used handguns when weapons were used (1.2%).

Table 3: Exchange Descriptives – All Data (N=1,743)

	Min	Max	Mean/Percent	Standard Deviation
Dependent Variables				
Maximum Force	1.00	6.00	4.29	1.23
Level 1	--	--	5.3%	--
Level 2	--	--	5.3%	--
Level 3	--	--	15.4%	--
Level 4	--	--	4.2%	--
Level 5	--	--	68.0%	--
Level 6	--	--	1.7%	--
Maximum Resistance	1.00	6.00	3.37	1.30
Level 1	--	--	11.2%	--
Level 2	--	--	0.3%	--
Level 3	--	--	57.2%	--
Level 4	--	--	13.1%	--
Level 5	--	--	7.9%	--
Level 6	--	--	10.2%	--
Force Factor	-5.00	5.00	0.93	1.80
Key Independent Variables				
Total Actions	2.00	25.00	8.41	4.35
Starting Force	1.00	6.00	2.25	1.58
Level 1	--	--	55.0%	--
Level 2	--	--	9.0%	--
Level 3	--	--	8.7%	--
Level 4	--	--	11.6%	--
Level 5	--	--	14.8%	--
Level 6	--	--	0.9%	--
Starting Resistance	1.00	6.00	2.62	1.27
Level 1	--	--	30.6%	--
Level 2	--	--	0.8%	--
Level 3	--	--	54.7%	--
Level 4	--	--	7.3%	--
Level 5	--	--	2.7%	--
Level 6	--	--	3.8%	--
Officer Variables				
Canine	0.00	1.00	15.4%	--
Pepper Spray	0.00	1.00	4.0%	--
Pepper Ball	0.00	1.00	6.0%	--
TASER	0.00	1.00	41.7%	--
Baton	0.00	1.00	0.5%	--
Handgun	0.00	1.00	4.4%	--
Rifle	0.00	1.00	0.3%	--
Other Weapon	0.00	1.00	0.6%	--
Suspect Variables				
Knife	0.00	1.00	3.2%	--
Blunt Object	0.00	1.00	0.5%	--
Projectile	0.00	1.00	0.9%	--
Handgun	0.00	1.00	2.3%	--
Rifle	0.00	1.00	0.3%	--
Other Weapon	0.00	1.00	1.0%	--

Table 4: Exchange Descriptives – Tulsa (N=979)

	Min	Max	Mean/Percent	Standard Deviation
Dependent Variables				
Maximum Force	1.00	6.00	4.35	1.20
Level 1	--	--	5.0%	--
Level 2	--	--	3.8%	--
Level 3	--	--	16.6%	--
Level 4	--	--	2.7%	--
Level 5	--	--	69.9%	--
Level 6	--	--	2.0%	--
Maximum Resistance	1.00	6.00	3.56	1.43
Level 1	--	--	11.2%	--
Level 2	--	--	0.4%	--
Level 3	--	--	49.3%	--
Level 4	--	--	14.8%	--
Level 5	--	--	8.2%	--
Level 6	--	--	16.0%	--
Force Factor	-5.00	5.00	0.78	1.89
Key Independent Variables				
Total Actions	2.00	25.00	8.78	4.66
Starting Force	1.00	6.00	2.40	1.65
Level 1	--	--	51.5%	--
Level 2	--	--	7.5%	--
Level 3	--	--	11.1%	--
Level 4	--	--	10.1%	--
Level 5	--	--	18.8%	--
Level 6	--	--	1.0%	--
Starting Resistance	1.00	6.00	2.73	1.32
Level 1	--	--	27.9%	--
Level 2	--	--	0.9%	--
Level 3	--	--	55.4%	--
Level 4	--	--	7.8%	--
Level 5	--	--	2.1%	--
Level 6	--	--	5.9%	--
Officer Variables				
Canine	0.00	1.00	25.2%	--
Pepper Spray	0.00	1.00	6.2%	--
Pepper Ball	0.00	1.00	10.7%	--
TASER	0.00	1.00	22.2%	--
Baton	0.00	1.00	0.5%	--
Handgun	0.00	1.00	5.8%	--
Rifle	0.00	1.00	0.5%	--
Other Weapon	0.00	1.00	1.0%	--
Suspect Variables				
Knife	0.00	1.00	5.4%	--
Blunt Object	0.00	1.00	0.7%	--
Projectile	0.00	1.00	1.4%	--
Handgun	0.00	1.00	3.2%	--
Rifle	0.00	1.00	0.5%	--
Other Weapon	0.00	1.00	1.6%	--

Table 5: Exchange Descriptives – Cincinnati (N=764)

	Min	Max	Mean/Percent	Standard Deviation
Dependent Variables				
Maximum Force	1.00	6.00	4.22	1.27
Level 1	--	--	5.8%	--
Level 2	--	--	7.3%	--
Level 3	--	--	13.9%	--
Level 4	--	--	6.2%	--
Level 5	--	--	65.6%	--
Level 6	--	--	1.3%	--
Maximum Resistance	1.00	6.00	3.11	1.04
Level 1	--	--	11.3%	--
Level 2	--	--	0.3%	--
Level 3	--	--	67.3%	--
Level 4	--	--	11.0%	--
Level 5	--	--	7.6%	--
Level 6	--	--	2.6%	--
Force Factor	-5.00	5.00	1.11	1.66
Key Independent Variables				
Total Actions	2.00	24.00	7.93	3.87
Starting Force	1.00	6.00	2.05	1.47
Level 1	--	--	59.6%	--
Level 2	--	--	11.0%	--
Level 3	--	--	5.6%	--
Level 4	--	--	13.5%	--
Level 5	--	--	9.7%	--
Level 6	--	--	0.7%	--
Starting Resistance	1.00	6.00	2.48	1.19
Level 1	--	--	34.0%	--
Level 2	--	--	0.7%	--
Level 3	--	--	53.9%	--
Level 4	--	--	6.8%	--
Level 5	--	--	3.4%	--
Level 6	--	--	1.2%	--
Officer Variables				
Canine	0.00	1.00	2.7%	--
Pepper Spray	0.00	1.00	1.0%	--
Pepper Ball	0.00	1.00	0.0%	--
TASER	0.00	1.00	66.6%	--
Baton	0.00	1.00	0.4%	--
Handgun	0.00	1.00	2.6%	--
Rifle	0.00	1.00	0.0%	--
Other Weapon	0.00	1.00	0.1%	--
Suspect Variables				
Knife	0.00	1.00	0.4%	--
Blunt Object	0.00	1.00	0.3%	--
Projectile	0.00	1.00	0.3%	--
Handgun	0.00	1.00	1.2%	--
Rifle	0.00	1.00	0.1%	--
Other Weapon	0.00	1.00	0.3%	--

Exchange Multivariate Models

The primary approach to understanding the nature of use of force incidents is the estimation of multivariate models. Such models identify the cumulative ability of the independent variables to explain the variance (difference from case to case) in the dependent variable with the R squared statistic, while also identifying the relationship between each independent variable and the dependent variable (while simultaneously considering the impact of all other independent variables in the model). In all subsequent tables, the presence of an asterisk(s) marks a statistically significant relationship between the independent variable and the dependent variable, the coefficient reports the strength of that relationship, and the beta value identifies the most impactful independent variable.

Maximum Force

The multivariate model examining maximum force and including all the independent variables listed in Table 6 explains 23.4% of the variation in maximum level of force (see the R squared value). Across all cases, the total number of actions was positively related to the maximum level of force used in the exchange (see Table 6). This relationship is statistically significant at the 0.001 level (three asterisks) which indicates that this result would only appear by chance one time out of 1,000; in other words, this level of statistical significance is robust and should communicate a strong level of confidence in its accuracy. The coefficient of 0.09 and beta value of 0.3 reflect the degree of effect on maximum level of force. Comparing the beta value against other independent variables reveals total actions is one of the strongest influencers of maximum level of force (i.e., beta of 0.3 compared to other beta values for statistically significant variables). Other statistically significant variables include various starting levels of force (e.g., 1, 4, 5, & 6); importantly, these effects are relative to a starting level of force and resistance of Level 3, which was excluded from the model as the referent category. Note that the most impactful of these variables was a starting level of force at Level 4 & 5 (beta values of .3 and .4, respectively). Of note, none of the starting level of resistance variables were influential on the maximum level of force used in the exchange. Finally, and most unexpected, the maximum level of resistance was weakly and negatively related to the maximum level of force. This suggests that as the maximum level of resistance increased in an exchange, the corresponding level of maximum force decreased. The implications of this finding are discussed in more detail below.

