ACADEMY OF CRIMINAL JUSTICE SCIENCES - POLICE SECTION

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From the Editor

Dear Readers,

As summer's symphony dances through the air, we are delighted to present the latest edition of the *Police Forum*. The Police Section's strength lies in the collaborative spirit of its members, fostering a vibrant community where ideas are exchanged, partnerships are formed, and innovative approaches to policing are born. We are delighted to report that the Section has experienced a renewed vitality, with the Board taking a more active stance—we look forward to the Section's next chapter.

In her letter from the Chair (p. 4), Veronyka James introduces the new Executive Board Members and reveals our new social media pages! We are currently accepting nominations for our Section's awards, and we appreciate your participation in the nomination process—please see page 17 for complete details.

Dispensing with formalities, I am pleased to introduce you to the highlight of this edition: the feature article titled "Bayesian Inference in Criminological Research" by Scott M. Mourtgos.

Mourtgos is a distinguished pracademic whose multifaceted expertise spans the realms of academia and professional law enforcement—currently a Ph.D. Candidate in the Political Science Department at the University of Utah, Mourtgos, brings a wealth of knowledge and scholarly acumen to his research endeavors.

In addition to his academic pursuits, Mourtgos boasts an impressive background as a Deputy Chief of Police, amassing nearly two decades of invaluable law enforcement experience. His practical insights and real-world perspective inform his scholarly work, rendering it academically rigorous and deeply grounded in the challenges and intricacies of policing.

Mourtgos is a strong advocate for the Bayesian paradigm of statistical inquiry. For readers with little statistical training, there are two main ways people think about and use numbers: the frequentist and Bayesian paradigms. The frequentist approach involves studying the available data and drawing inferences and conclusions by considering the properties of the observed data and the hypothetical population it represents. It doesn't take into account any prior beliefs or opinions.

On the other hand, the Bayesian approach considers both the data you have and any prior beliefs or opinions you might have. It combines them to come up with conclusions that take into account more information and can be useful when there isn't a lot of data available.

Like many criminologists and policing scholars, my statistical training was based on the frequentist paradigm. However, after reading some of Scott's work and attending a few of his conference presentations, I noticed a common theme: a strong emphasis on Bayesian inference.

My limited exposure to the competing Bayesian paradigm left me eager to learn more about Scott's experiences. After all, Scott is a full-time police practitioner and administrator, meaning he only moonlights as an academic and Bayesian statistician! I wanted to learn more about Bayesian statistics, their application in policing research, and how Scott developed such a unique skill set for a deputy police chief. Our subsequent conversations exceeded my expectations.

Finding our conversations illuminating and recognizing the immense potential and unique applications of the Bayesian framework within policing research, I invited Scott to share an extended narrative of our dialogue here. We acknowledged that many individuals within the readership might have limited familiarity with the Bayesian paradigm and its applications for the field.

In his article, Scott unravels the intricacies and practical applications of Bayesian inference in a comprehensive and accessible manner. While our readers can find more in-depth introductions and texts on the Bayesian framework, Scott's essay focuses explicitly on applying the Bayesian framework to policing research, using his published research as a guiding example. This lens allows our readers to see more detail and explanation than a typical methods section would offer.

By embracing a Bayesian approach, researchers can effectively handle uncertainty, incorporate prior knowledge, and produce robust findings that aid in evidence-based decision-making within the criminal justice system.

"Bayesian Inference in Criminological Research" is a valuable resource for seasoned researchers and aspiring scholars seeking to expand their methodological toolkit and embrace cutting-edge statistical techniques. Whether you have prior knowledge of Bayesian inference or are entirely new to the concept, Mourtgos presents the material in a clear and accessible manner, making it appropriate for our wide range of readers. As a result, we hope our practitioners will find this essay an approachable introduction to the topic.

As always, I would like to thank our dedicated readers for their continued support and engagement. Your contributions, feedback, and active participation make the *Police Forum* a thriving platform for knowledge exchange and professional growth.

I encourage you to take advantage of this interactive community by submitting your articles, book reviews, announcements, and job openings for inclusion in future editions. Your perspectives are invaluable and contribute to the richness of our discussions. Your contributions will be of great value to our broad and diverse readership. Please email your submissions to acjspoliceforum@gmail.com.

