

Fame through surprise: How fame-seeking mass shooters diversify their attacks

Rayan Succar^{a,b}, Roni Barak Ventura^{a,b}, Maxim Belykh^a, Sihan Wei^a, and Maurizio Porfiri^{a,b,c,*},¹

^aCenter for Urban Science and Progress, New York University, Brooklyn, New York, 11201, USA; ^bDepartment of Mechanical and Aerospace Engineering, Tandon School of Engineering, New York University, Brooklyn, New York, 11201, USA; ^cDepartment of Biomedical Engineering, Tandon School of Engineering, New York University, Brooklyn, New York, 11201, USA

This manuscript was compiled on March 17, 2023

Mass shootings are becoming more frequent in the United States, as we routinely learn from the media about attempts that have been prevented or tragedies that destroyed entire communities. To date, there has been limited understanding of the *modus operandi* of mass shooters, especially those who seek fame through their attacks. Here, we explore whether the attacks of these fame-seeking mass shooters were more surprising than those of others and clarify the link between fame and surprise in mass shootings. We assembled a dataset of 189 mass shootings from 1966 to 2021, integrating data from multiple sources. We categorized the incidents in terms of the targeted population and shooting location. We measured “surprisal” (often known as “Shannon information content”) with respect to these features, and we scored fame from Wikipedia traffic data – a commonly used metric of fame. Surprisal was significantly higher for fame-seeking mass shooters than non-fame-seeking ones. We also registered a significant positive correlation between fame and surprisal controlling for the number of casualties and injured victims. Not only do we uncover a link between fame-seeking behavior and surprise in the attacks, but also we demonstrate an association between the fame of a mass shooting and its surprise.

Aggression | Fame-seeker | Information theory | Mass shooting | Surprisal

Aggression can be seen all over nature, from human civilizations to the animal kingdom. For animals, aggressive actions are generally traceable to functional purposes, that is, gaining access to valuable resources such as food, shelter, and mates (1). In the case of humans, aggression can be remarkably more complex (2); for example, no tangible benefits can be identified in the actions of a mass shooter, who often dies during or at the end of the attack.

Mass shootings have become frequent in the United States (U.S.), and their lethality has steadily increased over time (3). What motivates mass shooters? Different factors may spark mass violence, including mass shooters’ extreme ideologies, mental health conditions, and interpersonal conflicts (4). One of the least understood drivers is seeking fame (5, 6). Mass shooters who seek to gain fame, known as fame-seeking mass shooters, are individuals who execute their acts explicitly to make a name for themselves (5). Fame-seeking mass shooters are usually identified through statements expressing their thirst for fame (7); for example, the perpetrator of the Rose-Mar College of Beauty shooting, known as the first fame-seeking mass shooter, explicitly said “I wanted to get known, just wanted to get myself a name” (8).

Many attempts have been made to study fame-seeking mass shooters. For example, Lankford studied characteristics of mass shooters in the U.S. and abroad, concluding that some of them may “respond to their failure to achieve success by seeking fame and glory through killing” (9). Bushman argued

that low self-esteem should not be taken as the only factor behind fame-seeking behavior, demonstrating a link between narcissistic tendencies and the appetite for fame of this class of shooters (10). In a later study about media coverage of mass shooters, Lankford & Madifs supported the link observed by Bushman, proposing that “narcissists often want to be the center of attention and are willing to use aggression to protect their egos, and the media are essentially offering them a stage” (11). Langman (12) studied copycat behavior among fame-seeking mass shooters suggesting that they do not imitate the methodology of their role models, but rather that they are inspired by their role models’ personality and motivation. Silva & Lankford (13) showed that fame-seeking mass shooters around the world are more influenced by U.S. perpetrators than perpetrators from all other countries combined. Silva & Greene-Colozzi (7) examined the extent to which fame-seeking perpetrators and attack characteristics differ from other mass shooters, concluding that these perpetrators tend to be “young white students, with signs of mental illness, suicidal tendencies, and grandiose behaviors” and “they [are] also more likely to target schools and use a combination of weapons” (7).

Several studies have indicated higher lethality of fame-seeking mass shooters as compared to other mass shooters (5, 14). Lankford (5) suggested that this higher lethality is due to the greater fame that could be attained with more fatalities. In another study, Lankford (15) proposed that the desire for fame

Significance Statement

Mass shootings perpetrated by shooters seeking fame are the most lethal and, likely, the least understood. Fame is sought in many ways, such as attempting to be deadlier and leaving behind manifestos for the public to read. Here, we apply the information-theoretic concept of “surprisal” to elucidate the *modus operandi* of fame-seekers. Our results demonstrate that these individuals carefully plan their attacks to be different from past shooters and that the tendency to deviate from history is, in fact, rewarded by fame. These findings warn against the presentation of excessive details by the media towards responsible reporting of mass shootings and offer insight into the pursuit of “Red Flag” laws and validation of potential threats, against all odds.

Conceptualization—R.S., R.B.V., M.P.; methodology—R.S., R.B.V., M.P.; software—R.S., M.P.; formal analysis—R.S., M.P.; resources—M.P.; data curation—R.S., R.B.V., M.B., S.W.; writing—original draft preparation—R.S., R.B.V., M.P.; writing—review and editing—R.S., R.B.V., M.P.; visualization—R.S., M.P.; supervision—M.P.; funding acquisition—R.B.V., M.P.

The authors declare no competing interests.

¹To whom correspondence should be addressed. E-mail: mporfiri@nyu.edu

and attention can be of real value in identifying fame-seeking mass shooters before they act and preventing their attacks, as they exhibit clear warning signs, especially when combined with suicidal traits. In an effort to better connect fame with lethality, Silva & Capellan (14) manually compiled an extensive dataset of articles related to mass shootings from 1996 to 2016 published in the New York Times; the collection of articles included those that specifically dealt with a mass shooting or mentioned it. Through a regression analysis, Silva & Capellan determined that casualties and injuries are predictors of the fame attained by mass shooters.

The relationship between fame and achievements – casualties and injuries for mass shooters – is widely documented in the scientific literature, beyond the field of aggression. For example, Simkin & Roychowdhury (16) demonstrated that the reputation of fighter pilots in World War I increased exponentially with their merit, measured by the number of opponent aircraft destroyed. The same authors later showed that a similar phenomenon occurs with the fame of chess players' and Nobel laureates in physics (17), leading to the formulation of a mathematical theory relating fame with achievement and success (18). Achievements are not the only driving force of fame, as demonstrated by Yucesoy & Barabási (19), who found that the relationship between success and fame of tennis players is moderated by their standing. The fame of top players is affected by their success, but the same does not hold true for less accomplished players.

Fame, defined as the state of being known or talked about by many people (20), is associated with human attention. Human attention is, in turn, often attracted towards surprising events (21–24). For example, humans tend to fear rare events rather than common ones (25): people tend to worry about plane crashes more than road accidents, even though the latter cause significantly more fatalities than the former (26). Several hypothesis-driven studies in laboratory settings support that novel and unexpected behaviors are likely to draw more attention and leave a more lasting impression than predictable or familiar ones (26–30). In the study of eye movements of humans, Itti & Baldi (28, 29) found more saccades towards locations in videos which were more “surprising” than average. Ranganath & Rainer (27) employed auditory, visual, and somatic stimuli in humans and monkeys to demonstrate that neural response to repeated stimuli (such as simple pure tone sounds) decayed more rapidly than response to novel stimuli (such as dog barks). Extending beyond laboratory settings, it is tenable that “retained rare events may also and crucially contribute to the cognitive history of an individual, since rare events may affect memory with particular emphasis” (31).

