Scientometrics (2024) 129:847–868
https://doi.org/10.1007/s11192-023-04921-0

Universalism and particularism in the recommendations of the nobel prize for science

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Received: 6 February 2023 / Accepted: 14 December 2023 / Published online: 13 January 2024

Abstract
From the viewpoints of universalism and particularism, this paper investigates the process of recommendation by focusing on peer review for the Nobel Prize for Science from 1901 to 1970. The results indicate that self-recommendation practices are routine, especially in developed countries, and that the recommendation network is fundamentally built on mutually beneficial relationships between countries. The analysis also reveals that political, economic, military, biological, and colonial factors irrelevant to scientific performance impact the recommendations. During the study period, the Cold War evoked severe tensions between the Western and Eastern Blocs and influenced recommendations on each side; political and military factors also played a role. The main findings imply apparent evidence for particularism, indicating the presence of bias in the recommendation process. This paper provides suggestions for improvement of the selection process for the Nobel Committee.

Keywords Nobel prize for science · Recommendation network · Universalism · Particularism · Peer review

Introduction

The Nobel Prize for Science is the most prestigious award in the world and a recognition of high achievement in the scientific community (Merton, 1973). Nobel laureates have often been regarded as belonging to a scientific elite. Many have banded together to become a social force shaping scientific development (Zuckerman, 1977). Winning this award improves the status of the recipients' nations in the world of science, lending them a particular scientific hegemony (Heinze et al., 2019).

The process of selecting nominees for the Nobel Prize starts every September with the sending of recommendation forms to nominators in as many countries as possible.[1]

[1] www.nobelprize.org/nomination/

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The nominators' list includes academic professors, scientists, and previous laureates. After each nominator recommends a candidate to be recognized for achievements in specific fields, the Physics, Chemistry, and Physiology or Medicine committees select laureates from among the nominees. Therefore, nomination is not only the first step, but also a prerequisite for winning the award.

Recommendation practices can influence the selection of laureates. Studies have proved that recommendation is strongly related to age, gender, and the likelihood of winning the award (Baffes & Vamvakidis, 2011; Gallotti & Domenico, 2019; Mahmoudi et al., 2019). The process involves critical official data, which only began to be released by the Nobel Committee in the late twentieth century. In academic circles, the argument has arisen that research should be conducted on recommendations for the Nobel Prize for Science (Tyutyunnik, 2013).

This paper investigates the process of recommendation for the Nobel Prize for Science. Despite its importance, there is not much research on this topic. Crawford (2002) showed that France, Germany, the United Kingdom, and the United States recommended scientists from their own countries with a remarkably high percentage from 1901 to 1933. That study also revealed a decrease in the number of nominations between enemies during the First World War. Central Powers and Allies rarely recommended each other during World War I. Gallotti and Domenico (2019) revealed that Russian nominators were less than 10% German, French, or American from 1901 to 1960. That study demonstrated a change of focus from Germany to the USA as the central nation in the nomination network after World War II; the concept of *country homophily*, that is, self-recommendation, was introduced in that study for the first time. Singh (2007) focused on colonial relations, especially between India and the United Kingdom, identifying rare cases in which colonial nominees were supported by colonizer nominators despite their close political relations. Conversely, the opposite was very rare.

Previous analyses were too restricted in terms of time of recommendation, targets, and influential factors, and they merely outlined what happens in the recommendation process, possibly due to the lack of clearly established theoretical frameworks. Therefore, we lack a common understanding to interpret these various elements related to the recommendation for the Nobel Prize for Science based on fundamental theories. This paper was designed to fill this gap. We propose theoretical concepts underlying practical findings. The most significant difference in this study from previous literature is its theoretical framework, which includes universalism and particularism, and its focus on peer review. We cover the period from 1901, the first year of the Nobel Prize, to 1970, the last year for which data were accessible. We also analyze data from all 63 participating countries, both nominators and nominees. Factors included in this study are those that may affect recommendations based on previous literature. Several variables identified in this study relate to political, economic, military, genetic, cultural, colonial, and host effects and are irrelevant to scientific performance. The reliability of these variables has been verified in various studies (Choi et al., 2019; Spolaore & Wacziarg, 2009, 2016).

In the next section, we outline the theoretical background and present the hypotheses of this paper. We then show the process by which networks are generated and describe our three selected methodologies. We then specify factors influencing recommendations for the Nobel Prize for Science. Academic implications based on our theoretical framework are then revealed, and suggestions for follow-up research and the limitations of this paper are presented.

Theoretical background and developing hypotheses

Peer review

Peer review is the basis of recommendation for the Nobel Prize for Science (Smith, 2006). In other words, the Nobel Prize is based on careful evaluation of peers (Furnham, 2023). The theoretical framework of this paper, therefore, requires a thorough consideration of peer review. Peer review has been the cornerstone and gold standard of evaluation of scientific performance since the eighteenth and nineteenth centuries (Chapelle, 2014; Kovanis et al., 2017; Squazzoni et al., 2017). It is defined as a critical assessment of scientific works by experts who do not usually work directly with the scientist being evaluated (Jana, 2019). Such experts act as gatekeepers of science, recommending only the highest-quality work (Bornmann & Daniel, 2005). In recent years, assistance has been solicited from outside sources due to increasing diversity and specialization in the scientific community (Spier, 2002). The peer review system works in multiple areas of science, such as publication, grant allocation, faculty recruitment, scholarships, degrees, and awards.

The peer review system has several shortcomings and has been subject to much criticism (Alberts et al., 2008; Chapelle, 2014). The most noticeable concern is the possibility of bias among reviewers. In this study, bias is defined as systematic prejudice that prevents accurate interpretation of scientific works (Benos et al., 2007). Studies have revealed that peer review is not free from bias; this is true in the contexts of publications, grants, research fellowships, and even scientific policy (Bornmann & Daniel, 2005; Casnici et al., 2017; Cole et al., 1981; Huber et al., 2022; Langfeldt, 2006; Pier et al., 2018). Numerous alternatives have been suggested, and debate continues about whether the peer review system is in crisis.