Table 6: Exchange Linear Regression, Maximum Force – All Cases (N=1,743)

	Coefficient	Standard Error	Beta
Intercept	3.44***	0.13	--
Total Actions	0.09***	0.01	0.31
Starting Force			
Level 1	0.21*	0.10	0.09
Level 2	-0.20	0.12	-0.05
Level 4	0.99***	0.12	0.26
Level 5	1.23***	0.11	0.35
Level 6	2.49***	0.30	0.19
Starting Resistance			
Level 1	-0.02	0.06	-0.01
Level 2	-0.43	0.29	-0.03
Level 4	-0.18	0.10	-0.04
Level 5	0.21	0.17	0.03
Level 6	0.25	0.16	0.04
Maximum Resistance	-0.09**	0.03	-0.09
R Squared	.234		

*** p<0.001, ** p<0.01, * p<0.05, Excluded categories: Starting Force Level 3, Starting Resistance Level 3

In Tulsa, the cumulative power of all independent variables explained 22.5% of the variance in maximum force (see Table 7). Total actions and starting levels of force in an exchange at 4, 5, and 6 all increased the level of maximum force in the exchange. Examination of the beta values reveal that starting Level 5 (0.4) and total actions (0.3) were most impactful on the maximum level of force. Exchanges that started with a resistance Level 4 reduced the maximum level of force compared to those that began at a resistance Level 3. The maximum resistance level throughout the exchange did not influence the maximum level of force.

Table 7: Exchange Linear Regression, Maximum Force – Tulsa (N=979)

	Coefficient	Standard Error	Beta
Intercept	3.47***	0.15	--
Total Actions	0.07***	0.01	0.28
Starting Force			
Level 1	0.18	0.11	0.07
Level 2	-0.15	0.16	-0.03
Level 4	0.97***	0.15	0.24
Level 5	1.25***	0.13	0.41
Level 6	2.49***	0.36	0.21
Starting Resistance			
Level 1	0.05	0.09	0.02
Level 2	-0.45	0.36	-0.04
Level 4	-0.28*	0.13	-0.06
Level 5	0.40	0.24	0.05
Level 6	0.11	0.17	0.02
Maximum Resistance	-0.06	0.03	-0.07
R Squared	.225		

*** p<0.001, ** p<0.01, * p<0.05, Excluded categories: Starting Force Level 3, Starting Resistance Level 3

Table 8 summarizes the multivariate model for maximum force in Cincinnati. The cumulative effect of all independent variables explained 25.9% of all variation from all cases in the maximum level of force. Key independent variables include total actions and starting level of force at 4, 5, & 6. These variables were all statistically significant at the 0.001 level with total actions exerting the strongest influence on the maximum level of force (β = 0.4). No starting level of resistance was statistically related to maximum level of force; however, the maximum level of resistance in the exchange was negatively related to the maximum level of force as it was in the combined city model. In other words, as the level of maximum resistance increased in an exchange, the level of maximum force decreased.

Table 8: Exchange Linear Regression, Maximum Force – Cincinnati (N=764)

	Coefficient	Standard Error	Beta
Intercept	3.40***	0.24	--
Total Actions	0.12***	0.01	0.37
Starting Force			
Level 1	0.31	0.18	0.12
Level 2	-0.18	0.21	-0.04
Level 4	1.04***	0.20	0.28
Level 5	1.15***	0.21	0.27
Level 6	2.51***	0.53	0.16
Starting Resistance			
Level 1	-0.13	0.10	-0.05
Level 2	-0.35	0.50	-0.02
Level 4	0.05	0.17	0.01
Level 5	0.15	0.24	0.02
Level 6	0.71	0.40	0.06
Maximum Resistance	-0.17**	0.05	-0.14
R Squared	.259		

*** p<0.001, ** p<0.01, * p<0.05, Excluded categories: Starting Force Level 3, Starting Resistance Level 3.

Maximum Resistance

The second dependent variable of interest, maximum resistance, was explored using the same analytic strategy as applied to maximum force. Table 9 summarizes the results of the multivariate model examining maximum resistance across all cases. Collectively, the independent variables explain 41.9% of all variation in maximum resistance across all exchanges. Statistically significant variables include total actions at the 0.001 level. Starting force Level 4 reduced the maximum level of resistance compared to starting force Level 3, while starting force Level 6 increased the maximum resistance in the exchange. Starting level of resistance also impacted the maximum level of resistance, with higher starting levels of resistance exerting a positive effect on the maximum level of resistance (e.g., 4, 5, & 6), while starting resistance at Level 1 reduced the maximum level of resistance (compared to starting resistance Level 3). Finally, maximum force exerted a statistically significant, negative effect on maximum resistance, such that exchanges with higher levels of maximum resistance also contained lower levels of maximum force. The most impactful variables were total actions (β = 0.3) and starting resistance Level 6 (β = 0.4).

Table 9: Exchange Linear Regression, Maximum Resistance – All Cases (N=1,743)

	Coefficient	Standard Error	Beta
Intercept	3.01***	0.12	--
Total Actions	0.09***	0.01	0.30
Starting Force			
Level 1	-0.03	0.09	-0.02
Level 2	-0.10	0.11	-0.02
Level 4	-0.28*	0.11	-0.07
Level 5	0.08	0.11	0.02
Level 6	0.77**	0.28	0.06
Starting Resistance			
Level 1	-0.79***	0.06	-0.28
Level 2	-0.16	0.27	-0.01
Level 4	0.80***	0.09	0.16
Level 5	1.58***	0.15	0.20
Level 6	2.70***	0.13	0.40
Maximum Force	-0.08**	0.02	-0.07
R Squared	.419		

*** p<0.001, ** p<0.01, * p<0.05, Excluded categories: Starting Force Level 3, Starting Resistance Level 3

The multivariate model of maximum resistance across exchanges in Tulsa revealed that the independent variables cumulatively explained 38.6% of the dependent variable (see Table 10). The number of total actions in the exchange exerted a positive influence on the maximum level of resistance in exchanges, and the effect was statistically significant at the 0.001 level. Starting force Level 4 was negatively related to maximum resistance (compared to starting force Level 3) suggesting exchanges that started at this level of force had lower level of maximum resistance. The starting level of resistance was influential on the maximum level of resistance with higher starting levels exerting a positive influence on the maximum (e.g., 4, 5, & 6). Finally, the maximum level of force was not related to the maximum level of resistance. The strongest predictors of maximum resistance in Tulsa were starting resistance Level 6 ($\beta = 0.4$) and total actions ($\beta = .3$).

Table 10: Exchange Linear Regression, Maximum Resistance – Tulsa (N=979)

	Coefficient	Standard Error	Beta
Intercept	3.09***	0.18	--
Total Actions	0.09***	0.01	0.29
Starting Force			
Level 1	-0.02	0.12	-0.01
Level 2	-0.12	0.17	-0.02
Level 4	-0.39*	0.16	-0.08
Level 5	0.03	0.15	0.01
Level 6	0.47	0.39	0.03
Starting Resistance			
Level 1	-0.79***	0.09	-0.25
Level 2	-0.44	0.38	-0.03
Level 4	0.69***	0.14	0.13
Level 5	1.52***	0.25	0.15
Level 6	2.61***	0.16	0.43
Maximum Force	-0.06	0.03	-0.05
R Squared	.386		

*** p<0.001, ** p<0.01, * p<0.05, Excluded categories: Starting Force Level 3, Starting Resistance Level 3

Maximum resistance in Cincinnati largely conforms to the patterns demonstrated in Tulsa. The cumulative effect of all independent variables explains 46.9% of the variance in maximum resistance (see Table 11). Variables that increase the maximum level of resistance included total number of actions, starting force Level 6, and higher levels of starting resistance. Specifically, total actions, starting resistance Level 5, and starting resistance Level 6 were all statistically significant at the .001 level and exerted a relatively similar effect on maximum resistance (β = .3). Of note, maximum force was not related to maximum resistance.

Table 11: Exchange Linear Regression, Maximum Resistance – Cincinnati (N=764)

	Coefficient	Standard Error	Beta
Intercept	2.82***	0.16	--
Total Actions	0.08***	0.01	0.30
Starting Force			
Level 1	0.11	0.12	0.05
Level 2	0.07	0.15	0.02
Level 4	0.01	0.14	0.00
Level 5	0.02	0.15	0.06
Level 6	1.47***	0.37	0.11
Starting Resistance			
Level 1	-0.75***	0.06	-0.34
Level 2	0.32	0.35	-0.03
Level 4	0.94***	0.11	0.23
Level 5	1.71***	0.16	0.30
Level 6	2.91***	0.26	0.30
Maximum Force	-0.08	0.03	-0.10
R Squared	.469		

*** $p<0.001$, ** $p<0.01$, * $p<0.05$, Excluded categories: Starting Force Level 3, Starting Resistance Level 3

Force Factor

The final dependent variable of interest is the Force Factor. This potentially ranges from -5 to +5 and reflects the relative difference between the maximum level of force and the maximum level of resistance. Lower values (i.e., negatives) reflect more resistance compared to force, while higher values (i.e., positives) indicate more force relative to resistance. All models included total actions, starting force levels, and starting resistance levels; maximum force and maximum resistance were not included since they comprise the dependent variable.