In the context of mass shootings, fame-seeking mass shooters may tend to diversify their attacks from history to maximize the attention they could draw and leave a larger historical footprint, as originally predicted by Lankford who stated “fame-seeking rampage shooters will “innovate” new ways to get attention” (5). In this study, we investigated how unique the decisions of fame-seeking mass shooters are with respect to earlier mass shooters, and how the uniqueness of an attack relates to its attainment of fame. Specifically, we formulated the following two hypotheses:

H1. The attacks of fame-seeking mass shooters are more surprising than those of mass shooters who were not seeking fame.

H2. The more surprising a mass shooting is, the more famous the perpetrator becomes.

In order to test these hypotheses, we studied “completed” mass shootings (shootings with four or more fatalities (32, 33); later on simply referred to as mass shootings) from 1966 to 2021. For these mass shootings, we assembled a dataset of characteristics that could have been considered by the shooters prior to their attacks in an effort to maximize fame. Specifically, we presumed that fame-seeking mass shooters might attain surprise by targeting a novel population (such as white policemen in the 1973 Howard Johnson shooting) or selecting an unusual location (such as a movie theater in the 2012 Century 16 Movie Theater shooting). From this dataset, we quantified the surprise associated with each mass shooting by borrowing tools from the field of information theory. Specifically, we utilized the notion of “surprisal” (often known as “Shannon information content”) of an observation: an observation that is very much unexpected would convey a large information content, that is, high surprisal (34).

For each mass shooting, we collected the daily Wikipedia visit counts of the corresponding pages of the shooting and/or shooter(s) to measure fame, extending current practice in the study of fame (16, 17, 19) to the case of mass shootings. The use of Wikipedia traffic to score the fame of mass shooters is another element of novelty of this study, which called for an independent analysis to validate this metric with respect to the literature. Towards this aim, we sought to verify the claim by Silva & Cappellan (14) regarding the relationship between fame and lethality using our objective, data-driven definition of fame.

Data on lethality was also used to go beyond the *modus operandi* of fame-seeking mass shooters, in an effort to unveil the reasons why they chose to surprise. Were they viewing lethality as the path to fame and planning a surprising attack to then increase death and victim toll in their search for fame? Or were they valuing surprise as an independent path to fame? To offer some insights into these questions, we tested whether lethality is associated with surprise, so that fame-seeking mass shooters might view surprise as a means to lethality. To exclude the possibility that a potential lack of association could be due to unforeseen circumstances in the attack, we collected further data on the number and type of weapons carried by fame-seeking mass shooters – indirect measures of an intent to attain higher lethality – and we tested whether these variables are associated with surprise.

Results

Mass shootings. Overall, 189 mass shootings, carried out by 195 perpetrators, were assembled from three public datasets: Washington Post (35), the Violence Project (36), and Mother Jones (37) (see Table S1 in the Supplementary Information for details). Each incident was characterized by two features that could be considered by perpetrators during the design of their attacks in order to draw attention to themselves: “Target Group” and “Shooting Location” (details in the Materials and Methods section). Two additional features, “Leakage” and “Level of Security,” were examined, as detailed in Supplementary Information S2. Since the Target Group feature was not reported in any of the three datasets, five reviewers manually scored it, with each reviewer cataloging all of the shootings independently. In 11 cases, there was a tie, broken by a sixth

reviewer. The corresponding Cronbach's Alpha was 0.8464 and Randolph's Kappa value was 0.5822. The Cronbach's Alpha corresponds to good internal consistency and inter-rater reliability of the collected data, while the Randolph's Kappa indicates only moderate agreement, as the Randolph's Kappa is a more conservative test. For Shooting Location we had to label 15 of the 189 shootings, as they were not part of the Violence Project dataset. The 15 new cases spanned only four of the nine possible classes: none of them included shootings in *Workplace, House of Worship, K-12 School, College/University, or Government Building or Place of Civic Importance*.

Most of the instances of Targeted Group were *Past Interaction* (47.09%) and the least frequent observation was *School Community* (7.41%). Mass shootings mostly occurred at a *Workplace* (26.45%), and the least frequent venue was *Government Building or Place of Civic Importance* (4.23%). Finally, out of the 195 shooters in total, 28 shooters were identified as fame-seekers in agreement with the definition of Silva & Greene-Colozzi (7) (see Table 1 & Table S1 in the Supplementary Information).

#	Date	Shooting
2	11/12/1966	Rose-Mar College of Beauty shooting
38	01/17/1989	Cleveland Elementary School shooting
43	11/01/1991	University of Iowa shooting
70	05/21/1998	Thurston High School shooting
72	04/20/1999	Columbine High School shooting
75	09/15/1999	Wedgwood Baptist Church shooting
84	09/08/2001	Burns International Security shooting
95	03/21/2005	Red Lake Indian reservation shooting
102	04/16/2007	Virginia Tech shooting
104	12/05/2007	Westroads Mall shooting
105	12/09/2007	Youth With a Mission and New Life Church shooting
107	02/14/2008	Northern Illinois University shooting
112	04/03/2009	Immigration services center shooting
121	01/08/2011	Safeway parking lot shooting
130	07/20/2012	Century 16 movie theater shooting
133	12/14/2012	Sandy Hook Elementary School shooting
140	05/23/2014	Santa Barbara County shooting
144	10/01/2015	Umpqua Community College shooting
149	06/12/2016	Pulse nightclub shooting
158	10/01/2017	Las Vegas Strip massacre
159	11/05/2017	First Baptist Church shooting
162	02/14/2018	Marjory Stoneman Douglas High School shooting
165	05/18/2018	Santa Fe High School shooting
169	11/07/2018	Borderline Bar & Grill shooting
175	08/03/2019	Walmart shooting
176	08/04/2019	Oregon District shooting
183	01/09/2021	Hyde Park shooting

Table 1. List of mass shootings where the perpetrator(s) were identified as fame-seeker(s), according to the criteria proposed in Silva & Greene-Colozzi (7). All cases were identified by either Silva & Greene-Colozzi (7) or Silva & Lankford (13), except for the Hyde Park shooting. The first column labels the order of occurrence of a mass shooting in time, with 1 being the first recorded incident in 1966 and 189 the last in 2021. The second column reports the date in which the mass shooting took place. The third column contains the name of the shooting.

Fame. Following previous efforts to quantify fame (38, 39), we relied on the Wikipedia traffic data. Specifically, we scored fame as the median of the time series of the counts of daily visits to mass shootings/shooters Wikipedia pages. Overall, we collected data from 86 pages in total, for 77 mass shootings.

Of the 189 shootings, 100 did not have a Wikipedia page and 12 shootings had Wikipedia pages that were not available on “WikiShark” (the online tool that allows the extraction of Wikipedia traffic data (40)). Sixty-eight shootings were associated with a single Wikipedia page and nine were associated with two. All the time series were stationary with a significance level of $\alpha = 0.05$ (augmented Dickey–Fuller test).

The most famous mass shooting was the 1999 Columbine High School shooting (median visits = 5387.0 visits per day), followed by the 2012 Sandy Hook Elementary School shooting (median visits = 2204.5 visits per day) and the 2017 Las Vegas Strip massacre (median visits = 2193.0 visits per day) (Figure 1). The least famous shooting was the 1999 Day-trading Firms shooting (median visits = 0 visits per day), followed by the 1982 Russian Jack Springs Park shooting (median visits = 3 visits per day) and the 1982 Western Transfer Co. shooting (median visits = 3 visits per day).