Universalism and particularism

The exploration of bias in the peer review process inevitably points to both universalism and particularism. The dichotomy between these two concepts in terms of scientists' claims is crucial in various areas of science. Treatises written from the perspective of universalism emphasize scientific performance regardless of the personal attributes of the scientists. Universalism is rooted in the impersonal attributes of science, as distinct from other institutions in society (Merton, 1942, 1973). Particularism emerged from the criticism that universalism is too idealistic; scientists' personal characteristics, such as age, gender, religion, and nationality, influence the judgment of their work. Particularism is, therefore, rooted in the personal characteristics of individual scientists (Mitroff, 1974). In the context of particularism, the social and psychological attributes of a scientist play a significant role in influencing how their work is evaluated, potentially resulting in certain scientists receiving preferential treatment over others (Mitroff et al., 1974). In sum, universalism entails that the acceptance or rejection of claims for inclusion in the realm of science should not be contingent upon the personal or social characteristics of the individuals making those claims. On the contrary, particularism suggests that the acceptance or rejection of claims in the realm of science is heavily influenced by the identity of the claimant (Boguslaw, 1968). The distinction between universalism and particularism can also be elucidated by focusing on the allocation of rewards. Universalism dictates that rewards should be assigned solely based on a scientist's merit and contributions, irrespective of other factors, while particularism entails the consideration of functionally irrelevant characteristics like race or gender when distributing rewards. (Long & Fox, 1995). Historically, universalism has represented the professional interests of scientists (Mulkay, 1976), although considerable evidence of particularism may also be found (Rothman, 1972; Long & Fox, 1995). Some scholars argued that, to a great extent, science approximates the ideals of universalism (Cole & Cole, 1974). Moreover, universalism did not lose prestige until supporters of particularism demonstrated processes that violated it (Andersen, 2001; Cole, 1992). Numerous debates have occurred between proponents of these conflicting viewpoints (Kim & Kim, 2018).

The Nobel Prize for Science is linked to universalism. The founder of the Nobel Prize, Alfred Nobel, truly endorsed universalism, stating: "It is my express wish that when awarding the prizes, no consideration be given to nationality, but that the prize be awarded to the worthiest person, whether or not they are Scandinavian."[2] According to Nobel, personal attributes should not be considered; the focus should be on performance. If the deliberations leading to the selection of a winner support particularism, it may be seen as a violation of the Nobel's wishes and of the spirit of the Nobel Prize for Science.

Developing hypotheses

We now explain our own perspective on a recommendation for the Nobel Prize for Science. In this study, a recommendation is regarded as an interaction between countries instead of an individual connection. Crawford (2002) argued that a recommendation is, in essence, an exchange of honor between two countries; this is also the stance in this study. We generate a dyadic recommendation network between nominator and nominee countries, asking the following research questions. First, how often do nominators recommend scientists from their own country? This is another way of asking who contributes to nationalistic, biased situations. Second, what is the core structure of the recommendation network between countries? Finally, what are the factors (politics, economy, genetics, culture, military, colonial relations, and host effects) that affect recommendations? We consider these questions to be linked with the interactions between universalism and particularism in peer review in science. Primarily based on clues from previous research, we assume that particularism affects the recommendation process and that this research can capture the evidence of particularism. Following these theoretical backgrounds, previous studies, and the aims of the present paper, we developed the research questions for the hypotheses as follows.

Hypothesis 1 Nominators recommend scientists from their own country more than the expected number in a random network as nominees for the Nobel Prize for Science.

Hypothesis 1-1 Especially in developed countries, nominators recommend scientists from their own country much more than the expected number in a random network for the Nobel Prize for Science.

Hypothesis 2 The core structure of the recommendation networks between countries is to be cooperative with each other.

[2] www.nobelprize.org/alfred-nobel/alfred-nobels-will/

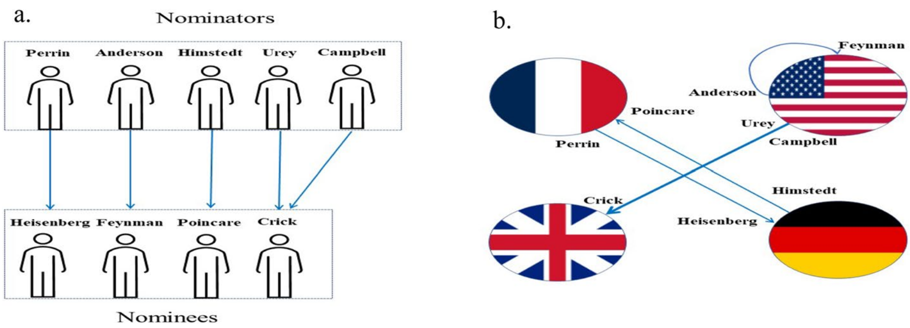

Fig. 1 Projection process. **a** When a nominator recommends a nominee, a direct link is generated. **b** Both nominators and nominees are projected to their countries, and a new link from the nominator country to the nominee country is generated. If the direction of the link is different, the link is different, although it bridges the same countries. Self-loops mean the nominators recommended scientists from their own country, like the USA. The thickness of the link represents the total frequency of recommendations (Source: Gallotti & Domenico, 2019)

Hypothesis 3 The frequencies of recommendations between countries are influenced by factors including politics, economy, genetics, culture, military, colonial relations, and host effects.

In this paper, these hypotheses can be interpreted as the recommendation of the Nobel Science for Science shows biases in the peer review process. The authors also ask, if so, what are some suggestions for improvement?

Data and methodology

Data

We obtained data regarding Nobel Prize recommendations from the Nobel Committee website.[3] We utilized the Beautiful Soup package in Python for data crawling. The extracted data encompassed a range of details for both nominees and nominators, including their name, gender, birth year, death year, profession, university, city, and country. From this comprehensive dataset, we specifically chose the names and countries of the nominees and nominators. The purpose of making this selection was to create a network for subsequent analysis. Data for both Physics and Chemistry were available for the years from 1901 to 1970, while data for Physiology and Medicine were available only for the years 1901 to 1953 due to a rule of the Nobel Foundation that the nomination data should only be revealed 50 years later.

We generated a dyadic recommendation network between nominator and nominee countries. The network was generated so as to connect nominees recommended by nominators. This directed dyadic network was constructed to represent connections between countries. We then projected the network from human relations to visualize country interactions. Figure 1 illustrates the process of projection. During the period of analysis, from 1901 to 1970,

[3] www.nobelprize.org/prizes/

Table 1 Data validity check

Population	Sample	Unmatched data	Rate (confidence interval)	Confidence level
7,445	365	10	2.74 ± 1.63%	95%

the boundaries of some countries changed, and other countries changed their names. We corrected country names according to historical background. For example, before 1922, what is the Soviet Union was the Russian Empire. So, we made that correction.

