Adrian Martin Bethencourt 04/02/2021

Publications

To whom it may concern,

I would like to share with my list of publications. The first is a conference paper which is currently being peer reviewed by the ROMCIR 2021: *"Bias and truth in science evaluation: a simulation model of grant review panel discussions"*. The results of this process will be released in March. The second paper is the result of my work on my Bachelor´s final dissertation presented at the Spanish Sociological Conference: "*Twitter and the nutrition debate"*. This text is written in Spanish, however, you will find the abstract written in English.

Best regards,

Adrian Martin

Bias and truth in science evaluation: a simulation model of grant review panel discussions

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Abstract
Research funding organizations rely on the expertise of peer review panels to decide which research proposals to fund. That of review panels is a collective task of information acquisition that is hindered by social influence dynamics and biases. The combination of social influence effects and biases in peer review panel discussions has gone understudied in the literature, and to date it is not clear what dynamics and what biases are at play. We rely on an empirically calibrated agent-based simulation model of peer review panel discussions to explore which dynamics and biases might explain the opinion patterns we empirically observe in review panels from Science Foundation Ireland, our case study. This investigation moves first steps to allow future investigation of strategies that reduce the risks of poor evaluation due to social influence dynamics and attitude biases.
Our results tentatively suggest that discussion dynamics in grant review panels are (1) guided by compromise/consensus seeking discussions; (2) affected more by negative bias than positive bias. This can be a result of, for example, gender biases or by early carrer stage discrimination biases.
Keywords
Peer review, research evaluation, bias, social influence, social simulation.

1. Introduction

Information identification, selection, and retrieval are crucial for scientific peer review. When selecting research grant proposals to recommend for funding, peer review panels face the challenge of evaluating the submissions fairly and competently. Misjudgments and biases, however, are looming, as ample evidence shows [1]. To curb these issues, research funding organizations (RFOs) rely on different safeguards—of which this paper considers two: structured review forms and sitting panel discussions.

Review forms are structured to guide the reviewer through the evaluation of a proposal against a set of predetermined, objective and transparent evaluative criteria, such as “feasibility” and “impact”. Despite efforts to standardize review forms and to define clear criteria, personal and cultural differences between reviewers mean that reviewers often evaluate these criteria differently [2]. Additionally, the evaluation of different criteria might be subject to different sources of bias: gender bias, for instance, might matter more in the evaluation of the applicant’s scientific record, and less on the evaluation of the project’s feasibility.

The second safeguard deserves scrutiny, too. Sitting review panels are review stages where panel members engage in a discussion often moderated by a panel chair; the discussion is to exchange opinions about the proposals, and to collectively form a sound final panel judgment. There is increasing awareness that, due to group dynamics, discussions among small deliberative groups such as juries, online fori, and indeed peer review panels [3,4] can be detrimental to effective collective decision making.

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In this paper we examine these three elements and their interaction: biases, evaluation criteria, and social influence dynamics in review panel discussions. We investigate which combinations of biases and social influence dynamics are responsible for the opinion shifts observed in review panels during a panel discussion.

This is achieved in three steps. First, we develop an agent-based simulation model (ABM) of panel discussions that incorporates the three ingredients (biases, criteria, influence dynamics). Second, we measure reviewer opinions about competing proposals: across several criteria, and before and after a panel discussion. Third, we take as a reference the opinion distributions pre- and post-discussion, and we use the ABM to find which combinations of biases and influence dynamics reproduce the observed change in opinion distribution.

Peer review panels are modeled after real-world panels at a RFO, Science Foundation Ireland (SFI), for which we have access to the empirical data on the characteristics of the factors in the discussion processes and the resulted outcome of the discussion, i.e. the change of the reviewers' opinions before and after of the panel discussion.

The next section (2) elaborates on the conceptual ingredients of the model; Section 3 explains how empirical data were collected and outlines the simulation model. Results are presented in Section 4, and their implications are discussed in Section 5.

2. Background

Here we define the central concepts in our study and provide the theoretical background.

2.1. Bias in peer review

While most researchers agree peer review to be the most reliable instrument for science evaluation [5,6] evidence on peer review (in academic journals and RFOs alike) shows that the system suffers from bias against novel research [7,8], females [9,10,11], young researchers [12], and ethnic and linguistic minorities [13]. Crucially, even small review biases and errors can negatively impact the decisions of the review panel [14,15]. This can in turn accelerate a self-perpetuating uneven distribution of resources in science that favors privileged few: a phenomenon known as Matthew effect [16].

Crucially, biases might affect reviewer evaluation not only directly (e.g. by influencing reviewer's opinion of the evaluated proposals), but indirectly, too. Specifically, we study whether some forms of biases may be accentuated by the group dynamics at play during panel discussions. While a debate among experts on the merit of a submission can curb some biases, some other biases might in fact be ignored or even rationalized. Thus, some biases might be perpetuated and their effects accentuated during the panel discussion.

To explore this idea, we distinguish between three classes of bias: negative, positive, and ambivalent bias. Negative bias encompasses those forms of bias that lead to a more severe than fair evaluation of submissions. Intuitive examples include bias against female, early-career or non-native English speaking applicants: when these forms of biases are at play, these discriminated groups are treated less favorably than deserved. Positive bias, by contrast, is what leads to evaluations that are more positive than fair. Examples include old-boyism, or bias in favor of applicants from very prestigious institutions [17, 12]. Last, ambivalent bias describes forms of bias that sometimes play against and sometimes in favor of some applicants. Conservatism is an ideal typical example of ambivalent bias: in grant peer review innovative proposals are often treated favorably—however, when too innovative, a proposal's innovativeness and non-conventionality might be biased against [18].