Surprisal analysis. The first objective of this study was to determine whether fame-seeking mass shooters tend to diversify their attacks from previous incidents. To this end, we borrowed an information-theoretic measure referred to as the surprisal or Shannon information content (34). Surprisal is formally defined as the information required to encode or describe an outcome of a random variable, or, in other words, surprisal is the amount of information gained by observing a realization. Specifically, the surprisal of outcome x of random variable X is $\eta(x) = -\log_2 p(x)$ bits, with $p(x)$ being the probability of $X = x$.

For each shooting, we computed four surprisal values, each corresponding to one of the four features that might diversify an attack (two of them are detailed in Supplementary Information S2). Specifically, using $f = 1, \dots, 4$ to denote the features of a shooting, we set $f = 1$ for Target Group; $f = 2$ for Shooting Location; $f = 3$ for Level of Security (see Supplementary Information S2); and $f = 4$ for Leakage (see Supplementary Information S2). To score surprisal for the f th feature, we introduce the stochastic process $\{X_t^f\}_{t=1}^T$, where $T = 189$ and $f = 1, \dots, 4$. The process takes values in the set $\{x^{f,1}, x^{f,2}, \dots, x^{f,K^f}\}$ of cardinality K^f , which is a function of the feature ($K^1 = 4, K^2 = 9, K^3 = 3$, and $K^4 = 2$). Calculating the four surprisal values of shooting t with feature realizations x_t^1, x_t^2, x_t^3 , and x_t^4 requires the estimation of the probabilities $p(X_t^f = x_t^f)$, with $f = 1, \dots, 4$. We estimated these probabilities using a simple plug-in estimator with additive smoothing (41), by counting the number of instances in which x_t^f appeared in the features of the preceding shootings

$$p(X_t^f = x_t^f) = \frac{\sum_{\tau=1}^{t-1} \mathbf{1}_{x_t^f}(x_\tau^f) + \alpha}{t-1 + \alpha K^f}, \quad [1]$$

where $\mathbf{1}_A$ is the indicator function (42) (which is equal to one if the argument is equal to A and is zero otherwise), α is a smoothing parameter used to avoid singularity (herein chosen to be equal to 1 – so called Laplace smoothing (43)), and $t = 2, \dots, T$. Hence, we calculated the surprisal of shooting t with respect to feature f as

$$\eta_t^f = -\log_2 p(X_t^f = x_t^f) = -\log_2 \left(\frac{\sum_{\tau=1}^{t-1} \mathbf{1}_{x_t^f}(x_\tau^f) + \alpha}{t-1 + \alpha K^f} \right) + \log_2 (t-1 + \alpha K^f). \quad [2]$$

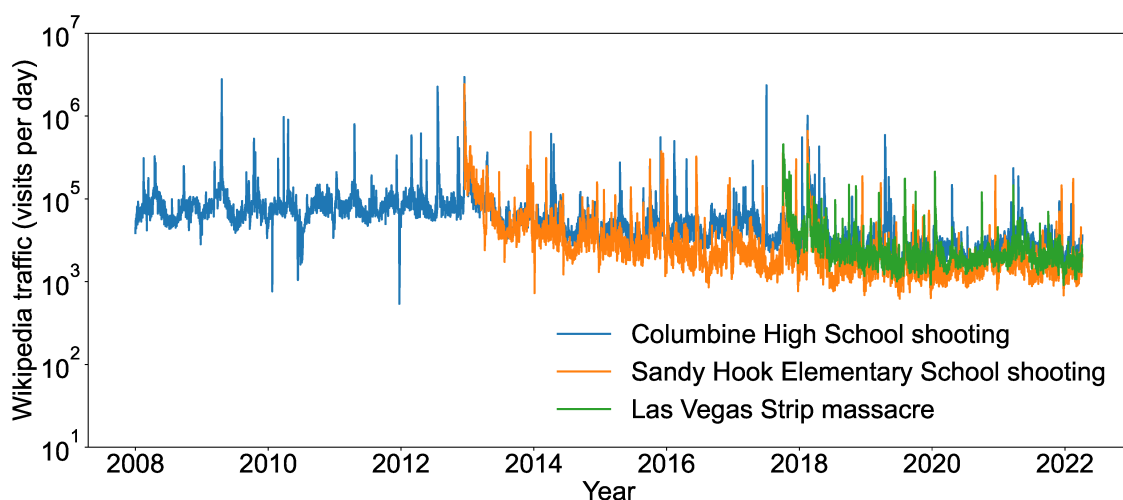


Fig. 1. Daily Wikipedia visits count for the three most famous mass shootings from January 1, 2008 to April 7, 2022.

To illustrate the computation with an example, we consider the surprisal with respect to Shooting Location ($f = 2$) for shootings 17 and 18, respectively (see Table S1 in the Supplementary Information). The Shooting Locations of the first 16 shootings were distributed as follows: 5 *Workplace*, 2 *Retail*, 2 *Restaurant/Bar*, 2 *Residence*, 0 *House of Worship*, 0 *K-12 School*, 2 *College/University*, 0 *Government Building or Place of Civic Importance*, and 3 *Outdoors*. The 17th shooting was executed in a *Restaurant/Bar* leading to a surprisal of $\eta_{17}^2 = -\log_2(3/25) = 3.06$ bits. The next shooting was executed in a *House of Worship*, a venue never seen before that conveyed a larger surprisal of $\eta_{18}^2 = -\log_2(1/26) = 4.70$ bits.

Surprisal of fame-seekers versus non-fame-seekers. Results of Mann–Whitney U tests showed that fame-seeking mass shootings are significantly more surprising than non-fame-seeking mass shooters with respect to Target Group ($U = 958.0$, $p < 0.0001$) and Shooting Location ($U = 1097.0$, $p < 0.0001$) (see Figure 2). Results are robust with respect to the choice of α and the number of samples whose surprisal values were discarded (see Supplementary Information S3).

Surprisal and fame. With respect to the association between fame and surprisal, we found a significant correlation in terms of Target Group ($\rho = 0.3895$, $p = 0.0006$) and Shooting Location $\rho = 0.4229$, $p = 0.0002$). For the validation of Silva & Cappelan (14), we found a significant correlation between fame and number of injured victims ($\rho = 0.4957$, $p < 0.0001$) and between fame and number of fatalities ($\rho = 0.5238$, $p < 0.0001$) (see Figure 3). Results are robust with respect to α , the number of samples whose surprisal values were discarded, and the choice of mean over the median to score fame (see Supplementary Information S3 and S4).

Robustness of associations with respect to data coding. To ensure our statistical claims were robust with respect to ambiguities in data coding of Target Group, we randomized the outcome of the 47 shootings in which the pool of reviewers expressed a slim majority vote and run 20,000 simulations (see Supplementary Information S5). For example, in the case of the Lockheed Martin shooting two reviewers voted for *Demographic Group* and three for *Past Interaction*. Hence, in the simulations we

randomly assigned the Target Group to *Demographic Group* or *Past Interaction* with probabilities 0.4 and 0.6, respectively. Simulation results support that our claims are robust against individual differences of the reviewers in the classification of the Target Group feature (see Supplementary Information S5).