May your summer days be adorned with sunshine, warmth, and rejuvenation.

Eric Dlugolenski

Editor, *Police Forum*
Vice-Chair — ACJS Police Section

From the Chair

Greetings!

I hope everyone is enjoying summer, relaxing before the fall semester, taking some wonderful trips, or enjoying the warmer weather.

As the Police Section goes, we met during ACJS in March in National Harbor, MD. The Police Section participated in the joint section reception with the 12 other ACJS sections. Many enjoyed the great event; the only downside was that the food disappeared quickly.

The Executive Board, in conjunction with the executive boards of the other sections, is in discussions about the future of this event and what it will look like in Chicago next year. Stay tuned for updates on this.

The Police Section's own reception was well-attended for the Friday evening of the conference. The food was excellent, and it was enjoyed amidst great company! Conversations were productive, and the event symbolized a post-pandemic resurgence of the Section. We held a brief business meeting prior and discussed the new Board, the future of our social media, *The Forum*, and the status of our Section. We plan to move the reception day for the next conference. We are looking to schedule the reception for Thursday or Wednesday to accommodate more members' schedules and conference departures.

As far as our Board, we now have a full executive board minus a student representative. If you have a student representative in mind, please contact the Board. Following the recent elections, the current Police Section Executive Board is:

Veronyka James, Chair
Eric Dlugolenski, Vice-Chair
Jeff Bumgarner, Secretary
Jay Wachtel, Executive Counselor
Clint Rand, Executive Counselor
Zachary Powell, Executive Counselor

Our Section is healthy and thriving, and we now have official Twitter and LinkedIn pages. Please follow our new pages and spread the word to your networks.

Twitter: https://twitter.com/ACJS_Police
LinkedIn: https://www.linkedin.com/company/police-section-academy-of-criminal-justice-sciences/

We are currently accepting nominations for our awards at ACJS next year. These are the Outstanding Service Award and the O.W. Wilson Award. We are also discussing plans for a student award or two, though these are not finalized yet. I will share and solicit nominations for these awards as soon as there is more information. Stay connected for more information.

For now, those are all the updates. Have a safe and wonderful summer!

Veronyka James

Chair — ACJS Police Section

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Feature Article

Bayesian Inference in Criminological Research

Scott Mourtgos
Deputy Chief, Salt Lake City Police Department, UT
Ph.D. Candidate, University of Utah

"Bayesian inference is not just a tool for solving problems; it is a philosophy for solving problems."

- Sharon Bertsch McGrayne[1]

In the aftermath of psychology's replication crisis, warnings have emerged from criminologists cautioning their own field against a similar fate. A lack of proper accounting and management of uncertainty within statistical models can lead to an increased risk of false discovery rates and inflated effect size estimates.[2] Barnes and colleagues argue that a shift towards Bayesian statistical analysis from the prevailing frequentist paradigm could serve as a safeguard against a potential credibility crisis in criminological research.

While I endorse Barnes and his team's call-to-action, my fascination with Bayesian statistics predates their 2020 article. This narrative describes my transition from a frequentist to a Bayesian mindset and why I believe Bayesian thinking should underpin statistical practice.

Understanding Bayesian Inference: A Curious Journey through Bayes' Theorem

My apprehension towards statistics began during my Master's program in 2013. Mathematics had never been my strong suit nor an area of personal interest. However, as part of my Master's degree, a mandatory univariate statistics course was included. I am grateful to Dr. Thomas Petros of the University of North Dakota's Psychology Department, whose course ignited my passion for statistics, transforming it from an object of dread to a tool for understanding the social world. Interestingly, Dr. Petros had numerous bobbleheads of himself, one of which still sits on my desk today, serving as a reminder of the impact he had on my statistical journey.

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[1] Sharon Bertsch Mcgrayne, *The Theory That Would Not Die: How Bayes' Rule Cracked the Enigma Code, Hunted down Russion Submarines & Emerged Triumphant from Two Centuries of Controversy* (New Haven, CT: Yale University Press, 2011).
[2] J. C. Barnes et al., "How Powerful Is the Evidence in Criminology? On Whether We Should Fear a Coming Crisis of Confidence," *Justice Quarterly* 37, no. 3 (2020): 383–409.