2.2. Social influence dynamics

Peer review at most RFOs is set up in multiple review stages, typically two: a postal review stage, and a sitting panel stage. The main distinction between these two stages is the interaction between the reviewers. Interaction is absent in postal review, where reviewers review alone and often do not know each other's identity. By contrast, interaction is the defining feature of sitting panels, where reviewers discuss proposals together and jointly form opinions about them.

Sitting panel discussions is where social influence dynamics take place, and is the focus of our study. The function of panel discussions is to allow reviewers to bridge their differences and find a consensus over the true merit of the evaluated proposals. To find consensus is the explicit mandate of sitting panels at some RFOs; and even where it is not, a reduction in opinion differences still is the often-expected, often-observed outcome of a review panel discussion [19]: this is the reason why, for example, low inter-rater reliability is often regarded as a mark of inefficient or unreliable peer review processes [20,21].

To reflect the idea of consensus-seeking panel discussions, we focus on one prominent type of opinion dynamics that explains the convergence of opinions: assimilative models [22]. Grounded in the theories of social conformity, persuasion and cognitive dissonance [23,24,25] assimilative dynamics represent the idea that, by interacting, individuals tend to reduce their attitudinal and behavioral differences. Section 3.2 presents a computational model of assimilative dynamics that builds on the established literature on assimilation.

2.3. Role of the panel chair

A prominent role in peer review panel discussions is that of the panel chair: the person whose role is to moderate and facilitate the panel discussion and also to make it fair and balanced [19]. Panel chairs can promote a discussion that is more or less structured, effective, or otherwise conducive to productive interactions between reviewers. When the chair fails in this task, the panel discussion might be less likely to find a balanced consensus [26,7]. In our study, we treat the role of the panel chair as a proxy for how effective the discussion is at tempering the most extreme views expressed in the panel, ultimately enabling the emergence of consensus via assimilative opinion dynamics.

2.4. Peer review at Science Foundation Ireland

The evaluation of grant proposals consists of grading and providing comments about different evaluation criteria. SFI review forms are structured around three evaluation criteria, named: 'applicant', 'research programme', and 'potential for impact'. The evaluation of each criterion requires reviewers to consider different aspects of the proposal [2]; thus each evaluation criterion can be affected by different sources for bias. In summary, the deliberation process in peer review is a complex phenomenon in which many interdependent actors and factors are involved. Hence the method of social simulation (ABM specifically) becomes useful to explore the interactions between the actors and factors and the effects of the interactions towards the evaluation outcomes, in this case, the distribution of reviewers' opinions on various evaluation criteria.

3. Methods

3.1. Qualitative coding of reviews Agent-based model of assimilative dynamics

We use empirical data from a 2016 funding scheme by SFI called "Investigators Programme". The peer review process at SFI is structured in two stages: first, a postal review stage (no interactions between reviewers). The second stage is a sitting panel stage where the discussion takes place. Each reviewer only takes part in either one of the two stages. In both stages, SFI review forms allow reviewers to evaluate proposals against the three evaluation criteria. The evaluation of each aspect consists of a grade and comments. The grade is expressed on a 5-point Likert scale from "very bad" to "outstanding") and is used to rank the proposals within competing pools. The review comments allow the reviewer to explain and contextualize the grade. While the literature of grant review usually relies on grades as a proxy of reviewer' opinions [19], our team conducted qualitative coding of the review comments which we believe more fully reflect reviewers' opinions on the evaluation criteria [27]. Our qualitative coding of review sentiments uses the five-point scale, compatible with the grading scales at SFI.

We exploit the difference between the two review stages to calibrate reviewers' opinion distribution at the start and at the end of the panel discussion. Reviewers in the postal review stage (first stage) form their opinions autonomously, without a panel discussion. Thus, the sentiments of their comments is a proxy for the opinion that reviewers have before the panel discussion. Then, the sentiments of the sitting panel reviews (second stage) is a measurement of the opinions that reviewers have after the panel discussion. The two stages of reviews are performed by two different sets of reviewers. Nevertheless, differences in the opinion distribution between first and second stage can be attributed to the social influence dynamics at play during a panel discussion since the presence of a panel discussion is the main difference between the two stages. This paper seeks to explain what social influence dynamics better explain the difference between the two opinion distributions.

3.2. Agent-based model of assimilative dynamics

Agent-based models (ABMs) are useful tools for simulating the repeated interactions of agents whose attitudes and behaviors are interdependent. ABMs allow to explore the macro-level consequences of the micro-level interactions [24] We resort to this tool to find if and how simulated sitting panel discussions can result in the changes in reviewers' opinion distribution that we observed empirically at SFI.