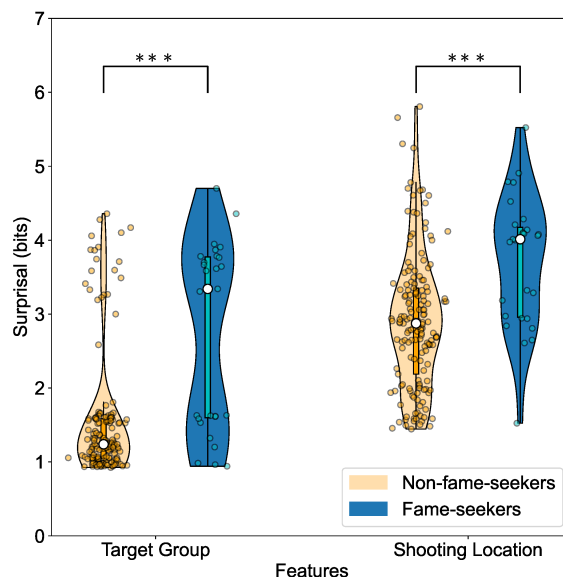


Fig. 2. Violin plots comparing summary statistics and distributions of surprisal of fame-seeking ($n = 27$) and non-fame-seeking mass shooters ($n = 161$) for Target Group and Shooting Location. For each violin plot, we report the complete set of realizations as colored dots, which is used to estimate the distributions that are shown as colored regions. White dots represent medians, the thick rectangles identify the first (Q_1) and third (Q_3) quartiles, and the thin lines the rest of the distribution (excluding outliers and estimated as $Q_1 - 1.5IQR$ and $Q_3 + 1.5IQR$, with $IQR = Q_3 - Q_1$). *** corresponds to p -value of Mann–Whitney U less than 0.0001. Note that the number of observations for the analysis is 188 rather than 189, as we did not compute surprisal values for the first shooting under the premise that the perpetrator would not have history to differentiate their actions from.

Discussion and conclusion

Human attention is known to be attracted toward unexpected events (21–24), from neural mechanisms (27) to collective be-

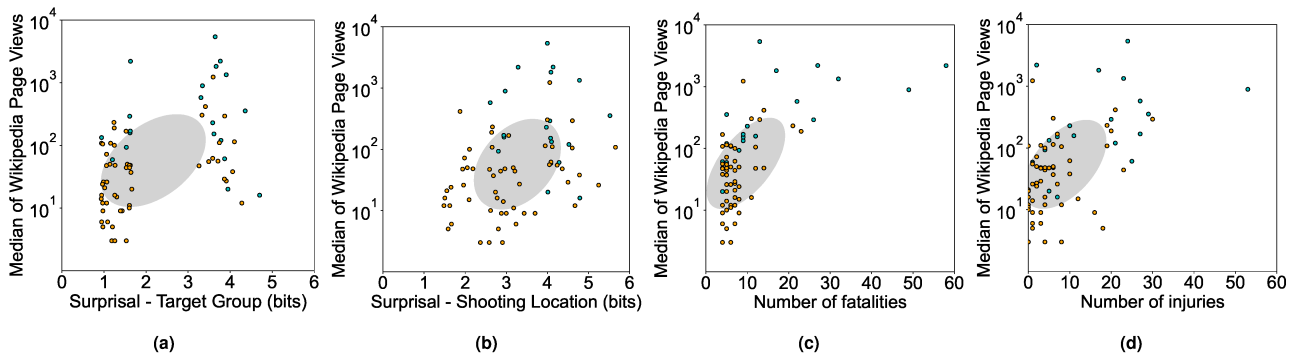


Fig. 3. Scatter plots of the relationships between the number of Wikipedia page views, surprisal, and lethality ($n = 76$). Shaded regions represent the association between the variables. Blue circles represent fame-seeking mass shooters and orange circles represent non-fame-seeking mass shooters. (a) Fame versus surprisal of Target Group feature ($\rho = 0.3895$, $p = 0.0006$). (b) Fame versus surprisal of Shooting Location feature ($\rho = 0.4229$, $p = 0.0002$). (c) Fame versus number of fatalities ($\rho = 0.5238$, $p < 0.0001$). (d) Fame versus number of injured victims ($\rho = 0.4957$, $p < 0.0001$).

havior (26). The first question this study sought to answer is whether the attacks of fame-seeking mass shooters tend to be more diverse with respect to history than those of other mass shooters (H1). For each incident, we detailed four features: Target Group, Shooting Location, Leakage, and Level of Security.

The dataset is not intended to minutely detail every aspect of a mass shooting, whereby it omits some of the features that are typically reported (35–37) in documenting mass shootings but may not directly relate to the attack planning. For example, we did not consider whether an incident resulted in the detention or death of the perpetrators, as these characteristics were unlikely to be in full control of the shooter. Likewise, shooters would not be able to control their own background characteristics, such as age, race, and mental health conditions. That is, a shooter would not be able to change their demographics in order to become more surprising. Therefore, these variables were not considered in the analysis.

We borrowed the information-theoretic quantity of surprisal or Shannon information content (34) to examine the extent to which a specific mass shooting would differ from history. We specifically scored the surprisal of a mass shooting with respect to any of the four features curated in our dataset. Surprisal is negatively proportional to the probability of observing that realization: the less likely the event is, the higher its surprisal. The concept of surprisal has countless applications in different areas of science and engineering (44–47); for example, it is extensively used in behavioral language processing (48–51), where the surprisal of words in a text are linked to the time that is needed to read and process the words. In this vein, words that unpredictably appear in a sentence carry high surprisal that lead to higher processing time by the reader due to their high information content. Likewise, surprisal analysis has been used in molecular biology to elucidate the mechanism of the epithelial-to-mesenchymal transitions (52) and detect changes in transcription levels in cell models that can be cancer markers (53).

Upon scoring surprisal for each mass shooting with respect to each of the selected four features, we offered statistical evidence in favor of H1. In agreement with our expectations, we registered that fame-seeking mass shootings are more surprising than non-fame-seeking ones in terms of the selection of attack location, choice of target population, and communication of the shooting (Target Group, Shooting Location, and

Leakage, respectively). For example, a school was attacked for the first time in the 1989 Cleveland Elementary School shooting, which resulted in high surprisal values for both Target Group and Shooting Location (*School Community* and *K-12 School*) features. In partial disagreement with our expectations, we did not observe a difference in surprisal values of fame-seeking shooters with respect to the Level of Security feature. Given that the vast majority of mass shootings occurs in public locations with limited level of security, one could have predicted that fame-seeking shooters might attempt at gaining their fame by attacking *High Security* locations, such as the 2009 Army Processing Center shooting the Fort Hood army post in Texas. At the same time, pursuing an attack in these locations could be difficult or even unfeasible, due to the additional levels of security they offer in the form of security checkpoints, presence of armed personnel onsite, and surveillance systems. Just as these factors may deter mass shooters from choosing these venues for their attack, they may also prevent the success of the attack – failed mass shooting attempts are not part of our dataset, thereby creating some selection bias in the analysis.

The second question of this study entails the extent to which surprisal leads to fame (H2). To tackle this second question, we needed a robust measure of fame. Previous studies (16, 54) attempted to measure fame from “Google hits” – the number of web-pages returned upon searching Google for a specific term. The stability of this approach is, however, questionable, as irrelevant web-pages could outnumber relevant ones. For example, searching for the name of the shooters and filtering by the word “shooting” will result in web-pages about movie shootings, including namesakes. For our problem, we found no consistent filtering scheme that would yield stable, consistent estimates from Google hits. In their study of newsworthiness of mass shooters, Silva & Capellan (14) manually compiled data from the New York Times historical dataset (up to 2018) provided by the search engine “ProQuest.” While insightful, such an approach is limited to the use of a single newspaper, which may be skewed towards reporting more frequently about mass shootings occurring near its headquarters (Northeast) and is prone to inherent biases related to its single point of view. Another issue, also acknowledged by the authors, is that measuring newsworthiness through the total amount of articles might bias results against new incidents that may have accrued only limited coverage due to their recentness.

Manual filtering of information from multiple newspapers would address some of these issues, but would be practically difficult, if not unfeasible.

