UNDERSTANDING DISCRIMINATION IN ACADEMIC COLLABORATION NETWORKS

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by

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The undersigned, appointed by the dean of the Graduate School, have examined the thesis entitled

UNDERSTANDING DISCRIMINATION IN
ACADEMIC COLLABORATION NETWORKS

presented by Angela Vasishta,

a candidate for the degree of master of Anthropology,

and hereby certify that, in their opinion, it is worthy of acceptance.

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Professor Karthik Panchanathan

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Professor Rob Walker

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Professor Greg Blomquist

DEDICATION

I dedicate my thesis to my loving family and close friends. I would like to express my sincere gratitude to my dad and mom, David and Jyoti Vasishta, for their unconditional love and encouragement. My best friend and little sister, Ayaana Vasishta, has always been my biggest supporter for which I am also extremely grateful. I would also like to thank my grandparents, Sham S. and Ram Kumari Vasishta, for always offering me sage advice and their continuous encouragement. My family has shown me the value of not only hard work, perseverance, and determination, but of kindness, gratitude, and compassion as well. I could not have done this without them.

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Abstract

Diversity in backgrounds, ideas, and beliefs plays an important role in the scientific research community yet researchers belonging to minority groups are often discriminated against in academic collaborations. Here I replicate game-theoretic models originally described in a 2018 publication by Hannah Rubin and Cailin O'Connor in an attempt to reproduce their findings. Findings from these replicated models followed the same trends reported by Rubin and O’Connor including an increased likelihood of discrimination associated with smaller minority group sizes as well as a decrease in researchers working with out-group partners as a result of discriminatory norms in collaborative research networks. I then build on these base models and their findings to propose future model extensions that will provide insight into both the short-term and long-term impacts of discrimination faced by minority researchers within and beyond collaboration networks.

Keywords: diversity, discrimination, bargaining strategies, academic collaboration, collaboration network, game theory model

Understanding Discrimination in Scientific Collaboration Networks

Coauthorship of scientific manuscripts has gained popularity as reflected by the average number of collaborators on a publication rising across several fields since the early 1900s (Leahey, 2016; Thelwall & Maflahi, 2022), but how do researchers choose these collaborators? Amabile et al. (2001) refer to research collaborations as involving "individuals who differ in notable ways sharing information and working toward a particular purpose." They attribute success in collaboration to factors such as relevant skills, knowledge, and motivation, but highlight diversity in perspectives and knowledge among research team members as one of the most important components of successful collaborations.

The importance of diversity, especially of social identities and beliefs, has been emphasized in numerous other publications as well with greater diversity in research collaborations reported to be associated with greater productivity, higher quality results, more citations, better problem solving, increased creativity, and greater access to expertise, knowledge, and resources (Bukvova, 2010; Freeman & Huang, 2014; Leahey, 2016; Rubin & O'Connor, 2018). Based on these findings, those in established research networks should aim to alter their social network structures to incorporate researchers with varied backgrounds and identities to improve their research (Rubin & O'Connor, 2018), however, discrimination against minorities remains widespread throughout these networks and others like it. For example, women are less likely to hold prestigious first or last author positions across many fields, are less likely to be cited when controlling for relevant variables as compared to men, are less likely to be sole authors of publications, and may put a significant amount of work into manuscripts but be less likely to be granted authorship on them (Haslam et al., 2008; Schneider et al., 2017; Wang et al., 2021).

Examining the reported benefits of diverse collaboration networks in relation to the discrimination minorities face throughout these same networks raises some important questions about the emergence and persistence of discriminatory norms in academic networks. What factors influence diversity within collaboration networks? What are the effects of discrimination in these same collaboration networks? Can discrimination perhaps cause members of different identity groups to work only with others that share their identity in their network thereby decreasing the number of out-group collaborations they take part in within their network? Hannah Rubin and Cailin O'Connor (2018) aimed to gain insight into these three questions by understanding how those belonging to a minority group interacted with majority group members in research networks. Specifically, they modeled how discriminatory norms emerged in fixed collaborative networks, how collaborative networks evolved out of populations already under discriminatory norms, and how discrimination coevolved with collaboration network structure. Here I intend to replicate the models described in their 2018 publication in an effort to reproduce their results, gain a better understanding of the models they have built to study discrimination in academia, and propose extensions to these models that can provide insight into both the short-term and long-term impacts of discrimination faced by minority researchers within and beyond collaboration networks.

Studying Academic Collaboration Networks

There is some debate as to how to study collaboration networks as it can be difficult to operationalize collaboration. Some researchers choose to track co-authorship by analyzing some combination of author names, home institutions, emails, and office addresses to track collaborative connections. Others choose to study the collaborative networks themselves by utilizing different forms of social network analysis and integrating cooperation games to study the evolution of these networks over time. Neither of these methods is perfect as not all collaboration leads to publication, not all co-authored papers come from collaboration, and not all collaborators on a paper are cited as coauthors (Bukvova, 2010). Rubin and O'Connor (2018) chose the latter method of studying collaborative networks by integrating social network model analysis with the Nash demand game, a game theory model, to create a simplified representation of interactions and credit bargaining in research networks.

Simple networks can be created to study collaboration by creating agents, or nodes, which are researchers open to collaborating within an academic community and linking them together through links, or edges, which represent an established collaboration between researchers. When integrating the Nash demand game, agents can use some sort of personal strategy to influence how they interact with others throughout their network. In academic collaboration specifically, Rubin and O'Connor state that two agents, or potential collaborators, can demand a low, medium, or high portion of the credit that is tied to their collaboration from each other. The total credit available to split between collaborators in their models is ten points and collaborative demands must be compatible. This means that medium demands refer to a demand of five points each while the sum of low and high demands must be ten points in total such as a low demand referring to four points and a high demand referring to six points or a low demand referring to three points and a high demand referring to seven points. When demands from collaborators exceed the total number of credit points available, both collaborators receive a poor credit point payoff since they are not able to agree on a division of points.