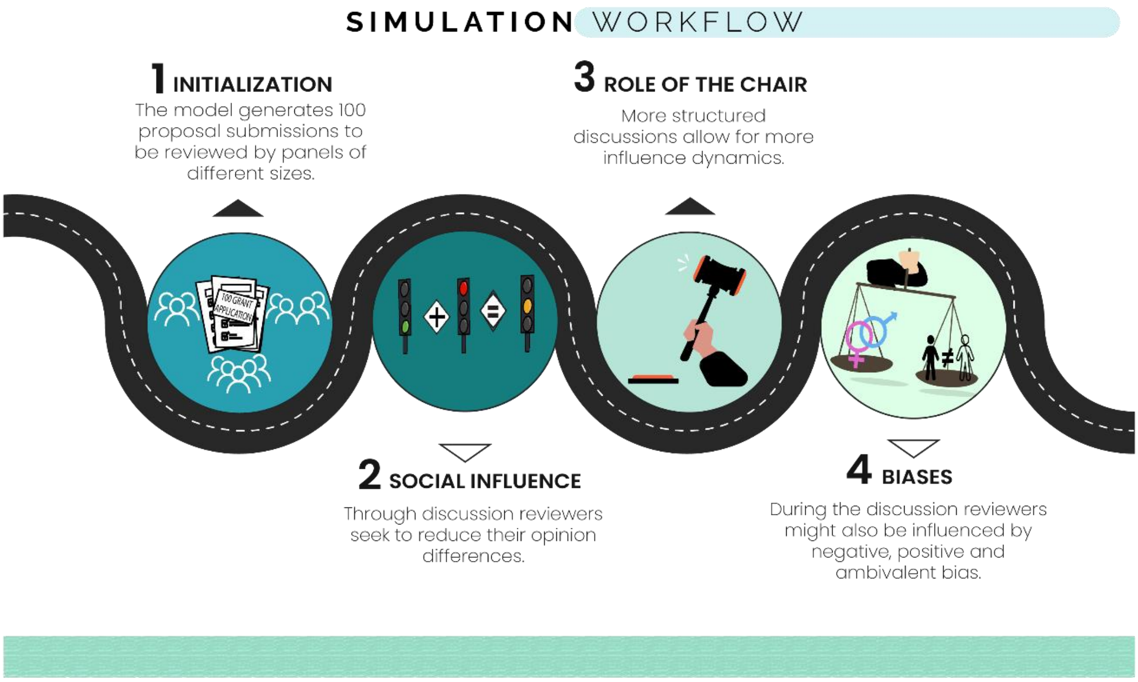

Figure 1: Overview of the ABM scheduling. Images credit to [25-27], 2020.

Following the overview provided in Figure 1, each simulation run simulates a discussion between N reviewers about a proposal on one of the evaluation criteria. N is set to {3, 4, 5}, which is the size of typical review panels. The simulation is initialized by assigning reviewers an initial opinion on how to grade the proposal on the given evaluation criterion. The initial opinions are based on the reviews from the first postal review stage (pre-discussion). From the bag of sentiments on the given evaluation criterion (taken from all reviews of any proposal), we randomly draw each reviewer's initial opinion (with uniform probability). This results in an opinion distribution that resembles how sentiments are distributed across reviewers who have not yet interacted with one another.

Sentiment scores (integers in [1,5]) are transformed into an opinion scale where values range from 0 to 1 in steps of 0.25: this corresponds to the opinion range in the social influence ABM. Then, the simulation determines whether and how bias will influence the discussion. Bias has a valence, a level of strength, and a probability to be at play (see Table 1). A value of bias ε is selected by means of a random trial, where bias is determined to be positive, negative or null depending on the probabilities of a negative, positive, or null bias (which are three model parameters - see Table 1). Whichever bias is drawn, its strength (or "magnitude") is another model parameter. This setup allows to model the three classes of biases: positive, negative and ambivalent. These three classes and their parameterization in the model are summarized in Table 2.

Once opinions are initialized and a level of bias ε is set, the discussion is simulated. This happens in 10 simulated discrete time points, following the assimilative opinion dynamics adapted from [22]. During each time point, reviewers synchronously update their opinion. For reviewer i at time point t, the opinion at the next time point ($o_{i,t}$+1) is:

$$o_{i,t+1} = o_{i,t} + \varepsilon + \rho \frac{1}{N-1} \sum_{j \neq i} (o_{j,t} - o_{i,t}) \tag{1}$$

where ε is the bias and ρ is rate of opinion change - a proxy for how effective the discussion is, how open-minded are the discussants, and ultimately how competent is the panel chair at moderating the discussion. Thus, at every time step, agents will update their opinion to move closer to the average opinion among the other panelists, and non-null bias exerts an influence that continuously pushes the agents in one or the other direction. Note that when $\varepsilon \neq 0$, opinions may be pushed outside of the interval [0,1]. To prevent this, opinions exceeding the range [0,1] are truncated.

Table 1 illustrates the parameter space we explored. For each unique parameter configuration, we simulated 300 independent runs (100 for each evaluation criterion) with unique initial random seeds.

Table 1. *Parameter space overview.*

Parameter	Label	Value
Number of proposals		100
Number of reviewers	N	3, 4, 5
Number of interactions		10
Panel chair strength	ρ	0.025, 0.05
Bias probabilities		Positive: 0, 0.25, 0.5 Negative: 0, 0.25, 0.5
Bias strength	ε	Positive: 0.025, 0.05, 0.1 Negative: -0.025, -0.05, -0.1

Table 2. *Biases: examples and parameterization.*

Bias	Corresponding parameter values	Example
Negative	*probability of* positive *bias = 0, probability of* negative *bias > 0*	Bias against female applicants [11].
Positive	*probability of* positive *bias > 0, probability of* negative *bias = 0*	Old-boysm [17].
Ambivalent	*probability of* positive *bias > 0, probability of* negative *bias > 0*	Conservatism: innovativeness can at times be a desired quality of proposals, and sometimes pose a risk [18].

3.3. Outcome variable: the similarity index

To determine which conditions and biases might be at play in real-world peer review panels, we define a fitness function with which to measure the performance of each parameter configuration. A fitness function informs us on which parameter configuration(s) produce opinion distributions more similar to the observed distributions at the end of panel discussions.

This is achieved in five steps. First, for each parameter configuration, we fill a bag with the opinions of all the reviewers on all the evaluation criteria (i.e. from all simulation runs under the given parameter configuration). Second, we discretize all the generated opinions to match a 5-point scale (integers in [1,5]). Third, we calculate the relative frequency of each of the five integers among both simulated opinions and observed post-discussion opinions. Fourth, for each of the five integers, we take the absolute difference between its two relative frequencies. Last, fitness is calculated as 1 - the average of the five absolute differences. We call this measure similarity, because it ranges in [0,1], and values close to 1 are given to parameter configurations that generate opinion distributions very similar to those observed at the end of SFI panel discussions.

4. Results

We first examine the observed opinion distributions before and after the discussion (i.e. opinions at the end of the first and second stage, respectively). Figure 2 shows the opinion distributions for each aggregation criterion separately: at the top, before the discussion (gray); at the bottom, after the discussion (blue).