Table 12 summarizes the multivariate model for all exchanges. Collectively, the independent variables explain 28.2% of all variance in the Force Factor. Total actions did not influence the Force Factor, but the starting levels of force and resistance were largely consistent with exerting an expected influence on this outcome. For example, higher levels of starting force were influential on a higher Force Factor (i.e., a higher level of force relative to resistance), while higher levels of starting resistance exerted a negative effect on the Force Factor. Starting force Levels 4 & 5 and starting resistance Level 6 were the most impactful variables on the Force Factor.

Table 12: Exchange Linear Regression, Force Factor – All Cases (N=1,743)

	Coefficient	Standard Error	Beta
Intercept	0.43**	0.15	--
Total Actions	-0.00	0.01	-0.01
Starting Force			
Level 1	0.26	0.14	0.07
Level 2	-0.11	0.18	-0.02
Level 4	1.38***	0.17	0.25
Level 5	1.24***	0.16	0.25
Level 6	1.85***	0.42	0.10
Starting Resistance			
Level 1	0.85***	0.08	0.22
Level 2	-0.28	0.41	-0.01
Level 4	-1.07***	0.15	-0.16
Level 5	-1.50***	0.23	-0.14
Level 6	-2.69***	0.20	-0.29
R Squared	.282		

*** p<0.001, ** p<0.01, * p<0.05, Excluded categories: Starting Force Level 3, Starting Resistance Level 3

In Tulsa, the cumulative effect of the independent variables explains 29.6% of the variance in the Force Factor (see Table 13). Similar to the pattern found when examining all cases, exchanges that began with higher levels of starting force resulted in higher levels of the Force Factor, while higher levels of starting resistance negatively impacted the Force Factor. All these variables were statistically significant at the .001 level with starting force Levels 4 & 5 and starting resistance Level 6 as the most influential variables.

Table 13: Exchange Linear Regression, Force Factor – Tulsa (N=979)

	Coefficient	Standard Error	Beta
Intercept	0.43*	0.19	--
Total Actions	-0.02	0.01	-0.04
Starting Force			
Level 1	0.21	0.17	0.06
Level 2	-0.03	0.24	-0.01
Level 4	1.45***	0.23	0.23
Level 5	1.30***	0.20	0.27
Level 6	2.17***	0.54	0.12
Starting Resistance			
Level 1	0.89***	0.12	0.21
Level 2	-0.01	0.54	-0.00
Level 4	-1.03***	0.20	-0.15
Level 5	-1.18***	0.36	-0.09
Level 6	-2.64***	0.23	-0.33
R Squared	.296		

*** p<0.001, ** p<0.01, * p<0.05, Excluded categories: Starting Force Level 3, Starting Resistance Level 3

Use of force exchanges in Cincinnati differed slightly from the pattern of findings demonstrated in the complete data. The independent variables cumulatively explain 27.2% of the variance in the Force Factor. Key independent variables include total actions with the results indicating exchanges with more total actions exhibited a higher Force Factor, a difference from the overall model. Higher levels of starting force (with the exception of Level 6) were related to a higher Force Factor, while higher starting resistance levels reduced the Force Factor. Finally, the starting levels of force and resistance exerted a roughly similar impact on Force Factor (β is roughly 0.2 across these variables).

Table 14: Exchange Linear Regression, Force Factor – Cincinnati (N=764)

	Coefficient	Standard Error	Beta
Intercept	0.38	0.25	--
Total Actions	0.04**	0.01	0.09
Starting Force			
Level 1	0.21	0.23	0.06
Level 2	-0.28	0.27	-0.05
Level 4	1.13***	0.26	0.23
Level 5	1.02***	0.28	0.18
Level 6	1.02	0.68	0.05
Starting Resistance			
Level 1	0.75***	0.12	0.22
Level 2	-0.77	0.65	-0.04
Level 4	-1.07***	0.21	-0.16
Level 5	-1.88***	0.29	-0.21
Level 6	-2.70***	0.48	-0.18
R Squared	.272		

*** $p<0.001$, ** $p<0.01$, * $p<0.05$, Excluded categories: Starting Force Level 3, Starting Resistance Level 3

One-to-One Exchange Descriptives

Data from Tulsa and Cincinnati were evaluated for incidents involving only a single officer and a single suspect. These situations offered the ability to attach additional variables to further explore the nature of use of force encounters. This section explores the 454 cases that meet this criterion using both descriptive statistics and multivariate models.

Across the 454 cases maximum force ranged from two to six, with Level 5 as the most common category of maximum force (88.3%) (see Table 15). Maximum resistance ranged from one to six with Level 3 as the most common maximum level of suspect action. Across all cases the average level of maximum force was 4.8 and the maximum level of resistance was 3.3. This difference is reflected in the average Force Factor (1.6) which was positive and greater than 1, indicating a slightly higher average level of maximum force relative to the maximum level of resistance.

The total number of actions ranged from two to 25 with an average of slightly more than nine actions per exchange (9.5). The most common starting point of force was Level 1 (58.4%), while the most common starting point of resistance was Level 3 (54.4%). Additional contextual variables added to these on-to-one exchanges included whether or not the situation occurred on a weekday (70.3%) or during the daytime (47.6%).

Officer characteristics were also added to these data. On average, officers were 40 years of age, and the majority were male (93.0%) and White (76.0%). They averaged nearly 12 years of service (11.8) and most frequently possessed the rank of police officer (81.1%). Suspect characteristics were also attached to these cases. On average, suspects were 32 years of age (31.5), predominately male (91.2%), and the majority were Black (58.1%).

In Tulsa, the average maximum level of force was 4.9 with Level 5 as the most common level of force (90.0%) (see Table 16). Maximum resistance averaged 3.5 and was most frequently at Level 3 (50.7%). The average Force Factor was 1.4 indicating a slightly higher maximum level of force compared to the maximum level of resistance. The average total number of actions across all cases was 10 with force most frequently starting at Level 1 (55.9%) and with an average of 2.3. Resistance most frequently started at Level 3 (55.0%) and averaged 2.6. Officers averaged 40 years of age, and the majority were male (95.7%) and White (76.8%). Length of service for these officers averaged 13 years (13.1) and the majority ranked as Police Officers (82.9%). Suspects were slightly younger (33 years of age), but the majority also were male (92.4%) and White (51.2%).

In Cincinnati, the maximum level of force was most frequently Level 5 (86.8%) with the average maximum level of force slightly less than five (4.8) (see Table 17). Maximum resistance was most common at Level 3 (75.7%) with a similar average (3.0). The average Force Factor was 1.8 indicating a higher ratio of force to resistance across all exchanges. On average, total actions were roughly nine per exchange (9.1) with most exchanges starting at force of Level 1 (60.5%) with an average of 2.1. Level 3 was the most common starting point on the resistance scale (53.9%) with an average of 2.3. Officers in Cincinnati were roughly 40 years of age, most commonly male (90.5%) and White (75.3%). They averaged 11 years of service (10.7) and were predominately ranked as Police Officers (79.4%). Suspects averaged roughly 30 years of age (30.5), were most frequently male (90.1%) and mostly Black (75.7%).