Rubin and O’Connor argue that the integration of the Nash demand game provides a good substitute for academic collaborations as collaborations create more credit points than individually-created research projects and require joint action and bargaining from both collaborators as they must decide who will do certain tasks, how much work each will put into their project, and how much credit each collaborator will receive which then has important impacts on things like author order (2018). These sorts of demands are well translated into a Nash demand game scenario where agents can bargain resources such as when collaborators bargain and make demands related to the credit they will receive from their joint projects. Specifically, a combination of the way work is divided among collaborators and the credit each gets for their work relates directly to the low, medium, and high demands collaborators can make from one another. If an individual does a majority of the work in a collaborative project and asks for first authorship on the resulting publication they will be making a medium demand of their partner while an individual who does a majority of the work in a collaborative project and asks for second authorship on the resulting publication will be making a low demand of their partner (Rubin & O’Connor, 2018).

Social network formation and the Nash demand game can be combined to study collaboration effectively, however, to analyze the effects of discrimination in these networks, we must also assign each collaborator in the network a specific social identity. As such, each agent is assigned a majority or minority identity label. When agents of the same social identity interact with one another it is considered a within-group interaction while interactions between agents of different social identities are considered a between-group interaction. The Nash demand game assumes that agents use their personal bargaining strategies and behaviors to influence how they interact with others. When studying discrimination we can then assume that collaborators change their strategies and behaviors based on the identity of the researcher they are collaborating with. The social identity labels assigned to minorities, therefore, must be thought of as features of a collaborator that they cannot change that may affect how others interact with them such as their race, gender, or religion (McPherson et al., 2001; Rubin & O'Connor, 2018).

Model Predictions

Applying cultural evolutionary theory to the types of social network models integrated with the Nash demand game as described above can help us understand how discrimination may develop in these models. In the field of biology, a Red King effect "occurs when a speed differential between evolving populations makes it more likely that the evolutionary dynamics carry those populations to an outcome that advantages the slow population." (O'Connor, 2017) In simpler terms, the Red King effect refers to the advantage some species gain as a result of evolving more slowly than others and, therefore, the disadvantage other species can face as a result of learning more quickly.

In cultural evolutionary research, the Red King effect has been shown to affect the evolution of bargaining and resource division norms when a majority and minority group is present in a population (O'Connor, 2017). More specifically, when group sizes in a population are different as they are with majority and minority groups, minority groups will be more likely to face unfair outcomes such as a smaller portion of total resources or discrimination even in the absence of any specific biases against them (Mohseni et al.,

2021) leading to majority group domination (O'Connor, 2017). These outcomes can be due to the size of the groups alone as minority group members are likely to interact with majority group members at a far greater rate than majority group members will interact with minority group members. Due to this differential rate of interaction, minorities may learn how to interact with majority group members more quickly putting them at a disadvantage as predicted by the Red King effect (O'Connor, 2017; Rubin & O'Connor, 2018). These conclusions can be applied to make predictions about the likely outcomes of Rubin and O'Connor's models as well. If minority group members interact with majority group members more frequently and, as a result, learn how to structure these interactions more quickly as well, we may see them become disadvantaged as common bargaining strategies emerge in collaborative networks. Minority researchers that are connected to multiple majority groups researchers, for example, may quickly learn that it is safer for them to make low demands of their majority group partners as it is better for them to receive some credit payoff from their collaborations rather than no credit payoff at all even if it means they are under discriminatory norms. More minority group members adopting the same strategy due to their high rate of interacting with majority group members can lead to this outlook of some credit being better than none becoming the norm in their networks and, therefore, the emergence and persistence of discriminatory norms (Rubin & O'Connor, 2018).

There is a small chance that the opposite effect could also be seen. The Red Queen effect refers to the reversed scenario in which differences in learning speeds can instead create an advantage for the fast-evolving group rather than for the slower learning group (O'Connor, 2017; Rubin & O'Connor, 2018). Under certain conditions, such as differences in underlying strategies, minorities may quickly learn to make high demands of the majority group despite any risk they may face in doing so leading to minority domination (Amadae & Watts, 2022; O’Connor, 2017).

When considering the cultural Red King and Red Queen effect we can begin to make predictions about what we may see as a result of models incorporating social network analysis integrated with the Nash demand game to learn more about discrimination in academic collaboration networks. If each researcher in a collaboration can change their approach to credit demands by modifying the strategies they use based on their collaborator's social group identity, we may be able to observe separate norms emerging in interactions between within-group and outside-group members. When working with members of their own group, agents will be likely to demand medium, or fair, credit from their collaborators. When working with members outside their social group, however, there are three possibilities as to what sort of norms could develop informed partly by the Red King and Red Queen effect. The groups will either make fair demands of one another or one group will learn to consistently make either high demands or low demands from the out-group leading to the development of discriminatory norms where in-group and out-group members are treated differently. Therefore, I am interested in tracking cases of three specific outcomes in my model replications. The first is the majority discrimination outcome, or Red King effect, in which the majority group learns to demand high of the minority while the minority group learns to demand low of the majority. The second is the minority discrimination outcome, or Red Queen effect, in which the minority group learns to demand high of the majority while the majority group learns to demand low of the minority. The final outcome of interest is the fair division outcome in which both groups learn to demand medium credit from one another (Rubin & O’Connor, 2018).

Model One

Purpose

Model one of the Rubin and O’Connor (2018) publication focuses on understanding the emergence of discriminatory norms in fixed collaboration networks. Understanding how network structure affects the evolution of discriminatory norms over time is important as researchers could potentially be disadvantaged simply because of the proportion of the research network their social identity group takes up. In this model, the collaboration network of each researcher is fixed but they are able to update their bargaining strategies throughout the model run.

Method

The model begins with twenty, forty, sixty, eighty, or one hundred agents (researchers) that are assigned to either the majority or minority social group based on the proportion of the population that is set to be labeled as a minority (ten, twenty, thirty, forty, or fifty percent of the total population). Each agent is also randomly assigned two strategies that will influence how they interact with their collaborators by shaping the demands they make of others. Their first strategy, their in-group strategy, affects the demands they will make of collaborators in their own identity group (either high, fair, or low). Their second strategy, their out-group strategy, affects the demands they will make of collaborators outside their own identity group (either high, fair, or low). In this model, medium (fair) demands always correlate to five credit points. High demands correlate to a demand of six credit points with the associated low demand being four, therefore all researchers that demand high of their collaborator will ask for six credit points while all researchers that demand low of their collaborator will ask for four.