For all three evaluation criteria, we found a positive correlation between the two stages ($R2 > 0.25$, p-value < 0.01). At the same time, Figure 2 shows that the opinion distributions are different before and after the panel discussion. After a discussion, opinions tend to follow a bell-shaped distribution; they are overall less positive, and extremely positive scores are seen more rarely.

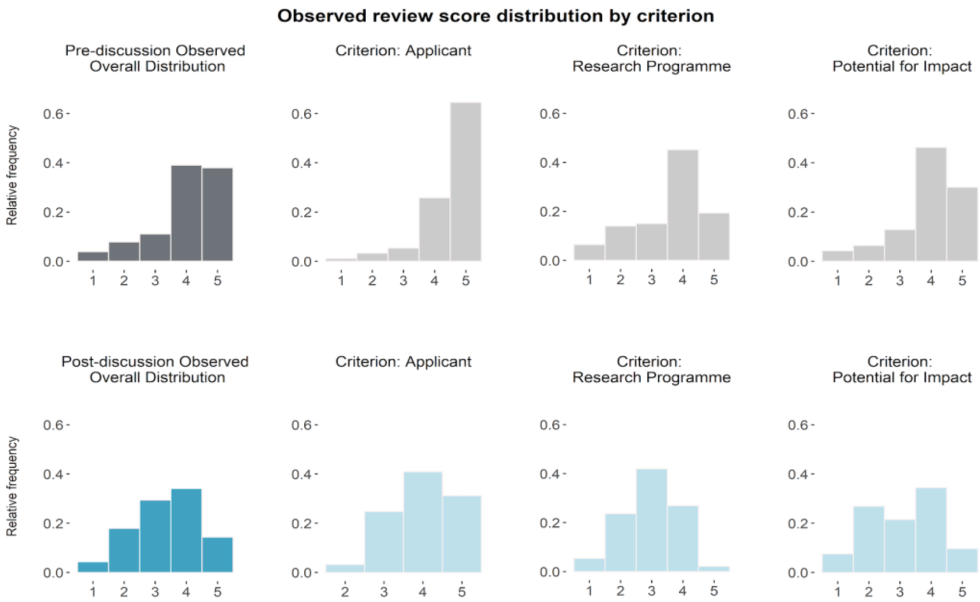

Figure 2. Distribution of scores in panels without (top) and with a panel discussion (bottom). The difference between the two distributions can be attributed to influence dynamics at play during the panel discussion.

Next, we point our attention to whether the simulation model can replicate the observed change in the distribution. For each parameter configuration, we calculated the similarity between its predicted opinion distribution (averaged across 100 independent runs and across the three evaluation criteria) and the observed post-discussion distribution.

The similarity index took values between 0.95 and 0.67 - thus, some parameter configurations produce simulated discussions that yield opinion distributions very similar to those of real-world panel discussions. Figure 3 shows the opinion distribution for the parameter configuration with the best fit: N = 5; ρ = 0.05; ε = 0.025 (positive bias) and -0.1 (negative bias); probability = 0.25 (positive bias) and 0.25 (negative bias). Even this most realistic parameter configuration does not fully reproduce all the features of the observed distribution. This is most evident for the evaluation criterion "Potential for Impact" (Figure 3, right-most histograms), for which the observed distribution is bi-modal and roughly symmetric, whereas the simulated distribution is bell-shaped and left-skewed.

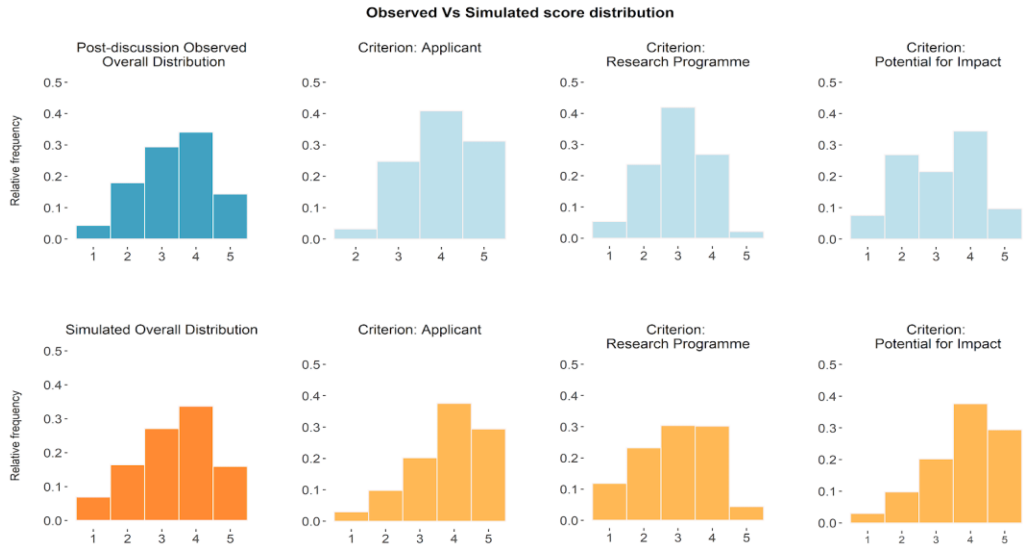

Figure 3. Observed (top) and simulated (bottom) score distribution. The simulated distribution shown is that from the parameter configuration that most closely resembles the observed distribution.

Generalizing, we can inspect the parameter configurations that recorded the highest values of similarity and identify some patterns.

For instance, parameter configurations that generated the most realistic-looking distributions vary in number of reviewers (N) and strength of the panel chair (ρ): this signals that these two factors might not play a significant role in the discussion dynamics. In fact, we found only negligible differences in average performance between parameter configurations that vary in N and ρ.