Dr. Petros assigned David C. Howell's Statistical Methods for Psychology[3] text, where I encountered an unfamiliar theorem on just four pages out of the 700+: Bayes' Theorem. A quintessential example in the book demonstrating the application of Bayes' Theorem is breast cancer testing:

- The prevalence of breast cancer is 1%, indicating that out of 1,000 people, ten have the disease.
- The test for breast cancer has a sensitivity of 90%, meaning it can accurately identify 90% of genuine positive cases.
- The specificity of the test is also 90%, denoting that it correctly identifies 90% of true negative cases.

The question then arises: if you receive a positive test result, what is the likelihood that you genuinely have breast cancer? Bayes Theorem offers an answer, applying the principle of inverse probability, where we infer causes from observed effects. Here, the test result is the "effect," and having or not having the disease is the "cause."

Often, we intuitively think in terms of "forward" probabilities. For instance, upon hearing that a test has a 90% sensitivity, one may erroneously believe that a positive test result signifies a 90% chance they have the disease. This assumption fails to account for the base rate or prevalence of the disease in the population. That's where the power of inverse probability comes in. It considers the base rate, along with the reliability of the test (its sensitivity and specificity), to provide a more accurate probability of having the disease given a positive test result.

Let's elucidate this with Bayes' Theorem formula:

$P(A|B) = [P(B|A) * P(A)] / P(B)$

Where:

- $P(A|B)$ is the probability of event A (having cancer), given that event B (a positive test result) has occurred.
- $P(B|A)$ is the probability of event B (a positive test), given that event A (having cancer) has occurred.
- $P(A)$ is the probability of event A (having cancer).
- $P(B)$ is the probability of event B (a positive test).

When we substitute the given values, we find that even if you receive a positive test result, there is only about an 8.3% chance that you genuinely have breast cancer—significantly lower than the intuitive 90% chance that many would guess.[4] This example underlines the importance of Bayes Theorem and inverse probability for a more accurate understanding of probabilities.

[3] David C. Howell, *Statistical Methods for Psychology*, 8th edition (Cengage Learning, 2012).
[4] Given: $P(A) = 0.01$ (prevalence of breast cancer, or 1%)

Bayesian analysis fundamentally revolves around conditioning our hypotheses based on the available data. This concept is what solidifies my advocacy for the Bayesian approach. Conventional, or frequentist, statistics encourage us to evaluate the data in light of the hypothesis. Essentially, we aim to ascertain if the data align with the assumed hypothesis distribution for the observed phenomenon, be it normal, Poisson, or any other distribution.

Yet, frequentist statistics are founded on the principle of repeated sampling, which introduces a dilemma: the hypothesized distribution that we compare the data against is never truly observed. It's an assumed construct, envisioned to manifest if we perpetually sampled the population—an impractical scenario. The data we currently possess is the only definitive information we have. Bayesian inference offers a solution, reversing the frequentist paradigm and analyzing the hypothesis in relation to the available data. Put simply, it assesses whether the hypothesis fits the actual data we possess—a perfect illustration of inverse thinking.

While this might seem like a subtle difference, it signifies a crucial shift in statistical comprehension. It introduces an element of honesty to our estimations that is absent in the frequentist approach. The only firm fact is the data we have. Therefore, the pressing question becomes: does the hypothesis correspond with the available data? Furthermore, Bayesian inference allows us to update our estimations as more data becomes accessible, providing a more dynamic and realistic approach to statistical data and hypothesis testing.

P(B|A) = 0.9 (sensitivity of the test, or the probability of a positive test given the presence of breast cancer)
P(B) = ?