We checked each country's name in the given dataset using a sampling test. Unmatched data compared to what is known via online sources made up 2.74% of the sample (see Table 1). The conventions of the Nobel Committee explain the discrepancies. Crawford (2002) noted that the nationalities of both nominees and nominators were determined according to the countries where a person was working at that time; they were regarded as representing a given nationality if they had spent a minimum of 8 years in that country. The idea behind this convention is that the nationality recognized by others might be more important for giving and receiving recommendations than a scientist's legal nationality. We did not correct the unmatched data because we regard this convention of the Nobel Committee as valid. We also made this decision with consideration of the nature of the results. Methods for handling recommendation data in this paper differ from those in previous research (Gallotti & Domenico, 2019) and provide advance. We utilized the research data in two ways. First, we used the complete dataset. Second, we used a preprocessed version that excludes self-loops. These approaches were chosen to align with different methodologies.

Methodology

Assortative mixing

Assortative mixing,[4] or the assortativity coefficient, is a normalized value of modularity (Newman, 2003, 2006, 2010). A positive coefficient indicates the tendency of nodes to be attached to other nodes of the same type. A negative coefficient indicates the tendency of nodes to be attached to other nodes of a different type. The formal equation of assortative mixing is as follows:

$$\frac{Q}{Q_{\max}} = \frac{\sum ij(A_{ij} - k_i k_j/2m)\delta\left(c_i, c_j\right)}{2M - \sum ij(k_i k_i/2m)\delta\left(c_i, c_i\right)}, \quad (1)$$

where Q is modularity. In the context of this study, modularity refers to the extent to which nodes can be grouped into communities sharing the same attributes. A_{ij} indicates whether nodes i and j are connected, which is 1 if they are, 0 if not. k_i and k_j are the numbers of connections for nodes i and j, respectively. m is the network's total connections. The Kronecker delta function, $\delta(c_i, c_j)$, checks if nodes i and j are in the same community, which is 1 if yes, 0 if no. Modularity measures how the actual links between nodes in a community

[4] Assortative mixing is also called homophily.

compare to what would be expected by chance.$Q_{\max}$ is the maximum value of modularity in the same network. Thus, assortative mixing is a fractionalized value; the observed value of modularity is divided by the maximum value of modularity for the perfectly matched mixed network. Assortative mixing takes a maximum value of 1 and a minimum of -1. Values can be compared to each other to determine which is stronger or weaker.

In the present study, assortative mixing was used to measure the self-recommendations, that is, cases in which the nominator recommended a scientist from its own country as a nominee. Thus, positive values resulting from assortative mixing indicate the presence of self-recommendation, while negative values resulting from assortative mixing indicate a tendency to nominate scientists from other countries. If the directions of the coefficients of values from the two countries are the same, it may indicate a stronger or weaker tendency toward self-recommendation. The analyses were conducted using both assortative mixing and modularity. Modularity alone is not sufficient for comparing coefficients, as it does not provide normalized values. This method differs from the approach taken in previous research (Gallotti & Domenico, 2019), marking a potentially significant advancement.

Exponential random graph model

The Exponential Random Graph Model (ERGM) represents a recent advancement in social network methodology. Studies in top-tier journals in many fields, including Political Science, Strategic Management, and Communication, have actively introduced this methodology to address the limitations of existing regression methodologies, paving a new path for social network research (Hernández et al., 2021; Kim et al., 2016; Miller & Sutherland, 2023; Shumate & Palazzolo, 2010; Xu, 2022). ERGM reveals the substructural configuration underlying an entire network (Lusher et al., 2013). For example, it has been used to estimate the core structures of the EU's nuclear trade network and the global arms trade network (Jang & Yang, 2022a, 2022b). The first distinct feature of the ERGM is that it is based on the dependence of variables. The second is that it identifies significant variables via comparison in a random graph model. If a parameter is positive, it means that the configuration activates the entire network. If a parameter is negative, it means the configuration deactivates the network. The ERGM equation is as follows:

$$\Pr(X = x|\theta) = \frac{1}{\kappa(\theta)} \exp\{\theta_1 z_1(x) + \theta_2 z_2(x) + \cdots + \theta_p z_p(x), \quad (2)$$

where X is an adjacency matrix of a network, x is the adjacency matrix of the network formed by given data, θ is a series of parameter vectors, $\Pr(X = x|\theta)$ is the probability of connecting between nodes, κ is a constant, and z is a statistic representing the effects of activating.

In this study, we analyze the properties of the basic relationship between nominator and nominee countries using the ERGM. We assess three parameters: Mutual, Indegree2, and Outdegree2. In a directional network, Mutual indicates that two nodes have a relationship with each other; that is, it shows reciprocity. Indegree2 represents two directional links concentrated on one node, which can be interpreted as popularity. Outdegree2 shows two directional links from one node to two nodes. This is

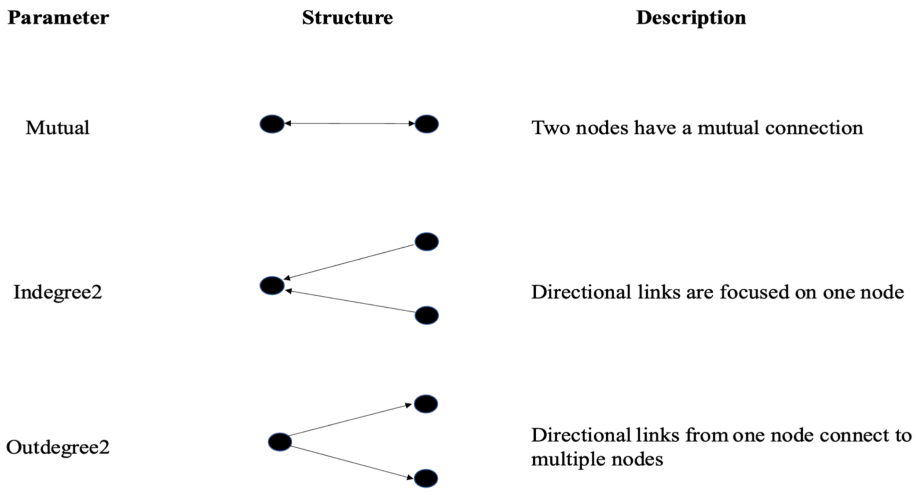

Fig. 2 Network parameters for, structure of, and description of the ERGM

described as an activity. Figure 2 represents the structure and provides a description of the ERGM used in this study.

