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The Power of Rank Information

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People, organizations, and products are continuously ranked. The explosion of data has made it easy to rank everything, and, increasingly, outlets for information try to reduce information loads by providing rankings. In the present research, we find that rank information exerts a strong effect on decision making over and above the underlying information it summarizes. For example, when multiple options are presented with ratings alone (e.g., "9.7" vs. "9.5") versus with ratings and corresponding ranks (e.g., "9.7" and "1st" vs. "9.5" and "2nd"), the presence of rank information increases preference for the top ranked option. This effect of ranking is found in a variety of contexts, ranging from award decisions in a professional sports league to hiring decisions to consumer choices, and it is independent of other well-known effects (such as the effect of sorting). We find that the influence of ranks is explained by the extent to which decision makers attend to the top ranked option and overlook the other options when they are given rank information. Because they invest a disproportionate amount of attention to the top ranked option when they are given rank information, decision makers tend to learn the strength of the top ranked option, but they fail to process the strengths of the other options. We discuss how rank information may operate as one of the processes by which those at the top of the hierarchy maintain a disproportionate level of popularity in the market.

Keywords: rank information, ranking, decisions, preference, choice

Online and digital transformation has presented decision makers with a vast amount of information on countless topics, and decision makers are in need of tools that can effectively organize the overabundant information. A number of distinct solutions have emerged to help people address this challenge (e.g., Häubl & Trifts, 2000; Kramer, 2007). One highly popular approach among them is providing rank information based on a specific attribute or metric (Koning & van der Wiel, 2013; Monks & Ehrenberg, 1999; Pope, 2009). Because of its usefulness in simplifying choice, rankings are widely used in a variety of contexts such as websites that list information about products (e.g., "Best SUVs and Crossovers of 2020" by Car and Driver), businesses (e.g., "Best Italian Restaurants in New York City" on TripAdvisor), and organizations (e.g., "Best Global Universities Rankings" on U.S. News).[1]

Research in several fields has examined the effect of rank information. In particular, research has examined how people react to and process information when they *themselves* are ranked (Brown et al., 1996; Charness et al., 2014; Chevalier & Ellison, 1997; Garcia & Tor, 2007; Gill et al., 2019; Vriend et al., 2016) and how they attempt to strategically use such information (Luca & Smith, 2015; Monks & Ehrenberg, 1999). In contrast, the effect of ranking on how people evaluate external options and decide among them remains relatively unexplored. An exception is Koning and van der Wiel's work (2013), which found that Dutch students' school choice was significantly affected by ranking. However, rank information in this work was the only information available for the school's academic quality, meaning that people had to rely on the rank information to assess the academic quality of the schools. In this setting, it is impossible to test the effects of ranking over and above the raw information about targets' quality. Pope's work (2009) on American hospitals accounted for this issue by examining a situation in which patients had the raw information about the targets' quality as well as the ranks. However, its analysis addressed the effect of a *change* in rankings instead of how the options' specific rankings (e.g., 1st or 3rd) influenced patient choice at a given moment.

To fill the gap in the literature, the present research isolates the unique influence of ranking, testing its effect over and above the attribute that underlies the ranking. For example, two basketball players might be ranked 1st and 2nd in average points scored per game, which might be 28.4 and 28.1. In an initial study using field data, we study the effect of rankings (1st and 2nd) on choice while controlling for scores per game (28.4 and 28.1) to test the effect of

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[1] Often times, these ranking processes not only perform *ranking* but also *selection* (e.g., "Top *10* Italian Restaurants in New York City"). In the present research, we focus on the ranking in isolation for two main reasons. First, selection is neither a necessary nor a sufficient condition for ranking; ranking can be used with or without selection. Second, the effect of selection has been investigated in prior research on other topics (e.g., recommendation systems).

rank information. In the remaining experimental studies, we test the effect of rankings on choice by providing identical information about each options' underlying attributes in a ranking condition and a control condition. The only feature that we add in the ranking condition is the rank information based on one of the attributes. Because such rankings are simple translations of the underlying attribute, they do not provide additional information regarding the targets' characteristics. Although the rank information can thus be viewed uninformative from a normative perspective, our findings overall show that rank information significantly increases decision makers' preference for the best option in the ranked attribute—*the top ranked option*. This holds when ranks are assigned based on a single attribute (e.g., quality) or when ranks are assigned based on a composite attribute across many (e.g., equal-weighted average of quality, price, and appearance).

Our work contributes to the existing body of research on how people engage in differentiation when evaluating targets (Monroe, 1973; Tajfel & Wilkes, 1963). Evaluators tend to experience amplified differences among their options particularly when the options are assessed with respect to an attribute of value or importance (Montgomery & Svenson, 1989; Russo et al., 1996; Tajfel, 1957; Veltkamp et al., 2008). Because ranks symbolize value and prestige, they can accentuate the options' differences in the underlying attribute. We demonstrate this process of accentuation—driven by rank information—using people' choice. We further show that the accentuation does not emerge to similar strengths across the rank order. The top ranked options enjoy the greatest benefit from rank information. This pattern implies that people who make decisions based on rank information may categorize their options into those at the top of the hierarchy and those not at the top, and the accentuation occurs between the two categories.

Moreover, our questions relate to prior work on relative comparisons versus absolute evaluations (White et al., 2015). We propose that, when presented with rank information, people may perform relative comparisons based on the options' strength *in the ranked attribute*. This will lead to greater processing of the top-ranked option's strength on the ranked attribute and reduced processing of other options' strengths on other attributes. The net result of this shift is increased preference for the option that is best on the ranked attribute.

Extant Research and Predictions

In addition to the work discussed above (Koning & van der Wiel, 2013; Pope, 2009), there is research that indirectly suggests ranking may shape decision makers' attention and preferences. Past studies have examined how sorting can affect decision makers' search processes. Dellaert and Häubl (2012) found that participants inspected fewer consumer options when they thought the options were sorted based on their attractiveness (vs. when they did not). This pattern was consistent with other findings in which sorting led people to compare only a few options instead of exploring a large set of them (Häubl & Trifts, 2000). These studies indicated that sorting on an attribute, which implies an option's relative position, can reduce the breadth of people's attention. Lynch and Ariely (2000) reported a similar effect when sorting on an attribute was performed by decision makers themselves. Participants who sorted wines based on the price demonstrated higher price sensitivity in terms of their purchase decisions. Although the causal relationship between sorting and final choice was vague in this study, it is consistent with the idea that sorted information concentrates decision makers' attention to those options at the top.

Rank information, like sorting, also summarizes hierarchical relationships by directly communicating the relative position of each option (Zitek & Tiedens, 2012). Moreover, rank information is simple. Ranks are typically integers and often single digits; they rarely incorporate decimals (except for ties). It thus makes it very easy for a perceiver to rapidly encode the relative positions of the options. Finally, rank information is familiar. Ranking exists in almost every area of human society (Monks & Ehrenberg, 1999; Pope, 2009). Even in domains where people significantly vary in tastes and preferences (e.g., musical taste, political beliefs, appreciation of literature or movies), rank information is common (e.g., "The 100 Greatest Guitarists of All Time," "Historical Rankings of Presidents of the United States," "Modern Library 100 Best Novels," "The 100 Greatest Horror Movies of all Time"). The ubiquity of ranks can strengthen decision makers' tendency to rely on them during evaluation processes (Wood et al., 2002; Wood & Neal, 2007).

We thus expect that decision makers who are given rank information will use the information and focus on the option located at the top of the ranking. Greater attention paid to the top ranked option may in turn lead decision makers to attend to and encode the strengths of the top ranked option. In contrast, decision makers are likely to allocate less attention to lower ranked options and therefore process their characteristics less. The confluence of these processes can result in decision makers' tendency to recognize the strengths of the top ranked options while overlooking those of the non-top ranked options, which contributes to their preferences for the top ranked options.

As noted, we examine whether rank information can influence decisions even when it does not provide additional information regarding the characteristics of the options. We conduct this test by examining a situation in which decision makers have full information regarding the options' ratings in the underlying attribute (e.g., "9.7" and "9.5" etc.) along with the ranking (e.g., "1st" and "2nd" etc.). This situation is common in many online interfaces. When decision makers are aware that the rankings are from a specific set of ratings that they are also given, rankings do not provide additional information about the options' characteristics because they are a sheer translation of ratings. If anything, ranks obscure information because they do not reflect the absolute difference on the ranked attribute (e.g., a 1.0 difference and a 0.1 difference on a 5-point scale can yield the same spacing in terms of ranks). Thus, a rational model of decision making would suggest that rankings based directly on available attribute information are uninformative and should not affect decisions. We show that ranks nonetheless shape decision makers' attention and thus influence their choice.

To illuminate the nature of our effect, we address whether the effect of ranking emerges simply because decision makers receive information both in terms of rankings and ratings. Research on heuristic choice processes has proposed a majority-rule strategy by which people add up how many times a given alternative has the best value on each attribute (such as price, quality, size, color, etc; Payne et al., 1993; Zhang et al., 2006). If the addition of rank information to ratings leads to a double-counting process in which ranking is treated as another attribute, decision makers may prefer the top

ranked option because it is counted best twice based on the ranked attribute (in terms of its rating *and* ranking) whereas the other options can be counted best only once per attribute (in terms of the ratings). Our findings do not support the operation of a simple double-counting process. In one of our studies (Study 2), we present a focal attribute in three different formats of multiattribute choice: rating only, ranking only, or rating *and* ranking. We find that (a) decision makers' preference for the top ranked option is stronger in the ranking only format than the rating only format whereas (b) decision makers prefer the top ranked options to a similar extent in the rating and rating format and the ranking only format. Our findings thus show that it is the presence of rankings that changes preferences, whether it is presented along with ratings or not.