However, bias seemed to have a much larger role for the accurate simulation of the observed opinion distributions. We found that top-performing parameter configurations tend to have high values for negative bias (probability = {0.25, 0.5}; ε = {-0.1, -0.05}). By contrast, positive bias seems unimportant: among the 15 best-performing parameter configurations, we found roughly equal shares of high, mid and low levels of both positive bias probability and ε. In sum, simulation results suggest that the opinion distributions of panel discussions might be the result of assimilative influence and some form of negative biases, not necessarily in combination with positive biases.

5. Conclusion and discussion

Our study showcased the use of social simulation methods (such as ABM) to study social dynamics in social settings where, under uncertainty and under the effects of various biases, small groups seek some objective truth. We studied the discussion dynamics in peer review panels that seek to find the true merit of each submission. Using a simulation model, we explored whether a combination of assimilative influence and various kinds of biases could reproduce the opinion changes observed in real-world peer-review panel discussions. We found that assimilative dynamics (consensus-oriented, disagreement-reducing panel discussions) and some degree of negative bias against some proposals are compatible with the observed opinion changes occurring in panel discussions.

Some limitations to our study are worth examining: one the one hand, these warn caution in interpreting and generalizing these results; on the other hand, they indicate further directions for follow-up work. A first limitation is that we have examined the effects of only one type of influence dynamics (assimilative influence). More realistically, multiple kinds of social influence dynamics might be at play in real-world panel discussions. Secondly, in the limited scope of this paper we explored only a small subset of the parameter space: this opens the possibility that other combinations of biases and conditions perform even better at replicating the observed opinion changes in review panels. A third limitation concerns our calibration data and measurement instrument: our data was based on one research funding scheme provided by one research funding agency (Science Foundation Ireland) - ideally, our results need to be validated by (1) using data from other funding schemes, funding organizations, countries; (2) using a different operationalization of reviewer opinions.

We conclude by highlighting another promising direction for future work. We did not identify any model parameter configuration that successfully replicated the observed opinion distributions across all of the evaluation criteria that proposals are evaluated against. On the one hand, this suggests that our simulation model misses some theoretical components. On the other hand, this can be interpreted as tentative support for the intuition that panel discussions over different evaluation criteria might be guided by different influence dynamics and/or be affected by different kinds of biases. Differences in the dynamics of panel discussions between different evaluative criteria remain open for investigation.

6. Acknowledgements

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Twitter y el debate alimentario

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Abstract
Social media debates have become an essential element to understand nowadays society. We will be focused on the nutrition debate on Twitter by analyzing the characteristics of users ‘networks with opposite goals: health nutrition promoters and high-processed food promoted. Our main goal will be to understand the similarities and differences of these groups in order to generate insights to develop a efficient health nutrition campaign on Twitter.
Key words: Twitter, Nutrition, Social Network Analysis.

Introducción
La obesidad se presenta como uno de los grandes problemas sociales a los que se enfrenta la humanidad. La denominada “epidemia no infecciosa del siglo XXI” se explica, en gran medida, por la proliferación de entornos obesogénicos que favorecen el crecimiento de pautas alimentarias inapropiadas (Mendez, 2012). La alimentación sana supone enfrentarse diariamente a espacios mercantilizados en los cuales se toman las decisiones de consumo y, por lo tanto, es en estos entornos en los que se propicia una alimentación que favorece la obesidad. En definitiva, si queremos entender el problema social que acarrean los malos hábitos alimentarios no podemos dejar a un lado las lógicas industriales y económicas de las industrias agroalimentarias (Swinburn y Egger, 2002).
El crecimiento de malos hábitos alimentarios parece ser imparable, sin embargo, surgen voces críticas al respecto (Pilar, 2017). Destacaremos el proyecto artístico Sinazucar.org que dedica su esfuerzo a evidenciar la cantidad de azúcar libre que existe en muchos productos que consumimos a diario (Rodríguez, 2019). Este proyecto crítico con los productos ultraprocesados ha conseguido expandirse a través de las redes sociales virtuales. Las industrias, por su parte, participan activamente en la implantación de hábitos de vida “equilibrados” donde se incita a consumir productos ultraprocesados de manera “responsable”. Ambas posturas responden a unos intereses específicos y opuestos que nos permiten clasificar estas actuaciones en dos grupos: los Insiders formados por empresas agroalimentarias que buscan fomentar el consumo de productos ultraprocesados, y los Outsider que persiguen combatir los malos hábitos alimentarios.
Dentro de los múltiples escenarios donde se enfrentan las posturas de los grupos elegiremos el entorno virtual y, en particular, la red social virtual Twitter debido a la predisposición de sus usuarios para mantener la información de sus perfiles pública (Lehmann, Onnela, Ahn, Niels, 2011). De esta forma, analizaremos en el grupo de Insider el perfil de usuario de una de las empresas multinacionales más reconocidas en el mundo que tiene cuenta oficial en España: Cocacola_Es. Dentro del grupo Outsider nos centraremos en el perfil del proyecto artístico SinAzucarOrg debido a su constante crítica a la industria alimentaria, así como su notoria popularidad en la red.

Objetivos y formulación de hipótesis

Tanto el grupo Insider como el Outsider tienen unos intereses específicos y opuestos. En este trabajo pretendemos investigar si las características asociadas a la centralidad de los actores relevantes que mencionan a cada perfil en Twitter serán diferentes en cada red. Esta tarea la realizaremos en dos etapas. En primer lugar, describiremos las características de cada red con relación a un número de variables que consideramos relevantes. En segundo lugar, hallaremos si existen diferencias estadísticamente significativas entre las redes de Outsiders e Insiders con relación a dichas características.