Gravity model

The gravity model originated from Newton's law of universal gravitation, published in 1687, which defines the force of attraction between two objects by measuring their mass and mutual distances. In the applied gravity model, a modified version of the original equation is based on extensive theoretical background from many pioneering works. One of the most frequently used equations in the context of trade is as follows (Silva & Tenreyro, 2006):

$$\ln T_{ij} = ln\beta_0 + \beta_1 lnY_i + \beta_2 lnY_j + \beta_3 lnD_{ij} + ln\eta_{ij}, \tag{3}$$

where $\ln T_{ij}$ is trade flows between country i and country j, lnY_i, lnY_j indicate the economic mass of country i and country j, respectively, lnD_{ij} denotes the distance between the two countries, and β_0 is constant.β_1,β_2, and β_3 are parameters and $ln\eta_{ij}$ is an error term. This model has been widely used to identify factors influencing the flows between two parties, not only in trade, but also in the contexts of migration (Karemera et al., 2000), transportation (Jung et al., 2008), tourism (Khadaroo & Seetanah, 2008), sports (Choi et al., 2019), and the spread of COVID-19 (Woo et al., 2022). This model is a prominent methodology for analyzing interactions between countries. For instance, Avdeev (2021) utilized this model to study international collaboration patterns in multidisciplinary fields.

In this study, we use the applied gravity model to investigate factors influencing the recommendation of scientists for the Nobel Prize for Science between countries. All factors considered in this paper were sourced from reputable references (Bolt & Zanden, 2020; Gibler, 2013; Marshall & Gurr, 2018; Spolaore & Wacziarg, 2009). After thoroughly reviewing these sources, the authors pinpointed key factors for inclusion. For instance, from the 'Ancestry, Language, and Culture' database, which features over a hundred factors, only two—Genetic and Language distance—were selected after a rigorous review. In this way, we include distinctive variables representing political, economic, genetic, cultural, military, and colonial relations. The host effect represents whether Sweden takes advantage of the fact that the Nobel Prize is based in Sweden. Our applied gravity model for Nobel Prize nominations is as follows:

$$W_{ijt} = ln\alpha_0 + \beta_1 lnPOP1_{it} + \beta_2 \ln GEO_{ij} + \beta_3 GDP_{pc_{ijt}} + \beta_4 \ln GENE_{ij} + \beta_5 \ln LANG_{ij} + \delta_1 POLITY_{ijt} + \delta_2 ALLIANCE_{ijt} + \delta_3 COLONY_{ijt} + \delta_5 Host1_{it} + \delta_5 Host2_{jt} + \varepsilon_{ijt}, \quad (4)$$

where W_{ijt} is the nomination frequency between countries i and j in year t, and $POP1$ is a mass variable representing the population of the nominee country. We exclude the variable *nominator population* due to a lack of meaning. *GEO* indicates the geographical distance between two countries.GDP_{PC} measures economic distance as a ratio of GDP per capita between two countries, calculated as larger *GDPpc* divided by smaller *GDPpc*. The value increases when the GDP_{PC} gap is larger, while it decreases when the GDP_{PC} gap is smaller. *GENE* and *LANG* reflect the genetic and linguistic distances between the two countries. All others are dummy variables with values ranging from 0 to 1 depending on data attributes. *Polity* takes a value of 1 if the government types of the two countries (democracy, autocracy, anocracy) were the same in year t. An alliance is coded as 1 if two countries have signed a treaty (nonaggression, defense, neutrality, entente). The *Colony* variable takes a value of 1 if the nominator country is a colonial state and the nominee country is a ruler state. This is also true if a colonial relationship ended since 1901. We also include two host effect variables. *Host 1* represents Sweden as a nominee, with a value of 1 if the nominee country is Sweden. *Host 2* indicates Sweden as a nominator, with a value of 1 if the nominator country is Sweden. Detailed descriptions and sources of all variables are provided in Table 2.

Log values are used for all variables except the independent variable and dummy variables. We use Poisson pseudo-maximum likelihood to resolve issues related to heteroscedasticity, which frequently occur with log variables. Heteroscedasticity, also referred to as heterogeneity of variance, is a significant issue in regression analysis because it can invalidate statistical tests of significance. Silva and Tenreyro (2006) demonstrated that PPML estimators exhibit less bias compared to OLS, NLS, and Tobit. This led us to choose the PPML estimator for the Gravity Model in our study. Another concern in research data is the Zero-flow problem, where a connection has no weight. For instance, in studying trade factors between African and Asian countries, there might be a pair of countries with no trade exchange. Since the Gravity model employs logarithms, the Zero-flow problem can introduce bias because the logarithm of zero is undefined. Fortunately, our study does not encounter the zero-flow issue as the data comprises pairs of countries, each linked to a single recommendation.

Results

Assortative mixing and self-loops

We use assortative mixing to measure self-recommendations for the Nobel Prize for Science and modularity for cross-checking. Data for Physiology or Medicine were available

Table 2 Variables

Variable	Description	Source
W (Weight)	Nomination frequency between two countries	Nobelprize.org, Nomination archive (www.nobelprize.org/nomination/archive/)
POP1 (population)	Population of nominee countries (thousands)	Maddison Project Database 2020 (Bolt & Zanden, 2020)
GEO (Geographic distance)	Distance between two countries' capitals (km)	The Diffusion of Development (Spolaore & Wacziarg, 2009)
GDPpc	Larger GDP per capita divided by smaller GDP per capita ($)	Maddison Project Database 2020 (Bolt & Zanden, 2020)
GENE (Genetic distance)	Fst distance_dominant	Ancestry, Language, and Culture. 2016 (Spolaore & Wacziarg, 2016)
LANG (Linguistic distance)	lingdist_weight_formula	Ancestry, Language, and Culture. 2016 (Spolaore & Wacziarg, 2016)
Polity	1 if two countries have the same government type	POLITY5 (Marshall & Gurr, 2018)
Alliance	1 if two countries are in a formal alliance	Correlates of War Formal Interstate Alliance Dataset v.4 (Gibler, 2013)
Colony (Colonial relationship)	1 if the nominator country is a colonial state and the nominee country is the ruler state	The Diffusion of Development (Spolaore & Wacziarg, 2009)
Host 1	1 if the nominee country is Sweden	Nobelprize.org, Nomination archive
Host 2	1 if the nominator country is Sweden	Nobelprize.org, Nomination archive