Table 15: Exchange Descriptives – All Data (N=454)

	Min	Max	Mean/Percent	Standard Deviation
Dependent Variables				
Maximum Force	2.00	6.00	4.83	0.59
Level 1	--	--	0.0%	--
Level 2	--	--	0.2%	--
Level 3	--	--	7.9%	--
Level 4	--	--	2.0%	--
Level 5	--	--	88.3%	--
Level 6	--	--	1.5%	--
Maximum Resistance	1.00	6.00	3.26	1.13
Level 1	--	--	9.5%	--
Level 2	--	--	0.2%	--
Level 3	--	--	64.1%	--
Level 4	--	--	13.9%	--
Level 5	--	--	5.7%	--
Level 6	--	--	6.6%	--
Force Factor	-3.00	4.00	1.57	1.26
Key Independent Variables				
Total Actions	2.00	25.00	9.51	4.59
Starting Force	1.00	6.00	2.17	1.57
Level 1	--	--	58.4%	--
Level 2	--	--	7.9%	--
Level 3	--	--	7.0%	--
Level 4	--	--	12.8%	--
Level 5	--	--	12.8%	--
Level 6	--	--	1.1%	--
Starting Resistance	1.00	6.00	2.44	1.18
Level 1	--	--	35.2%	--
Level 2	--	--	0.7%	--
Level 3	--	--	54.4%	--
Level 4	--	--	5.7%	--
Level 5	--	--	2.4%	--
Level 6	--	--	1.5%	--
Weekday	0.00	1.00	70.3%	--
Daytime	0.00	1.00	47.6%	--
Officer Variables				
Age	24.00	67.00	40.38	8.59
Male	0.00	1.00	93.0%	--
White	0.00	1.00	76.0%	--
Black	0.00	1.00	14.5%	--
Hispanic	0.00	1.00	2.6%	--
Other (Asian, N.A., Other)	0.00	1.00	7.3%	--
Length of Service	0.00	43.70	11.79	8.26
Rank: Police Officer	0.00	1.00	81.1%	--
Suspect Variables				
Age	12.00	72.00	31.49	11.21
Male	0.00	1.00	91.2%	--
White	0.00	1.00	36.1%	--
Black	0.00	1.00	58.1%	--
Hispanic	0.00	1.00	3.7%	--
Other (Asian, N.A., Other)	0.00	1.00	2.0%	--

Table 16: Exchange Descriptives – Tulsa (N=211)

	Min	Max	Mean/Percent	Standard Deviation
Dependent Variables				
Maximum Force	2.00	6.00	4.90	0.55
Level 1	--	--	0.0%	--
Level 2	--	--	0.5%	--
Level 3	--	--	5.7%	--
Level 4	--	--	0.5%	--
Level 5	--	--	90.0%	--
Level 6	--	--	3.3%	--
Maximum Resistance	1.00	6.00	3.54	1.30
Level 1	--	--	9.0%	--
Level 2	--	--	0.0%	--
Level 3	--	--	50.7%	--
Level 4	--	--	20.9%	--
Level 5	--	--	7.1%	--
Level 6	--	--	12.3%	--
Force Factor	-3.00	4.00	1.36	1.40
Key Independent Variables				
Total Actions	2.00	25.00	9.96	5.03
Starting Force	1.00	6.00	2.29	1.69
Level 1	--	--	55.9%	--
Level 2	--	--	9.0%	--
Level 3	--	--	7.6%	--
Level 4	--	--	7.1%	--
Level 5	--	--	18.0%	--
Level 6	--	--	2.4%	--
Starting Resistance	1.00	6.00	2.60	1.24
Level 1	--	--	30.8%	--
Level 2	--	--	0.5%	--
Level 3	--	--	55.0%	--
Level 4	--	--	8.1%	--
Level 5	--	--	2.8%	--
Level 6	--	--	2.8%	--
Weekday	0.00	1.00	73.0%	--
Daytime	0.00	1.00	53.1%	--
Officer Variables				
Age	26.00	63.00	40.32	7.95
Male	0.00	1.00	95.7%	--
White	0.00	1.00	76.8%	--
Black	0.00	1.00	4.3%	--
Hispanic	0.00	1.00	4.7%	--
Other (Asian, N.A., Other)	0.00	1.00	14.2%	--
Length of Service	0.00	35.00	13.11	7.76
Rank: Police Officer	0.00	1.00	82.9%	--
Suspect Variables				
Age	15.00	72.00	32.68	11.40
Male	0.00	1.00	92.4%	--
White	0.00	1.00	51.2%	--
Black	0.00	1.00	37.9%	--
Hispanic	0.00	1.00	7.1%	--
Other (Asian, N.A., Other)	0.00	1.00	3.8%	--

Table 17: Exchange Descriptives – Cincinnati (N=243)

	Min	Max	Mean/Percent	Standard Deviation
Dependent Variables				
Maximum Force	3.00	5.00	4.77	0.61
Level 1	--	--	0.0%	--
Level 2	--	--	0.0%	--
Level 3	--	--	9.9%	--
Level 4	--	--	3.3%	--
Level 5	--	--	86.8%	--
Level 6	--	--	0.0%	--
Maximum Resistance	1.00	6.00	3.02	0.90
Level 1	--	--	9.9%	--
Level 2	--	--	0.4%	--
Level 3	--	--	75.7%	--
Level 4	--	--	7.8%	--
Level 5	--	--	4.5%	--
Level 6	--	--	1.6%	--
Force Factor	-3.00	4.00	1.75	1.09
Key Independent Variables				
Total Actions	2.00	24.00	9.12	4.14
Starting Force	1.00	5.00	2.06	1.46
Level 1	--	--	60.5%	--
Level 2	--	--	7.0%	--
Level 3	--	--	6.6%	--
Level 4	--	--	17.7%	--
Level 5	--	--	8.2%	--
Level 6	--	--	0.0%	--
Starting Resistance	1.00	6.00	2.30	1.12
Level 1	--	--	39.1%	--
Level 2	--	--	0.8%	--
Level 3	--	--	53.9%	--
Level 4	--	--	3.7%	--
Level 5	--	--	2.1%	--
Level 6	--	--	0.4%	--
Weekday	0.00	1.00	67.9%	--
Daytime	0.00	1.00	42.8%	--
Officer Variables				
Age	24.00	67.00	40.43	9.12
Male	0.00	1.00	90.5%	--
White	0.00	1.00	75.3%	--
Black	0.00	1.00	23.5%	--
Hispanic	0.00	1.00	0.8%	--
Other (Asian, N.A., Other)	0.00	1.00	1.2%	--
Length of Service	0.80	43.70	10.65	8.53
Rank: Police Officer	0.00	1.00	79.4%	--
Suspect Variables				
Age	12.00	66.60	30.45	10.96
Male	0.00	1.00	90.1%	--
White	0.00	1.00	23.0%	--
Black	0.00	1.00	75.7%	--
Hispanic	0.00	1.00	0.8%	--
Other (Asian, N.A., Other)	0.00	1.00	0.4%	--

One-to-One Exchange Multivariate Models

Multivariate models are the primary approach to understanding the nature of use of force incidents. These models identify the cumulative ability of the independent variables to explain the variance (difference from case to case) in the dependent variable with the R squared statistic, while also identifying the relationship between each independent variable and the dependent variable (while simultaneously considering the impact of all other independent variables in the model). In all subsequent tables, the presence of an asterisk(s) marks a statistically significant relationship between the independent variable and the dependent variable, and the coefficient reports the strength of that relationship. Each of the following tables reports two models: a base model and a full model. The base model includes the same independent variables as those included in the exchange models discussed previously with the addition of two contextual variables: weekday and daytime. The full model includes officer and suspect characteristics. The models are presented in a stepwise fashion, but discussion will be limited to the full model.

Maximum Force

The full, multivariate model examining maximum force and including all the independent variables listed in Table 18 explains 18.1% of the variation in maximum level of force. Encounters involving more total actions and those starting at higher levels of force resulted in higher maximum levels of force. Additionally, situations that began with a resistance Level 5, those occurring during the daytime, and those involving male suspects increased the maximum level of force. Finally, the maximum level of resistance was negatively related to the maximum level of force. This suggests that as the maximum level of resistance increased in an exchange, the corresponding level of maximum force decreased. The implications of this finding are discussed in more detail below.

Table 18: One to One Incidents - Linear Regression, Maximum Force – All Cases (N=454)

	Base Model		Full Model	
	Coefficient	**Standard Error**	**Coefficient**	**Standard Error**
Intercept	4.34***	0.14	4.18***	0.23
Total Actions	0.02**	0.01	0.02**	0.01
Starting Force				
Level 1	0.38***	0.10	0.36**	0.11
Level 2	-0.03	0.13	-0.03	0.14
Level 4	0.49***	0.12	0.46***	0.12
Level 5	0.60***	0.12	0.58***	0.13
Level 6	1.78***	0.29	1.71***	0.29
Starting Resistance				
Level 1	-0.09	0.06	-0.07	0.06
Level 2	0.12	0.32	0.12	0.32
Level 4	-0.18	0.12	-0.21	0.12
Level 5	0.32	0.18	0.36*	0.18
Level 6	-0.16	0.24	-0.17	0.24
Maximum Resistance	-0.03	0.03	-0.03	0.03
Weekday	0.03	0.06	0.02	0.06
Daytime	0.12*	0.05	0.13*	0.05
Officer Variables				
Male			-0.07	0.10
White			-0.03	0.06
Length of Service			-0.00	0.00
Rank: Officer			-0.01	0.07
Suspect Variables				
Age			0.00	0.00
Male			0.25**	0.09
Black			0.03	0.06
Hispanic			0.12	0.14
Other			0.20	0.19
R Squared	.160		.181	

*** p<0.001, ** p<0.01, * p<0.05, Excluded categories: Starting Force Level 3, Starting Resistance Level 3

In Tulsa, the full, multivariate model for one-to-one situations indicated that the cumulative effect of all independent variables explains 23.9% of the variance in maximum force (see Table 19). Statistically significant relationships include encounters starting at force Levels 5 or 6, which increased the maximum force used by officers, and situations occurring on weekends, which also increased the maximum level of force. Of note, neither total actions nor maximum resistance were related to maximum force.