We also account for how rankings may have a signaling effect. Specifically, we consider whether rankings presented with ratings may shape decision makers' perceptions of attribute importance: It is possible decision makers infer that the ranked attribute is more important than other attributes because the communicator has chosen to present it in two forms (Grice, 1975). We examine this possibility (in Study 7) by asking participants to report the perceived importance of a ranked attribute versus non-ranked attributes. We conduct the test in two separate situations: with versus without making decisions. If rankings (in addition to ratings) shape attribute importance via a purely perceptional process, people should report the ranked attribute to be more important than the non-ranked attribute even without making decisions. We do not find evidence for such an effect. We instead find that decision makers report greater importance of the ranked attribute over the non-ranked ones *only after making decisions* (in favor of the top ranked option). Without making decisions, people do not perceive greater importance of the ranked attribute.

Finally, our findings suggest that the benefit from rank information does not fall equally along the spectrum of ranks. Instead, the benefit accrues disproportionately to the top ranked option. In the General Discussion, we consider how ranking may be one of the elements that create and maintain disparity between those at the top versus those below them (Frank & Cook, 1995), a phenomenon observed in various contexts including labor markets (e.g., Aguinis & O'Boyle, 2014). Even when the ranked option is only marginally different from the other options, its ranking can help it appear superior to other options and thus perpetuate its dominance.

Overview of the Studies

We present seven studies demonstrating the effect of rank information on preference. In Study 1, we used historical data from a professional sports league and found that ranking first in major performance categories increased the players' likelihood to be chosen for an important award, controlling for their performance in those categories. Ranking second or third had much weaker effects. Because ranking first increased the chance of being chosen for the award even for players without the strongest overall performance, rank information weakened the relationship between players' overall performance and the award.

In subsequent studies, we used experimental designs to establish causality while addressing alternative processes. In Study 2, focusing on people's decisions for restaurants, we demonstrated that rank information on a single attribute increased decision makers' preference for the top ranked option. We showed that this effect was driven by the presence of the rankings and not by presenting rankings and ratings simultaneously. In Study 3, we used a rank based on a summary score that averaged across multiple attributes. We once again found that rank information increased preference for the top ranked option. In addition, the presence of an overall rank weakened the tendency for people to choose the option that was highest on the attribute that they stated was most important. In Study 4, we attempted to examine the process by which rank information shaped people's decisions. When decision makers were given rankings, they invested more time attending to the information regarding the top ranked option, which was related to their successful encoding of the option's strength (as captured by their later recall). Conversely, rank information reduced the amount of time invested in the other options, which was related to decision makers' failure to recognize those options' strengths. These processes were collectively associated with decision makers' preference for the top ranked option.

In the remaining three studies, we focused on demonstrating the robustness of the ranking effect and addressing alternative accounts. In Study 5, we manipulated both ranking and sorting in order to confirm that ranking influences choice independently of sorting. In Study 6, we tested whether ranking effects arose simply because the top ranked option features the number "1," which may possess a special quality. We did so by shifting the ranks of the available options such that the best option was ranked 3rd and others ranked worse (eliminating 1 as an option); the presence of ranks still increased preference for the top ranked option even in a shifted set. Study 7 was designed to test whether the presence of rankings (in addition to ratings) signaled to decision makers that the ranked attribute was more important than other non-ranked attributes. Those who simply appraised the options without making choice did not rate the ranked attribute as more important. In contrast, those who made choice in favor of the top ranked option based on rank information emphasized the importance of the ranked attribute, indicating that they engaged in a process of aligning perceived importance with their choice.

For Study 1, we did not have control over the sample size because we used historical data. For Studies 2, 4, and 7, our decisions regarding the sample sizes were guided by the results from pilot experiments. We determined the sample sizes of the remaining studies based on the results from Studies 2, 4, and 7. We used manipulation checks in pilot experiments (which demonstrated high awareness of participants) but not in the actual studies that we report here. We report every measure and instrument that we used for every study; there is no additional element not reported in the article.

Except for Study 1, we used online platforms for data collection, which have been reported to provide more diverse population than typical American college participants pools (Buhrmester et al., 2011; Mason & Suri, 2012; Palan & Schitter, 2018; Paolacci & Chandler, 2014; Peer et al., 2017). However, we acknowledge that our samples were comprised of individuals participating mostly from the United States or the United Kingdom with a high level of English proficiency.

Study 1

In this study, we tested the effect of rank information on events that have large social and economic ramifications. We collected data on professional basketball players who have played for the National

Basketball Association (NBA) and examined whether rankings in major performance categories influenced the award decisions for each season, taking into consideration the players' actual performance in those categories. The award we considered was the All-NBA Team. As explained below, being selected for the All-NBA Team is one of the greatest honors for professional basketball players, and thus the decisions regarding the All-NBA Team have received much attention from the players, the teams, and the media.

Method

Data

We compiled performance data for every player who played for the NBA from its first season to record information for our study variables (1950–1951 season) to its most recently closed season as of this writing (2019–2020 season).[2] In terms of the independent variable, we focused on the players' rankings in three major performance categories: points, assists, and rebounds per game. Players' rankings in these categories are updated each day and announced through various formats such as sports magazines (e.g., Hoop, Basketball Times) and websites that cover the NBA (e.g., nba.com, espn.com). The main independent variable we examined was whether a player ranked first in one of the three focal performance categories at the end of a regular season (0 = did not rank first, 1 = ranked first).[3] To capture the unique effect of ranking first, we also created variables for ranking second and third in the same three categories. As we discuss below, we also collected data on Win Shares, a second-order statistic that captures a player's overall performance. Win Shares quantify the number of team wins that can be attributed to individual players for a given season based on statistical models that assign a weight to each category of performance by its predictive value.[4]

The dependent variable was whether a player was chosen for the All-NBA Team for a given season. This award has been given to 10 or 15 players (10 players until the 1987–1988 season; 15 players afterwards) believed to show the best performance in the league during the regular season.[5] The All-NBA Team is determined by the votes from a panel of sportswriters and broadcasters at the end of each regular season.[6] The award is thus a great honor for players and has significant consequences on the size of future contracts they can pursue with their teams. Moreover, many teams offer contingent rewards when their players are selected for the All-NBA Team.

As controls, we included three variables capturing the underlying attribute values for the ranked performance categories: points, assists, rebounds per game. Because typical levels of performance vary by season, these three variables were standardized within seasons. In addition, to consider the achievements of the players' teams, we included the winning percentage of the teams in the model.[7]

Results and Discussion[8]

The players' performance for each season was nested within teams, with teams being further nested within seasons. We thus used hierarchical linear models (with the probit link function) with teams within seasons as random intercepts.[9, 10, 11, 12] Table 1 reports descriptive statistics and correlations of the study variables.

We call points per game, assists per game, and rebounds per game the PAR categories for short. The results reported in Table 2 revealed that, controlling for the performance in the PAR categories and winning percentage (team performance), ranking first in a PAR category significantly increased players' likelihood to be chosen for All-NBA Team ($z = 5.94$, $p < .001$). While ranking second and third also had significant positive effects (ranking second, $z = 2.57$, $p = .010$; ranking third, $z = 3.71$, $p < .001$), the Wald tests revealed that these effects were found to be significantly weaker (difference between ranking first and second, $z = 3.08$, $p = .002$; difference between ranking first and third, $z = 2.37$, $p = .018$).

To further examine how these findings influenced the way players were evaluated, we tested how standardized Win Shares (capturing players' overall performance for a given season) interacted with ranking first to predict the likelihood to be chosen for the All-NBA Team. The analysis (with teams within seasons as random intercepts) revealed that there was a significant interaction, $b = -.49$, $SE = .12$, $z = -4.00$, $p < .001$. As can be seen in Figure 1, the interaction showed that although standardized Win Shares had an overall positive relationship with the likelihood to be chosen for All-NBA Team, the slope was flatter for those who ranked first in a PAR category than those who did not.

[2] Although the population consisted of 21,685 observations, there were 13 cases in which the information regarding the players' performance was missing due to the lack of specific records (nine cases in the 1954–1955 season, one case in the 1955–1956 season, and three cases in the 1956–1957 season). These cases were thus not included in the data, resulting in 21,672 observations in the data set.

[3] Among 202 observations where players ranked first in one of the three categories for a given season, only eight of them were cases where the players ranked first in two categories (there was no case where a given player ranked first in all three categories). Given the rarity, we did not predict that the findings regarding those events would provide reliable results. We thus used a variable representing whether the players ranked first in at least one of the three categories as our main independent variable.

[4] For detailed information regarding the calculation and characteristics of Win Shares, refer to the following page: https://www.basketball-reference.com/about/ws.html.

[5] All-NBA Team can be further differentiated into the NBA First Team, Second Team, and Third Team (subsequent to the 1987–1988 season), each team consisting of five players. To maximize the reliability of our analyses, we included all three teams for our dependent variable. The statistical significance of the results that we report below did not change when we considered only the NBA First Team or only the NBA First or Second Teams.

[6] For specific voting procedures, refer to the following webpage: https://en.wikipedia.org/wiki/All-NBA_Team.

[7] Players sometimes changed their teams during regular seasons due to trades. Because the All-NBA Team is determined after the end of a regular season, we used the last team that the players played for as their team.

[8] All appendices can be accessed via the following URL: https://osf.io/j7bvk/

[9] The statistical models that we used can be found in the Online Appendix A.