- El *estatus socioeconómico* es un condicionante de la obesidad. A menor renta, mayor consumo de productos ultraprocesados e insanos. De esta forma el interés por perfiles de Twitter que critican los productos ultraprocesados (Outsider) y el de los que los incentivan (Insider) dependerá del nivel de renta medio del que disponen los usuarios por CCAA.
- La *obesidad* se explica, en gran medida, por el consumo de productos ultraprocesados. De esta forma el interés por perfiles de Twitter que critican los productos ultraprocesados (Outsider) y el de los que los incentivan (Insider) dependerá del grado de sobrepeso y obesidad que tienen los usuarios por CCAA. Así, el porcentaje de personas con sobrepeso y obesidad por CCAA será diferente entre los grupos de Insider y Outsider.
- En ambas redes hallamos dos tipos de nodos: instituciones e individuos. Dado que cada usuario de Twitter deja tras de sí un rastro identificable y clasificable consideramos que, los intereses de una empresa y una iniciativa de carácter social no son los mismos. De esta forma esperamos que en la red Insider el porcentaje de instituciones será mayor que en la Outsider.
- La red de Insider y la red de Outsider no tienen por qué mostrar las mismas características topológicas. En concreto pueden diferir en el *tipo de actor predominante en cada red*. Grosso modo, es posible establecer una diferencia entre los actores bien insertos en el conjunto de la red y los actores que controlan el flujo de información [1]. Aunque ambos tipos podrían coincidir, esto no es habitualmente el caso.

A partir de estas consideraciones, derivamos las siguientes hipótesis:

- Hipótesis 1: Debido a la fuerte relación entre estatus socioeconómico y el consumo de alimentos sanos esperamos que, el interés por participar en estas redes esté asociado al nivel de renta. La centralidad de los actores variará con relación al nivel de renta.
- Hipótesis 2: Por la misma razón la centralidad de los actores variará con relación al nivel de sobrepeso. Esperamos que este efecto sea mayor en el caso de la red Outsider.
- Hipótesis 3: La población de ambas redes será diferente. El porcentaje de instituciones será mayor en el grupo Insider que en el grupo Outsider donde predominarán las personas. Estas diferencias se mantendrán en cuanto a la centralidad de los actores.

[1] La diferencia entre “ bien insertado” y “controlar” se explica en el apartado de variables dependientes.

- Hipótesis 4: El tipo de actor bien insertado predominará en la red Insider, mientras que el tipo de actor capaz de controlar flujos de información predominará en la red outsider.

Metodología

A continuación, expondremos los procedimientos seguidos para realizar este trabajo.

Selección de redes

El día 2 de marzo de 2019 descargamos de Twitter las menciones a los perfiles de @Cocacola_Es (grupo Insider) y @SinAzucarOrg (grupo Outsider) a través del software de análisis de redes NodeXL. Los grafos de ambas redes se pueden observar a continuación.

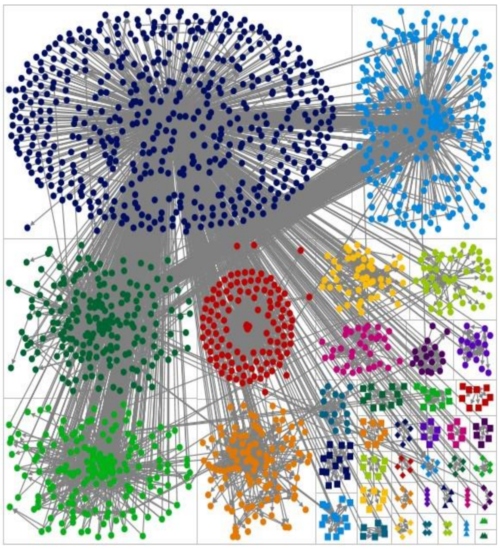

Figura 1. Grafo de menciones al perfil @Cocacola_ES

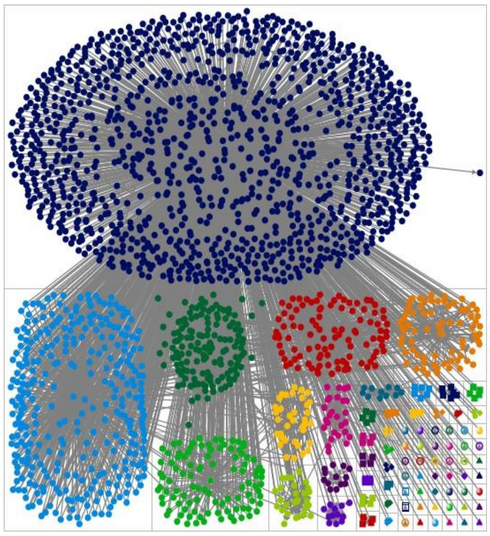

Figura 2. Grafo de menciones al perfil @SinAzucarOrg

Tipo de grafo	Directo
Vértices	1661
Vértices únicos	3766
Vértices con duplicaciones	7878
Vértices totales	11644
Connected Components	3
Maximim Geodesic Distance (Diameter)	7
Average Geodesic Distance	2,73
Densidad del grafo	0,001773

Tipo de grafo	Directo
Vértices	1271
Vértices únicos	2404
Vértices con duplicaciones	895
Vértices totales	3299
Connected Components	22
Maximim Geodesic Distance (Diameter)	8
Average Geodesic Distance	2,9
Densidad del grafo	0,001683

Variables Independientes

Twitter proporciona a los investigadores una cantidad de información limitada. Investigamos los aspectos sociales disponibles: localización, nombre de usuario y tipología de usuario. Esta información la adaptamos a los objetivos de nuestro estudio para obtener, finalmente, tres variables: Tipología de actor, Renta media por comunidad autónoma, Sobrepeso por comunidad autónoma.

Tipología de actor: Nuestro objetivo es el de entender quién está detrás de los perfiles de cada red. Para ello diferenciamos los usuarios según su comportamiento en la red obteniendo así un grupo de personas y otro de instituciones.