Table 3 Assortative mixing and modularity

Fields	Assortative mixing	Modularity		Previous research
	1901–1970	1901–1970	1901–1965	1901–1965
Physics	0.3	0.25	0.26	0.28
Chemistry	0.37	0.32	0.33	0.34
Physiology or Medicine	0.48	0.43	0.43	0.44

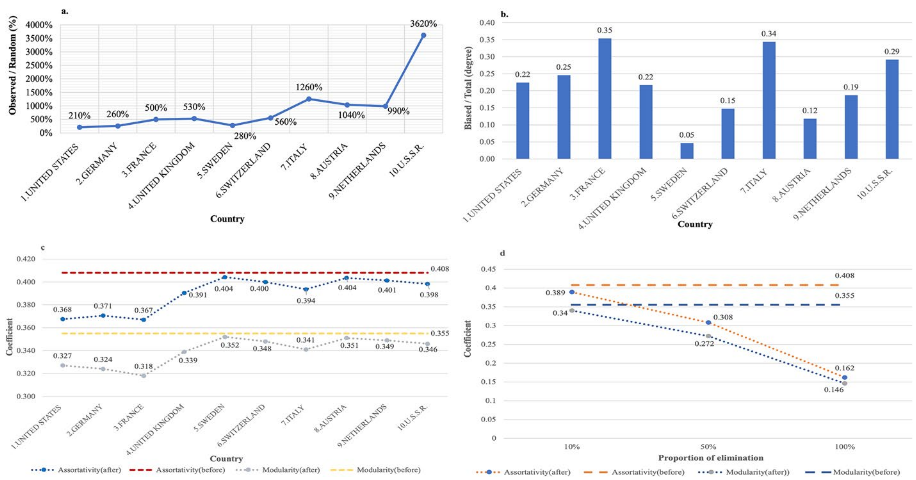

Fig. 3 Biased self-loops and elimination. **a** Values for each country are the ratios of observed self-loops divided into random expectations and actual self-loops. **b** Proportions are the ratios of biased self-loops divided by the total number of links for each country. **c** Measure (after) shows changes after the elimination of each country's bias. Measure (before) indicates original values. **d** Measure (after) shows changes after the elimination of biases for all 10 countries by proportion. Measure (before) indicates original values. Note: USSR is the Soviet Union

only from 1901 to 1953, while data for Physics and Chemistry were available from 1901 to 1970. The results can be seen in Table 3.

The first notable point is that the assortative mixing coefficients of the three fields are all positive, indicating a tendency to recommend scientists from the same country that is doing the nominating. In other words, self-recommendation for the Nobel Prize for Science is a common phenomenon. Between fields, the Chemistry coefficient is higher than the Physics coefficient. Although fewer data were available for Physiology or Medicine than for the two other fields, the coefficient is the highest among the three. A positive coefficient is also evident for the other measure, modularity. Our findings are consistent with those of previous research (Gallotti & Domenico, 2019).

In another analysis, we determine which countries have the most self-recommendations. Self-loops mean, in this research, that a country recommends its own scientists. The inclusion of this variable directly increases the coefficients of assortative mixing and modularity. In our data, 38 countries have self-loops among 63 countries. However, the top 10 countries in terms of recommendation frequency account for 87% of all self-loops. Most of these are scientifically developed countries, such as the USA, Germany, France, and the United Kingdom. Thus, we conclude that developed countries frequently recommend their own scientists.

We now examine the self-loop situation in more detail. We generate a random network to determine self-loop statistics for the top 10 countries. A comparison between random expectations and actual observations can be seen in Fig. 3. Observed self-loops in the top 10 countries far exceed random expectations (see Fig. 3a) by a magnitude of at least 2, but sometimes as much as 36 times. We regard such excessive amounts as evidence of biased self-loops caused by nationalism. Biased self-loops are represented as values for random expectations minus values for observations. We also compare the ratio of biased self-loops to all degrees in the top 10 countries. Figure 3b illustrates that biased self-loops make up 5% to 35% of all degrees in the top 10 countries. An interesting point is that the country hosting the Nobel Prize, Sweden, recommends its own scientists the least. The ratio for Sweden is 0.05 (ranked 37 out of 38 countries), while the mean ratio of all 38 countries is 0.224.

Biased self-loops in a given country increase the coefficients of assortative mixing and modularity. However, if we eliminate each country's bias, the coefficients of assortative mixing and modularity may decrease. The result of testing this inference is depicted in Fig. 3c. Before eliminating bias, the coefficients of assortative mixing and modularity are 0.408 and 0.355, respectively. After we eliminate each country's bias, these coefficients all decline. However, the extent of the decline differs depending on the country. When we eliminate the USA, Germany, and France, the coefficients of both assortative mixing and modularity decrease vertically. In contrast, when we eliminate Sweden, Switzerland, and Austria, the coefficients drop only slightly. In Fig. 3d, we simultaneously eliminate biases for all 10 countries at rates of 10% to 100%; the coefficients decline differently depending on the elimination rate. In conclusion, an effective way to reduce the coefficients of assortative mixing and modularity is to eliminate the self-loops of developed countries at a high rate.

ERGM

We now exclude the degree of self-loops for all countries and use the ERGM to investigate the basic properties of the relationships between nominee and nominator countries. We divide the data into seven groups representing each decade for effective analysis. Table 4 shows the results of the ERGM.