To determine P(B), we need to consider both true positive and false positive cases: P(B) = P(B|A) * P(A) + P(B|not A) * P(not A)

P(B|not A) is the probability of a positive test result given the absence of breast cancer, which can be calculated as 1 - specificity: P(B|not A) = 1 - 0.9 = 0.1 (specificity of the test, or the probability of a negative test given the absence of breast cancer)

P(not A) = 1 - P(A) = 1 - 0.01 = 0.99 (probability of not having breast cancer)

Now we can calculate P(B): P(B) = P(B|A) * P(A) + P(B|not A) * P(not A)
= 0.9 * 0.01 + 0.1 * 0.99
= 0.009 + 0.099
= 0.108

Now let's calculate P(A|B) using Bayes' Theorem:
P(A|B) = [P(B|A) * P(A)] / P(B)
= (0.9 * 0.01) / 0.108
≈ 0.0833 or 8.3%

The Benefits of Bayesian Methods: Probability Distributions and Confidence Intervals

Contrary to conventional, or frequentist, statistics, the Bayesian method enables the estimation of complete probability distributions for every parameter in our models. The former presumes a singular, definitive population parameter—essentially a static, unknown parameter coefficient. In social sciences, however, it's challenging to envision a situation where this would realistically apply.

In the Bayesian paradigm, all unknown parameters are treated as uncertain, represented by a probability distribution. Consequently, Bayesian methods yield not a single result but a distribution encapsulating the probability of containing the parameter coefficient in question. Hence, we work with actual probabilities as opposed to often misinterpreted p-values and confidence intervals.

In the frequentist approach, confidence intervals rely on the principle of repeated sampling. A 95% confidence interval does not mean there is a 95% chance that the parameter we are interested in lies within that interval. Instead, it indicates that if the experiment were repeated indefinitely, the unknown yet fixed coefficient would fall within the interval. However, in reality, our studies usually work with a single sample, making the notion of repeated sampling quite unrealistic.

By contrast, a Bayesian confidence interval—also known as a credible interval—conveys the probability that the population parameter falls between the credible interval's lower and upper bounds based on the existing data. This interpretation more closely aligns with the claims we typically aim to make, offering a practical and intuitive understanding of statistical analysis.

The Debate over Priors: From Flat to Weakly Informative

A significant part of the Bayes Theorem, the prior distribution, is frequently the target of criticisms against Bayesian methods. Within the Bayesian framework, the uncertainty surrounding parameter values is captured by a pre-data-determined distribution known as the prior distribution.

Critics of Bayesian inference often discredit it due to its incorporation of "subjective" prior beliefs. Many researchers adhere to the 'principle of indifference,' assigning equal probabilities to all events.[5] These uninformative (or "flat") priors assign equal probability to all potential values of the model parameters. While some argue these should be the default as they maximize

[5] Amos Golan, *Foundations of Info-Metrics: Modeling, Inference, and Imperfect Information* (New York, NY: Oxford University Press, 2018).

entropy[6] and reduce error probabilities[7], this approach is seldom explicitly discussed in frequentist modeling.

Bayesian methods, in contrast, typically employ weakly-informative priors. These priors help constrain parameters to reasonable ranges, offering conservative estimates of any available prior knowledge about the parameter with minimal influence on the final parameter estimate. It is often argued that unless one truly believes all events are equally probable, weakly-informative priors should be used.[8]

Consider, for example, a criminology study aiming to predict recidivism rates—the likelihood of a convicted criminal to reoffend. In this context, a weakly informative prior could be more sensible than a flat prior. If we are predicting whether a person with a violent crime history will reoffend within ten years after their release, a flat prior implies that recidivism rates from 0% to 100% are equally likely—clearly an implausible assumption.

On the other hand, a weakly informative prior mirrors our basic understanding of the situation without being overly specific. We know that recidivism rates aren't usually zero or 100%, but somewhere in between. So a weakly informative prior might represent this general knowledge—perhaps a Beta distribution centered around the average recidivism rate with a broad spread to reflect our uncertainty. This allows us to avoid favoring any specific recidivism rate while not giving equal plausibility to highly unlikely scenarios.

As data is collected, this weakly informative prior allows the data to 'speak for itself,' but it also prevents our estimates from being unrealistically influenced by outliers or sparse data, which is a common issue in criminological studies.

By using a weakly informative prior, we build on our existing knowledge that not all outcomes are equally likely, while still remaining open to what the data tells us. This makes Bayesian analysis with weakly informative priors a potent tool in criminological research.