[10] To estimate the degree of freedom for our models, we used the R package "lmerTest" (Kuznetsova et al., 2018) that relies on Satterthwaite tests to best approximate the *F* distribution.

[11] We explored alternative approaches in model specifications by using only the seasons or teams as random intercepts. As can be found in the Online Appendices B–E, the results that we report below did not change in terms of statistical significance.

[12] Because the All-NBA Team considers players' positions, we ran additional analyses to explore the effects of players' positions by including binary variables indicating whether they played guards, forwards, or centers that season. These variables did not change the statistical significance of our results. Thus, we report the results without these variables.

Table 1
Descriptive Statistics and Correlations in Study 1[a]

Variable	*M*	*SD*	1	2	3	4	5	6	7	8
1. All-NBA Team	.04	.20	—							
2. Ranked 1st	.01	.10	.36	—						
3. Ranked 2nd	.01	.10	.26	.07	—					
4. Ranked 3rd	.01	.10	.26	.04	.01	—				
5. Points per game[b]	.00	1.00	.46	.21	.19	.19	—			
6. Assists per game[b]	.00	1.00	.32	.22	.20	.18	.62	—		
7. Rebounds per game[b]	.00	1.00	.31	.20	.17	.16	.62	.20	—	
8. Win Shares[b]	.00	1.00	.53	.27	.21	.21	.81	.54	.67	—
9. Team wins	.50	.15	.17	.06	.04	.03	.03	.03	.01	.26

Note. $n = 21{,}672$. NBA = National Basketball Association.
[a] *rs* > .01 are significant at .05 level. [b] Variables are standardized within season.

Visually, it can be seen that the two simple slopes diverged from each other except in the areas near the end points of the standardized Win Shares in Figure 1. This suggests that ranking first in a PAR category seems to lift a player above peers who demonstrated comparable performance over much of the observed range. The graph also makes apparent the degree to which ranking first in a PAR category can dominate better overall performance. For example, on average a player with 2.5 standardized Win Shares will be selected at a lower rate than a player with 1.5 standardized Win Shares if the latter player ranked first in a PAR category whereas the former did not (Figure 1).

To quantify this gap in another way, we focused on 245 cases in which players demonstrated top five Win Shares in a season but did not rank first in a PAR category. Among them, there were 35 cases where the players were not chosen for the All-NBA Team. Importantly, nine of these cases happened along with other players who did *not* have top five Win Shares but ranked first in a PAR category and *were* chosen for the team.[13] In sum, as players who ranked first in a PAR category were granted recognition, there were players who demonstrated greater overall performance yet did not get the recognition.

The findings depicted in Figure 1 can be further examined. Particularly, it should be noted that the difference between players who ranked first and those who did not rank first disappeared toward the higher end of standardized Win Shares.[14] We calculated the Johnson-Neyman interval, and the results showed that when players achieved standardized Win Shares of 3.59 or higher, the difference between the top ranked and non-top ranked players became nonsignificant in terms of their likelihood to be chosen for the All-NBA Team. These findings imply that when players were already demonstrating extremely high levels of performance overall, they enjoyed an almost maximum likelihood to be chosen for the All-NBA Team regardless of whether they were top ranked or not, rendering the effect of rank information nonsignificant. However, this level of overall performance was rare: There were only 60 cases in which players achieved this level of overall performance (or higher) in the entire 70 seasons of the NBA (Figure 2).

Overall, we found that players who ranked first in major performance categories enjoyed a higher likelihood of being chosen for the All-NBA Team, controlling for their performance. Ranking second or third had significantly weaker effects. These findings indicated that the benefit from rank information was not equally distributed across the players. It was the top ranked players who enjoyed a disproportionately greater likelihood to be chosen for the award. Further analyses revealed that rank information weakened the relationship between players' overall performance and the likelihood to be chosen for the All-NBA Team, increasing the chance for players without the strongest overall performance to be chosen for the award. The benefit the top ranked players enjoyed very often brought disadvantages to non-top ranked players. Finally, players who demonstrated an extremely high level of overall performance were almost guaranteed to be chosen for the award regardless of whether they ranked first or not. This provides valuable information regarding the scope condition of our effect: When the target is incomparably superior to their peers based on their overall characteristics, rank information may not exert significant influences. It may be only when the options are

Table 2
Coefficients of Variables Predicting Likelihood to Be Chosen for All-NBA Team in Study 1[a]

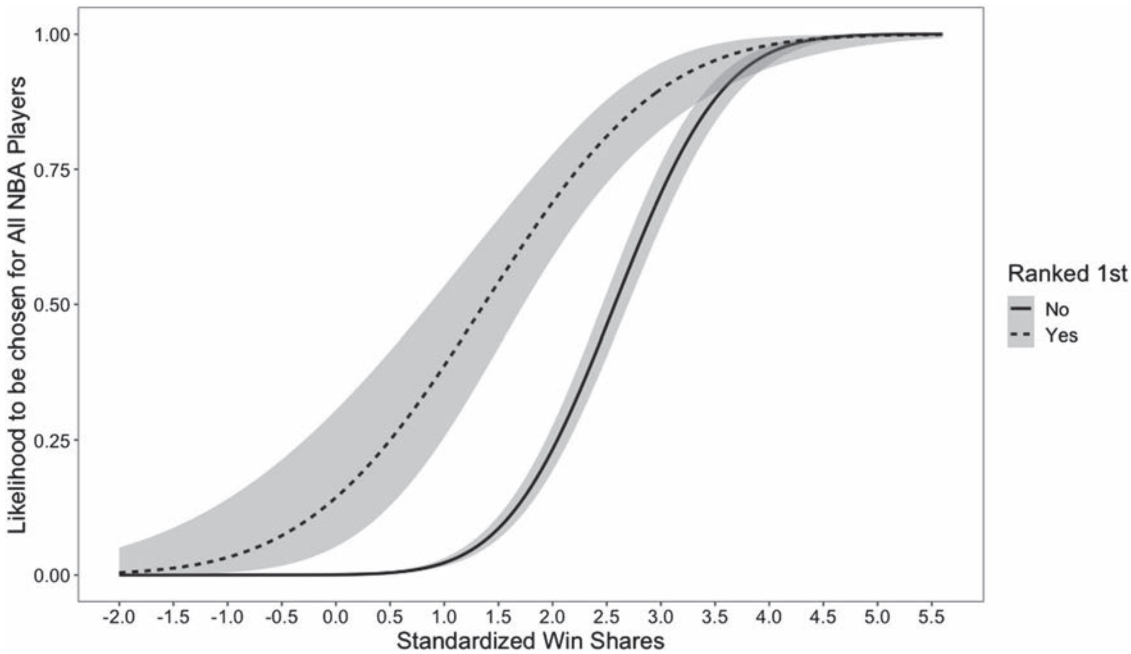
Variable	All-NBA Team
Ranked 1st	.97 (.16)*
Ranked 2nd	.36 (.14)*
Ranked 3rd	.50 (.14)*
Points per game[b]	.23 (.01)*
Assists per game[b]	.21 (.02)*
Rebounds per game[b]	.14 (.01)*
Team wins[b]	6.27 (.31)*

Note. $N = 21{,}672$ from 70 seasons, and 1,495 teams/seasons. NBA = National Basketball Association.
[a] Values in parentheses are standard errors. [b] Variables are standardized within season.
* $p < .05$.

[13] Due to the nature of the All-NBA Team that considers players' positions (since the 1955–1956 season), we counted only the cases in which the position of the players in the two categories (non-top ranked players *with* top five Win Shares vs. top ranked players *without* top five Win Shares) were matched.

[14] The difference disappeared in the lower end as well, but this pattern is meaningless because no top-ranked players belonged to the lower end of overall performance.

Figure 1
Relationship Between Win Shares and Likelihood to Be Chosen for All-National Basketball Association (NBA) Team in Study 1



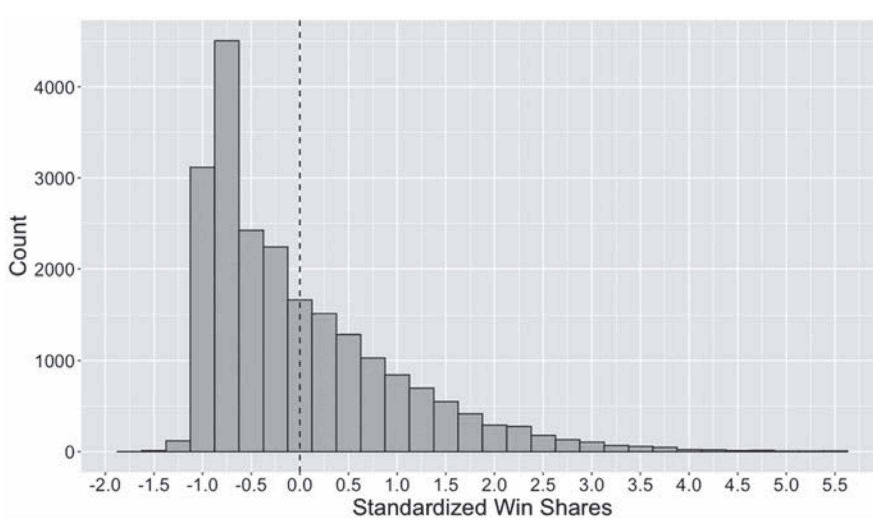
comparable to each other that rank information can shape people's preferences and choice.