Here, we attempted to measure the fame of mass shooters through the traffic in the related Wikipedia pages. In doing so, we bring several innovations: i) we automate the process of scoring fame (without the need for manual curation of a dataset); ii) we eliminate the dependence on a single source, by working with a crowdsourced dataset; iii) we switch perspective regarding fame quantification, by assessing the extent to which the public seeks knowledge about an incident, rather than how much the media covers it; and iv) we work with stationary time series, which are not penalizing newer incidents in favor of older ones. The validity of Wikipedia traffic data to measure fame has been documented in a number of studies (19, 39, 55) – none in the context of mass violence. To gain confidence about the appropriateness of Wikipedia traffic data for mass shooters, we verified the conclusions drawn by Silva & Capellan (14) regarding the relationship between fame and number of victims. Just as they found that the numbers of fatalities and injured victims are significant predictors of newsworthiness, we determined that both these numbers positively correlate with fame.

Our results point at a significant positive correlation between fame and surprisal values with respect to the two of three features that were distinctive of fame-seeking shooters (Target Group and Shooting Location), upon controlling for the number of casualties and injured victims. To the best of our knowledge, an association between surprisal and fame has never been documented. Our findings suggest the diversification of an attack with respect to previous history is related to the fame that is gained by the perpetrator. For example, the fame-seeking perpetrator of the Cleveland Elementary School shooting is among the top 13% most famous mass shooters in terms of the amount of Wikipedia page visits gathered, arguably because of the high surprisal associated with the perpetrator's attack that targeted an elementary school, for the first time in history. Similarly, the recent 2022 New York City Subway attack gained a great deal of media traction (56). Even though the attack was not a mass shooting, it was relatively unique in terms of its location and how it developed. The lack of a correlation between fame and surprisal with respect to Leakage could be related to the coarseness of this feature, which takes only two values and thus brings limited saliency to the choice made by a shooter. In this context, our observations offer more ground in favor of an association between human attention and surprise with respect to the notion of fame.

The explanation we offer for hypothesis H1 is that fame-seeking mass shooters tend to diversify their attacks in order to draw the attention of the public and become famous. Within this realm, the diversification of the attacks, or as Lankford says their choice to “innovate,” reflects an intent to gain fame, so that “fame-seeking rampage shooters have a powerful incentive to continue to attack in new and different ways” (5). Another interpretation of our findings is that fame-seeking shooters search for fame by identifying ways to maximize the number of fatalities and injured victims in their attacks and they see diversification with respect to history as a way to achieve this goal. They would choose locations and communities that have never or seldom been targeted before so

that they would catch the society off-guard and have a higher chance to carry on a successful attack. Although tenable, this alternative interpretation finds no support throughout our analysis, based on the following grounding.

First, the existence of a correlation between fame and surprise under H2, upon controlling for the number of fatalities, does not seem to favor this alternative interpretation. Rather, it suggests that the pursuit of fame through surprise is a viable one for fame-seeking mass shooters. Second, we found no evidence of a relationship between surprise and lethality, either achieved by the shooters in terms of death and injury toll, or sought after by bringing more or deadlier weapons (see Supplementary Information S6). As such, it is likely that pursuing surprising attacks is perceived as an independent path to fame for fame-seeking mass shooters. Despite our findings do not support this alternative interpretation, we warn some prudence in regard to inherent limitations of observational studies that do not permit experimental manipulations (57) and in the reliance of negative results to infer independence between variables (58).

The inability to exactly pinpoint the reasons beyond the *modus operandi* of fame-seeking mass shooters is not the only limitation of this study. First, the proposed approach to quantify surprisal from time series cannot take into consideration fine details about the incidents, which could be determinants of fame. More specifically, with 189 mass shootings, a statistical approach that searches for robust differences and similarities cannot consider more than a handful of categories to compare. Paradoxically, should one contemplate the use of an excessively fine categorization of the incidents, they would encounter a ceiling effect in the surprisal values, whereby all the incidents would be unique in history – and equally surprising. Hence, our approach is not suitable for detecting fine details that were unique to a shooting and might have fueled their fame. For example, the 2012 Century 16 Movie Theater shooting was unique in many aspects, such as execution of the shooting during the show of a famous movie, the hair color of the shooter, and the way the shooter handed himself to the law enforcement officers without any resistance (5). Second, Wikipedia coverage of mass shootings was incomplete, whereby not all shootings had Wikipedia pages (40.7%), thereby weakening our conclusions regarding the association between fame and surprisal.

In 2017, the Centers for Disease Control (CDC) issued guidance for reporters covering mass shootings, which articulate several best practices to avoid inadvertently “provok[ing] copycat incidents by people who may see the perpetrators as models or heroes” (59). In this context, CDC recommends to “minimize reporting on the perpetrators as others might identify with or be inspired by them,” and to “do not oversimplify or sensationalize the incident because it may encourage people who may seek notoriety. (e.g. do not say, “The deadliest incident since Columbine.”)” While our work reinforces the need to avoid sensationalizing any mass shooting to deter fame-seeking behavior, it raises another question for responsible reporting. How many details should be shared about the incident? Given the observed connection between fame and surprisal, excessive reporting of details may offer fame-seeking shooters ground for planning that would maximize their fame. The opportunity cost of not reporting these details should be further studied.

Conclusions drawn from our study have potential implications in law enforcement, as well. New insight into the *modus operandi* of fame-seeking shooters can help prevent tragedies. Our observation of a tendency to diversify attacks as a means to gain fame poses a great challenge to law enforcement agencies, whose resources would be strained by attempting at increasing presence in locations that have never been the object of a mass shooting (60, 61). At the same time, recognizing such a tendency could be used in strategic policy implementations (62). For example, “Red Flag” laws that “allow loved ones or law enforcement to intervene by petitioning a court for an order to temporarily prevent someone in crisis from accessing guns” (63).

Red Flags laws are promising tools for preemptive action against fame-seeking mass shooters, who often openly express their desire to become famous before their attack (15). For example, Lankford has documented 24 cases where offenders explicitly stated that they were seeking attention or even directly contacted media organizations to gain attention before carrying out their attack (5). In many other cases (both mass shootings and attempts), perpetrators have demonstrated fascination with previous mass shooters, declared them as role-models, and copied their behaviors in everyday life (10, 64, 65). We acknowledge that it is challenging to identify these warning signs in advance by professionals alone: alerts from concerned family and friends would significantly improve early identification of potential mass shooters. Widespread educational campaigns could be initiated to raise the public’s awareness of warning signs. With respect to law enforcement, we believe that more resources need to be allotted toward timely investigation of potential threats, which are increasingly occurring in the country (60, 61). More debatable is how to act on warning signs from a law enforcement perspective without impinging on one’s rights. For example, the person accused of the Club Q shooting was previously dismissed from trial for kidnapping their grandparents and threatening to bomb the building using stockpiled weapons and explosives (66, 67). At that time, the shooter spoke of their plans to become the “next mass killer,” but living in a county that was a “Second Amendment Sanctuary” would challenge the seizure of their weapons by law enforcement.

We acknowledge the controversy of publishing this kind of work, as it can be argued that we are offering mass murderers insights into successful tactics toward gaining fame. However, studies about fame-seeking mass shooters have been mostly descriptive in nature, thereby hindering our understanding of the *modus operandi* of these perpetrators. Our work offers new, quantitative insight into the behavior of fame-seeking mass shooters and the role of surprise on fame. The theoretical basis of our work could carry over other behavioral domains, within and beyond the context of aggression.