The only significant parameter in all fields and periods is Mutual. Values for Indegree2 are not significant for any periods or fields. Those for Outdegree2 are significant for specific periods and fields. Therefore, we focus on Mutual as a basic property. The steady, positively significant values for Mutual indicate that the substructure representing the reciprocal relationship between giving and receiving recommendations between countries dominates the formation of the network. Its specific meaning is as follows. First, this relationship is interdependent (Hansen et al., 2010). In general, a one-way relationship in network analysis indicates influence or popularity. On the other hand, a mutual relationship is regarded as mutually dependent because it is a relationship in which two actors exert influence and receive influence simultaneously. Second, it is a mutually beneficial relationship (Lusher et al., 2013). As mentioned earlier, in ERGM analysis, the Mutual parameter is also called reciprocity. Generally, a mutually positive relationship between actors is formed

Table 4 ERGM results

Period	Physics			Chemistry			Physiology or Medicine		
	Mutual	Indegree2	Outdegree2	Mutual	Indegree2	Outdegree2	Mutual	Indegree2	Outdegree2
1901–1910	1.6163***	− 0.9518	− 0.9123	1.0488	0.5645	− 0.4111	1.8741***	− 1.266	− 1.9581
1911–1920	1.6277***	− 0.9049	− 0.9643	1.1034*	0.1181	− 0.5217	2.0830***	− 0.8403	− 1.5902*
1921–1930	1.3040**	0.1551	− 0.524	1.2967**	− 0.4681	− 1.7137	2.3537***	− 0.5535	− 0.5575
1931–1940	2.4237***	− 1.0526	− 1.5577	1.3121**	− 0.4563	− 1.7048	2.3408***	− 0.9462	− 1.6838*
1941–1950	1.539***	− 1.22	− 0.5017	2.0883***	− 0.8432	− 2.1131*	2.1043***	− 0.5224	− 1.5288*
1951–1960	1.8176***	− 1.3498	0.2827	1.0409**	− 1.4937	− 2.1973*	0.5123	− 0.796	− 1.1176
1961–1970	1.6679***	− 0.1547	− 1.4542	1.9508***	0.1105	− 2.1585*			

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

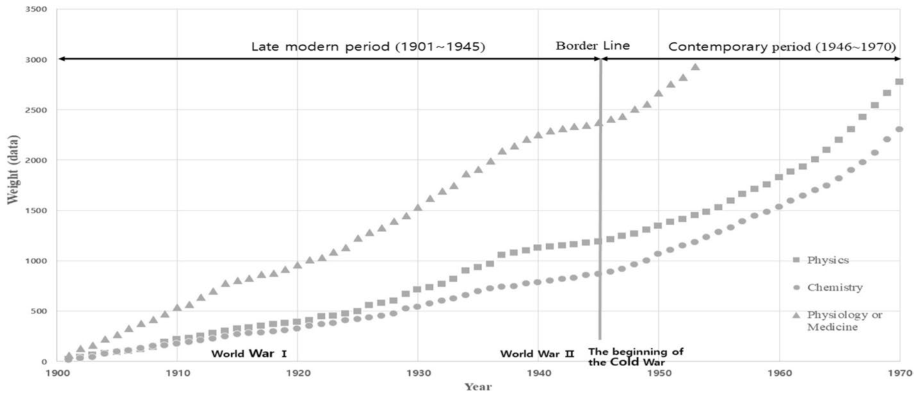

Fig. 4 Cumulative recommendation data

when they perceive each other positively. The results indicate an interdependent and reciprocal relationship between recommending countries and receiving countries.

In ERGM analysis, assessing the model's goodness of fit to the data is crucial. This assessment can be achieved by examining Goodness-of-Fit (GOF) statistics. Within R's Statnet, a t-ratio value exceeding 2.0 is deemed an outlier, suggesting that a statistic with such a value likely did not arise from the model (Koskinen et al., 2013). We performed GOF evaluations for all datasets and consistently obtained values below 2.0. This indicates that our selected model aptly fits the data.

Gravity model

The gravity model is used to investigate factors influencing interdependent and reciprocal relationships between countries and positive or negative effects. In a gravity model analysis, the dataset is partitioned into two time periods. We infer that the character of each era influenced the recommendations differently. First is the Late Modern period, beginning in 1901, the first year of the Prize, and continuing to 1945, the last year of World War II. The second era is the Contemporary period, covering the years from 1946 to 1970. The academic literature supports this division (Brivati et al., 1996; Gingras & Wallace, 2010). The Late Modern period includes Imperialism, World War I, and World War II. Second is the Contemporary period that is politically dominated by the Cold War, from 1946 to 1970. Also, this period coincides with the independence of many colonial states and the emergence of the USA as a hegemonic nation.

Figure 4 represents the cumulative dyadic recommendation data for each field. The data for Physiology or Medicine were excluded from this analysis due to a lack of data in the Contemporary period (after 1953). Data for Physics and Chemistry were aggregated to show the results effectively.

The results in Table 5 show that various factors affected recommendations for the Nobel Prize for Science. We mitigate the potential endogeneity problem using the random shuffling test (Kim et al., 2015). After random shuffling of the dyadic data, values for all variables lose significance in both the Late Modern and Contemporary periods. Thus, all variables represent unique connections and are not correlated with error terms, indicating that endogeneity is not a problem.

Table 5 Gravity model

Variables	Late modern period		Contemporary period	
	(1901–1945)	Random	(1946–1970)	Random
Population (nominee)	0.144***	– 0.0534	0.220***	– 0.00701
	(– 6.4)	(– 1.67)	– 9.12	(– 0.25)
Distant cap	– 0.00473	0.0494	0.158***	– 0.0179
(Between two countries)	(– 0.15)	– 1.23	– 7.02	(– 0.65)
GDPpc	– 0.116	– 0.0499	– 0.181**	0.0924
(Similarity in terms of economic size)	(– 1.70)	(– 0.48)	(– 2.79)	– 1.33
Genetic	– 0.0318**	– 0.00985	– 0.0530***	– 0.00126
(Genetic distance)	(– 2.65)	(– 0.56)	(– 3.80)	(– 0.08)
Language	– 0.261	– 0.069	0.0386	0.22
(Linguistic distance)	(– 1.65)	(– 0.41)	– 0.25	– 1.56
Polity	– 0.0305	– 0.0377	0.312***	0.124
(Same government type = 1, otherwise = 0)	(– 0.47)	(– 0.51)	– 5.25	– 1.54
Alliance	– 0.198*	– 0.00235	0.135*	0.0742
(Formal alliance = 1, otherwise = 0)	(– 2.56)	(– 0.02)	– 2.22	– 1.07
Colony	– 0.141	0.206	– 0.745***	0.0682
(Colonial relationship = 1, otherwise = 0)	(– 0.79)	– 0.54	(– 4.46)	– 0.41
Host 1 (Nominee)	0.0764	0.288	0.0602	0.106
(Nominee country is Sweden = 1, otherwise = 0)	– 0.74	– 1.49	– 0.64	– 0.98
Host 2 (Nominator)	0.353***	– 0.0324	0.313***	0.0433
(Nominator country is Sweden = 1, otherwise = 0)	– 3.92	(– 0.24)	– 3.54	– 0.33
_cons	– 1.034***	0.917*	– 3.388***	0.792*
	(– 3.29)	– 2.51	(– 9.95)	– 2.28
N	1052	1052	1305	1305
R-squared	0.060	0.013	0.187	0.006
Wald	83.76	11.14	213.51	10.32