Study 2

Using archival data from a professional sports league, Study 1 found evidence suggesting that rank information was significantly associated with events of practical significance. However, because we could not specifically control which information was available to the decision makers, it was not possible to conclude that the effect was driven by the rank information. In the remaining studies, we took experimental approaches to establish the causality of the effect.

In an initial study to demonstrate the effect of rank information, Study 2 examined people's decisions for restaurants, a context

Figure 2
Distribution of Standardized Win Shares in Study 1



Note. The dashed line represents the mean.

where rank information is easily accessible via various platforms on the internet (e.g., OpenTable.com, TripAdvisor.com, Yelp.com). We created an experimental paradigm using the information from one of these platforms and tested the effect of rank information on people's decisions. The ranking in this study was based on ratings that captured perceptions of overall dining experience (i.e., "Overall" ratings). As explained below, we created three experimental conditions to show that the effect of ranking was driven by ranking, not by the presentation of the same attribute in both ratings and rankings.

Method

Sample

We recruited 1,202 participants on Prolific Academic, M_{age} = 32.9; 613 female (51%), 576 male (48%), 13 nonbinary (1%); 92 Asian or Pacific Islander (9%), 83 Black (8%), 46 Hispanic (5%), 9 Native American (.9%), 882 White (73%), 88 two or more races (7%), two unspecified (.2%).

Procedure

In the first part of the study, we asked participants five questions regarding their experiences of eating out. We asked (a) their average frequency of eating out per week, (b) whether they would eat out more often or less often if they had a choice, (c) whether they liked to go to their favorite restaurants or try new restaurants, (d) what their favorite category of cuisine was, and (e) whether they ate out on weekdays more frequently or on weekend.[15] After answering these questions, we informed participants that they would be given information about popular restaurants in Manhattan, New York City, under the category of American cuisine. Participants were informed that the restaurants had been rated by their customers in three specific attributes: Food, Service, and Overall. These attributes were being used on OpenTable.com, an online platform providing information about restaurants. We noted that the Overall attribute is a distinct, separate rating, and not a summary statistic based on other inputs.

On the following page, we provided participants a list of six restaurants (which existed at the time of the experiment) and information about them. Participants learned the names of the restaurants and price ranges (which were identical across the restaurants). The information regarding Food, Service, and Overall was presented differently across three experimental conditions (to which participants were randomly assigned). In the rating-only condition, participants were given the six restaurants' ratings on all three attributes.[16] In the ranking-only condition, participants were given rankings instead of ratings for the Overall attribute ("1st"–"6th"). In the rating-and-ranking condition, participants were given the restaurants' ratings on all three attributes *and* rankings for the Overall attribute. In the ranking-only condition and the rating-and-ranking condition, we made it clear that the rankings were determined among the six restaurants based on their Overall ratings. Among the six restaurants, Restaurant 5 had the highest Overall rating (and the second highest Food rating). In contrast, Restaurant 4 had the highest Food rating (and second highest Overall rating). Figure 3 presents the information that participants were given (with the names and the addresses of the restaurants covered). Based on the information, participants were asked to decide which restaurant they were "most attracted to visit." Finally, they provided demographic information.

Results and Discussion

Table 3 reports the frequency of participants' decisions in each condition. We first found that participants' choice of restaurants significantly differed across the three conditions, $\chi^2(10) = 18.82$, $p = .043$. Moreover, their likelihood of choosing Restaurant 5, the restaurant with the highest Overall rating, differed significantly across the three conditions, $\chi^2(2) = 14.26$, $p < .001$. Based on this result, we conducted pairwise comparisons of participants' choice of Restaurant 5 using the Tukey method for comparing a family of three estimates. We found that there was a significant difference in participants' likelihood of choosing Restaurant 5 between the ranking-only condition and the rating-only condition (40% vs. 30%), $p = .008$. Similarly, there was a significant difference between the rating-and-ranking condition and the rating-only condition (42% vs. 30%), $p = .001$. Finally, there was no significant difference between the rating-and-ranking condition and the ranking-only condition (42% vs. 40%), $p = .840$.

Participant's choice of Restaurant 4, the option with the highest Food rating, also differed significantly across the three conditions, $\chi^2(2) = 8.15$, $p = .017$. The comparisons using the Tukey method revealed that participants' likelihood to choose Restaurant 4 was significantly different between the rating-and-ranking condition and the rating-only condition (41% vs. 51%), $p = .016$. No significant differences were found between the ranking-only condition and the rating-only condition (44% vs. 51%), $p = .118$, or between the rating-and-ranking condition and the ranking-only condition (41% vs. 44%), $p = .705$.

These results revealed that the effect of ranking emerged both when the rank information was presented along with ratings and when it was not. In other words, ranks were sufficient to cause an increase in preference for the top rated option in the ranked attribute, and the additional presentation of ratings was not necessary to cause it. This suggests that the effect of ranks did not operate simply via a double-counting process. In the ranking condition of our remaining studies, we presented ratings along with rank information to show that the effect of rank information emerged even when it did not provide additional information about the options' characteristics.

Study 3

In Study 2, the rank information was based on a single attribute that captured overall characteristics of the options. Another popular practice is to rank options based on their average ratings across

[15] Participants reported that (a) their average frequency of eating out per week was 2.23, (b) they would eat out more (68%) than less (32%) if they had a choice, (c) they liked to go to their favorite restaurants (54%) than try new restaurants (46%), (d) their favorite category of cuisine was American (27%), followed by Asian (25%), Mexican (20%), Italian (16%), Indian (5%), Middle Eastern (3%), Greek (2%), French (1.5%), and Spanish (1%), and (e) they ate out on weekend more frequently (64%) than weekdays (36%).

[16] All this information was directly drawn from OpenTable.com.

Figure 3

Presentation of Information in Study 2: Rating-Only Condition (Top), Ranking-Only Condition (Middle), and Rating-and-Ranking Condition (Bottom)

Name	Food	Service	Overall	Price
	4.1/5	4.2/5	4.2/5	$$
	4.2/5	4.1/5	4.3/5	$$
	4.2/5	4.2/5	4.1/5	$$
	4.4/5	4.3/5	4.4/5	$$
	4.3/5	4.5/5	4.5/5	$$
	4.1/5	3.8/5	4.0/5	$$

Name	Food	Service	Ranking of Overall	Price
	4.1/5	4.2/5	4th	$$
	4.2/5	4.1/5	3rd	$$
	4.2/5	4.2/5	5th	$$
	4.4/5	4.3/5	2nd	$$
	4.3/5	4.5/5	1st	$$
	4.1/5	3.8/5	6th	$$

Name	Food	Service	Overall	Ranking of Overall	Price
	4.1/5	4.2/5	4.2/5	4th	$$
	4.2/5	4.1/5	4.3/5	3rd	$$
	4.2/5	4.2/5	4.1/5	5th	$$
	4.4/5	4.3/5	4.4/5	2nd	$$
	4.3/5	4.5/5	4.5/5	1st	$$
	4.1/5	3.8/5	4.0/5	6th	$$

multiple attributes. We tested the effect of ranking based on such average ratings in Study 3.

Simple average ratings weight all attributes equally, but it may be the case that people a priori value one attribute more highly than others in determining what is attractive to them. Thus, without rank information, they may demonstrate an overall preference for the option that has the highest rating on the attribute they value most. We tested whether rank information based on average ratings would pull participants' decisions away from preferences they would otherwise have revealed. In Study 3, participants were asked to make decisions regarding gym memberships.

Method

Sample

We recruited 501 participants on Amazon.com's Mechanical Turk, $M_{\text{age}} = 36.5$; 260 female (52%), 241 male (48%); 31 Asian or Pacific Islander (6%), 49 Black (10%), 29 Hispanic (6%), 4 Native American (1%), 370 White (74%), 18 two or more races (4%).

Procedure

Participants were first asked to answer five questions regarding their experiences of exercising. We asked (a) their average

Table 3
Decisions in Study 2

Restaurants	Number of participants who chose the restaurants: Rating only, $n = 400$ (%)	Ranking only, $n = 402$ (%)	Rating and ranking, $n = 400$ (%)	Total, $n = 1{,}202$ (%)
Restaurant 1	2	2	3	2
Restaurant 2	8	4	7	6
Restaurant 3	10	9	7	9
Restaurant 4	51	44	41	45
Restaurant 5	30	40	42	37
Restaurant 6	1	1	1	1

Note. Restaurant 5 was the option ranked highest on the ranked attribute.

frequency of working out per week, (b) whether they would work out more often or less often if they had a choice, (c) whether they would like to focus on weight training or cardio exercises, (d) which weight training exercises they had done before, and (e) whether they worked out on weekdays more frequently or on weekend.[17] We also included three items to measure participants' baseline preferences in evaluating gyms by asking the extent to which they considered three attributes to be important when evaluating gyms: facilities, staff, and vibe (1 = *not at all important* to 9 = *extremely important*). After these questions, we informed participants that they would be given a list of gyms that had been rated by customers on the three attributes.

Participants were given a list of six gyms along with information about them. The gyms were hypothetical entities named "A"–"F." The list provided information regarding the gyms' ratings on the three attributes (facilities, staff, and vibe), the average ratings across the three attributes, and the price for the memberships (which was identical across the gyms). Among the gyms, C, B, and A had the highest ratings on facilities, staff, and vibe, respectively. Another gym, D, did not have the highest ratings on any of the individual attributes but had the highest average rating among the six gyms.