Materials and Methods

Collection of data about mass shootings. Data on 189 mass shootings between August 1966 and April 2021 were collected by combining reports from three sources: Washington Post (35), the Violence Project (36), and Mother Jones (37). Incidents contained in these sources are sometimes specifically referred to as “public mass shootings” or “mass public shootings” to emphasize that they “occur in public locations and in which victims are selected indiscriminately” (68) – a detailed

overview of publicly available datasets has been presented by Huff-Corzine & Corzine (69).

Specifically, the Washington Post and the Violence Project define a mass shooting as an attack carried out with firearms, usually by a lone shooter, in which four or more people are killed excluding the perpetrator(s), following the Congressional Research Service’s definition of a mass shooting (70). Shootings tied to gang-related activities, robberies that went awry, and domestic shootings that occurred exclusively in private homes are not considered in these datasets. The Mother Jones dataset was assembled following the Congressional Research Service definition of mass shootings until December 2012. In January 2013, researchers at Mother Jones adopted the mandate issued by President Barack Obama, lowering the baseline of fatalities in a mass shooting to three or more victims killed, for a federal investigation of mass shootings. Thus, dating from January 2013, this dataset includes attacks in which three or more victims were killed. The Mother Jones dataset contains also 19 cases known as “spree killings” (37), in which attacks occurred in more than one location, but over a short period of time that would otherwise fit the above criteria.

In order to avoid ambiguities in our dataset and maintain a consistent definition of mass shooting, we chose to adhere to the stricter definition that is adopted by the majority of mass shooting researchers (71), where at least four people were killed. Such mass shootings are often referred to as “completed” mass shootings to distinguish them from attempted, failed, foiled, or thwarted incidents (72). As such, we excluded events with three fatalities that were otherwise identified as mass shootings by Mother Jones after 2013.

In four of the incidents, the perpetrator was not apprehended and information on their motive was not available: the Investor shooting (09/06/1982), the Halloween Party shooting (10/31/2019), the Beatties Ford Road shooting (6/22/2020), and the Englewood Block Party shooting (07/04/2020) (35). Therefore, we removed these incidents from the analysis. We also excluded the Football-Watching Party shooting (11/17/2019), as it was later determined to be a gang-related incident (35), and the Sunny Dunes Road shooting (2/3/2019), which, although not gang-related, involved criminal activity (73).

In our integrated dataset, we recorded the date of occurrence of each incident, the number of injured victims, and the number of fatalities from the Washington Post, Mother Jones, or Violence project datasets. Next, we focused on four features that could be considered by perpetrators during the design of their attacks in order to draw attention to themselves: “Target Group,” “Shooting Location,” “Level of Security,” and “Leakage.” The Level of Security and Leakage are detailed in Supplementary Information S2. These features are, in principle, accessible to the perpetrator during the planning stage of their attack. Albeit in different contexts and with different levels of granularity, several authors have focused on them in their reporting of mass shootings (5, 7).

The first feature, Target Group, was categorized into the following four types: *Demographic Group*, where the targeted group was selected based on shared demographic traits, such as race, gender, religion, occupation, or political belief; *Past Interaction*, where the targeted group had been acquainted with the shooter as family, friends, neighbors, or colleagues; *School Community*, where the targeted group consists of students,

academic staff, or faculty; and *Random*, where the targeted group is selected randomly, lacking any of the aforementioned attributes/connections. Acquaintances that were made only hours prior to the shooting were not considered as *Past Interaction*; if the attacker was employed at a school, then the group would be considered *Past Interaction*.

For the second feature, Shooting Location, we adopted the classification provided by the Violence Project (36). Therein, the location of each incident was classified into nine types: *Workplace, Retail, Restaurant/Bar, Residence, House of Worship, K-12 School, College/University, Government Building or Place of Civic Importance*, and *Outdoors*. For the cases that were not part of the Violence Project dataset but were listed by Mother Jones and/or the Washington Post, we labeled the location through careful media research, looking at Wikipedia pages, news articles, and Murderpedia, among other sources.

Since Target Group involves some level of subjectivity, we adopted a classification scheme that minimized potential biases. Specifically, five individuals reviewed each mass shooting independently and specified their Target Group. The class of each incident was determined as the majority rule. For cases where there was a tie between reviewers and not a single category could be selected (two reviewers picked one class, two other reviewers picked a second class, and the fifth reviewer picked a third class), a sixth reviewer broke the tie. To assess the reliability and consistency of the collected data, Cronbach's Alpha (74) and Randolph's Kappa (75) were computed.

Once information about the characteristics of each mass shooting was summarized, we distinguished fame-seeking shooters from non-fame-seeking ones so that we could compare their choices. Specifically, we followed Silva & Greene-Colozzi's (7) criteria to identify fame-seeking shooters where "evidence was drawn from perpetrators' words and actions before/during/after an incident, suicide notes, manifestos, homemade videos, police evidence, and online profiles". Such criteria were used by the authors to classify fame-seeking mass shootings from 1966 to 2018; the same criteria were recently applied by Silva & Lankford (13) to study fame-seeking mass shootings from 1999 to 2022, correcting some of the classifications by Silva & Greene-Colozzi's (7) of recent shootings for which new evidence had surfaced. Of the 70 mass shootings from 1966 to 1998, four were classified as fame-seeking mass shootings (perpetrated by four shooters) based on Silva & Greene-Colozzi's (7). Of the 119 mass shootings from 1966 to 1998, 22 were classified as fame-seeking mass shootings (perpetrated by 23 shooters) based on Silva & Lankford (13). Upon curating our dataset, we found that the perpetrator of the 2021 Hyde Park shooting also satisfied Silva & Greene-Colozzi's (7) third criterion of fame-seeking ("posting on media platforms right before/during the incident to capitalize on the interest they plan to receive after the attack"), since the shooter posted videos online about his plan before the shooting (76). Hence, we included this incident among the fame-seeking mass shootings together with those identified by Silva & Greene-Colozzi's (7) or Silva & Lankford (13), totaling 27 fame-seeking mass shootings (perpetrated by 28 mass shooters, Table 1).

For fame-seeking mass shooters, we also collected data from the Violence Project dataset (36) about the details of the weapons used in the attack, specifically, "Total Firearms Brought to the Scene" and "Used an Extended Magazine." The former is the number of weapons carried by the perpetrators,

and the latter is a binary feature distinguishing whether the shooters used extended magazines to increase the capacity of the weapons (see Table S2 in the Supplementary Information).

Collection of data about fame. Following previous studies on the quantification of fame using Wikipedia page views for tennis players (38) and the prediction of the box office movies' success from Wikipedia data (39), we used the counts of daily visits to Wikipedia pages of mass shootings and mass shooters (when available). For example, the 2007 Virginia Tech shooting had a page titled "Virginia Tech shooting" and a page titled with the perpetrator's name. For such instances, values of the two time series were added. We did not find instances of attack perpetrated by multiple shooters with individual Wikipedia pages for each of the shooter; for example, there was only one page titled with the names of the perpetrators of the Columbine shooting. Given that Wikipedia officially publishes the number of page visits in the last two months only, we utilized the online tool WikiShark (40) to collect the daily number of Wikipedia page visits from January 1, 2008 (the first day from which data is available through Wikishark) to April 7, 2022 (the day in which we retrieved the data).

In order to measure the fame that a mass shooting gained, we computed the median of each time series. As opposed to the time series' peak, the median represents the consistent amount of attention a shooting received. This measure captures how memorable a shooting is and how much people talk about it, even after the media's attention faded out (typically after a couple of weeks). Ensuring the time series' stationarity is critical, as we want to make sure that the measure has reached a steady state, guaranteeing that the results will not change if the analysis is done at different times. An augmented Dickey-Fuller test was performed on all the time series ensuring stationarity of the time series; the null hypothesis of the test is that there is a unit root in the time series (77).