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

Values for three variables, *Population of nominee countries*, *Genetic distance*, and *Host 2*, are significant in both the Late Modern and Contemporary periods. The coefficient of the *Population of nominee countries* is positive, which means that more large-population countries are recommended than small-population countries. The coefficient of *Genetic distance* is negative, which denotes that two countries are more likely to recommend each other when they are genetically closer. We infer that this is related to ethnocentrism. The coefficient of *Host 2* is positive, which reveals that Sweden has recommended nominees more than other countries. By contrast, the coefficient of the *Host 1* variable is not significant. In other words, the inference that Sweden has been recommended more than other countries is rejected.

Values for four variables, *Distant capital*, *GDP per capita*, *Polity*, and *Colony*, are significant only in the Contemporary period. The coefficient of *Distant capital* is positive, which indicates that two countries recommend each other more when they are geographically far apart rather than close together. This is unusual, as it violates the law of universal gravitation; thus, we conduct further analysis, the results of which are reported later.

The coefficient of *GDPpc* is negative, which implies that two countries are more likely to recommend each other when they are similar in terms of economic size or individual income. In other words, recommendations for the Nobel Prize for Science are influenced by economic tier. The concern arises when rich countries recommend scientists from other rich countries more than underdeveloped countries. Because most recommendations occur within developed countries, this factor represents a significant obstacle for scientists from underdeveloped countries to be nominated. The coefficient of *Polity* is positive, which denotes that two countries are more likely to recommend each other when their governments are the same type. Thus, democratic countries recommend other democratic countries more than autocratic countries; autocratic countries recommend other autocratic countries more than democratic countries. The coefficient of the *Colony* variable is negative, which means that colonial countries recommend ruler countries less frequently than other countries. This may be due to the antipathy of colonial states for ruler states.

The only variable for which the coefficient sign changes significantly when crossing the period border is *Alliance*. The coefficient of *Alliance* is negative in the Late Modern period; however, it becomes positive in the Contemporary period. A positive coefficient means two countries with an alliance treaty recommend each other more frequently than other pair countries that have no alliance treaty. Negative, opposite results in the Late Modern period need further analysis. In that period, two countries with an alliance treaty recommended each other less frequently. We infer that a strong social force such as a World War may influence this result. In the Late Modern period, both World War I and World War II occurred. During these wars, countries broke off alliances with neighbor nations that formerly frequently recommended each other and entered alliances with very few other countries. We evaluate this reasoning by generating new data for every country except Germany. Germany was the main enemy in World War I and World War II. The coefficient of *Alliance* loses significance during this period (P-value = 0.708) using the new data, supporting the hypothesis. The variables for *Linguistic distance* and *Host 1* are not significant in either the Late Modern period or the Contemporary period. Thus, the inference that these variables influenced recommendations must be rejected. Re-examining the *Linguistic distance* variable, we infer that the data used in the statistical analysis for this variable do not capture significant meaning because most scientists use only representative languages such as English, German, and French, regardless of their native language, when writing international papers or communicating at international conferences.

For this analysis using the gravity model, the dataset was divided into two time periods to compare the effect of the era; distinctive differences are observed in the Contemporary period compared to the Late Modern period. These crucial changes may be strongly related to the Cold War and the emergence of the USA as a superpower. To assess this possibility, we utilize an alternative dataset excluding the USA. Table 6 shows the results and a comparison between the two models.

The most significant change is evident for the variable *Distant capital*. The USA has the most connections in the recommendation network, although it is in North America, far from Europe. Therefore, the variable *Distant capital* becomes negative compared to the positive value in the dataset with the USA excluded. This result indicates that two countries tend to recommend each other when they are close. This result is understandable. The *Polity* and *Alliance* variables lose significance in the new dataset. These results are strongly related to the status and roles of the USA during the Cold War. During the study period, the USA was an irreplaceable leader in the Western World, advocating for democracy throughout the Cold War. The USA has also led the North Atlantic Treaty Organization since 1949. The strong influence of this country may explain why the *Polity* and *Alliance* variables lose

Table 6 Comparison of the two models

Variables	Contemporary period (1946 ~ 1970)		
	All countries	USA excluded	Random
Population (nominee)	0.220***	0.0433*	0.0242
	− 9.12	(2.08)	(0.68)
Distant capital	0.158***	− 0.124***	− 0.0109
(Between two countries)	− 7.02	(− 4.90)	(− 0.33)
GDP pc	− 0.181**	− 0.171**	− 0.0168
(Similarity of economic size)	(− 2.79)	(− 3.13)	(− 0.19)
Genetic	− 0.0530***	0.0313	0.0330
(Genetic distance)	(− 3.80)	(1.95)	(1.83)
Language	0.0386	− 0.166	− 0.0856
(Linguistic distance)	− 0.25	(− 0.93)	(− 0.50)
Polity	0.312***	− 0.00220	0.0378
(Same government type = 1, otherwise = 0)	− 5.25	(− 0.04)	(0.45)
Alliance	0.135*	− 0.0302	0.0267
(Formal alliance = 1, otherwise = 0)	− 2.22	(− 0.47)	(0.29)
Colony	− 0.745***	0.284	0.0917
(Colonial relationship = 1, otherwise = 0)	(− 4.46)	(1.54)	(0.51)
Host 1 (Nominee)	0.0602	− 0.0814	− 0.00741
(Nominee country is Sweden = 1, otherwise = 0)	− 0.64	(− 1.02)	(− 0.07)
Host 2 (Nominator)	0.313***	0.393***	0.225
(Nominator country is Sweden = 1, otherwise = 0)	− 3.54	(4.61)	(1.59)
_cons	− 3.388***	1.121**	0.707
	(− 9.95)	(3.17)	(1.46)
N	1305	832	832
R^2	0.187	0.072	0.009
Wald	213.51	85.14	7.28

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

their significance in the USA-excluded network. The variable *Colony* also loses significance, which supports the idea of the USA playing a substitution role. Many colonial countries became independent states because of World War II, after which they began to choose scientists from the USA as candidates for the Nobel Prize for Science instead of choosing those from colonizing countries such as the United Kingdom or France. Therefore, values for the *Colony* are not significant in the network without the USA. However, those for the *GDPpc* variable maintain significance even without the USA. Clearly, economic similarity is a deep-rooted factor that influences recommendations between countries, even when the USA is excluded.