In both the control condition and the ranking condition (to which participants were randomly assigned), participants were provided the same information regarding the above characteristics (i.e., the three attributes, averages, and price). The only difference was whether participants were given rank information. In the control condition, no rank information was given. In the ranking condition, participants were given rank information ("1st"–"6th") based on the *average* ratings. We clearly noted that the rankings were based on the average ratings across the three attributes. Figure 4 presents the information that participants were given. Based on the information about the gyms, participants were asked to decide which gym they were most attracted to by typing in its name ("Among the six memberships above, please type the name of one membership you are most attracted to"). Finally, they provided demographic information.

Results and Discussion

Ratings of the three attributes revealed that participants considered facilities to be more important on average ($M = 8.20$, $SD = 1.11$) than staff ($M = 6.44$, $SD = 1.84$; $t = 20.62$, $p < .001$) or vibe ($M = 6.86$, $SD = 1.79$; $t = 16.01$, $p < .001$). Reflecting this pattern, 43% of participants overall chose C, the gym with the highest facilities rating (see Table 4 for participants' decisions). More importantly, participants' choices differed significantly between the two conditions, $\chi^2(5) = 33.06$, $p < .001$. Fifty-three percent of participants chose C (which rated highest on facilities) in the control condition, whereas only 32% did so in the ranking condition, Cohen's $h = -.43$, $\chi^2(1) = 20.07$, $p < .001$. The opposite pattern emerged for participants' choice of D, the gym with the highest average rating. In the control condition, 26% of participants chose D, whereas 44% did so in the ranking condition, Cohen's $h = .38$, $\chi^2(1) = 18.11$, $p < .001$.

We further investigated the extent to which participants' baseline preferences predicted their decisions in the two conditions. To do so, we focused on 341 participants who reported that one of the three attributes was more important than the other two attributes (the remaining participants did not report that one attribute was more important than the others). For this analysis, we examined whether participants chose the option that was highest on the attribute that they said was most important a priori. There was a significant difference between the two conditions, Cohen's $h = .34$, $\chi^2(1) = 8.78$, $p = .003$. In the control condition ($n = 171$), 60% of participants chose the gym that scored best on their most important attribute, whereas in the ranking condition ($n = 165$), 43% did so.

Using rankings based on average ratings, Study 3 replicated the effect of rank information on people's decisions. When participants were given rankings based on the average ratings, they were more likely to choose the option with the highest average rating. Additionally, our analyses revealed that the rank information appeared to pull participants away from the options that had the highest rating on the attribute they considered to be most important. In the General Discussion, we return to the question of the conditions under which this tendency is likely to harm decisions or improve them.

Study 4

In Studies 1–3, we found that the presence of rank information shaped decision makers' preference for the top ranked option even though the rankings were a simple translation of the ratings that were already available. In Study 4, we attempted to examine the psychological processes associated with this effect. We predicted that rank information would draw decision makers' attention to the top ranked option. Such attention may predict decision makers' accurate

[17] Participants reported that (a) their average frequency of working out per week was 4.75, (b) they would work out more (92%) than less (8%) if they had a choice, (c) they would like to focus on cardio exercises (56%) than weight training (44%), (d) the most common weight training exercises they had done before were squats (77%) and bicep curls (73%), and (e) they worked out on weekdays more frequently (83%) than weekend (17%).

Figure 4
Presentation of Information in Study 3: Control Condition (Left) and Ranking Condition (Right)

Name	Rating (Average = average across Facilities, Staff, Vibe)	Price
A	Facilities: 4.42 Staff: 4.52 Vibe: 4.80 Average: 4.58	$$
B	Facilities: 4.45 Staff: 4.82 Vibe: 4.50 Average: 4.59	$$
C	Facilities: 4.83 Staff: 4.50 Vibe: 4.53 Average: 4.62	$$
D	Facilities: 4.68 Staff: 4.65 Vibe: 4.65 Average: 4.66	$$
E	Facilities: 4.62 Staff: 4.69 Vibe: 4.61 Average: 4.64	$$
F	Facilities: 4.81 Staff: 4.40 Vibe: 4.50 Average: 4.57	$$

Name	Rating (Average = average across Facilities, Staff, Vibe)	Price	Ranking (based on Average)
A	Facilities: 4.42 Staff: 4.52 Vibe: 4.80 Average: 4.58	$$	5th
B	Facilities: 4.45 Staff: 4.82 Vibe: 4.50 Average: 4.59	$$	4th
C	Facilities: 4.83 Staff: 4.53 Vibe: 4.50 Average: 4.62	$$	3rd
D	Facilities: 4.80 Staff: 4.60 Vibe: 4.58 Average: 4.66	$$	1st
E	Facilities: 4.62 Staff: 4.69 Vibe: 4.61 Average: 4.64	$$	2nd
F	Facilities: 4.62 Staff: 4.51 Vibe: 4.58 Average: 4.57	$$	6th

awareness of the top ranked option's strengths in the ranked attribute. Conversely, decision makers may spend less time attending to other options' characteristics and end up overlooking those options' strengths. These processes may collectively be involved in decision makers' preference for the top ranked option. We tested these effects in the context of a job promotion decision.

Method

Sample

We recruited 823 participants on Prolific Academic, $M_{\text{age}} = 31.8$; 392 female (48%), 420 male (51%), 11 nonbinary (1%); 63 Asian or Pacific Islander (9%), 48 Black (6%), 20 Hispanic (5%), 3 Native American (.5%), 637 White (79%), 1 unspecified (1%), 51 two or more races (1%).

Table 4
Decisions in Study 3

	Number of participants who chose the gym		
Gyms	Control, n = 251 (%)	Ranking, n = 250 (%)	Total, n = 501 (%)
A	5	10	8
B	2	4	3
C	53	32	43
D	26	44	35
E	6	3	4
F	9	7	8

Note. D was the option ranked highest on the ranked attribute.

Procedure

Participants were asked to imagine that they were a manager of a large store that specialized in electronics and computers. They were told that their workload had increased in recent years, and they were planning to promote one of their sales associates to the position of assistant manager. Participants were informed that they were considering six associates as candidates: Casey Bowen, Taylor Wilcox, Riley Smith, Jordan Culver, Charlie Vosburg, and Hollis Williams.

On the next page, participants were provided with profiles of the six sales associates. Each candidate's profile consisted of ratings on three attributes: evaluation from coworkers, customer satisfaction, and sales goal achievement. While each candidate had a unique profile in terms of the three ratings, the sum total across the three ratings was the same across the six candidates. We also provided information regarding the candidates' organizational tenures, which were identical across the six candidates (5 years).

Similar to Studies 2 and 3, participants were randomly assigned to either the control or the ranking condition. In both conditions, participants were given the full information regarding the candidates' three ratings along with their organizational tenures. The only difference between the two conditions was that participants in the ranking condition were given rank information based on the sales goal achievement ratings ("1st"–"6th"). The rank information indicated that Riley Smith was the top ranked candidate in sales goal achievement among the six candidates. Casey Bowen was the highest rated candidate on evaluation from coworkers. Figure 5 presents the information in the two conditions.

Building on the "mouselab" paradigm used in research on multiattribute choice (Payne et al., 1993), information regarding the six

Figure 5

Presentation of Information in Study 4: Control Condition (Top) and Ranking Condition (Bottom)

Name	Evaluation from coworkers	Customer satisfaction	Sales goal achievement	Organizational tenure
Casey Bowen	4.40/5	4.11/5	4.30/5	5 years
Taylor Wilcox	4.18/5	4.42/5	4.21/5	5 years
Riley Smith	4.22/5	4.23/5	4.36/5	5 years
Jordan Culver	4.27/5	4.30/5	4.24/5	5 years
Charlie Vosburg	4.23/5	4.25/5	4.33/5	5 years
Hollis Williams	4.32/5	4.22/5	4.27/5	5 years

Name	Evaluation from coworkers	Customer satisfaction	Sales goal achievement	Ranking of sales goal achievement	Organizational tenure
Casey Bowen	4.40/5	4.11/5	4.30/5	5th	5 years
Taylor Wilcox	4.18/5	4.42/5	4.21/5	6th	5 years
Riley Smith	4.22/5	4.23/5	4.36/5	1st	5 years
Jordan Culver	4.27/5	4.30/5	4.24/5	5th	5 years
Charlie Vosburg	4.23/5	4.25/5	4.33/5	2nd	5 years
Hollis Williams	4.32/5	4.22/5	4.27/5	4th	5 years

candidates was hidden originally (except for organizational tenures). In each cell of the table was a black box hiding that cell's content, and participants had to hover their mouse cursor over the black box to acquire the information in that cell. Once participants placed their cursor over the cell, the black box disappeared, allowing participants to attend to the information in the cell. When participants moved their cursor elsewhere, the black box reappeared. Therefore, participants could only attend to a specific piece of information when they were hovering their cursor over the black box covering the information. We recorded the amount of time participants hovered their cursor over each black box during the experimental session (in ms). Figure 6 presents a snapshot of the experiment.

Based on the information, participants decided which candidate to promote. After participants made their decisions, we asked them to recall the six candidates' rankings in sales goal achievement (ranked attribute) and evaluation from coworkers (non-ranked attribute) by putting the numbers from 1 to 6 beside the candidates' names. Finally, participants provided demographic information.