Table 19: One to One Incidents - Linear Regression, Maximum Force – Tulsa (N=211)

	Base Model		Full Model	
	Coefficient	**Standard Error**	**Coefficient**	**Standard Error**
Intercept	4.68***	0.19	4.23***	0.37
Total Actions	0.02	0.01	0.02	0.01
Starting Force				
Level 1	0.19	0.14	0.20	0.14
Level 2	-0.19	0.17	-0.24	0.18
Level 4	0.34	0.19	0.33	0.19
Level 5	0.43**	0.16	0.40*	0.16
Level 6	1.53***	0.29	1.49***	0.30
Starting Resistance				
Level 1	0.01	0.08	0.06	0.09
Level 2	-0.26	0.52	-0.18	0.53
Level 4	-0.19	0.14	-0.18	0.14
Level 5	0.29	0.22	0.41	0.23
Level 6	-0.24	0.24	-0.22	0.25
Maximum Resistance	-0.02	0.03	-0.01	0.03
Weekday	-0.13	0.08	-0.19*	0.09
Daytime	0.03	0.07	-0.00	0.08
Officer Variables				
Male			-0.05	0.18
White			0.12	0.09
Length of Service			0.00	0.01
Rank: Officer			0.11	0.11
Suspect Variables				
Age			-0.00	0.00
Male			0.25	0.14
Black			0.10	0.08
Hispanic			0.10	0.15
Other			0.15	0.19
R Squared	.202		.239	

*** p<0.001, ** p<0.01, * p<0.05, Excluded categories: Starting Force Level 3, Starting Resistance Level 3

The full, multivariate model examining maximum force in one-to-one situations in Cincinnati featured several statistically significant relationships (see Table 20). The cumulative effect of all independent variables explains 22.5% of the variance in maximum force. More total actions in the encounter, situations that began at force Levels 1, 4, or 5, and those occurring during the daytime all increased the maximum level of force. Of note, higher levels of maximum resistance reduced the maximum level of force. Finally, non-White officers and those with more years of service also were associated with increased levels of the maximum force.

Table 20: One to One Incidents - Linear Regression, Maximum Force – Cincinnati (N=243)

	Base Model		Full Model	
	Coefficient	**Standard Error**	**Coefficient**	**Standard Error**
Intercept	4.19***	0.22	4.31***	0.32
Total Actions	0.02*	0.01	0.03**	0.01
Starting Force				
Level 1	0.55**	0.16	0.51**	0.16
Level 2	0.09	0.21	0.11	0.21
Level 4	0.67***	0.17	0.63***	0.17
Level 5	0.78***	0.20	0.69**	0.20
Level 6	--	--	--	--
Starting Resistance				
Level 1	-0.15	0.08	-0.16	0.09
Level 2	0.30	0.42	0.39	0.42
Level 4	-0.10	0.21	-0.11	0.21
Level 5	0.36	0.28	0.43	0.28
Level 6	0.06	0.61	0.08	0.62
Maximum Resistance	-0.08	0.05	-0.11*	0.05
Weekday	0.12	0.08	0.15	0.08
Daytime	0.16*	0.08	0.19*	0.08
Officer Variables				
Male			-0.06	0.13
White			-0.19*	0.10
Length of Service			-0.01*	0.01
Rank: Officer			-0.20	0.11
Suspect Variables				
Age			0.00	0.00
Male			0.23	0.13
Black			0.07	0.09
Hispanic			0.64	0.43
Other			0.22	0.60
R Squared	.169		.225	

*** p<0.001, ** p<0.01, * p<0.05, Excluded categories: Starting Force Level 3, Starting Resistance Level 3

Maximum Resistance

Table 21 summarizes the multivariate models for maximum resistance in all one-to-one cases. The cumulative explanatory power of the full model explains 35.7% of the variance in maximum resistance. A greater number of total actions slightly increased the maximum resistance throughout the encounter. Situations that began with a force Level 6, and starting resistance Levels 4, 5 and 6 also increased the maximum level of resistance. Of note, suspect characteristics also influenced the maximum level of resistance. Specifically, the presence of Black suspects reduced the maximum level of resistance, while the involvement of Hispanic and Other suspects increased the maximum level of resistance (compared to White suspects).

Table 21: Exchange Linear Regression, Maximum Resistance – All Cases (N=454)

	Base Model		**Full Model**	
	Coefficient	**Standard Error**	**Coefficient**	**Standard Error**
Intercept	2.66***	0.41	2.85***	0.50
Total Actions	0.08***	0.01	0.08***	0.01
Starting Force				
Level 1	0.27	0.18	0.23	0.18
Level 2	0.19	0.23	0.15	0.23
Level 4	0.04	0.21	0.04	0.21
Level 5	0.43	0.22	0.38	0.22
Level 6	1.39**	0.51	1.09*	0.51
Starting Resistance				
Level 1	-0.40***	0.10	-0.38***	0.10
Level 2	0.35	0.55	0.40	0.55
Level 4	0.84***	0.20	0.86***	0.20
Level 5	1.71***	0.30	1.67***	0.30
Level 6	2.62***	0.39	2.64***	0.39
Maximum Force	-0.09	0.08	-0.09	0.08
Weekday	-0.02	0.10	-0.02	0.10
Daytime	0.07	0.09	0.09	0.09
Officer Variables				
Male			0.21	0.18
White			-0.06	0.11
Length of Service			0.00	0.01
Rank: Officer			-0.03	0.13
Suspect Variables				
Age			-0.01	0.00
Male			-0.02	0.16
Black			-0.21*	0.10
Hispanic			0.51*	0.25
Other			0.68*	0.33
R Squared	.326		.357	

*** p<0.001, ** p<0.01, * p<0.05, Excluded categories: Starting Force Level 3, Starting Resistance Level 3

In Tulsa, the maximum resistance model explained 31.3% of the variance in this outcome (see Table 22). Statistically significant variables included total actions, which were weakly but positively related to maximum resistance; the more actions in the encounter, the higher the level of maximum resistance. Situations that began with resistance Levels 4, 5, or 6 also reflected higher levels of maximum resistance. Interestingly, female suspects demonstrated higher levels of maximum resistance compared to male suspects in Tulsa.

Table 22: Exchange Linear Regression, Maximum Resistance – Tulsa (N=211)

	Base Model		Full Model	
	Coefficient	**Standard Error**	**Coefficient**	**Standard Error**
Intercept	2.97**	0.84	3.94***	1.04
Total Actions	0.07***	0.02	0.07***	0.02
Starting Force				
Level 1	0.39	0.31	0.31	0.32
Level 2	0.30	0.40	0.26	0.40
Level 4	-0.01	0.42	-0.11	0.44
Level 5	0.47	0.37	0.44	0.37
Level 6	1.31	0.69	1.19	0.70
Starting Resistance				
Level 1	-0.32	0.19	-0.31	0.19
Level 2	0.10	1.18	0.29	1.19
Level 4	0.72*	0.30	0.80*	0.32
Level 5	1.66**	0.49	1.51**	0.51
Level 6	2.48***	0.52	2.64***	0.52
Maximum Force	-0.10	0.16	-0.06	0.16
Weekday	-0.16	0.18	-0.13	0.19
Daytime	0.02	0.16	0.05	0.17
Officer Variables				
Male			0.03	0.41
White			0.01	0.20
Length of Service			-0.01	0.01
Rank: Officer			-0.12	0.24
Suspect Variables				
Age			-0.01	0.01
Male			-0.62*	0.31
Black			-0.20	0.18
Hispanic			0.32	0.34
Other			0.49	0.44
R Squared	.269		.313	

*** p<0.001, ** p<0.01, * p<0.05, Excluded categories: Starting Force Level 3, Starting Resistance Level 3

The maximum resistance model in Cincinnati for one-to-one encounters explained 43.9% of the variance in the outcome of interest (see Table 23). Again, a higher number of total actions was weakly and positively associated with greater maximum resistance. Encounters that began with a resistance Level 4, 5, or 6 were also related to higher maximum levels of resistance. Finally, male suspects and Hispanic suspects were also related to higher levels of maximum resistance.

