

Camacho, J., & Brown, W. (2018). The Evolution of the Tattoo in Defiance of the Immutable Definition of Deviance: Current Perceptions by Law Enforcement of Tattooed Arrestees. *Deviant Behaviour*, 39(8): 1023–1041.



Chapter 10

PERSONAL LIFE

Although we like to think of ourselves as fully autonomous beings, in Chapter 10 we looked at how our personal lives are shaped by wider social structures, ideas and trends. In this chapter, we looked at the body as a one of the most important components of personal life and introduced the idea of body projects (Shilling 1993). The notion of body projects refers to ways that individuals relate to their bodies in an active way in contemporary society. Bodies aren't merely biological entities that we are 'given' and have to live with, but social objects that can be worked upon, adapted, and modified to create a particular individual identity. One of the most common ways that bodies are adapted is through tattooing.

Though tattooing has a long history that spans the whole globe and across different time periods, one of the most abiding framings of tattoos in the West is through the lens of deviance. Although tattoos are also associated with self-expression and sub-cultural identity, Camacho and Brown (2018: 1024) argue that 'individuals with tattoos are still found to be strongly associated with deviant behavior'.

Given this, Camacho and Brown set out to understand whether people who work in law enforcement perceive tattoos as marks of deviance. This is an important question because law enforcers may profile individuals based on them having tattoos which might lead to unequal and unfair treatment of those individuals. Therefore, Camacho and Brown used an analysis technique called logistic regression to determine the relationship between tattoos and offence charges.

Specifically, they 'scraped' the webpage of the Sheriff's Office in one county in a Southern US state to collect the details of all 44,753 cases where an arrest had been made for a misdemeanour (fairly minor crime such as vandalism or traffic violations) or felony (more serious crimes like murder, robbery, or sexual assault) in 2011. Web scraping is 'a computer programming method which programmatically captures data found on a webpage' (page 1029) and is being increasingly used in sociology as data collection method. This increased use of web scraping stems from the huge increase in data generated and stored on the internet (Lupton 2013). Think, for example, of the huge amount of activity which happens every day on Twitter – millions of people tweeting about thousands of subjects across hundreds of countries. All of those tweets are stored online and freely available to access through web scraping and

could be analysed in all sorts of ways by sociologists. Huge repositories of data like this are known as ‘big data’ simply because of the enormous quantities of data within them which could be analysed for patterns and trends.

Accessing and analysing these big data sets is starkly different from traditional social science ‘where collecting data has always been hard, time consuming, and resource intensive’ (Olmedilla et al. 2016: 79). As such, big data accelerates ‘the way phenomena are studied’ (Olmedilla et al. 2016: 79) and enables sociologists to ‘capture phenomena that were previously either unobservable or even non-existent’ (Stelmaszak and Hukal 2017). Sounds great, doesn’t it? Well, big data certainly represents a positive evolution of sociological methods. Particularly, sociologists’ increased use of big data might avoid the ‘coming crisis of empirical sociology’ that Savage and Burrows (2007) wrote about where they warned us that sociology would lose its legitimate claims to methodological innovation by not engaging with newly emerging big data.

But we also need to be cautious about using big data. Big databases can be unstructured, ‘messy’ (Schöch 2013) and in need of ‘cleaning’ prior to analysis. This cleaning process can take a very long time and can identify numerous inconsistencies and omissions in the data, especially in the case of data which has been manually generated like in Camacho and Brown’s research. In this case, Camacho and Brown wanted to interrogate their police data to find all the cases where arrestees had visible tattoos on their face, neck or hands (as these tattoo locations are associated with prisoners or gang members). However, there were several instances where ‘raw data was not consistent or concise in stating if an arrestee had a scar, a mark, or a tattoo’ (page 1030). In these cases, Camacho and Brown had to code the data to state that arrestee had no tattoos which may not have been the case.