Results and Discussion

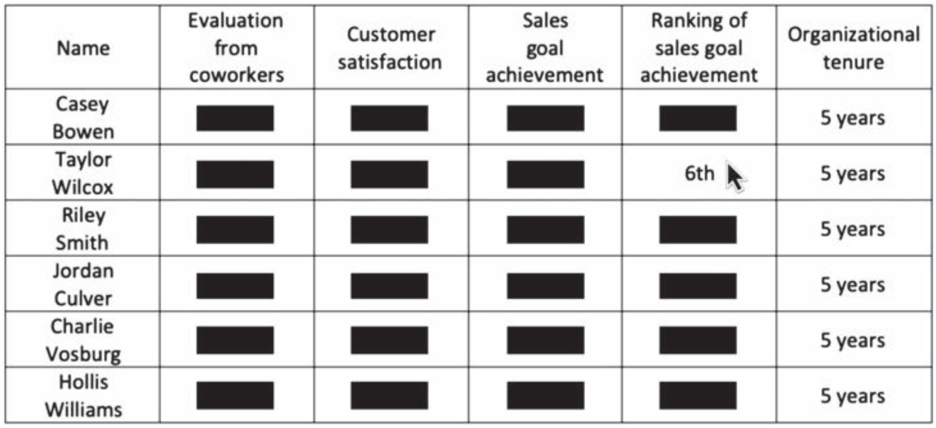
Participants' decisions differed significantly between the two conditions, $\chi^2(5) = 92.10$, $p < .001$. Consistent with findings from Studies 2 and 3, participants in the ranking condition were more likely to promote Riley Smith (48%) compared to those in the control condition (19%), Cohen's $h = .63$, $\chi^2(1) = 73.63$, $p < .001$ (see Table 5). Again, rank information increased decision makers' preference for the top ranked option.

Participants in the ranking condition were also more likely to accurately recall Riley Smith's ranking in sales goal achievement (64%) as compared to those in the control condition (31%), Cohen's $h = .67$, $\chi^2(1) = 87.06$, $p < .001$. In contrast, there was no difference in participants' accurate recall of Riley Smith's ranking in evaluation from coworkers (15%) as compared to those in the control condition (17%), Cohen's $h = -.05$, $\chi^2(1) = .55$, $p = .457$.

We also analyzed the proportion of time participants invested in attending to information about each candidate among the six.[18] We used proportion for two reasons. First, the number of columns containing information about the candidates was different between the two conditions (control = 3, ranking = 4). Second, we attempted to account for the individual-level variance of the overall time participants spent for information search. The results revealed that participants in the ranking condition invested a greater proportion of time attending to the information regarding Riley Smith

[18] The total amount of time that participants spent for information search for the candidates did not on average significantly differ between the ranking condition (61 s) and the control condition (55 s), $p = .207$.

Figure 6
Snapshot of Study 4 in Ranking Condition



Name	Evaluation from coworkers	Customer satisfaction	Sales goal achievement	Ranking of sales goal achievement	Organizational tenure
Casey Bowen					5 years
Taylor Wilcox				6th	5 years
Riley Smith					5 years
Jordan Culver					5 years
Charlie Vosburg					5 years
Hollis Williams					5 years

(20%) than those in the control condition (15%), Cohen's d = .45, t = 6.57, p < .001.

Based on these findings, we examined how the effect of rank information on decision makers' preference for Riley Smith was explained by (a) the proportion of time they invested attending to Riley Smith and (b) their accurate recall of Riley Smith's ranking in the ranked attribute. We tested a serial indirect path in which the rank information affected (a), which predicted (b), which ultimately explained participants' preference for Riley Smith. We estimated this path based on 5,000 nonparametric bootstrap resamples (using a general linear model with the probit link function). The results revealed that the indirect effect was statistically significant: the 95% percentile interval was [.170, .407].[19]

In parallel with the above analysis, we examined whether the effect of rank information on the preference for the top ranked option was also explained by participants in the ranking condition (c) investing a lower proportion of time attending to Casey Bowen, who was the top rated candidate in a non-ranked attribute, and (d) inaccurately recalling Casey Bowen's ranking in the non-ranked attribute. We estimated the serial indirect effect running from the rank information to (c), which predicted (d), which in turn explained participants' preference for Riley Smith.[20] Importantly, while testing this path we also addressed the first indirect process by controlling for (a) and (b). Using the 5,000 nonparametric bootstrap resamples along with the probit link function, we found a significant indirect effect (95% percentile interval = [.004, .070]).[21]

The results revealed that the effect of rank information on decision makers' preference was associated with their recognition of the options' strengths, which were in turn explained by the proportion of time they invested attending to those options. When rank information was available, decision makers spent more time attending to the top option in the ranked attribute and accurately recognized the option's strength in the ranked attribute. In parallel, rank information led decision makers to invest less time attending to the top rated option in a non-ranked attribute and disrupted their accurate recognition of the option's strength in the non-ranked attribute. These two processes were collectively associated with decision makers' preference for the top option in the ranked attribute (i.e., top ranked option).

Study 5

Studies 1–4 illustrated the effect of ranking on decisions and investigated possible psychological processes underlying preferences for top-ranked options. In Study 5, we tested the extent to which the ranking effect is a distinct process from another popular mode of presenting information about multiple options: sorting (Dellaert & Häubl, 2012; Lynch & Ariely, 2000). Sorting can influence preferences through several processes, such as directing attention to the first option (Hendrick & Costantini, 1970; Jones et al., 1968) and inducing satisficing versus maximizing decisions (Schwartz et al., 2002). We gave participants information that was sorted either by a rating of each option's quality or by each option's name (alphabetically). This sorting manipulation was crossed with a ranking manipulation in which ranking was based on quality. Using this design, we tested whether ranking influenced people's decisions independent of sorting.

In Study 5, we also introduced price as an attribute in decision making. In numerous domains such as shopping for groceries ("US Select beef" vs. "U.S. Prime beef"), booking hotels (one-star hotel vs. four-star hotel), and buying airline tickets (economy vs. business), options with higher quality tend to be more expensive. This situation forces people to navigate a tradeoff between quality and price. We examined how rank information changed the way individuals made decisions in such tradeoffs. We manipulated the availability of rank information based on quality and tested whether the information shaped people's

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[19] The statistical models and detailed results regarding the estimation of the indirect effects can be found in the Online Appendix F.

[20] Before we tested this serial indirect path, we first checked whether the rank information had significant main effects on (c) and (d). It did. Participants in the ranking condition invested a lower proportion of time attending to the information regarding Casey Bowen (22%) than those in the control condition (24%), Cohen's d = −.16, t = −2.31, p = .021. They were also less likely to accurately recall Casey Bowen's ranking in evaluation from coworkers (56%) as compared to those in the control condition (69%), Cohen's h = −.27, $\chi^2(1)$ = 14.12, p < .001.

[21] We also tested whether the preceding serial indirect path via (a) and (b) remained significant while controlling for (c) and (d). It did, yielding a 95% percentile interval [.186, .443].

Table 5
Decisions in Study 4

	Number of participants who promoted the sales associate		
Candidates	Control, n = 409 (%)	Ranking, n = 414 (%)	Total, n = 823 (%)
Casey Bowen	34	20	28
Taylor Wilcox	19	12	15
Riley Smith	19	48	34
Jordan Culver	10	6	8
Charlie Vosburg	8	11	10
Hollies Williams	9	3	6

Note. Riley Smith was the option ranked highest on the ranked attribute.

preference for an option with higher quality but a more expensive price.

Method

Sample

We recruited 405 participants on the Amazon.com's Mechanical Turk platform, M_{age} = 37.0; 218 female (54%), 187 male (46%); 24 Asian or Pacific Islander (6%), 34 Black (8%), 19 Hispanic (5%), three Native American (1%), 305 White (75%), three other/unspecified (1%), 17 two or more races (4%).

Procedure

The study had a 2 (control vs. ranking on quality) × 2 (quality sorting vs. name sorting) factorial design, and participants were randomly assigned to one of the four cells. In all conditions, we asked participants to imagine that they were looking for a clog remover online because water was draining slowly in their kitchen sink. We further asked them to imagine that they had found four clog removers ("A"–"D") with the highest effectiveness ratings (which we consider quality ratings). Then participants were given information regarding those options' effectiveness ratings and prices. Importantly, B and C had higher effectiveness ratings and lower prices than A and D, respectively. In other words, B dominated A, and C dominated D. Thus, we expected most participants would choose either B or C. B and C did not dominate each other: C had a higher effectiveness rating than B, but B had a lower price than C.

In the control condition, participants were given information regarding the effectiveness ratings and the prices of the four clog removers. In the ranking condition, participants were additionally given rank information based on the effectiveness ratings ("1"–"4"); the rank information was solely based on the effectiveness ratings, and participants were informed of this.

Information about the clog removers was sorted in two ways. In the quality sorting condition, the options were sorted by the effectiveness ratings in descending order (highest [top] to lowest effectiveness ratings [bottom]). In the name sorting condition, the options were sorted by their names in alphabetical order (A [top] to D [bottom]). Figure 7 presents the information that participants were given. Based on the information about the four clog removers, we asked participants to decide which one to purchase ("Please choose the item that you'd like to purchase"). Finally, they provided demographic information.

Results and Discussion

As expected, the majority of participants across the two conditions (96%) chose either B or C (see Table 6 for participants'

Figure 7
Presentation of Information in Study 5: Control Condition (Top) and Ranking Condition (Bottom)

Name	Effectiveness Rating (Highest rating = 100)	Price
A	89	$8.85
B	93	$6.77
C	95	$9.35
D	94	$10.05

Name	Effectiveness Rating (Highest rating = 100)	Price	Effectiveness Ranking (Highest ranking = 1)
A	89	$8.85	4
B	93	$6.77	3
C	95	$9.35	1
D	94	$10.05	2

Note. Only the name sorting condition is presented.