Interestingly, the debate over priors overlooks the fact that frequentist methods *do* choose a prior: equal plausibility for all outcomes. Bayesian methods (which allow for flat priors if desired) simply make this choice transparent and explicit.

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6 Golan.
7 Deborah G. Mayo, *Statistical Inference as Severe Testing: How to Get beyond the Statistics Wars* (New York, NY: Cambridge University Press, 2018).
8 Richard McElreath, *Statistical Rethinking: A Bayesian Course with Examples in R and Stan*, 2nd ed. (Boca Raton, FL: CRC Press, 2020).

Bayes in Practical Research Applications

Before I conclude, I would like to illustrate my arguments for Bayesian methods by sharing an example from a real-world research project I worked on with my frequent collaborators, Ian T. Adams and Sharon Mastracci. In 2021, we published a study in the *Journal of Criminal Justice* titled "Improving Victim Engagement and Officer Response in Rape Investigations: A Longitudinal Assessment of a Brief Training."[9]

This research focused on the impact of a four-hour training program specially designed to improve police responses to rape victims in a U.S. state capital. We recognized a need for this intervention, acknowledging that the initial interaction between rape victims and law enforcement significantly influences case progression through the criminal justice system. Regrettably, we identified substandard initial responses from the police agency under review, characterized by low victim engagement and frequent negative stereotypes about rape victims in officer-written reports.

In response, we implemented a comprehensive training program, which approximately 600 sworn officers completed within four months. We evaluated the training's effectiveness by examining its impact on the percentage of rape victims who continued to participate in the investigative process after their initial encounter with law enforcement. In addition, we used a machine learning-based text analysis method to assess changes in the initial contact reports written by officers both before and after the training.

Our study yielded promising results. Compared to the six months prior to training implementation, victim engagement improved by 32% in the post-training period. Furthermore, we saw significant improvements in officer-written reports, including an increased use of victim-supportive language and a stronger emphasis on victim services. Therefore, our research highlighted the profound positive impact of dedicated training on enhancing police responses to rape victims, thus promoting more effective and sensitive interactions with them throughout the investigation process.

Bayesian Analysis

For this discussion, I will concentrate on our first analysis, which assessed the training's impact on the percentage of rape victims who stayed engaged in the investigative process following their initial contact with officers. We used Bayesian analysis for this part of the analysis, demonstrating the advantages this approach offers.

[9] Scott M. Mourtgos, Ian T. Adams, and Sharon H. Mastracci, "Improving Victim Engagement and Officer Response in Rape Investigations: A Longitudinal Assessment of a Brief Training," *Journal of Criminal Justice*, 2021, 10.

We gauged victim engagement by reviewing case records to determine whether a victim withdrew from the justice process after filing the initial police report. We categorized a victim as having withdrawn if they failed to make contact with the follow-up detective after the initial report, or if they explicitly told the detective that they no longer wished to proceed with their case.

To evaluate the change in victim engagement before and after training, we employed a Bayesian two-sample hypothesis test. We treated the pre- and post-training cases as separate parameters, estimated each parameter with beta distributions, and conducted Monte Carlo simulations to calculate the extent of change, if any, and the probability of observing that change due to chance.

Our analysis of victim engagement clearly showed that a non-informative prior does not accurately represent reality. Before the training, about 77% of all victims were classified as withdrawing from the justice process, while post-training, this figure dropped to approximately 67%. Given these statistics, a weakly informative prior better captured the situation than an assumption of equal probabilities for engagement or withdrawal. Consequently, we needed to determine the prior distribution for our analysis. To do this, we referred to three sources of prior information: expert opinion from the sergeant overseeing the Special Victims Unit at the department under study, data from the department's internal records management system from the two years preceding the training intervention, and a recent publication using National Incident-Based Reporting System (NIBRS) data from 2011 to investigate variables affecting sexual assault case closures.