After giving researchers a social identity and their in-group and out-group strategies, a fixed collaboration network is created for each meaning that the agent's network remains the same throughout the entire run of the model. It is assumed that all connected researchers are collaborating on projects throughout the model's run. Each researcher has a set probability of forming a collaboration link with others in their overall population group based on their social identity. Each has a forty percent chance of forming a link to a researcher in their own social group. Their probability of forming a link to a researcher that is outside their own social group, however, differs ranging between a probability of twenty percent to eighty percent, increasing in increments of ten percent. Although specifics are not given as to why a probability of 0.4 was chosen to represent the likelihood of connecting with an in-group member, Rubin and O'Connor (2018) do state that the range of probabilities for connecting with out-group members (0.2 to 0.8) represent a range of possibilities for a minority group member to potentially collaborate with the majority group. More specifically, the range covers a minority member being twice as likely to collaborate with other minorities to a minority member being twice as likely to collaborate with majority members. When the probability of a researcher connecting to an in-group member exceeds the probability of them connecting to an out-group member, they are said to exhibit homophily. Homophily describes how "contact between similar people occurs at a higher rate than among dissimilar people." (McPherson et al., 2001). In this model specifically, homophily refers to the tendency of researchers to form links and associate with members of their own identity group (Ertug et al., 2022; Rubin & O'Connor, 2018).

Each combination of parameters listed above was run one hundred times with each simulation running for 1,000 time steps. After the researcher's collaborative network and strategies are established as outlined previously, researchers were asked to interact with all of their links, or connected collaborators, at each time step. Each collaborator has a ten percent chance of updating their bargaining strategies at each step. Specifics as to why a probability of 0.1 was assigned to updating strategies were not given in the original publication. Producing research through collaborations, however, takes time. Perhaps we can assume that an agent updating their strategy correlates to them having finished a project and discussed the proper split of credit for it (as discussed earlier, demands made by a researcher are related to the amount of work they put into the project and the credit they will receive for it through proxies like author order). They can then use what occurred in this collaboration, such as a fair or unfair payoff, to inform how they will update their strategies. As such, 0.1 could have been picked as the update probability simply because it reflects the time it may take to finish collaborative research projects and get useful results from them to inform future bargaining strategies.

To update their strategies, researchers use the myopic best response method by calculating which strategy (high, fair, or low) would have given them the best total payoff from their collaborations in the current round in order to update their strategies for the next round. Researchers must update both their in-group and out-group strategies. To do so, they must determine what total payoff they will receive from all of their current in-group collaborators based on their assigned in-group bargaining strategy as well as the total payoff they will receive from all of their current out-group collaborators based on their assigned out-group bargaining strategy. They can then perform the same calculation for each strategy they are not assigned to see if either of those strategies would have given them a better total payoff in that round against in-group members or out-group members. For example, if a researcher that was assigned the fair strategy for in-group members and the high strategy for out-group members was chosen to update their strategy, they would first determine the total credit payoff they would receive from collaborating with all of their in-group members with their assigned fair strategy (demanding five of each in-group partner). If any of their in-group partners demanded high from them then they would both receive a payoff of zero since they have demanded over the total credit available. If any of their connected in-group collaborators demanded low or medium then the researcher would receive some payoff from each that they would then sum together. The researcher would then perform the same calculations using the two in-group strategies that they are not assigned (high and low) to determine the total credit payoff they would receive from collaborators based on demands from both. If the total credit payoff from either the high or low strategy is higher than the researcher's total credit payoff from their current fair in-group strategy, they will switch to the highest total payoff strategy for the next rounds until they are asked to update their strategy again. The same calculations will then be performed by the researcher for their out-group connections to determine which strategy would have given them the best possible payoff. The Rubin and O'Connor (2018) publication does not specify what happens if there is a tie between total credit payoffs from different strategies. In the rare event that payoffs are tied, this replication model picks whichever strategy is listed first in the outcome results.

Ultimately, researchers are trying to choose a strategy that will get them the most credit payoff from a successful collaboration as opposed to a poor credit payoff from a failed collaboration, one in which both collaborators are overdemanding resources (Rubin & O'Connor, 2018).

Results and Discussion

As mentioned previously, the three outcomes of interest are the majority group discriminating against the minority group, the minority group discriminating against the majority group, and fair division. To measure these, Rubin and O'Connor look for population convergence during each simulation run. Population convergence here refers to when populations have reached a particular norm when interacting with in-group members and a norm when interacting with out-group members. Under these norms, one bargaining strategy is more frequent than the others and reflects how researchers will likely behave when interacting with an in-group member or an out-group member of their collaboration network. Majority group discrimination against the minority group would be indicated by most majority group members demanding high from their minority collaborators at the end of the simulation run. Minority group discrimination against the majority group would be indicated by most minority group members demanding high from their majority collaborators at the end of the simulation run. Fair division between groups would be indicated by most group members demanding fair from their out-group collaborators at the end of the simulation run.

Examining the bargaining strategies each group settles on when interacting with in-group members and out-group members at the end of each run yields interesting results. When looking at in-group connections across all parameter combinations, both the majority and minority groups arrive at a norm of fair distribution with a large portion of each group evolving to demand fair credit from their in-group collaborators as did the groups reported on by Rubin and O'Connor (2018). When looking at out-group connections, groups typically also arrive at a norm of fair division with nearly sixty percent of both minorities and majorities demanding fair credit from one another across all parameter combinations. Notably, however, majority groups were also likely to demand high credit payoffs from minorities. These results support the trends reported by Rubin and O'Connor (2018) with between-group collaborations most often resulting in fair division but also evolving to a norm of discrimination a significant number of times.

Since majority discrimination was observed in between-group collaborations, we can also analyze the effect of minority group size on the level of discrimination faced by minority researchers. As found by Rubin and O'Connor (2018), the simulations run here indicate that as the minority group grows smaller, the level of discrimination faced by them grows larger as shown in **Figure 1**. As such, majority group members are more likely to demand high credit from minority collaborators when there are fewer minority members total in the population. As the minority group grows larger, majority collaborators are more likely to demand fair credit from them. As discussed with the Red King and Red Queen effect, the difference in the level of interaction with out-group members that minority members have with majority members likely affects how quickly they learn how to structure their future interactions. Each minority member, on average, will be connected to more majority collaborators than each majority member will be connected to minority collaborators due to the size of the minority group in relation to the