Table 23: Exchange Linear Regression, Maximum Resistance – Cincinnati (N=243)

	Base Model		Full Model	
	Coefficient	**Standard Error**	**Coefficient**	**Standard Error**
Intercept	2.76***	0.41	2.80***	0.51
Total Actions	0.08***	0.01	0.08***	0.01
Starting Force				
Level 1	0.17	0.20	0.07	0.20
Level 2	0.04	0.26	-0.02	0.26
Level 4	0.12	0.22	0.04	0.22
Level 5	0.32	0.26	0.24	0.25
Level 6	--	--	--	--
Starting Resistance				
Level 1	-0.43***	0.10	-0.48***	0.10
Level 2	0.56	0.53	0.54	0.52
Level 4	0.98***	0.25	0.93***	0.25
Level 5	1.80***	0.34	1.82***	0.33
Level 6	2.82***	0.75	2.65***	0.75
Maximum Force	-0.13	0.08	-0.17*	0.08
Weekday	0.08	0.10	0.11	0.10
Daytime	0.04	0.10	0.05	0.10
Officer Variables				
Male			0.19	0.16
White			-0.13	0.12
Length of Service			0.00	0.01
Rank: Officer			-0.12	0.14
Suspect Variables				
Age			-0.01	0.00
Male			0.34*	0.16
Black			-0.07	0.12
Hispanic			1.72**	0.52
Other			0.39	0.75
R Squared	.383		.439	

*** p<0.001, ** p<0.01, * p<0.05, Excluded categories: Starting Force Level 3, Starting Resistance Level 3

Force Factor

The final dependent variable examined in one-to-one situations was the Force Factor. Table 24 summarizes the results of this analysis and indicates that 27.2% of all variance in the Force Factor was explained by the cumulative independent variables. The total number of actions in an encounter was negatively related to the Force Factor indicating that more actions reduced the ratio of force to resistance. In other words, the longer (i.e., more actions) an exchange continued, the more aligned force and resistance became. Other statistically significant relationships include situations that began with resistance Levels 4, 5, or 6, which reduced the Force Factor. Finally, encounters involving Black suspects increased the Force Factor. In other words, the gap between force and resistance was greater in situations involving suspects with this characteristic.

Table 24: Exchange Linear Regression, Force Factor – All Cases (N=454)

	Base Model		Full Model	
	Coefficient	**Standard Error**	**Coefficient**	**Standard Error**
Intercept	1.98***	0.26	1.62***	0.44
Total Actions	-0.06***	0.01	-0.06***	0.01
Starting Force				
Level 1	0.14	0.21	0.15	0.21
Level 2	-0.23	0.27	-0.19	0.27
Level 4	0.49*	0.25	0.47	0.25
Level 5	0.21	0.25	0.25	0.25
Level 6	0.50	0.58	0.74	0.58
Starting Resistance				
Level 1	0.32**	0.12	0.31**	0.12
Level 2	-0.23	0.65	-0.27	0.65
Level 4	-1.06***	0.23	-1.12***	0.23
Level 5	-1.42***	0.35	-1.33***	0.35
Level 6	-2.86***	0.46	-2.91***	0.46
Weekday	0.05	0.12	0.05	0.12
Daytime	0.06	0.11	0.05	0.11
Officer Variables				
Male			-0.29	0.21
White			0.03	0.13
Length of Service			-0.00	0.01
Rank: Officer			0.02	0.15
Suspect Variables				
Age			0.01	0.01
Male			0.30	0.19
Black			0.25*	0.11
Hispanic			-0.40	0.29
Other			-0.49	0.39
R Squared	.242		.272	

*** p<0.001, ** p<0.01, * p<0.05, Excluded categories: Starting Force Level 3, Starting Resistance Level 3

In Tulsa, the Force Factor model explained 28.4% of the variance in this outcome (see Table 25). Situations with more total actions reduced the gap between force and resistance, and encounters beginning with a resistance Level of 4, 5, or 6 also decreased the overall Force Factor. Encounters involving male suspects were related to a higher force factor indicating that more force was being applied relative to resistance in these situations.

Table 25: Exchange Linear Regression, Force Factor – Tulsa (N=211)

	Base Model		Full Model	
	Coefficient	**Standard Error**	**Coefficient**	**Standard Error**
Intercept	2.11***	0.43	0.49	0.86
Total Actions	-0.06**	0.02	-0.06**	0.02
Starting Force				
Level 1	-0.19	0.35	-0.10	0.35
Level 2	-0.51	0.44	-0.52	0.44
Level 4	0.38	0.47	0.46	0.48
Level 5	-0.01	0.40	-0.02	0.40
Level 6	0.35	0.72	0.37	0.73
Starting Resistance				
Level 1	0.33	0.21	0.38	0.21
Level 2	-0.39	1.31	-0.48	1.31
Level 4	-0.94**	0.34	-1.00**	0.35
Level 5	-1.37*	0.54	-1.10*	0.56
Level 6	-2.79***	0.57	-2.90***	0.57
Weekday	0.02	0.20	-0.07	0.21
Daytime	0.02	0.18	-0.05	0.19
Officer Variables				
Male			-0.08	0.46
White			0.11	0.22
Length of Service			0.02	0.01
Rank: Officer			0.24	0.27
Suspect Variables				
Age			0.01	0.01
Male			0.89*	0.34
Black			0.31	0.20
Hispanic			-0.22	0.37
Other			-0.34	0.48
R Squared	.230		.284	

*** p<0.001, ** p<0.01, * p<0.05, Excluded categories: Starting Force Level 3, Starting Resistance Level 3

The Force Factor model in Cincinnati explained 27.9% of the variance in this outcome (see Table 26). Similar to the other Force Factor models, the total number of actions in an encounter was negatively related to the Force Factor suggesting that the longer that a situation continued the more closely aligned force was to resistance. Encounters beginning with a resistance Level 4, 5, or 6 were also aligned with a reduced Force Factor.

Table 26: Exchange Linear Regression, Force Factor – Cincinnati (N=243)

	Base Model		Full Model	
	Coefficient	**Standard Error**	**Coefficient**	**Standard Error**
Intercept	1.77***	0.32	1.97***	0.51
Total Actions	-0.06***	0.02	-0.05**	0.02
Starting Force				
Level 1	0.45	0.27	0.53	0.27
Level 2	0.06	0.35	0.15	0.35
Level 4	0.63	0.29	0.71*	0.30
Level 5	0.54	0.33	0.55	0.34
Level 6	--	--	--	--
Starting Resistance				
Level 1	0.31	0.13	0.36*	0.14
Level 2	-0.27	0.71	-0.15	0.72
Level 4	-1.19**	0.34	-1.18**	0.34
Level 5	-1.56**	0.45	-1.56**	0.46
Level 6	-3.01**	1.01	-2.91**	1.03
Weekday	0.06	0.14	0.06	0.14
Daytime	0.14	0.13	0.17	0.14
Officer Variables				
Male			-0.28	0.23
White			0.09	0.16
Length of Service			-0.02	0.01
Rank: Officer			-0.10	0.19
Suspect Variables				
Age			0.01	0.01
Male			-0.11	0.22
Black			0.16	0.16
Hispanic			-1.18	0.72
Other			-0.18	1.03
R Squared	.243		.279	

*** p<0.001, ** p<0.01, * p<0.05

Excluded categories: Starting Force Level 3, Starting Resistance Level 3

V. DISCUSSION AND CONCLUSION

Summary

The research team from the University of Texas at San Antonio (UTSA) and the University of Cincinnati obtained 30 months (January 2016 – June 2018) of police use of force narratives from the Tulsa (OK) Police Department and the Cincinnati (OH) Police Department, carefully coded these narratives to produce an action-by-action sequence of events, and then analyzed the resulting data for patterns, trends, and predictors of force and resistance. This dataset represents one of the most detailed and comprehensive accounts of how police-civilian use of force encounters unfold from the perspectives of the police officers and police supervisors who took part in or investigated the events (in the case of Cincinnati PD supervisors) described in the narratives.

Initially using 10 and 11-item scales of police use of force and civilian resistance, the encounters were broken down by trained coders into action-by-action sequences, resulting in a dataset of 1,743 separate actions that officers or suspects undertook across 1,180 use of force incidents captured by the two police agencies during the 30-month study period. For analytic purposes, force and resistance were recoded into corresponding 6-item scales and used to produce a series of descriptive and multivariate analyses.

Across all of the data, Level 5 force (hard hand control, pepper spray/ball, TASER, canine) was the most frequently employed maximum level of force used by the police (68% of use of force encounters), while Level 1 force (verbal commands) was the most frequent *starting* level of force (55% of use of force encounters). On the resistance side, civilians most frequently engaged in Level 3 resistance (defensive resistance, attempting to flee) as both their maximum and starting levels of resistance. The coding instrument allowed for the capture of up to 25 separate force or resistance actions in any use of force incident. The mean number of actions taken was eight across all incidents. When officers used weapons, their weapon of choice was most often the TASER (42% of use of force encounters); suspects most frequently employed knives (3.2%) and handguns (2.3%) when using a weapon to resist arrest.