Table 6
Decisions in Study 5

Clog removers	Number of participants who chose the clog remover					
	Rating sorting			Name sorting		
	Control, n = 101 (%)	Ranking, n = 103 (%)	Total, n = 204 (%)	Control, n = 103 (%)	Ranking, n = 98 (%)	Total, n = 201 (%)
A	2	0	1	0	6	3
B	58	40	49	61	34	48
C	38	60	49	32	60	46
D	2	0	1	7	0	3

Note. C was the option ranked highest on the ranked attribute.

decisions). However, there was a significant difference in participants' choices between the control and ranking conditions, $\chi^2(3) = 339.94$, $p < .001$. In the control condition, 60% of participants chose B (which had a lower price), whereas 35% chose C (which had a higher effectiveness rating). In the ranking condition where participants were given rank information based on the effectiveness ratings, the opposite pattern emerged: 37% of participants chose B, whereas 60% chose C. The likelihood of choosing B or C differed significantly between the two conditions, Cohen's h for choice of B = −.46, $\chi^2(1) = 20.51$, $p < .001$, Cohen's h for choice of C = .51, $\chi^2(1) = 25.18$, $p < .001$.

To test our full 2 (control vs. ranking) by 2 (sorted on quality vs. name) design, we used a general linear model with the probit link function to test each main effect and the interaction. As expected from the univariate tests, the presence of ranking had a significant main effect ($p < .001$). However, there was no main effect of sorting ($p = .403$) nor a two-way interaction ($p = .551$). Simple slopes revealed that the effect of rank information was significant regardless of whether options were sorted by quality ratings (38% of participants chose C in the control condition vs. 60% in the ranking condition, $z = 3.22$, $p = .001$) or by name (32% of participants chose C in the control vs. 60% in the ranking condition, $z = 4.00$, $p < .001$).

The results showed that rank information significantly changed the way participants weighed the tradeoff between quality and price. With ranking based on the quality of options, participants were much more likely to choose the option that was of higher quality but more expensive. The results also indicated that rank information significantly influenced people's decisions across different sorting options (by quality or by name).

Study 6

The previous experiments provided causal evidence to show that rankings shaped decision makers' preference for the top ranked option, and this effect was differentiated from sorting. The common characteristic of the studies was that the top ranked option was the first ranked option. In other words, there was always the number *1* or *1st* attached to the top ranked option. We recognize that there are many possible positive associations with the number 1. For example, in many year-end sports polls the number 1 reflects not just a subjective assessment of raters, but that a team has defeated other teams to win the national championship. In this study, we tested whether the effect of rankings would emerge even when the top ranked option was not the first ranked option. To do so, we created an experimental condition without 1 or 1st attached to the top ranked option. This study addressed a similar context as Study 4, focusing on promotion decisions in the workplace.

Method

Sample

We recruited 301 participants on Prolific Academic, $M_{age} = 35.4$; 152 female (50%), 146 male (49%), three nonbinary (1%); 12 Asian or Pacific Islander (4%), 17 Black (6%), 10 Hispanic (3%), 242 White (80%), 20 two or more races (7%).

Procedure

The study had three conditions: control vs. ranking with a #1 option vs. ranking without #1 option. Similar to Study 4, participants in all conditions were asked to imagine that they were a manager of a large store that specialized in electronics and computers, planning to promote one of their sales associates to the position of an assistant manager. Participants were informed that they were considering 15 sales associates as candidates, and they would be given information about six of them.

On the next page, participants were provided with profiles of the six sales associates, which were identical to Study 4 in terms of the attributes and each candidate's specific ratings (and organizational tenures). Participants were randomly assigned to one of the three conditions. The difference among the conditions was (a) whether participants were given rank information and (b) how the rank information was organized. In the control condition, participants were given only the ratings regarding the six candidates. In the ranking with #1 option condition, participants were given rankings of the six candidates based on their ratings in sales goal achievement, and the rankings ranged from *1st* to *6th*. In the ranking without #1 option condition, participants were given rankings based on sales goal achievement as well, but the rankings ranged from *3rd* to *8th*. The rankings were in the same order for the ranking with #1 option condition and the ranking without #1 option condition, and they indicated that Riley Smith was the top ranked candidate in sales goal achievement among the six candidates. Figure 8 presents the information that was used in the two ranking conditions (the control condition simply omitted the column containing rankings). Based on the information about the six candidates, participants were asked to

Figure 8

Presentation of Information in Study 6: Ranking With #1 Option Condition (Top) and Ranking Without #1 Option Condition (Bottom)

Name	Evaluation from coworkers	Customer satisfaction	Sales goal achievement	Ranking of sales goal achievement	Organizational tenure
Casey Bowen	4.40/5	4.11/5	4.30/5	3rd	5 years
Taylor Wilcox	4.18/5	4.42/5	4.21/5	6th	5 years
Riley Smith	4.22/5	4.23/5	4.36/5	1st	5 years
Jordan Culver	4.27/5	4.30/5	4.24/5	5th	5 years
Charlie Vosburg	4.23/5	4.25/5	4.33/5	2nd	5 years
Hollis Williams	4.32/5	4.22/5	4.27/5	4th	5 years

Name	Evaluation from coworkers	Customer satisfaction	Sales goal achievement	Ranking of sales goal achievement	Organizational tenure
Casey Bowen	4.40/5	4.11/5	4.30/5	5th	5 years
Taylor Wilcox	4.18/5	4.42/5	4.21/5	8th	5 years
Riley Smith	4.22/5	4.23/5	4.36/5	3rd	5 years
Jordan Culver	4.27/5	4.30/5	4.24/5	7th	5 years
Charlie Vosburg	4.23/5	4.25/5	4.33/5	4th	5 years
Hollis Williams	4.32/5	4.22/5	4.27/5	6th	5 years

choose the one they preferred the most as a candidate for the assistant manager. Finally, participants provided demographic information.

Results and Discussion

To properly compare participants' preferences among the six candidates, we created two linear contrasts. The first contrast compared participants' preferences in the control condition versus the two ranking conditions. The second contrast compared participants' preferences between the two ranking conditions. We tested the effects of these two contrasts on participants' decisions to prefer the top ranked candidate (using the probit link function). Consistent with our findings in the previous studies, participants in the two ranking conditions were more likely to prefer Riley Smith (who had the highest rating in sales goal achievement; 43%) as compared with those in the control condition (10%), Cohen's $h = .79$, $z = 5.64$, $p < .001$ (see Table 7). Again, rank information shifted decision makers' preference to the top ranked option.

We then compared participants' preference for Riley Smith between the two ranking conditions. The strengths of preference for Riley Smith were similar in the ranking with #1 option condition (39%) and the ranking without #1 option condition (47%). The difference between the two ranking conditions was not statistically significant, Cohen's $h = -.16$, $z = -1.14$, $p = .255$.

The results from this study not only replicated the ranking effect but also showed that the effect was not driven by the presence of 1 or 1st. In other words, rank information induced participants' preference for the top ranked option in a given set of options, regardless of whether the option was first ranked or not.

Study 7

In Study 6, we found that the effect of ranking on preferences persisted even in the absence of a first ranked option. In Study 7, we address another alternative explanation for the effect of rankings. It is possible that rankings presented with ratings convey additional information about the importance of the ranked attribute. Researchers have argued that people attend to the conversational logic of a situation and draw inferences about a speaker's intentions (Grice, 1975; Schwarz, 1994; Sher & McKenzie, 2006). For example, when something is mentioned in a conversation, people tend to infer it is relevant (e.g., "X must be relevant if X is mentioned"). If this logic is applied to our experimental designs, participants might have

Table 7
Decisions in Study 6

Candidates	Number of participants who promoted the candidate			
	Control, $n = 99$ (%)	Ranking 1st, $n = 101$ (%)	Ranking non-1st, $n = 101$ (%)	Total, $n = 301$ (%)
Casey Bowen	24	19	19	21
Taylor Wilcox	26	12	8	15
Riley Smith	10	39	47	32
Jordan Culver	20	14	10	15
Charlie Vosburg	10	12	11	11
Hollis Williams	9	5	6	7

Note. Riley Smith was the option ranked highest on the ranked attribute.

considered the ranked attribute to be more relevant because it was mentioned in terms of not only ratings but also rankings.

In this study, we examined whether perceived importance of attributes was indeed related to the presence of rank information. In doing so, we created two separate situations in which participants reported attribute importance: with or without making decisions. We propose that if the presence of rank information itself sends a signal about attribute importance, conversational norms would operate in both situations, and participants would report the ranked attribute to be more important than the non-ranked attribute even without making decisions.

In contrast, if the effect of rank information on perceived importance operates via decisions, decision makers would report greater importance of the ranked attribute over the non-ranked only when making decisions (in favor of the top ranked option). In this case, the perceived importance can be viewed as a byproduct of decision makers using the ranked attribute more in making their choice, and then reporting its greater importance (Bem, 1972; Brehm & Cohen, 1962). To test these two possibilities, we created a design in which we manipulated whether participants reported attribute importance with or without making a choice. We used an experimental context involving hiring decisions in the workplace.

Method

Sample

We recruited 402 participants on Prolific Academic, $M_{age} = 32.8$; 203 female (50%), 195 male (49%), four nonbinary (1%); 20 Asian or Pacific Islander (5%), 30 Black (7%), nine Hispanic (2%), one Native American (.2%), 312 White (78%), 30 two or more races (7%).

Procedure

We asked participants to imagine that they were a Director of the School of Continuing Education (SCE) at a university in the United States, and that they were looking to hire an Assistant Director for the computer education unit. We further explained that the job for this position would involve a lot of collaboration with the Department of Computer Science, rendering competencies in two domains particularly important: technical expertise in computer science and negotiation skills.