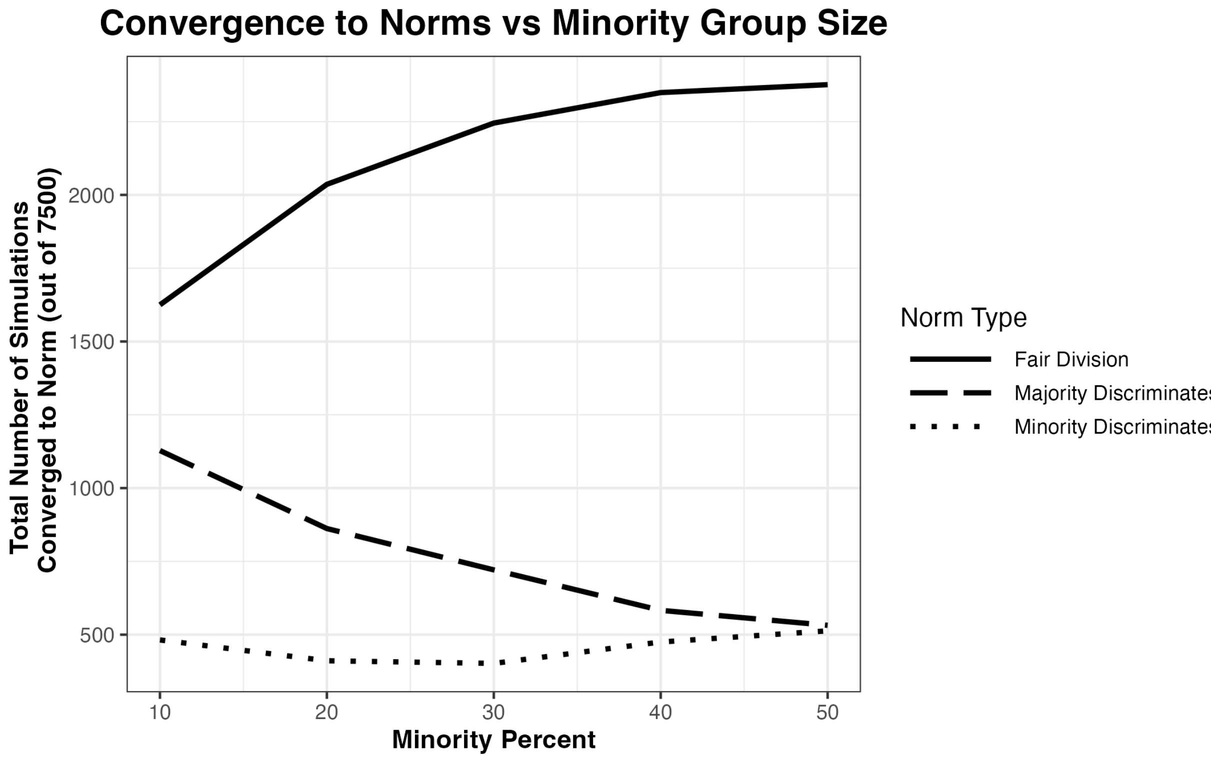

Figure 1. Convergence to norms as a function of the total proportion of the population that is composed of minority group members. The vertical axis reflects the total number of simulations out of 7,500 (at each minority percentage level) that were determined to have converged to either a norm of fair division (solid line), majority discrimination against minority (dashed line), or minority discrimination against majority (dotted line). As the proportion of minority members in the population grows, majority discrimination decreases while fair demands from the majority group increase.

total population. Minority group members will therefore learn more quickly due to their increased rate of interaction with majority group members. Finally, levels of homophily do not seem to relate to how likely either group is to discriminate since in-group and out-group strategies are updated separately independent of how likely researchers are to connect and collaborate with a member of their own social group as also reported by Rubin and O’Connor (2018).

Model Two

Purpose

Model two of the Rubin and O'Connor (2018) publication focuses on exploring how collaboration networks emerge and evolve when discriminatory norms are already in place within the population. Previous research has indicated that discriminatory norms in academic communities can lead to reduced collaboration, or increased homophily, between social identity groups within them. In this model, the collaboration networks of each researcher update and evolve throughout the model run but each researcher's bargaining strategies remain the same to understand how minority and majority group members grow and evolve their collaboration networks when discriminatory norms are in place.

Method

The model begins with ten, twenty, forty, sixty, eighty, or one hundred agents (researchers) that are assigned to either the majority or minority social group based on the proportion of the population that is set to be labeled as a minority (five, ten, twenty, thirty, forty, or fifty percent of the total population). It is not clear why additional parameter values were added to this simulation in the Rubin and O'Connor (2018) publication such as five percent of the population being a minority or ten agents total in the run. Since discriminatory norms are already in place within this simulation, each majority group member is assigned to automatically demand six credits when interacting with out-group members. As such, each minority group member is assigned to automatically demand four credits when interacting with out-group members. Any interactions that take place within groups are automatically assigned a credit payoff of five points, or the results of a fair demand.

Simulations are started with all researchers having no links to any of the researchers in their communities and, therefore, no pre-existing collaboration network. Each researcher has a maximum number of links they can form with other researchers in the population to reflect the limited number of collaborations they can reasonably be engaged in at once. The maximum number of collaboration links they can form is either three, ten, or twenty throughout the run depending on the combination of parameters being examined. If the specific parameter combination resulted in there not being enough minority members for the total number of maximum links to be formed between minority researchers, that specific combination of parameters was discarded. All combinations of parameters were run one hundred times.

At each of the 10,000 time steps, two researchers from the population are randomly selected. The first researcher is tasked with either forming a linkage (collaborating) or breaking a linkage (no longer collaborating) with the second who is a potential collaborator based on the payoff they would receive when bargaining with them for credit. Both researchers must agree to collaborate for a link to form but only one of the two researchers is needed to decide to break a linkage and end a collaboration. If both researchers are not yet connected and are not at maximum links, they form a link and collaborate as some payoff is better than none for both. If both researchers are not yet connected but one is at maximum links, they will break a link (end a collaboration) with a current collaborator that provides them with a lower credit payoff than their new, potential collaborator. For example, if researcher A, a minority member with all possible links connected to majority group members, and researcher B, a minority group member with only one link to a majority group member, are randomly selected to update connections, researcher A will randomly drop one of their majority group connections from which they receive a payoff of four and instead add researcher B to their collaboration network from which they will receive a payoff of five. A minority member would prefer to work with another minority group member over a majority group member. A majority member would prefer to work with a minority group member for the highest possible payoff of six but could choose to work with another majority group member for a fair payoff of five as well. If both chosen collaborators are at maximum links then both must benefit from the potential collaboration by receiving a higher payoff from their new partner than one of their already existing partners to form a new collaboration link.