There was some variation between the two agencies in weapon usage by officers. In Tulsa, canines were used more frequently than TASERs (25% v. 22%), and together pepper spray and pepper balls represented nearly 20% of actions involving weapons. In Cincinnati, TASERs dominated weapon usage (67%) followed by canines (3%) in a distant second place. In Tulsa, police displayed, threatened, or used handguns more than twice as often (5.8%) as officers in Cincinnati (2.6%).

From a multivariate perspective, the research team modeled predictors of maximum force, maximum resistance, and the Force Factor (force relative to resistance) (Alpert & Dunham, 1997, 1999) across all actions, actions involving only one officer and one suspect, and then separately for each agency. The primary purpose of these analyses was to assess the contribution of cumulative actions to force and resistance, but included in the models were variables for starting levels of force and resistance, maximum levels of force and resistance, and in the one-on-one models, contextual (day of week and time), officer (age, gender, race/ethnicity, length of service, rank) and suspect (age, gender, race/ethnicity) variables. Here we summarize the primary findings.

Across all actions modeled, the *total number* of actions was positively associated the maximum level of force used by the police. Each action taken was associated with a 0.9-unit increase (out of 6) in the maximum level of force used by officers. Not surprisingly, higher *starting* levels of force also were positively associated with higher *maximum* levels of force used; when police began an encounter using force at higher levels, they ended up using higher levels of force altogether. *Starting* levels of resistance were not associated with higher levels of maximum force, though.

However, one of the most surprising findings in the overall maximum force model was the contribution of maximum resistance to maximum force. Unlike most previously reported studies (Fridell & Lim, 2016; Gau et al., 2010; Lawton, 2007; Stroshine & Brandl, 2019; Terrill & Mastrofski, 2002; Terrill & Paoline, 2017), we found a weak (but statistically significant) *negative* relationship between maximum suspect resistance and maximum force used by the police. In other words, as suspect resistance increased along the continuum, the maximum force used by officers slightly decreased, a finding that was particularly pronounced in Cincinnati. We further discuss the potential implications of this unexpected finding below.

Like the force model, the overall maximum resistance model also showed a positive relationship between the number of actions taken and maximum resistance by suspects. Likewise, higher levels of starting resistance were associated with higher levels of maximum resistance. Maximum force used by the police was weakly and negatively correlated with maximum resistance; a one level increase in maximum force was associated with a slight decrease in maximum resistance. The maximum force and maximum resistance findings in the overall model were largely mirrored in the agency-specific models.

The overall Force Factor model and the one for Tulsa showed no relationship between the number of actions taken and the Force Factor – measured as the relative difference between maximum force and maximum resistance.[9] In Cincinnati, the total number of actions was weakly but positively associated with the Force Factor, indicating that more complex encounters with a greater number of actions taken resulted in slightly higher levels of force relative to resistance.

The single officer, single suspect incident models showed similar patterns with respect to the influence of total actions on maximum force and resistance. However, these models also allowed for the introduction of some contextual variables (weekday and daytime) and officer and suspect-level variables, most of which were non-significant. Daytime incidents were weakly and positively associated with higher levels of maximum force, but officer race/ethnicity, gender, rank, and years of service were not. Likewise, with the exception of actions involving male suspects, which were positively correlated with higher levels of maximum force, suspect

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[9] With a 6-item force and resistance scale, the Force Factor can range from 5 to -5.

race/ethnicity and age were unrelated to force. In particular, Black and Hispanic suspects were no more likely than White suspects to have higher levels of force used against them in the overall model or in either city individually.

The findings from the maximum resistance models involving one officer and one suspect largely tracked with those from the all cases models. In the combined model (both cities), none of the contextual or officer-levels variables were significant. On the suspect side, Hispanic suspects were more likely than White suspects to evidence higher levels of maximum resistance, while Blacks suspects were *less likely* than Whites to demonstrate higher levels of resistance. Suspect gender was a non-significant predictor of resistance in the combined single officer, single suspect model.

Interestingly, in Tulsa, male suspects were less likely than female suspects to show higher levels of maximum resistance while the opposite was true in Cincinnati. And in Cincinnati, Hispanic suspects (but not Black suspects) were more likely than White suspects to demonstrate higher levels of resistance. None of the contextual variables, officer-level variables, or the remaining suspect variables were significant in either city.

Finally, the combined city single officer, single suspect Force Factor model showed a slightly negative association between the total number of actions taken and the Force Factor. Recall, this relationship was non-significant in the all cases model discussed above. The only contextual, officer, or suspect-level variable to show a relationship with the Force Factor in the single officer, single suspect combined city model was the Black suspect variable, which showed a positive correlation with the Force Factor. In other words, Black suspects were slightly more likely than White suspects to experience higher levels of force relative to resistance in this model. Lastly, male suspects were more likely to experience higher levels of force compared to resistance in Tulsa but not in Cincinnati.

Implications

Expeditious control of suspects with minimum requisite force

A primary question of interest in this research was whether longer and/or more complex use of force incidents (those with greater numbers of exchanges) were associated with higher levels of force or resistance. For the most part, this proved to be the case, although the relationship was not particularly strong. This suggests that a marginal reduction in the severity of force used may be achievable with a more expeditious resolution of physical conflict situations, which may escalate to higher levels of force as events drag out. This does not mean that police should immediately escalate their levels of force above the resistance offered. Rather, all things being equal, the fewer actions required to bring the suspect safely under control the better (Willits & Makin, 2018). De-escalation strategies that emphasize verbal engagement with suspects are not contraindicated. Instead, the results from this study show it is repeated *physical* force or resistance actions that increase the likelihood that higher levels of force will be required to control increasing levels of resistance. Training and tactical approaches that emphasize verbal de-escalation techniques followed by skillful applications of appropriate force relative to resistance have the best chance at minimizing overall force and resistance levels.

Paradigmatic changes in police use of force may be occurring

As discussed above, an unexpected finding from this research was the weak and negative correlation between resistance and force found in the combined maximum force model and in Cincinnati and the lack of a relationship between resistance and force in Tulsa. These findings runs contrary to most of the published literature on use of force, which routinely finds a strongly positive relationship between resistance and force (Fridell & Lim, 2016; Gau et al., 2010; Stroshine & Brandl, 2019; Terrill & Mastrofski, 2002).[10] In fact, it is axiomatic among police use of force researchers that resistance is often one of the strongest and most consistent predictors of force and its severity (Garner et al., 2002; Johnson, 2011; Mulvey & White, 2014). However, our results do not bear this out with the current data. What might explain this unexpected finding?

Much has been written about the "Ferguson Effect" or the notion that police officers today are less willing and less likely to engage in proactive policing efforts than before the firestorm of events touched off by the shooting death of Michael Brown in 2014 at the hands of the police in Ferguson, Missouri (Deuchar et al., 2019; Hosko, 2018; Nix & Wolfe, 2016; Pyrooz et al., 2016; Wolfe & Nix, 2016). While empirical evidence of a "Ferguson Effect" is scant, there is growing recognition that some police officers and organizations have responded to the increased public scrutiny that has followed in the wake of Ferguson and other high-profile (and controversial) police shootings by disengaging from the public (Deuchar et al., 2019; Hosko, 2018). At the same time, and as a result of post-Ferguson public pressure, law enforcement agencies have changed the way they train and socialize their officers in the use of force. In particular, there has been an observable movement in American policing toward de-escalation training and tactics in an effort to reduce conflict and the need for physical, and especially deadly, force (Engel, McManus, & Herold, 2020; Zimring, 2017).

Likewise, the possibility of a single critical incident significantly impacting police practice is now more commonly recognized in police research (Engel et al., 2020; IACP, 2015). For the communities in Tulsa and Cincinnati, critical incidents involving the controversial and high-publicized shootings of unarmed Black civilians by White police officers likely impacted local policing practices during the study period. In Tulsa, Terence Crutcher, an unarmed 40-year old Black motorist, was shot and killed by Tulsa Police Officer Betty Shelby after an encounter in the middle of the road on September 16, 2016 (Vera, 2019). Multiple videos with different angles of the shooting widely circulated in the media and on the internet, including dashcam video and footage captured from a police helicopter. Officer Shelby was subsequently charged, and in May 2017 was acquitted of manslaughter in jury trial (Ortiz & Helsel, 2017). Within the Tulsa community there were ensuing protests and calls for greater transparency and improved police training (Blau et al., 2017).

In the aftermath of this critical incident and resulting concerns regarding police legitimacy, the TPD implement a number of changes. For example, TPD made significant changes to their use

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[10] But see Lawton (2007) who found no relationship between suspect resistance and higher levels of force once other officer, suspect, and area-level factors were controlled.

of force policy, which included: adding an emphasis on de-escalation tactics, updating the use of force continuum, removal of the lateral vascular neck restraint, updating for CALEA standards, and changing the use of force report distribution. These policies changes were accompanied by significant changes in their use of force training, which also emphasized the use of de-escalation tactics.