These sources provided a wide range of estimates for victim engagement priors. For a number of reasons, we retained the victim engagement prior based on expert opinion (30%), and we used a broad variance (i.e., weak prior) for our analysis. These conservative decisions allowed us to create a distribution where 0.3 is the mean but allows for a vast range of possible alternative rates. As with any statistical assumption, the use of priors in Bayesian analysis should be critically examined, particularly when no strong case exists for one prior over another, and multiple reasonable choices are available, as in our study. To this end, in an appendix, we analyzed the data with each of the three described priors to test the sensitivity of the inference to the prior's specification. We demonstrated that regardless of which of the three priors we used, our results remained unchanged. This outcome was expected since the likelihood function (i.e., observed data) quickly supersedes the prior assumption with even moderately sized samples, leading to similar inferences.

Another critical component in a Bayesian method is the likelihood function, which essentially represents the observed data. In our analysis, we were interested in the dependent variable of victim engagement. We modeled this dependent variable with the probability density function (PDF) of the beta distribution. Each victim has a unique probability of staying engaged in the justice process or withdrawing. These individual probabilities of victim engagement also share a common distribution, which is the beta distribution. Therefore, the beta distribution is essentially a probability distribution for probabilities.[10] By taking these unique probabilities into account when estimating the overall probability distribution, we incorporated more information and accounted for uncertainty more appropriately in our model.

We had to estimate two sample parameters (pre- and post-training). We generated a posterior distribution for each parameter by estimating the PDF for each. The data suggested an increase in victim engagement after training. However, there was an overlap between the distributions of the two parameters. This overlap created the possibility that the post-training gains might be due to chance, or that pre-training victim engagement could be higher than post-training. To investigate further whether the post-training improvements in victim engagement were due to chance, we used a Monte Carlo simulation. After drawing the samples, we calculated the ratio between instances when post-training victim engagement was superior and the total number of possibilities to arrive at an exact probability.

The results showed that in 86% of the one million samples we simulated, post-training victim engagement was better than pre-training victim engagement. Thus, based on the distribution of all possible scenarios, in 86% of those scenarios, post-training victim engagement was better than pre-training victim engagement. This finding suggests that even with a relatively small number of observed sexual assault cases, we can hold a relatively strong belief that post-training victim engagement was better than pre-training victim engagement.

Dealing with Alphas, p-values, and probability

The above findings can be interpreted such that there is a .86 probability that the observed increase in victim retention is due to the provided training and not a product of random chance. Some may be tempted to discard this finding because it is not a probability equal to or greater than .95, which is the threshold that is analogous to the .05 standard in frequentist statistics. We consider dismissing this evidence to be unwise for a number of reasons. First, it is often pointed out that the scientific field's continued use of this arbitrary cutoff distorts scientific evidence and the scientific process. Adherence to the arbitrary standard of .05 encourages p-hacking, increases the rate of false-negative results, and inflates false-discovery rates.[11] In recent years, there has been a growing acceptance of deemphasizing contemporary 'statistical significance,' with some scientific journals banning the use of p-values and others the Null Hypothesis Significance Testing Procedure.[12] In general, this trend suggests that statistical significance should not be considered a research goal and that alternatives to null hypothesis significance tests, such as the Bayesian modeling used in our study, should be employed more widely in criminological

[10] McElreath, *Statistical Rethinking: A Bayesian Course with Examples in R and Stan*.
[11] McElreath; Stuart Ritchie, *Science Fictions: How Fraud, Bias, Negligence, and Hype Undermine the Search for Truth* (New York, NY: Metropolitan Books, 2020).
[12] Yudi Pawitan, "Defending the P-Value" (Working Paper, Department of Medical Epidemiology and Biostatistics, Karolinska Institutet, Stockholm, Sweden, September 4, 2020), https://arxiv.org/pdf/2009.02099.pdf.

research.[13] By quantifying our level of certainty in the results through probability distributions using Bayesian inference, we can adopt a more comprehensive view of scientific findings beyond the constraints of an arbitrary p-value.

While I largely agree with the above criticisms, I also argue that practical concerns should carry even more weight. It is essential to update our beliefs about what policy interventions should achieve based on what the data are actually indicating. Improved police-victim interactions and increased victim retention are practical outcomes that police executives care about. I would argue that the probability of these positive returns being 'only' .86 rather than .95 is likely of little concern to busy police executives looking for low-cost (in terms of time and money) solutions to real-world problems. Of course, one could always make the slippery slope argument of how low is too low for a 'significant' finding. I acknowledge the inherent ambiguity of this question, but advocate for researchers and practitioners to logically think through the problem at hand, recognizing that different problems often require different solutions. Given the low-cost intervention we studied, and the high-probability increase in police-victim interactions and victim retention, rejecting the findings based on a final probability of .86 does not seem prudent or logical.