Results and Discussion

In this model, we are particularly interested in how minority and majority group members form and evolve their personal collaborative networks, or the development of homophily, under fixed discriminatory norms. To understand the development of homophily we must track the number and type of linkages formed in total at each time step of the model to map the evolution of collaborative networks for both minority and majority group members. As reported by Rubin and O'Connor (2018), the number of between-group links rises slightly at the beginning of model runs due to the random nature of linkages as researchers are not picky about their collaborators and credit payoffs until their research networks have filled to maximum size. Once maximum links are reached, within-group links begin to increase for both social groups as researchers,

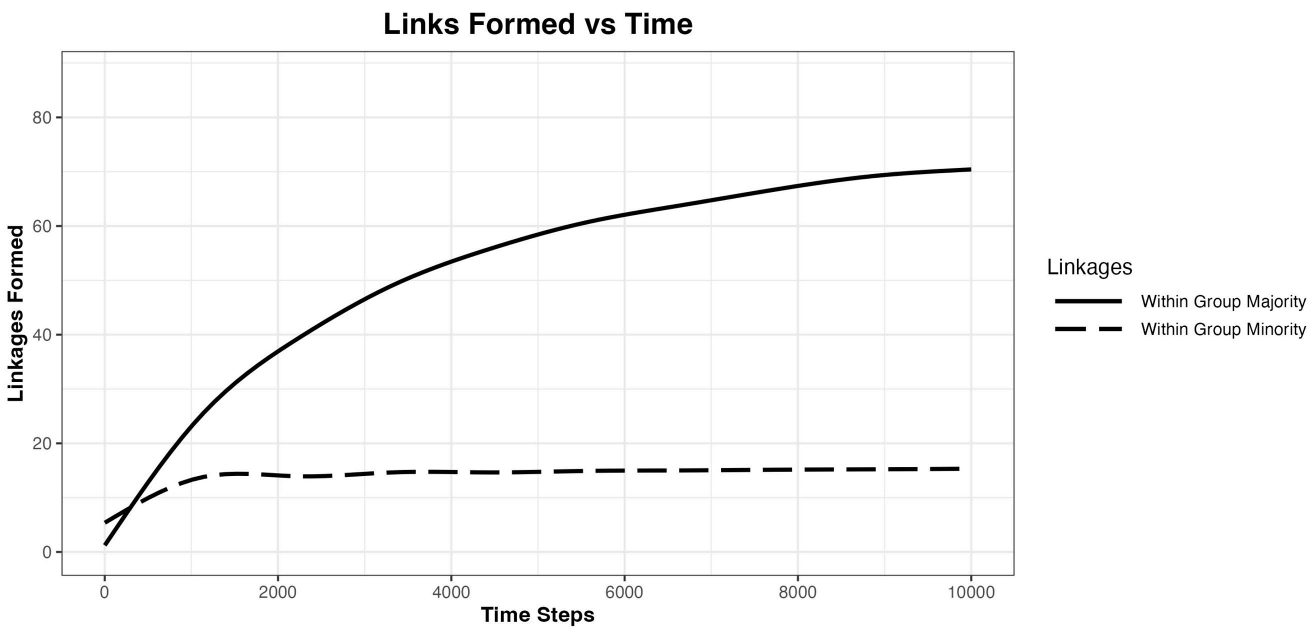

Figure 2. Total number of within-group majority (solid line) and within-group minority (dashed line) linkages over time in a simulation with one hundred individuals, forty percent minority group proportion, and three maximum linkages each. As time increases the number of within-group majority and within-group minority linkages increases while between-group linkages decrease.

particularly minority researchers, begin weighing the payoffs they will receive from new potential collaborators as compared to their current collaborators. As within-group links increase over runs of the model there is a correlated decrease in the number of between-group links over time. This increase in within-group links in both social groups, and the associated decrease in between-group links, is plotted for a randomly selected run in **Figure 2**. Ultimately, under discriminatory norms, researchers seem to form collaborative networks that evolve to mainly include members belonging to their own social identity group in an effort to avoid discrimination representing an overall increase in homophily in these populations.

Model Three

Purpose

Model three of the Rubin and O'Connor (2018) publication joins models one and two to explore the coevolution of discrimination and collaboration networks. Specifically, this model examines how agents' bargaining strategies evolve jointly with the structure of their collaborative research network.

Method

Model three joins the bargaining strategy updating component of model one with the collaboration network updating component of model two. An empty network of one hundred agents is created as described in model two with ten to fifty percent (increasing in increments of five percent) of the total population assigned a minority label. Each researcher is also randomly assigned an in-group and out-group bargaining strategy as in model one. The model runs for 20,000 time steps with each parameter combination replicated one hundred times. At each time step, there is a ten percent chance that each agent will perform an update. If meeting the ten percent updating probability, the researcher then has either an eighty percent chance of updating their bargaining strategy through myopic best response as described in model one or a twenty percent chance of updating their collaborators in their research network as described in model two (but with either three or nine maximum linkages instead). There is no indication as to why these probabilities specifically were chosen or why the number of maximum linkages changes between model two and model three in the Rubin and O'Connor (2018) publication.