In addition, to these initial changes, the TPD has recently developed a plan for additional action steps based on the findings from this research team's initial report delivered in December 2019 (see TPD, 2020). These action steps are to include: expanded use of force data collection, improved documentation of force, injuries, and civilian demeanor, capturing when deadly force could have been used but was not, review the training and force practices of the Canine Unit, and review of the use of force policy and training.

Likewise, the Cincinnati community experienced the trauma associated with the tragic officer-involved shooting incident that resulted in criminal charges against an officer. On July 19, 2015, University of Cincinnati Police Division (UCPD) Officer Raymond Tensing stopped Samuel DuBose about 0.5 mile off campus for minor equipment violation (Engel, McManus, & Isaza, 2020). After a brief exchange, Officer Tensing, a 25-year old White male, shot and killed DuBose, a 43-year-old unarmed Black male. Officer Tensing's department-issued body-worn-camera (BWC) captured the incident on footage. The circumstances surrounding the shooting were heavily debated within the Cincinnati community, with ensuing protests, independent investigations, criminal trials, and civil litigation. Tensing was indicted ten days after the incident for murder. The two criminal trials that were convened in November 2015 and June 2017 both ended with hung juries. In July 2017, the county prosecutor announced that he will not pursue a third criminal trial.

Although this incident involved a police officer from the UCPD rather than the CPD, comparisons were naturally made to the 2001 shooting of Timothy Thomas by a CPD Officer that sparked days of civil unrest, and ultimately led to years of federal monitoring of the CPD (Eck & Rothman, 2006). Further, the UCPD officer-involved shooting directly involved the CPD because they were the investigating agency, requiring CPD investigators to serve as witnesses during the criminal proceedings. And while the public initially focused on the practices of the UCPD, community concern quickly expanded to the CPD, requiring a comprehensive response to concerns about police legitimacy.

During this time period, the CPD made alterations to their use of force training to reinforce the use of de-escalation techniques as the preferred method of gaining voluntary compliance. Most recently, the CPD has again updated its use of force policy based on an extensive review of best practices, a national survey of use of force policies, and in consultation with the City's legal department and the Cincinnati Citizens Complaint Authority.

In summary, not only do the analyses reported here rely exclusively on data collected post-Ferguson, but they also were collected in the aftermath of critical use of force incidents that took place in both Tulsa and Cincinnati and which led to changes in policing practices that are continuing today. Further, while they reflect only two cities, the findings from both Tulsa and Cincinnati are consistent with one another in demonstrating a weakly *negative* correlation between suspect resistance and officer force. Because these findings run counter to much of the extant research, they suggest the possibility of a paradigmatic shift in how police in these two cities are employing physical force in response-to-resistance encountered from civilians. This is all the more likely given the specific critical use of force incidents that occurred in these cities just prior to or during the study period. Rather than escalating force in response to resistance, the data show that officers are doing the opposite, and this represents a significant shift from what we thought we knew about police use of force behavior.

While the jury is still out on the effectiveness of de-escalation training at minimizing the need for force and reducing officer and citizen injuries, efforts are currently underway to study its effectiveness using robust randomized controlled trial research designs (Engel, McManus, & Herold, 2020). In addition, testing whether the results reported here from Tulsa and Cincinnati hold true for other cities represents an important next step for researchers studying the use of force by police in the post-Ferguson era.

Future research must develop new data sources, coding mechanisms, and analytic approaches

The use of official police narratives as a primary data source has significant limitations. Narratives reflect only the officer's point of view, and that point of view is subject to intentional and unintentional bias. In addition, narratives vary considerably in their detail, sequential ordering, descriptiveness, and logical flow. In the end, a narrative account is simply one person's recollection of a rapidly unfolding and stress-filled event, and it likely departs from objective reality in many large and small ways.

Body-worn camera (BWC) footage arguably offers a more objective and accurate perspective on use of force encounters. Yet, despite the rapid adoption of body-worn cameras (BWCs) and the proliferation of BWC effectiveness research in the past decade (for review, see Lum et al., 2019), there have been few studies using BWCs as a source of data to examine police practices. Note that camera footage, too, has its limitations, including the inability to capture relevant events before the camera was turned on (or off) or actions that may have taken place outside of the camera's view among others (White & Malm, 2020). Nonetheless, researchers are beginning to make use of police camera footage as a data source because of the significant potential to provide detailed – and otherwise untapped – information on police-civilian interactions.

A thorough search of the literature resulted in only three known databases created from BWC video footage that have been used to analyze police behavior (see Broussard et al., 2018; Makin et al., 2019; Voigt et al., 2017; Willits & Makin, 2018). For example, Voigt and colleagues (2017) used BWC footage to analyze the respectfulness in officer's language toward Black and White civilians during routine traffic stops. BWC footage also offers a potential rich data source for understanding interactions between officers and civilians during use of force situations. For example, in an unpublished manuscript, Broussard and colleagues (2018) reported results from an examination of 288 annotated BWC videos, including 70 use of force incidents, from a single police agency. They found higher levels of civilian aggression were associated with more uses of force and higher maximum force levels. They also reported that force was also used more quickly against Black compared to White civilians.

Likewise, Makin and colleagues (2019) coded BWC videos to examine the contextual factors associated with 287 interactions between officers and civilians in one relatively small law enforcement agency over a three-year period. They found that civilians who used "an adversarial tone" had an increased probability that the observed officer's emotional state increased (Makin et al., 2019, p. 312). Further exploration of these data resulted in a coded footage of 95 use of force encounters. The authors reported that suspect resistance predicts both the time to force and the duration of the force applied. The authors note, however, the importance of examining the context within these situations, as their analyses demonstrated that in situations when a suspect is actively resisting, officers actually take significantly longer to use force compared to situations without active resistance. The authors suggest this lag time may be due to officers attempts to de-escalate situations or waiting for back-up officers to arrive on the scene. They further report that displays of civilian resistance are not treated equally within this department, as officers tended to use force faster and at higher levels against males compared to females, and against Black compared to White civilians. Ultimately, these researchers reiterate previous calls to carefully consider the contextual factors associated with how use of force occurs.

Regarding the use of BWC footage to study police behavior, Willits and Makin (2018) describe how challenging it was to accurately classify the type of force used, or the time at which force was used. They also report they were sometimes forced to make subjective judgments about the events they were watching to produce a coded dataset. Other challenges include reviewing multiple BWCs capturing a single incident (e.g., they report in one incident, footage from 27 different sources was produced) and that the average duration of video footage reviewed for use of force incidents was 20 minutes. As a result, the coding process was labor-intensive and time-consuming; the researchers watched 1,900 minutes of video, and the portion of each video involving force was reviewed twice.

Despite these operational constraints, we believe it will be imperative to take advantage of the availability of BWC footage as a data source moving forward. The primary advantage of using BWC videos as a data source is overcoming concerns with the objectivity of official narratives—in part due to the nature of the report being written for justification of officers' actions and problems with perceptual distortions that can affect officer recall of the facts and circumstances of an officer-involved shooting (see Atherley & Hickman, 2014; Engel & Smith, 2009; Klinger & Brunson, 2009; Willits & Makin, 2018). Also, there are additional concerns with the authenticity of laboratory experiments, as they do not carry the same risk as real-life incidents (see Fridell, 2016; Willits & Makin, 2018). Furthermore, body-worn cameras as a data source addresses the problem of the social desirability effect in observational research (i.e., the Hawthorne effect), and the footage can be re-watched and coded for additional detail, which clearly cannot be done with observational research (Willits & Makin, 2018). As a result, future research should make better use of body-worn cameras as a potential rich source of data on use of force incidents, allowing for the objectivity of outside coders and for the capture of detailed data on interactions between officers and civilians.

With the widespread proliferation and use of body worn cameras in American police forces, camera footage represents an enormous pool of potential data for studying and better understanding the complex dynamics of conflict between police and civilians. However, given the current time and labor constraints involved in making use of these data for research purposes, future social science researchers would be well-served to partner with colleagues from disciplines such as computer science, data analytics, and data visualization to identify new methods for using artificial intelligence and/or machine learning to automate the manual coding and analytic processes that currently dominate the research space. If researchers could identify reliable machine-driven techniques for coding and/or analyzing body worn camera footage, they could more fully realize the potential of the data. Importantly, when researchers better utilize BWC footage, they can also assist agencies in the use of this valuable source of information to dramatically expand our ability to learn from violent police-civilian encounters, improve police training, and thereby reducing the risk of injury to both officers and civilians.

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