Towards a Bayesian Criminology

In conclusion, I hope to have demonstrated the application and potential of Bayesian methods in criminological research, offering a compelling case for their broader adoption in the field. The use of these methods provides a nuanced understanding of research problems by allowing us to incorporate prior knowledge and generate posterior distributions that not only estimate the parameter of interest but also gives a distribution of all possible values, thereby providing a measure of uncertainty.

While traditional frequentist approaches remain dominant in the field, their limitations, such as the reliance on null hypothesis significance testing and arbitrary thresholds for statistical significance, have been increasingly recognized. Bayesian methods provide an opportunity to address these limitations, allowing for a more intuitive and realistic interpretation of data. Unlike p-values, which simply test the likelihood of the data given a null hypothesis, Bayesian statistics allow us to directly answer the research questions at hand by computing the probability of a hypothesis given the observed data.

In the study I used as an example, Bayesian methods provided meaningful insights into the impact of police training on victim engagement in sexual assault cases. These insights were derived not only from the analysis of observed data but also from the incorporation of prior

[13] Barnes et al., "How Powerful Is the Evidence in Criminology? On Whether We Should Fear a Coming Crisis of Confidence"; Andrew Gelman, T. Skardhamar, and M. Aaltonen, "Type M Error Can Explain Weisburd's Paradox," *Journal of Quantitative Criminology*, 2018, https://doi.org/10.31235/osf.io/ahnd4.

knowledge and understanding of the problem at hand. Furthermore, the use of a Monte Carlo simulation to generate a distribution of all possible scenarios gave us the capacity to estimate how often post-training victim engagement would exceed pre-training engagement and by how much, providing valuable quantitative predictions to inform police policy and practice.

Our findings, therefore, underscore the value of Bayesian methods in providing a more detailed and comprehensive understanding of complex criminological phenomena. They afford a more flexible and versatile statistical framework capable of addressing diverse research questions and accounting for different sources of uncertainty.

However, we must be mindful that the adoption of Bayesian methods does not equate to a panacea for all statistical issues. Bayesian methods have their own assumptions and limitations, and their use requires a sound understanding of the statistical principles involved. Moreover, they should be applied judiciously in line with the specific research question, data, and context.

Nevertheless, Bayesian methods offer substantial potential to enhance criminological research. They allow for the integration of a broad range of information, facilitate nuanced insights, and support probabilistic thinking, making them a powerful tool to navigate the complexities inherent in criminological data. As such, I recommend their broader adoption and urge criminologists to develop the necessary statistical skills and knowledge to apply them effectively. As the field continues to evolve and become more data-driven, embracing Bayesian methods will be crucial in advancing our understanding and responding to the complex nature of crime and justice.

Scott M. Mourtgos *is a Ph.D. Candidate in the Political Science Department at the University of Utah and a Deputy Chief of Police with nearly two decades of professional law enforcement experience. Mourtgos is a National Institute of Justice LEADS Scholar and is affiliated with Michigan State University's Police Staffing Observatory. He also serves on the Research Advisory Board of the Police Executive Research Forum (PERF) and the Editorial Board of the Journal of Criminal Justice. Mourtgos has been widely published in academic journals, including Criminology, Justice Quarterly, and the Journal of Experimental Criminology. Additionally, in 2022, he was honored with the American Society of Criminology, Division of Policing Outstanding Student Article Award.*

Call for Award Nominations

Section Awards:

The Police Section of the ACJS confers two awards annually at its general business meeting during the ACJS Annual Meeting. All Police Section members are encouraged to nominate individuals for the following awards. Nominations are due to Veronyka James, Police Section Chair, by the deadline October 16, 2023. Email nominations to Veronyka.James@harriscountytx.gov. Any questions about the awards can be directed to Dr. James. Awardees are selected by a committee of at least three Police Section members.