Results and Discussion

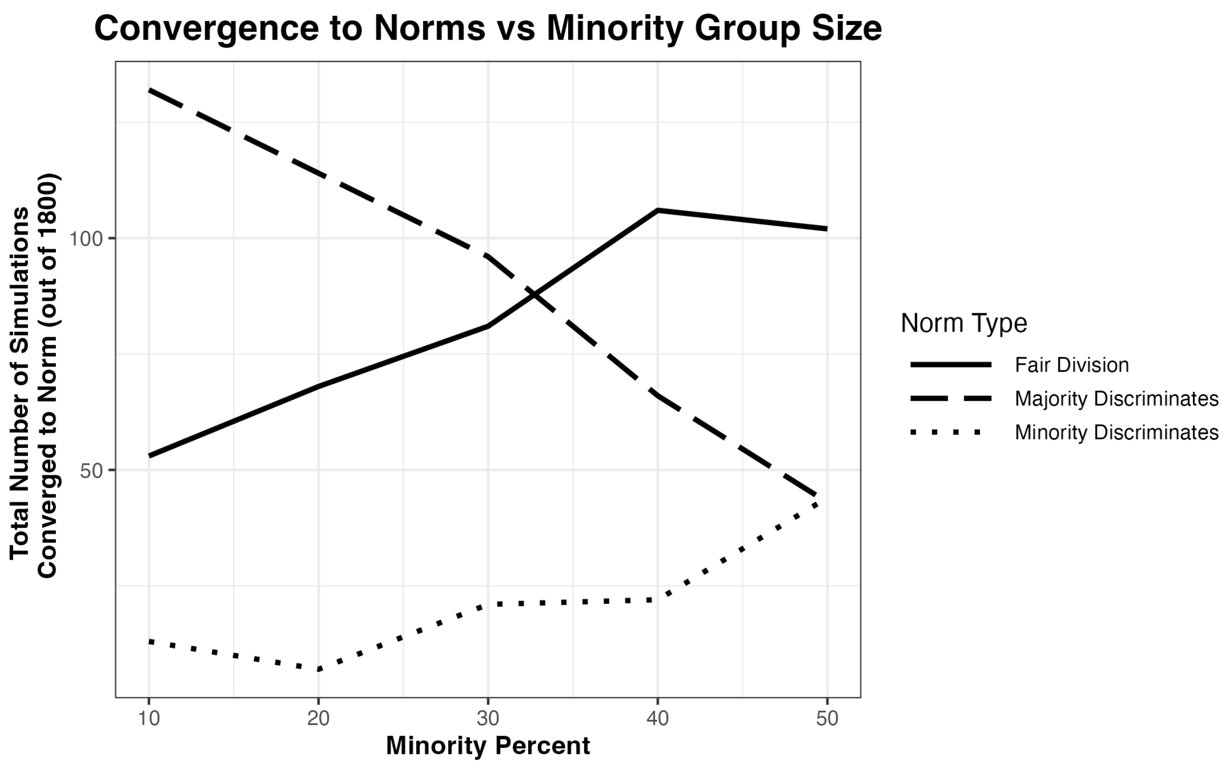

Figure 3. Convergence to norms as a function of the total proportion of the population that is composed of minority group members. The vertical axis reflects the total number of simulations out of 1,800 (at each minority percentage level) that were determined to have converged to either a norm of fair division (solid line), majority discrimination against minority (dashed line), or minority discrimination against majority (dotted line). Generally, as the proportion of minority members in the population increases, majority discrimination decreases while fair demands of the minority group from the majority group increase. Results, however, are more varied and random than those obtained from model one.

As this model is a combination of the two before it, the same outcomes are measured to analyze the evolution of discriminatory norms (number of majority group results contained far more variation than those seen in model one. Majority groups were almost equally as likely to demand fair credit and high credit from minority group collaborators across all parameter combinations. Minority group members were far more likely to demand high credit or, at a slightly smaller rate, fair credit division from their majority collaborators across all parameter combinations. Separating results based on the percentage of minority researchers in the total population provided a somewhat better understanding of the effect of minority group size on the coevolution of discriminatory norms and collaboration networks. As shown in **Figure 3** and the results from model one, as minority group size decreases, majority members are more likely to demand high credit and less likely to demand fair credit division of their minority collaborators. From this, we can conclude that as the minority group size increases it is less likely that the majority group will discriminate against them.

When integrating levels of homophily into these results, there is more variance and randomness in the results than seen in previous models likely because most runs of this model do not show full segregation of social identity groups or complete convergence of norms as did previous models. Generally, as discrimination increases homophily increases as well as is implied by results from model two. Overall, as discussed by Rubin and O'Connor (2018), results from this model fall on a continuum between two extremes with one of these extremes being a norm of fair division in the overall population with no associated homophily and the other extreme being a norm of discrimination in the overall population with entirely segregated social identity networks indicating great levels of homophily. Most runs of this model result in partially segregated networks between these two extremes with most majority group members upholding a discriminatory credit division norm due to the nature of updating bargaining strategies while also rearranging collaborative connections.

Conclusion and General Discussion

Rubin and O'Connor (2018) integrate game theory models with network analysis to study the evolution of discrimination and collaboration in research networks. All results returned from these model replications mirror those reported by Rubin and O'Connor (2018) with smaller minority groups being more likely to be discriminated against in collaboration networks and discrimination leading to greater homophily in overall network populations causing minorities to collaborate more frequently with other minority group members rather than with majority group members. Increased levels of homophily can limit the spread and reception of information (McPherson et al., 2001), lead to the spread of redundant knowledge in networks, and generally decrease opportunities for joint knowledge production (de Miranda Grochocki & Cabello, 2023). Researchers studying patterns of coauthorship across several fields have also reported increased homophily to be associated with publication in lower-impact journals and fewer citations as fewer eyes may fall on the publication due to a less diverse collaboration network to share it with (Freeman & Huang, 2014). With limited diversity in collaborative research networks, researchers lose valuable access to other knowledge experts, resources, information exchange, improved problem-solving, higher productivity, better quality results, and more citations (Bukvova, 2010; Freeman & Huang, 2014; Leahey, 2016; Rubin & O'Connor, 2018). To increase the quality, quantity, and efficiency of knowledge production in academic communities (Coccia & Wang, 2016; Rubin & O'Connor, 2018) it is vital for us to further examine the emergence and persistence of discriminatory norms in collaboration networks and their effects.

Limitations

While results from this replication mirror those produced by Rubin and O'Connor (2018) there may be issues in the replication of their models here as it is unclear if the models were translated into code for this replication in the same way the original models were written based on limited descriptions of them from the original publication. Parameter ranges, submodel descriptions, and overall function descriptions for each model were scattered throughout sections dedicated to each model making it difficult to gather information on their code structure. This meant that a few factors that could minorly affect model outcomes (such as what to do in the event of payoff ties) had to be added through a best guess as to what may have been implemented in the original models. It is unclear why parameter ranges changed throughout the three models as highlighted several times throughout the model descriptions above. It would be beneficial to know why parameter ranges varied throughout the original publication as well as how probabilities were chosen for events such as strategy and collaboration updates. These models could also possibly benefit from larger parameter ranges such as more timesteps for longer individual model runs and greater total group sizes. The former would provide a greater overview of network evolution patterns while the latter could increase the realism or applicability of these models to real-world collaboration networks. These models are clearly meant to be a basic representation of bargaining in academic communities to study the evolution of discrimination and collaboration networks. As such, I will end discussion on this publication by proposing model extensions that can extend the usage of these models to help us better understand the impacts of discrimination in academia on minorities as well as allow us to increase the applicability of these models to real-world academic collaboration networks by making them more sophisticated.