Part of this data cleaning process also involves converting data into a form where it can be used for quantitative analysis. Camacho and Brown wanted to find out whether those with a visible tattoo get charged more severely than those who do not have a visible tattoo. And, secondly, for those with a visible tattoo, does the location of the tattoo make a significant difference in charge severity? (page 1029). To answer these questions, Camacho and Brown used an analysis technique called ‘logistic regression’ which allows researchers to compare the relationship between two sets of variables – independent and dependent variables. In this case, the independent variables were the sex, race, ethnicity, presence or absence of tattoos, and the location of tattoos, and the dependent variable was the severity of the arrest charge. By running logistic regression tests, Camacho and Brown were able to analyse how far the severity of an arrest charge was *dependent* on each individual independent variable. They concluded that being Black, being Hispanic, and having a visible tattoo all increase the likelihood of a person being arrested on a more serious charge.

Logistic regression is not only useful for telling us about a particular phenomenon that has happened or is currently happening but also for predicting what might happen in the future. For example, based on Camacho and Brown’s research, we could predict that Black or Hispanic arrestees with visible tattoos are more likely to face felony, rather than, misdemeanour charges. But to make these kinds of predictions, researchers must be confident that their conclusions are right, and that

the correlations between variables are genuine rather than a quirk of a specific research sample. To test this, there are two crucial values in regression analyses that researchers must pay attention to – the p-value, and the r-squared (R^2). The p-value tells researchers what the risk is that their conclusion is wrong and the R^2 tells researchers how much the dependent variable can be explained by the independent variable. In this case, Camacho and Brown draw attention to the low R^2 which means that the independent variables do not go very far to explaining the severity of arrest charges. This might be because there are other variables (such as socio-economic status, age, neighbourhood, previous convictions etc.) which might better explain the severity of charges.

This indicates a drawback of regression analyses; that researchers are constrained by the data available which is unlikely to ever have *enough* information (i.e. enough people in a dataset or enough information about those people) to comprehensively explain a social phenomenon. As well as missing data about the arrestees, Camacho and Brown also did not have information about the arresting officers – what was their race? What was their ethnic background? Did they have visible tattoos? Had they previously arrested the arrestee? All of these variables might have affected each individual arrest and charge but was not captured in the dataset.

Fundamentally, social life is too complex to be completely described by a regression model because it is always changing and there are far too many factors which might explain any given dependent variable. But logistic regression models don't have to completely explain a social phenomenon to give us useful outcomes. In this case, Camacho and Brown suggest although visible tattoos don't explain *everything* about severity of charges, their conclusions that visible tattoos make a felony charge more likely indicate that police officers might benefit from bias training to avoid judgements about people with visible tattoos.

QUESTIONS:

1. What other independent variables might be missing from Camacho and Brown's data that might help explain severity of charges?
2. What other social phenomenon would logistic regression be particularly useful for explaining? What social phenomenon would be particularly difficult to explain through logistic regression analysis?
3. Are there negative stereotypes associated with visible tattoos?

REFERENCES

- Lupton, D. (2013). *Introducing Digital Sociology*. Sydney: University of Sydney. Available at: [INTRODUCING_DIGITAL_SOCIOLOG1.plain_txt.pdf \(d1wqtxts1xzle7.cloudfront.net\)](#).
- Olmedillaa, M., Martínez-Torresa, M.R., & Toralb, S.L. (2016). Harvesting Big Data in Social Science: A Methodological Approach for Collecting Online User-generated Content. *Computer Standards and Interfaces*, 46: 79–87.
- Savage, M., & Burrows, R. (2007). The Coming Crisis of Empirical Sociology. *Sociology*, 41(5): 885–899.
- Schöch, C. (2013). Big? Smart? Clean? Messy? Data in the Humanities. *Journal of Digital Humanities*, 2(3): 2–13.
- Stelmaszak, M., & Hukal, P. (2017). When Data Science Meets Social Sciences: The Benefits of the Data Revolution are Clear but Careful Reflection is Needed. LSE Blogs. Available: [When data science meets social sciences: the benefits of the data revolution are clear but careful reflection is needed | Impact of Social Sciences \(lse.ac.uk\)](#).