Statistics. To test hypothesis H1, which states that fame-seeking mass shooters tend to deviate from the behavior of preceding shooters, a right-tailed Mann-Whitney U test was performed between the surprisal of fame-seeking mass shootings and those by non-fame-seeking ones. The test was performed four times, once for each of the four features. The null hypothesis of the test was that the two distributions share the same mean, while the alternative hypothesis was that the surprisal of fame-seeking mass shootings was greater. Since the first shooter did not have a history of mass shootings to deviate from, the surprisal of the incident was deemed invalid and removed from the statistical analysis.

In order to test hypothesis H2, we performed a correlation analysis between the measure of fame of the mass shooting and the surprisal for each of the four features. Specifically, we tested for partial correlations while simultaneously controlling for the number of fatalities and number of injured victims to exclude the possibility that surprisal values were merely explained by the lethality of the attack. To offer some validation for the proposed measure of fame with respect to the claim of Silva & Cappelan (14), we performed two additional correlation analyses, exploring the association between fame and the number of fatalities, and the association between fame and the number of injured victims. All these correlation analyses were performed with the non-parametric Spearman correlation (78).

To delve into the reasons why fame-seeking mass shooters might have chosen to surprise in their attacks, we performed two Spearman correlation analyses between surprisal values and the number of fatalities or injured victims for fame-seeking mass shootings. To dismiss confounding factors in the study of the shooters' intentions related to unforeseen circumstances in the attacks, we performed two additional analyses. First, we conducted a Spearman correlation analysis between surprisal values and the number of weapons brought to the shooting by fame-seekers. Second, we performed a two-tailed Mann–Whitney U test comparing the surprisal values of fame-seekers who used extended magazines and those who did not (see Supplementary Information S6).

To control for type I errors in multiple hypothesis testing (four different features for the computation of surprisal – two of them being detailed in Supplementary Information S2), we employed a Bonferroni correction (79), so that the null hypotheses are rejected with a significance level of $\alpha = 0.05/4 = 0.0125$.

Acknowledgements

This study was supported by the National Science Foundation under award CMMI-1953135. R.B.V. was supported in part through a postdoctoral award from The National Collaborative on Gun Violence Research. The authors would like to express their gratitude to Rishita Das and Salvador Ramallo for the fruitful discussions.

Data sharing plans

Codes for the surprisal analysis are available on the [GitHub repository](#) of the Dynamical Systems Laboratory of the New York University Tandon School of Engineering; the dataset is not made publicly available due to its sensitivity, but will be made available to researchers upon request to M.P.

1. KS Peiman, BW Robinson, Ecology and evolution of resource-related heterospecific aggression. *The Quarterly Review Biology* **85**, 133–158 (2010).
2. J Archer, The nature of human aggression. *International Journal Law Psychiatry* **32**, 202–208 (2009).
3. A Lankford, J Silver, Why have public mass shootings become more deadly? Assessing how perpetrators' motives and methods have changed over time. *Criminology & Public Policy* **19**, 37–60 (2020).
4. JA Capellan, J Johnson, JR Porter, C Martin, Disaggregating mass public shootings: A comparative analysis of disgruntled employee, school, ideologically motivated, and rampage shooters. *Journal Forensic Sciences* **64**, 814–823 (2019).
5. A Lankford, Fame-seeking rampage shooters: Initial findings and empirical predictions. *Aggression Violent Behavior* **27**, 122–129 (2016).
6. JR Silva, Mass shooting outcomes: A comparison of completed, attempted, failed, and foiled incidents in America. *Deviant Behavior* pp. 1–20 (2021).
7. JR Silva, EA Greene-Colozzi, Fame-seeking mass shooters in America: Severity, characteristics, and media coverage. *Aggression Violent Behavior* **48**, 24–35 (2019).
8. Crime: Slaughter in the college of beauty. *Time* (1966).
9. A Lankford, Are America's public mass shooters unique? A comparative analysis of offenders in the United States and other countries. *International Journal Comparative Applied Criminal Justice* **40**, 171–183 (2016).
10. BJ Bushman, Narcissism, fame seeking, and mass shootings. *American Behavioral Scientist* **62**, 229–241 (2018).
11. A Lankford, E Madfis, Media coverage of mass killers: Content, consequences, and solutions. *American Behavioral Scientist* **62**, 151–162 (2018).
12. P Langman, Different types of role model influence and fame seeking among mass killers and copycat offenders. *American Behavioral Scientist* **62**, 210–228 (2018).
13. JR Silva, A Lankford, The globalization of american mass shootings? an assessment of fame-seeking perpetrators and their influence worldwide. *International Journal Comparative Applied Criminal Justice* pp. 1–24 (2022).
14. JR Silva, JA Capellan, The media's coverage of mass public shootings in America: Fifty years of newsworthiness. *International Journal Comparative Applied Criminal Justice* **43**, 77–97 (2019).
15. A Lankford, Identifying potential mass shooters and suicide terrorists with warning signs of suicide, perceived victimization, and desires for attention or fame. *Journal Personality Assessment* **100**, 471–482 (2018).
16. MV Simkin, VP Roychowdhury, Theory of acses: Fame by chance or merit? *Journal Mathematical Sociology* **30**, 33–42 (2006).