Model Extensions and Future Directions

As mentioned, these models were created with the purpose of providing a simple way to represent and track the evolution of discrimination and collaboration in academic networks. It may, however, be unrealistic to expect researchers to enter collaboration networks and randomly choose a strategy for how they will interact and collaborate with in-group members and out-group members. Similarly, it is unlikely that researchers will choose collaborators at random within an established academic population. As such, researchers having no prior information about the network they are entering into or access to any other form of information that may be useful to them once embedded within the network seems to be an unrealistic expectation across the described models. Future models could allow researchers within collaborative networks to have access to information that will allow them to determine who it would be useful and beneficial to work with and what sort of credit demand they should expect from a potential collaborator.

Researchers are more likely to work with other researchers that they share common collaborators with (Newman, 2001). Building on this knowledge, one way of providing useful collaboration information to researchers would be by allowing for the direct or indirect exchange of information through trusted current collaborators, or collaborators whom researchers have built a strong working relationship with. Researchers could perhaps indirectly pick up information from those they are connected to by observing factors related to the success of their collaborations with others. For example, instead of utilizing myopic best response as a way to update strategies, researchers could instead apply replicator dynamics by imitating the strategies of their connections that they know have led to maximized payoffs and successful participation in collaborations (O’Connor & Bruner, 2019). Such information would allow researchers to gain knowledge about how the people they are interested in collaborating with may behave in future interactions based on past ones with common connections. Connected, trusted collaborators could also provide information about the reputation and trustworthiness of others they have worked with directly to inform the researcher if they may be taken advantage of or discriminated against in a future collaboration. Simply increasing the amount of information available to a researcher to assist them in determining if they would still like to connect with a specific researcher or in choosing the strategy they may use when dividing credit with them can add realism to these models.

Relating to collaboration and coauthorship, perhaps it could be useful to allow researchers to choose to work alone on a project in these models as well. A multitude of factors can influence a researcher wanting to work alone on a publication as opposed to seeking out a team of researchers to work with including the relative age of their field and the number of knowledge gaps present in it. In relatively new fields with many knowledge gaps, there are many new research questions to answer constantly as well as new approaches to be developed. In these fields, researchers typically do not need to consult with specialized collaborators to answer questions of interest and, as such, are more likely to work alone. On the contrary, in relatively old fields with fewer knowledge gaps, there are fewer basic, structural research questions left to answer and fewer innovative approaches waiting to be developed. Instead, researchers in these fields will likely focus on the practical applications of already discovered information and how foundational principles can be joined to promote new discoveries. These researchers are more in need of specialized collaborators to reach their goals and are, therefore, more likely to want to collaborate with others (Jansen et al., 2010). When considering the factors that may drive a researcher to want to work alone, it is possible that discrimination in collaboration could be involved as well. If a minority group member is constantly taken advantage of in their collaborative network, could the payoff from an individual project be great enough for them to avoid working with others even with the potential drawbacks of attempting to research and publish alone? Could research networks evolve to have a significant number of minority individuals choosing to work alone on research projects under certain conditions?

As hinted at above, there seems to be no universal model of scientific production that drives research in all fields, instead, different fields generate knowledge in different ways. If researchers in certain fields are more likely to work alone based on the maturity of their field and the knowledge gaps present in them (Jansen et al., 2010) and the average number of coauthors on publications differs across fields as well (Thelwall & Maflahi, 2022), the evolution of discrimination and collaboration should also be expected to look different across fields of study. Ultimately, the production of new knowledge in different fields is driven by the structure of their research networks. Collaboration networks intended to reflect those existing in the real world should be expected to differ in structure unlike those modeled in this paper. Analyses of different fields have produced valuable data related to common collaboration structures within them. This data, such as the average number of collaborators on publications from the field or proportion of minority members estimated to be present in the total population of the field, can be applied to the models replicated here to better reflect actual network structures within specific fields providing more realistic data about the evolution of discriminatory norms and collaboration within them. Perhaps networks in certain fields are more likely to reach and maintain a norm of fair division while others are more likely to exhibit greater levels of homophily leading to lower diversity in collaboration due to their typical setup.

Another important factor that can increase the sophistication of these models allowing them to mirror real-world networks better and provide greater insight into discriminatory norm development and the evolution of collaboration is the introduction of a metapopulation or a hierarchical population network structure. In real-world academic structures, networks contain many nested clusters including college or university level clusters, department level clusters within each university, and clusters of researchers at certain points in their academic careers within those departments. The addition of hierarchical clusters and interaction dynamics between and within clusters could also lead to hierarchical credit totals in which the position an agent holds within a network correlates to the power they have and, therefore, the total credit points they produce (Rubin & O'Connor, 2018). Important members of scientific collaboration networks are those that are more central within their network. They tend to be those further in their career that have been productive in the past, have funding available to use, have important and influential connections to others in the network, and are good at connecting available researchers for collaboration. They also tend to produce work that is of high quality (Ebadi & Schiffauerova, 2015). As such, differential power or weight within a research network could mean that those in more prestigious or influential positions create projects that are worth more in total than those at lower, less prestigious, or less influential positions within the same network.

When considering the dynamics of a hierarchical collaboration structure, a minority group member may choose to work with an important member of one of their network clusters that belongs to the majority group upholding discriminatory norms over an in-group member leading to a shift in the dynamics seen under the models replicated here. This is because the minority group member would likely receive a greater total credit payoff after a high discriminatory demand from an important, influential, or prestigious majority group collaborator who will produce a greater total credit from their project than from a fair demand from an in-group member. In simpler terms, the total number of credit points generated as a result of working with the important majority group member is greater than the total number of credit points generated when working with another minority researcher (Rubin & O'Connor, 2018). The share or proportion of the total credit the researcher would receive from demanding low from the important majority group member would be greater than what they would receive from working with another minority group member fairly. Working with the well-established, high-reputation majority group member could also open the door for collaborations with other influential members of the community or researchers in a distant, neighboring field that the majority researcher is also connected to (Ebadi & Schiffauerova, 2015) providing further benefits to a minority group member in a population under discriminatory norms. Introducing weighted nodes or hierarchical clusters within groups could fundamentally alter the dynamics recorded and reported in the models replicated here.