Outstanding Service Award

Awarded to people who are deemed deserving of special recognition for their outstanding contribution to the Police Section. The Police Section Outstanding Service Award was established as an annual award to honor the person who has provided significant service to the Police Section.

O.W. Wilson Award

Given to recognize outstanding contributions to police education, research, and practice. The nominee should be a practitioner, policy maker, researcher, or educator who, over a number of years, has exemplified and supported the following ideals:

1. Quality higher education for the police field.
2. Careful and scientific police research.
3. Cooperation and collaboration among police educators, researchers, policy makers, and practitioners.
4. Effective, equitable, and accountable policing.

*The nominee is **not** required to be a member of the Police Section.*

Award Procedures

1. Nominations for each award must be submitted to the Chair of the Police Section by October 16, 2023.
2. Nominator must be a current Police Section member.
3. Submission of supporting materials with nominations is encouraged but not required.
4. The nomination is to include a brief summary of the nominee's contributions in accordance with the award criteria; an explanation of the significance of these contributions; and a current vitae or resume of the nominee.

ACJS Lifetime Membership

Please remember that you still must pay the Police Section dues annually to remain a member of the Police Section. Membership is $37 per year and includes a subscription to *Police Quarterly*. Payment of dues is made to ACJS.

Call for Papers, Authors, Applicants

If you are working on a project and need authors for book chapters or encyclopedia entries, let us know. We'll include that call in *Police Forum* for free.

Or, if you are hosting a conference or seminar and need participants, let us know that too. We'll be happy to help spread the word for free.

Or, if you have a job opportunity—particularly of interest to those teaching or researching in areas related to policing—we'd love to help you announce that position. Send any announcements that you would like to have included in the next issue of *Police Forum* to acjspoliceforum@gmail.com

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Submission Guidelines for *Police Forum*

Format Criteria

The format criteria for all submissions are as follows: reasonable length (less than 30 pages), double-spaced, and in a font similar to 12 pt Times New Roman. All submissions should be in Word format. All charts, graphs, pictures, etc. must be one page or smaller and contained within standard margins. Please attach these at the end of the submission as appendices. Due to formatting limitations, all appendices must be in a Word, Excel, or similar format - PDFs cannot be used.

Feature Articles

Feature Articles can be quantitative or qualitative. Tables, figures, and charts should be kept to a minimum and should be inserted at the end of the document with an appropriate reference to placement location within the text. The page limits are flexible, however, the editors reserve the right to edit excessively long manuscripts.

Practitioners Corner

Articles written from the perspective of persons currently or formerly working in the field, expressing personal observations or experiences concerning a particular area or issue. Page limits are flexible, however long articles may be edited for length.

Academic Pontification

Articles for this area should focus on making an argument, presenting a line of thought, or formulating a new conceptual idea in policing.

Point/Counterpoint

Authors are encouraged to work with another person to develop a point/ counterpoint piece. The initial argument should be between 2 and 5 pages. The initial argument should contain roughly 3 to 5 main points. Following the exchange of articles between debating authors, a 1 to 3-page rejoinder/ rebuttal will be submitted.

Research Notes

Research notes should describe a work in progress, a thumbnail outline of a research project, a conceptual methodological piece, or any other article relating to research methods or research findings in policing.

Reviews

Book reviews on any work relating to policing. Reviews of Internet sites or subjects concerning policing on the Internet are also welcome.

Policing in the News

News items of interest to the police section are welcomed in any form.

Legal News in Policing

Reviews of court cases, legal issues, lawsuits, and legal liability in policing are welcomed submissions.

Letters to the Editor

Questions, comments, or suggestions about a given Criminal Justice topic, article, or research.

This Date in History

Submissions on prior hot topics, research, or research methods in Criminal Justice from the past.

Good News

Submissions relating to professional and personal good news for our members - promotions, new jobs, marriages, etc.

How to Submit

Submissions may be made electronically by sending a copy in a Word format to acjspoliceforum@gmail.com.

Disclaimer

The editor(s) of this publication reserve the right to edit any submissions for length, clarity, or other issues.

Academy of Criminal Justice Sciences
Police Section

Executive Board

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