17. MV Simkin, VP Roychowdhury, Chess players' fame versus their merit. *Applied Economics Letters* **22**, 1499–1504 (2015).
18. Simkin, Mikhail V and Roychowdhury, Vwani P, A mathematical theory of fame. *Journal Statistical Physics* **151**, 319–328 (2013).
19. B Yucesoy, AL Barabási, Untangling performance from success. *EPJ Data Science* **5**, 1–10 (2016).
20. Oxford Dictionary, Fame (year?) <https://www.lexico.com/definition/fame>.
21. G Horstmann, Evidence for attentional capture by a surprising color singleton in visual search. *Psychological Science* **13**, 499–505 (2002).
22. HE Den Ouden, P Kok, FP De Lange, How prediction errors shape perception, attention, and motivation. *Frontiers Psychology* **3**, 548 (2012).
23. T Plewan, G Rinkenauer, Surprising depth cue captures attention in visual search. *Psychonomic Bulletin & Review* **25**, 1358–1364 (2018).
24. P Holonowicz, P Herrera, H Purwins, The role of loudness in detection of surprising events in music recordings in ESCOM 2009: 7th Triennial Conference of European Society for the Cognitive Sciences of Music. (2009).
25. RM Nesse, et al., Fear and fitness: An evolutionary analysis of anxiety disorders. *Ethology Sociobiology* **15**, 247–261 (1994).
26. RW Cobb, DM Primo, The plane truth: Airline crashes, the media, and transportation policy. (Brookings Institution Press), (2004).
27. C Ranganath, G Rainer, Neural mechanisms for detecting and remembering novel events. *Nature Reviews Neuroscience* **4**, 193–202 (2003).
28. L Itti, PF Baldi, Bayesian surprise attracts human attention in *Advances in Neural Information Processing Systems*. (Citeseer), pp. 547–554 (2006).
29. L Itti, P Baldi, Bayesian surprise attracts human attention. *Vision Research* **49**, 1295–1306 (2009).
30. A Alamia, R VanRullen, E Pasqualotto, A Mouraux, A Zenon, Pupil-linked arousal responds to unconscious surprisal. *Journal Neuroscience* **39**, 5369–5376 (2019).
31. G Longo, How future depends on past and rare events in systems of life. *Foundations Science* **23**, 443–474 (2018).
32. JR Silva, A comparative analysis of foiled and completed mass shootings. *American Journal Criminal Justice* **46**, 187–208 (2021).
33. M Rocque, M Gerdes, JA Fox, G Duwe, M Clark, Averting tragedy: An exploration of thwarted mass public shootings relative to completed attacks. *Criminal Justice Review* p. 07340168221117107 (2022).
34. T Bossomaier, L Barnett, M Harré, JT Lizier, Transfer entropy in *An introduction to transfer entropy*. (Springer), pp. 65–95 (2016).
35. B Berkowitz, C Alcantara, The terrible numbers that grow with each mass shooting (2021).
36. J Peterson, J Densely, The Violence Project (2021).
37. M Follman, G Aronsen, D Pan, US mass shootings, 1982–2021: Data from Mother Jones' investigation (2021).
38. AZ Yu, S Ronen, K Hu, T Lu, CA Hidalgo, Pantheon 1.0, a manually verified dataset of globally famous biographies. *Scientific Data* **3**, 1–16 (2016).
39. M Mestyán, T Yasseri, J Kertész, Early prediction of movie box office success based on Wikipedia activity big data. *PLoS ONE* **8**, e71226 (2013).
40. E Vardi, L Muchnik, A Conway, M Breakstone, WikiShark: An Online Tool for Analyzing Wikipedia Traffic and Trends. (Association for Computing Machinery, New York, NY, USA), (2021).
41. SF Chen, J Goodman, An empirical study of smoothing techniques for language modeling. *Computer Speech & Language* **13**, 359–394 (1999).
42. GB Folland, *Real analysis: Modern techniques and their applications*. (John Wiley & Sons) Vol. 40, (1999).
43. H Schütze, CD Manning, P Raghavan, *Introduction to information retrieval*. (Cambridge University Press Cambridge) Vol. 39, (2008).
44. R Levine, R Bernstein, P Kahana, I Procaccia, E Upchurch, Surprisal analysis and probability matrices for rotational energy transfer. *The Journal Chemical Physics* **64**, 796–807 (1976).
45. K Friston, A free energy principle for a particular physics. *arXiv preprint arXiv:1906.10184* (2019).
46. K Komarova, F Remacle, RD Levine, Surprisal of a quantum state: Dynamics, compact representation, and coherence effects. *The Journal Chemical Physics* **153**, 214105 (2020).
47. LP García-Pintos, SB Nicholson, JR Green, A del Campo, AV Gorshkov, Unifying quantum and classical speed limits on observables. *Physical Review X* **12**, 011038 (2022).
48. S Frank, Surprisal-based comparison between a symbolic and a connectionist model of sentence processing in *Proceedings of the Annual Meeting of the Cognitive Science Society*. Vol. 31, (2009).
49. R Levy, Memory and surprisal in human sentence comprehension in *Sentence Processing*. (Psychology Press), pp. 90–126 (2013).
50. A Zarcone, M Van Schijndel, J Vogels, V Demberg, Saliency and attention in surprisal-based accounts of language processing. *Frontiers Psychology* **7**, 844 (2016).
51. H Brouwer, F Delogu, NJ Venhuizen, MW Crocker, Neurobehavioral correlates of surprisal in language comprehension: A neurocomputational model. *Frontiers Psychology* **12**, 615538 (2021).
52. S Zadrán, R Arumugam, H Herschman, ME Phelps, R Levine, Surprisal analysis characterizes the free energy time course of cancer cells undergoing epithelial-to-mesenchymal transition. *Proceedings National Academy Sciences* **111**, 13235–13240 (2014).
53. A Gross, RD Levine, Surprisal analysis of transcripts expression levels in the presence of noise: A reliable determination of the onset of a tumor phenotype. *PLoS ONE* **8**, e61554 (2013).
54. AG Claes, MJ De Ceuster, Estimating the economics nobel prize laureates' achievement from their fame. *Applied Economics Letters* **20**, 884–888 (2013).
55. R Belz, Master's thesis (The University of North Dakota) (2020).
56. TNY Times, Brooklyn Subway Shooting (2022).
57. J Pearl, *Causality*. (Cambridge University Press), (2009).
58. MJ Lew, Principles: when there should be no difference—how to fail to reject the null hypothesis.

- Trends Pharmacological Sciences 27, 274–278 (2006).
59. Recommendations for reporting on mass shootings (<https://www.reportingonmassshootings.org/>) (no date) Accessed: 2022-09-19.
 60. False alarms, real fear: Even without gunfire, active shooter alerts create terror ("<https://tinyurl.com/2p8de59d>") (2019) Accessed: 2022-09-19.
 61. USA on edge: Mass-shooting false alarms has a 'hidden cost' for police, community (<https://www.usatoday.com/story/news/nation/2019/08/13/mass-shooting-false-alarms-have-hidden-cost-police-community/1956610001/>) (2019) Accessed: 2022-09-19.
 62. DS Nagin, CS Koper, C Lum, Policy recommendations for countering mass shootings in the united states. *Criminology & Public Policy* 19, 9–15 (2020).
 63. Extreme Risk Laws (<https://www.everytown.org/solutions/extreme-risk-laws/>) (no date) Accessed: 2023.
 64. RW Larkin, The columbine legacy: Rampage shootings as political acts. *American behavioral scientist* 52, 1309–1326 (2009).
 65. P Langman, Role models, contagions, and copycats: An exploration of the influence of prior killers on subsequent attacks. Available on www.schoolshooters.info (2017).
 66. Kaiser Health News, Colorado considers changing its red flag law after mass shooting at nightclub (<https://khn.org/news/article/colorado-considers-changing-its-red-flag-law-after-mass-shooting-at-nightclub/>) (2022) Accessed: 2023-02-02.
 67. PBS, Judge warned of gay bar attacker's shootout plans in 2021 (<https://www.pbs.org/newshour/nation/judge-warned-of-gay-bar-attackers-shootout-plans-in-2021>) (2022).
 68. R Smart, TL Schell, Mass shootings in the united states. The RAND Corporation (2021).
 69. L Huff-Corzine, J Corzine, The devil's in the details: Measuring mass violence. *Criminology & Public Policy* 19, 317–333 (2020).
 70. WJ Krouse, DJ Richardson, Mass murder with firearms: Incidents and victims, 1999–2013 (2015).
 71. RAND Corporation, Mass shootings: A growing problem? (<https://www.rand.org/research/gun-policy/analysis/essays/mass-shootings.html>) (2022) Accessed: 2023-02-02.
 72. JR Silva, Mass shooting outcomes: A comparison of completed, attempted, failed, and foiled incidents in america. *Deviant Behavior* 43, 1487–1506 (2022).
 73. The Desert Sun, Palm springs quadruple homicide: Jose larin-garcia goes to trial again (https://www.desertsun.com/story/news/crime_courts/2022/09/28/palm-springs-quadruple-homicide-jose-larin-garcia-goes-trial-again/10450768002/) (2022) Accessed: 2023-02-02.
 74. LJ Cronbach, Coefficient alpha and the internal structure of tests. *Psychometrika* 16, 297–334 (1951).
 75. JJ Randolph, Free-marginal multirater kappa (multirater k [free]): An alternative to fleiss' fixed-marginal multirater kappa. *Online Submission* (2005).
 76. C Tribune, Jason Nightengale, suspect in gun crime spree, dead after shootings in Evanston, Hyde Park (2021).
 77. JG MacKinnon, Approximate asymptotic distribution functions for unit-root and cointegration tests. *Journal Business & Economic Statistics* 12, 167–176 (1994).
 78. S Kokoska, D Zwillingner, *CRC standard probability and statistics tables and formulae*. (CRC Press), (2000).
 79. Y Hochberg, AC Tamhane, *Multiple comparison procedures*. (John Wiley & Sons, Inc.), (1987).