Actores:

"Son aquellos creados por personas físicas, con datos identificativos asociables directamente al gestor de la cuenta […] La gestión suele ser personal y no transferida, aunque encontramos casos como el de ciertas celebridades […]la tarea de administrar los contenidos publicados recae en un asistente o un gabinete de comunicación, sin que esto pervierta la relación icónica entre cuenta y persona a la que representa." (Detell, Congosto, Claes y Osteso, 2013)

Instituciones:

"*Son aquellos perfiles que pretenden representar a un colectivo empresarial, una asociación u organización de cualquier otra índole, sin importar si su fin es social, comercial o de otro tipo. La cuenta institucional se asocia a valores de marca, independientemente de las personas que se encarguen de regir dicha organización"* (Detell et al, 2013)

Renta por CCAA: recodificaremos las localizaciones recogidas en cada red y las agruparemos según los cuartiles de la renta media por persona de las comunidades autónomas a la que pertenezca el usuario.

Sobrepeso por CCAA: recodificaremos las localizaciones recogidas en cada red y las agruparemos según el porcentaje de Índice de Masa Corporal de personas con sobrepeso u obesidad por comunidades autónomas.

Tabla 1. Clasificación de CCAA por nivel de Renta Media por persona

Comunidad Autónoma	Renta media por persona	Gupo
País Vasco	14397	4
Navarra	13583	4
Madrid	13099	4
Cataluña	12712	4
Baleares	12665	4
Asturias	12244	3
La Rioja	12131	3
Aragón	12110	3
Cantabria	11239	3
Castilla y León	11239	2
Galicia	10753	2
Melilla	10161	2
Comunidad Valenciana	9801	2
Ceuta	9676	2
Andalucía	9116	1
Castilla La Mancha	9045	1
Canarias	8863	1
Murcia	8702	1
Extremadura	8250	1

Tabla 2. Clasificación de CCAA por nivel de sobrepeso

Comunidad Autónoma	Sobrepeso o más	Grupo
Melilla	66,24%	4
Galicia	58,68%	4
Andalucía	57,03%	4
Asturias	56,50%	4
Murcia	55,20%	4
Castilla La Mancha	55,04%	3
Aaragón	54,77%	3
Canarias	54,69%	3
Extremadura	54,55%	3
Comunidad Valenciana	53,73%	2
Ceuta	53,20%	2
Castilla y León	52,57%	2
Cantabria	52,11%	2
Cataluña	50,30%	2
La Rioja	49,23%	1
Navarra	48,76%	1
Baleares	46,64%	1
Madrid	46,48%	1
País Vasco	46,41%	1

Variables dependientes

Para estudiar las diferentes características de los actores utilizaremos las medidas de influencia y centralidad más frecuentes dentro del análisis de redes sociales: el Grado de Entrada, el Grado de intermediación y el grado de centralidad Eigenvector (Prell, 2011). El Grado de entrada, a partir de ahora GE, podemos definirlo como una medida del prestigio del actor donde, lo que importa, es el número de conexiones que recibe de otros. Cada mención en Twitter equivaldrá a un aumento en el GE del perfil mencionado. El Grado de intermediación (GI), al igual que el Grado de centralidad Eigenvector (GCE), va un paso más allá en el análisis y, para la centralidad de un actor, toma en consideración las características que tienen las conexiones de los actores a los que se conecta. Con el GCE se presta atención al grado de centralidad que tienen las personas a las que se conecta un actor, así que, para conseguir un alto grado centralidad el actor deberá rodearse de personas con muchas conexiones. El GI muestra la relevancia de un actor a través de su capacidad para controlar el flujo de información por medio de su capacidad para tender puentes entre los focos de información y los nodos desconectados de la red.

Resultados

Descripción

A continuación, exponemos los grafos resultantes del análisis de las menciones de cada perfil de Twitter, así como las características de la red.

Estatus Socioeconómico

Al comparar los diferentes indicadores de centralidad buscando posibles diferencias entre las CCAA por Renta encontramos algunas diferencias llamativas.

Tabla 3 Porcentaje de actores por CCAA-Renta media

Nivel de renta	Cocacola	SinAzucarOrg
Baja	32%	25%
Media	23%	23%
Alta	8%	7%
Muy alta	37%	45%
Total	100%	100%

En ambas redes destaca un elevado porcentaje de CCAA con renta Muy alta y un escaso porcentaje con renta Alta.

Tabla 4 Diferencias significativas de medias de las CCAA-Renta media

Nivel de Renta	Sub-Red Grado de Centralidad Eigenvector (GCE)		Sub-Red Grado de Intermediación (GI)		Sub-Red Grado de Entrada (GE)	
	Cocacola	SinAzucarOrg	Cocacola	SinAzucarOrg	Cocacola	SinAzucarOrg
Significación	0,003	0,404	0,549	0,785	0,492	0,267
F	4,779	0,976	0,706	0,356	0,804	1,320

Solo existen diferencias significativas de medias entre las rentas de la red Cocacola_Es del GCE. En definitiva, debido a la ausencia de diferencias de proporciones y de medias rechazamos la hipótesis de que la centralidad de los actores varía con relación al nivel de renta.

Sobrepeso

Si atendemos a la agrupación de CCAA por sobrepeso observamos interesantes cambios.

Tabla 5. Porcentaje de actores por CCAA-Sobrepeso

Nivel de Sobrepeso	Cocacola	SinAzucarOrg
Baja	27%	30%
Media	31%	36%
Alta	11%	9%
Muy alta	31%	25%
Total	100%	100%

La distribución es similar en ambas redes.