Discussion

Given all the results reported above, the answers to our hypotheses can be given. The results accept Hypothesis 1, 1–1, and 3. Self-recommendations are routine, especially in developed countries. The preference for genetic similarity and economic tier considerations consistently underlies recommendations for the Nobel Prize for Science. Moreover, strong social pressure caused by events such as the Cold War also promoted the effects of some variables during the period of this study. Severe tensions between the Western Bloc and Eastern Bloc created confusion in the scientific community and led scientists to focus more on their respective sides. The emergence of the USA as a superpower and the occurrence of a series of World Wars also strengthened the particularistic tendencies directly and indirectly. The results of our analysis confirm these effects in the values for the Polity, Alliance, and Colony variables. Hypothesis 2 is also accepted by the results of ERGM. Reciprocity between countries in the recommendation network activates the entire network. It is a mutually beneficial interaction between countries.

The recommendations for the Nobel Prize for Science have been influenced by the national backgrounds of scientists, although these are irrelevant to scientific performance. In other words, these recommendations show pronounced evidence for particularism. These findings align with prior research that identified evidence of particularism across different scientific disciplines (Long & Fox, 1995; Mitroff, 1974; Rothman, 1972).

The implications of this study's results indicate the need for changes in awareness of what underlies the process of recommendation for the Nobel Prize for Science. When a scientist is nominated for the Nobel Prize, it is indisputable that they have produced outstanding results. However, the findings of this study, that various biases are active, can raise numerous questions about the credibility and authority of the recommendation process. We call for further studies to provide evidence of universalism and particularism and to investigate the recommendation process more deeply.

In fact, the concern goes beyond recommendations. As previously mentioned, these recommendations can influence the selection of laureates. If the recommendation process cannot be free from particularism, the selection of laureates may be similarly affected. Considering the concerns related to bias, both the scientific community and the public need to be more cautious and refrain from excessive enthusiasm for winners of the Nobel Prize for Science.

This study also presents a challenge to the Nobel Committee. As mentioned earlier, the status of universalism would be affected by the demonstration of particularism (Andersen, 2001; Cole, 1992). Our results confirm that the recommendation process has not honored the express desire of Alfred Nobel that universalism be the principle on which the Prize is awarded. The Nobel Committee, therefore, has an obligation to make improvements. The initial step in instigating change involves scrutinizing past events and preparing for the future. The Nobel Committee's policy of keeping recommendation information secret for 50 years seems far from this demand. We suggest the Nobel Committee might better provide recent recommendation data for research (Crawford, 2002). The Nobel Committee may be concerned about potential controversy regarding the disclosure of recommendation data. However, 50 years is too long in our rapidly changing society (Jana, 2019). Moreover, it is imperative to keep in mind that secrets might be a condition to support particularism in science (Long & Fox, 1995).

This paper confirms the influence of particularism in the process of recommendation for the Nobel Prize for Science. However, its findings cannot be generalized to other fields or to science as a whole. Therefore, it is misleading to assume that particularism will prevail in other scientific fields based on the results of this study.

Conclusion

This study investigates the recommendations for the Nobel Prize for Science in view of universalism and particularism. We unveil a strong tendency of most developed countries to recommend themselves. They recommend scientists from their own countries much more frequently than would be indicated by random expectations. The basic property of the recommendations network, excluding self-recommendation, is mutually beneficial relationships. We test the influence on recommendations of factors such as politics, economics, ethnicity, culture, alliance, colonial relations, and host effects. Values for most variables are significant. The results confirm the influence of particularism in the recommendations for the Nobel Prize for Science. Social pressures caused by events such as the Cold War also strongly facilitate particularism.

The main contribution of this paper is to confirm the role of particularism in the process of recommendation for the Nobel Prize for Science. Considering the relation between particularism and bias in the peer review process, this paper verifies the existence of bias. Bias has been reported in many scientific fields in which peer review is prevalent (Bornmann & Daniel, 2005; Casnici et al., 2017; Cole et al., 1981; Huber et al., 2022; Langfeldt, 2006; Pier et al., 2018). However, to our knowledge, this is the first comprehensive analysis to reveal bias in the process of recommendation for the Nobel Prize for Science based on a theoretical framework.

We call for further research to investigate the detailed mechanisms underlying particularism in the process of recommending candidates for the Nobel Prize for Science. Various questions arise. For example, when two countries have the same type of government, does state intervention increase the number of recommendations between them? Does the latent consciousness of individual scientists have consequences? Future studies can provide answers to these questions.

The limitations of this paper should be recognized. First, this paper primarily focuses on quantitative analysis of the recommendations; no qualitative approaches, such as interviews with scientists involved in recommendations, were used. Complementary follow-up studies can clarify the decision-making process involved in Nobel Prize recommendations. Secondly, there is a lack of recent data because of the Nobel Committee's practices. Research incorporating data from the late 20th to the early twenty-first century would uncover shifts in the recommendation process over time. Thirdly, this paper predominantly centers on connections between countries, so other data perspectives like age, gender, and field were not considered. Future research should encompass a broader range of factors for a more comprehensive analysis. Fourth, this study could not include co-author relationships between countries that are considered to affect recommendations as analysis factors. Further research will unveil the connection between co-authorship and recommendation. The last limitation of this study lies in its exclusion of prizes in other fields. Future research may reveal crucial differences between the Nobel Prizes for literature and peace compared with that for science. In the area of literature, group recommendations are frequent. The Nobel Peace Prize is the only one that allows nominations for organizations or institutions. These differences could disrupt data consistency, and evidence of bias may or may not be found in a comprehensive analysis, including group nominations. However, no nomination data are available for the Nobel Prize for Economic Sciences, which began in 1969.

Funding Open Access funding enabled and organized by KAIST.

Declarations

Competing interest The authors received no support from any organization for the submitted work. The authors have no competing interests to declare that are relevant to the content of this article.

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