Finally, these base models could be extended to go beyond just studying the emergence and persistence of discrimination within academic collaboration networks and could even be used to trace the advancement of those belonging to a minority group in their research and the long-term impacts discriminatory norms may have on their career progression. Discrimination against minorities in academia can lead to the loss of opportunities necessary to career advancement with minority researchers being more likely to receive inadequate training related to pursuing grants, facing more barriers in their progress towards becoming independent researchers, receiving inadequate mentorship throughout the development of their career as researchers, and being less likely to receive NIH and NSF grant funding (Chen et al., 2022; Shavers et al., 2005). Factors such as these can be modeled into simulations similar to those replicated here to better understand how obstacles often unique to minority researchers can prevent them from progressing in their careers. Similar models can also be used, however, to understand the effects of interventions intended to reduce discrimination across academia as well. With what we have learned with the models replicated here and what we can learn in the future using extensions of these models like those discussed in this section, how can we help minority researchers avoid discrimination and potentially even reverse discriminatory norms that have emerged in many collaboration networks?

Unfortunately, reversing discriminatory norms may not be easy. Previous research has indicated that interventions that seem beneficial at the surface level to increase diversity and limit discrimination may actually have an effect reverse of what was intended or have unintended consequences instead (Schneider et al., 2017). For example, from models two and three of this replication, we learn that minority group members prefer to work with other minority group members when discriminatory norms are in place in their overall networks, indicating increased homophily. Using models integrating network analysis and the Nash demand game like those replicated above have allowed us to see that increasing the number of grants available specifically for projects that involve diverse collaborations decreases homophily levels temporarily. However, with existing discriminatory norms in place within the network, majority group members will still demand high credit from their minority group collaborators. As such, while diversity in collaborations increases temporarily under this grant initiative, minority group members still do not receive a portion of credit proportional to their work in the collaboration. Discrimination still exists even if homophily decreases temporarily in this scenario (Schneider et al., 2017). It is important to model the possible effects of initiatives aiming to increase diversity and decrease discrimination with models such as the ones replicated here before putting them into effect in real-world collaboration networks.

References

Amabile, T. M., Patterson, C., Mueller, J., Wojcik, T., Odomirok, P. W., Marsh, M., & Kramer, S. J. (2001). Academic-practitioner collaboration in management research: A case of cross-profession collaboration. Academy of management journal, 44(2), 418-431.

Amadae, S. M., & Watts, C. J. (2022). Red Queen and Red King Effects in cultural agent-based modeling: Hawk Dove Binary and Systemic Discrimination. The Journal of Mathematical Sociology, 1-28.

Bukvova, H. (2010). Studying research collaboration: A literature review.

Chen, C. Y., Kahanamoku, S. S., Tripati, A., Alegado, R. A., Morris, V. R., Andrade, K., & Hosbey, J. (2022). Systemic racial disparities in funding rates at the National Science Foundation. Elife, 11, e83071.

Coccia, M., & Wang, L. (2016). Evolution and convergence of the patterns of international scientific collaboration. Proceedings of the National Academy of Sciences, 113(8), 2057-2061.

de Miranda Grochocki, L. F., & Cabello, A. F. (2023). Research collaboration networks in maturing academic environments. Scientometrics, 128(4), 2535-2556.

Ebadi, A., & Schiffauerova, A. (2015). How to become an important player in scientific collaboration networks?. Journal of Informetrics, 9(4), 809-825.

Ertug, G., Brennecke, J., Kovacs, B., & Zou, T. (2022). What does homophily do? A review of the consequences of homophily. Academy of Management Annals, 16(1), 38-69.

Freeman, R. B., & Huang, W. (2014). Collaboration: Strength in diversity. Nature, 513(7518), 305-305.

Haslam, N., Ban, L., Kaufmann, L., Loughnan, S., Peters, K., Whelan, J., & Wilson, S. (2008). What makes an article influential? Predicting impact in social and personality psychology. Scientometrics, 76(1), 169-185.

Jansen, D., Von Goertz, R., & Heidler, R. (2010). Knowledge production and the structure of collaboration networks in two scientific fields. Scientometrics, 83(1), 219-241.

Leahey, E. (2016). From sole investigator to team scientist: Trends in the practice and study of research collaboration. Annual review of sociology, 42, 81-100.

McPherson, M., Smith-Lovin, L., & Cook, J. M. (2001). Birds of a feather: Homophily in social networks. Annual review of sociology, 27(1), 415-444.

Mohseni, A., O'Connor, C., & Rubin, H. (2021). On the emergence of minority disadvantage: testing the cultural Red King hypothesis. Synthese, 198, 5599-5621

Newman, M. E. (2001). The structure of scientific collaboration networks. Proceedings of the national academy of sciences, 98(2), 404-409.

Newman, M. E. (2004). Coauthorship networks and patterns of scientific collaboration. Proceedings of the national academy of sciences, 101(suppl_1), 5200-5205.

O'Connor, C. (2017). The cultural red king effect. The Journal of Mathematical Sociology, 41(3), 155-171.

O'Connor, C., & Bruner, J. (2019). Dynamics and diversity in epistemic communities. Erkenntnis, 84, 101-119.

Rubin, H., & O'Connor, C. (2018). Discrimination and collaboration in science. Philosophy of Science, 85(3), 380-402.

Schneider, M. D., Rubin, H., & O'Connor, C. (2017). Promoting diverse collaborations. Working paper. https://www. academia. edu/34240685/Promoting_Diverse_Collaborations _working_paper.

Shavers, V. L., Fagan, P., Lawrence, D., McCaskill-Stevens, W., McDonald, P., Browne, D., ... & Trimble, E. (2005). Barriers to racial/ethnic minority application and competition for NIH research funding. Journal of the National Medical Association, 97(8), 1063.

Thelwall, M., & Maflahi, N. (2022). Research coauthorship 1900–2020: Continuous, universal, and ongoing expansion. Quantitative Science Studies, 3(2), 331-344.

Wang, X., Dworkin, J. D., Zhou, D., Stiso, J., Falk, E. B., Bassett, D. S., ... & Lydon-Staley, D. M. (2021). Gendered citation practices in the field of communication. Annals of the International Communication Association, 45(2), 134-153.