Tabla 6. Diferencia de medias de CCAA-Sobrepeso

Nivel de Sobrepeso	Grado de Centralidad Eigenvector (GCE)		Grado de Intermediación (GI)		Grado de Entrada (GE)	
	Cocacola	SinAzucarOrg	Cocacola	SinAzucarOrg	Cocacola	SinAzucarOrg
Significación	0,003	0,072	0,031	0,705	0,017	0,267
F	4,789	2,352	2,984	0,467	3,413	1,320

Encontramos diferencias significativas de medias en todos los indicadores de centralidad de la red Cocacola_Es pero ninguna en la red de SinAzucarOrg. De esta forma rechazamos nuestra segunda hipótesis basada en que la centralidad de los actores variará con relación al Nivel de Sobrepeso puesto que, aunque en Cocacola_Es existan diferencias significativas de medias, no las hay en SinazucarOrg. Al parecer, a diferencia de lo que pensábamos, el efecto del Nivel de Sobrepeso es mayor en la red Insider que en la Outsider.

Tipología de actor

Dentro de esta variable encontramos las mayores diferencias entre las redes.

Tabla 7. Porcentaje de actores por Tipología de actor

Tipología de actor	Cocacola	SinAzucarOrg
Personas	61%	90%
Instituciones	39%	10%
Total	100%	100%

El actor mayoritario en ambas redes son las personas. Destaca la red SinAzucarOrg compuesta en un 90% por personas. Las instituciones cobran relevancia en la red Cocacola_Es donde alcanzan el 39%. La estructura poblacional alberga diferencias.

Tabla 8. Diferencia significativa de medias según la Tipología de actor

Tipología de actor	Grado de Centralidad Eigenvector (GCE)		Grado de Intermediación (GI)		Grado de Entrada (GE)	
	Cocacola	SinAzucarOrg	Cocacola	SinAzucarOrg	Cocacola	SinAzucarOrg
Significación	0,000	0,871	0,305	0,001	0,000	0,000
F	5,117	6,689	1,308	6,800	11,025	13,608

Existen diferencias significativas de medias entre los indicadores de centralidad de Cocacola_Es a excepción del GCE y de SinAzucarOrg menos el GI. Debido a las diferencias de proporciones y de medias observadas aceptamos la hipótesis de que la centralidad de los actores varía en relación con la Tipología de actor.

Topología de la red

Para estudiar con más detenimiento las diferencias entre las redes hemos comparado los actores más relevantes, es decir, aquellos que superan la mediana de cada indicador de centralidad (GCE y GI)

Tabla 9. Estadísticos básicos de la red

Cocacola_Es Estadísticos

		Betweenness Centrality	Eigenvector Centrality
N	Válido	1663	1663
Media		2860,421373	,0005993867
Mediana		,22200000	,0006570000
Percentiles	25	,00000000	,0000730000
	50	,22200000	,0006570000
	75	329,8040000	,0007660000

SinAzucarOrg Estadísticos

		Betweenness Centrality	Eigenvector Centrality
N	Válido	1271	1271
Media		2254,653016	,0008292683
Mediana		,00000000	,0000000000
Percentiles	25	,00000000	,0000000000
	50	,00000000	,0000000000
	75	2,00000000	,0010000000

Al estudiar los estadísticos observamos cómo las bajas centralidades de SinAzucarOrg hacen que la mediana se encuentre en una centralidad nula. Esto significa que los actores bajo la mediana de la red de SinAzucarOrg, cuando mencionan a @SinAzucarOrg, no menciona a otros perfiles. Fruto de estas diferencias observamos que la topología de las redes es diferente.

Tabla 10. Seguidores y menciones por red

Red	Seguidores	Menciones
Cocacola_ES	196000	1663
SinAzucarOrg	92000	1271

El número de seguidores de cada perfil no es proporcional al número de menciones conseguidas. Cocacola con un 47% más de seguidores que SinAzucarOrg, solo tiene un 23,57% de menciones más que esta.

Aceptamos la hipótesis 4. El tipo de actor bien insertado (GCI) predomina en la red Insider, mientras que el tipo de actor capaz de controlar flujos de información (GI) predomina en la red Outsider. Caben destacar dos descubrimientos no esperados:

- Gran parte de los Tweets que mencionan a @SinAzucarOrg no menciona a ningún otro perfil.
- @SinAzucarOrg consigue, en mayor medida, traducir sus seguidores en menciones.

Conclusiones

El debate alimentario surgido en las redes sociales es un interesante objeto de estudio para la Sociología. Dentro de las variables estudiadas destacamos como, aunque el nivel de Renta por CCAA no es significativo en nuestro análisis, atender al Sobrepeso si puede serlo. Encontramos como es el perfil Insider el único donde los nodos con mayor centralidad se pueden localizar en determinados lugares.

Estudiar la tipología de actor nos reporta el descubrimiento más relevante de nuestro trabajo. A diferencia de estudiar la localización de los actores, saber quiénes son los que Twittean nos puede ayudar a entender con más profundidad la red. En primer lugar, vemos como las personas son los actores principales partícipes de cada red. De hecho, la red Outsider destaca por tener un 90% de personas frente a un 61% de la Insider. A ello hemos de sumarle las diferencias significativas de medias observadas en la mayor parte de los indicadores de centralidad de las redes. En resumen, tanto la distribución de la población como su centralidad es desigual.

Al introducirnos en las características topológicas de las redes podemos observar como vuelven a aparecer discrepancias entre ellas. En primer lugar, a diferencia de la red de Cocacola_Es, SinAzucarOrg tiene la mediana de los indicadores de centralidad GCE y GI en 0, es decir, gran parte de sus menciones solo los mencionan a ellos. Aunque esto pueda verse como una desventaja a la hora de maximizar la popularidad de SinAzucarOrg la realidad es que, si comparamos la proporción de seguidores y menciones, es el perfil de SinAzucarOrg el que saca más partido a sus seguidores. Cabría preguntarse la posible relación de esta desigualdad con las diferencias en la tipología de actor.

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