Following this description, participants were given profiles of three candidates, Casey Bowen, Taylor Wilcox, and Riley Smith. The information regarding the candidates was provided for three attributes. The first attribute was the length of their managerial experiences (in years). The candidates were equal in this attribute; they all had 3 years of managerial experience. The second attribute was expertise in computer science (0 = weak, 100 = strong). On this attribute, Riley Smith had the highest rating, Casey Bowen the second, and Taylor Wilcox the third. The third attribute was negotiation skills rated by past coworkers (0 = lowest, 100 = highest). Regarding this attribute, Taylor Wilcox had the highest rating, Casey Bowen the second, and Riley Smith the third. In sum, Riley Smith had the highest rating for expertise in computer science, Taylor Wilcox had the highest rating for negotiation skills, and Casey Bowen was in the middle in both attributes. Figure 9 presents the information that participants were given.

In addition to the information regarding the three attributes, participants were given rank information ("1st"–"3rd"). In one condition, the rankings were based on expertise in computer science. In the other condition, the rankings were based on negotiation skills. The rank information was solely based on the attribute ratings, and participants were informed of which ratings the rankings were based on.

We also manipulated a second variable: Half the participants made a hiring decision and half did not. In the hiring decision condition, participants were asked to make a hiring decision among the three candidates ("Who would you hire as the Assistant Director of the SCE?"). In the no hiring decision condition, participants did not make a hiring decision and instead proceeded to the questions regarding perceived importance of the attributes described below. Thus, the study had a 2 (ranking based on expertise in computer science vs. ranking based on negotiation skills) × 2 (hiring decision vs. no hiring decision) factorial design, and participants were randomly assigned to one of the four cells.

Subsequently, participants in all conditions reported the perceived importance of all three attributes in making the hiring decision (for each attribute; "To what extent do you think that the following dimensions are important to consider in deciding which person to hire in this situation?"; 1 = *not at all* to 7 = *very much*). Finally, they provided demographic information.

Results

Decisions

We first present the decisions from the hiring decision condition. Participants' decisions differed significantly between the two ranking conditions (see Table 8), $\chi^2(2) = 29.11$, $p < .001$. Participants who received rank information based on expertise in computer

Figure 9

Presentation of Information in Study 7: Ranking Based on Expertise in Computer Science Condition (Top) and Ranking Based on Negotiation Skills Condition (Bottom)

	Years of managerial experiences	Expertise in computer science (100 = strong, 0 = weak)	Negotiation skills rated by past coworkers (100 = highest, 0 = lowest)	Ranking based on expertise in computer science
Casey Bowen	3 years	75	75	2nd
Taylor Wilcox	3 years	70	90	3rd
Riley Smith	3 years	90	70	1st

	Years of managerial experiences	Expertise in computer science (100 = strong, 0 = weak)	Negotiation skills rated by past coworkers (100 = highest, 0 = lowest)	Ranking based on negotiation skills rated by past coworkers
Casey Bowen	3 years	75	75	2nd
Taylor Wilcox	3 years	70	90	1st
Riley Smith	3 years	90	70	3rd

science were more likely to hire Riley Smith (who had the highest rating for expertise in computer science; 52%) as compared with those who received rank information based on negotiation skills (17%), Cohen's $h = .76$, $\chi^2(1) = 25.86$, $p < .001$. Conversely, participants who received rank information based on negotiation skills were more likely to hire Taylor Wilcox (who had the highest rating for negotiation skills; 60%) as compared with those who received rank information based on expertise in computer science (29%), Cohen's $h = .63$, $\chi^2(1) = 18.12$, $p < .001$. Finally, there was no significant difference between the two conditions in the likelihood of hiring Casey Bowen (who was in the middle for both attributes), Cohen's $h = .10$, $\chi^2(1) = .35$, $p = .553$. These findings replicated the results from our previous studies by showing that rank information significantly shaped people's preference for the top ranked option.

Perceived Importance of the Attributes

The perceived importance score was submitted to a 2 (basis of ranking; expertise in computer science vs. negotiation skills) × 2 (importance of attribute; expertise in computer science vs. negotiation skills) × 2 (the existence of hiring decision; yes or no) analysis of variance (ANOVA) with the second factor as a within-subject variable. The results demonstrated that there was a two-way interaction between the basis of ranking and importance attribute, $F(1, 398) = 10.83$, $p = .001$, which was qualified by the three-way interaction, $F(1, 398) = 8.13$, $p = .005$. We thus explored the two-way interaction within each of the two levels of hiring decision.

The interactions revealed that participants reported the ranked attribute to be more important than the non-ranked attribute, but only in the hiring decision condition. As can be found in Table 9, in the hiring decision condition, those who were given rank information based on expertise in computer science reported that expertise in computer science was more important ($M = 5.95$) than negotiation skills ($M = 5.52$), $t = 2.42$, $p = .017$, whereas those who were given rank information based on negotiation skills reported that negotiation skills were more important ($M = 5.93$) than expertise in computer science ($M = 5.42$), $t = 3.07$, $p = .003$. In contrast, as can be found in Table 10, in the no hiring decision condition, the perceived importance of the two attributes did not differ between the two bases of ranking (expertise in computer science vs. negotiation skill), $ps > .453$. Participants in the two ranking conditions reported almost identical levels of perceived importance of both expertise in computer science and negotiation skills.[22, 23, 24]

[22] In both the hiring decision condition and no hiring decision condition, there was no significant difference in perceived importance of managerial experiences between the two conditions, $ps > .552$.

[23] We report how the results regarding perceived importance (in the hiring decision condition) were further broken down by participants' specific hiring decisions in the Online Appendix G. The evidence strongly supported our interpretation that participants reported perceived importance of the attributes in ways that were consistent with their decisions.

[24] We ran another study with a similar design as Study 7 using an alternative method to capture perceived attribute importance in the no hiring decision condition. The hiring decision condition was identical as in Study 7: We asked participants to make the hiring decisions and then report the perceived importance of the attributes. In the no hiring decision condition, participants were asked to choose the attribute they considered to be most important without making hiring decisions ("Among the three dimensions above, which dimension do you consider to be most important in evaluating the candidates?"). The results from this study replicated the findings in Study 7: Participants in the hiring decision condition showed hiring preferences and ratings of perceived attribute importance that matched the ranked attribute. In contrast, participants in the no hiring decision condition showed no differences of perceived attribute importance as a function of which attribute was ranked. This alternative measure of attribute importance in the no hiring condition complements the results of Study 7, and the results can be found in the Online Appendices H–J.

Table 8
Decisions in Study 7

Candidates	Ranking based on expertise in computer science, $n = 101$ (%)	Ranking based on negotiation skills, $n = 99$ (%)	Total, $n = 200$ (%)
Casey Bowen	19	23	21
Taylor Wilcox	29	60	44
Riley Smith	52	17	35

Note. Riley Smith and Taylor Wilcox were the options ranked highest on expertise in computer science and negotiation skills, respectively.

Discussion

The results on hiring decisions replicated our basic finding: Participants preferred an option that had the highest rating on the ranked attribute than another option that had the highest rating on the non-ranked attribute. Moreover, we examined whether the presence of rankings led decision makers to report that the ranked attribute was more important than other attributes. Our findings suggest that decision makers reported greater importance of the ranked attribute as compared with the non-ranked attribute only after they made hiring decisions. The results thus suggest that rank information shaped perceived importance via its effect on choice. Subsequent to hiring decisions (which were significantly affected by rank information), participants rated the ranked attribute as more important than the non-ranked one, making their importance ratings consistent with their choice. In contrast, participants in the no hiring condition did not rate the attributes as different in importance; participants in the no hiring condition lacked a choice with which to be consistent. This pattern suggests that, if there is a conversational inference, it occurs in a way associated with the decision—perhaps at the time of decision. At the same time, the increase in attribute importance after the decision is also consistent with a justification process (Bem, 1972; Brehm & Cohen, 1962). The current design cannot distinguish between these processes—it can only show that making a decision is an important element to increasing the perceived importance of the ranked attribute.

General Discussion

Decision makers face an expanding sea of information, and ranking is one of the most popular tools for navigating this challenge. Because ranking organizes information about the options in a simple and familiar way, it has received much acceptance in various domains as an instrument that can facilitate decision making processes. The present research reveals how such rank information influences people's choice. We find that ranking reliably increases decision makers' preferences for the top ranked option even when it does not provide additional information about the options' features.

Our empirical evidence further illuminates the nature of the effect. First, the effect of rank information emerged both when it was presented with ratings and when it was not (Study 2). Second, the effect was found when the ranking was based on a particular attribute or an average score across various attributes (Study 3). Third, the effect was found independent of how information about the options was sorted (Study 5). Fourth, the effect was found even when the number 1 or 1st was not attached to the top ranked option: Rank information led decision makers to favor the *top* ranked option, regardless of whether it was the *first* ranked option or not (Study 6). Fifth, the presence of rank information did not in itself increase the perceived importance of the ranked attribute. However, after making a choice that was influenced by the presence of the rank, decision makers did report that it was more important—in directions that were consistent with their decisions (Study 7).

The effect of rank information was explained by the way decision makers allocated attention to the available options (Study 4). In the presence of rank information, decision makers spent more time attending to the information regarding the top ranked option, which helped them recognize the strength of the option. In contrast, rank information reduced attention to the other options, preventing decision makers from recognizing the strengths of those options. These processes explained decision makers' preference for the top ranked option.

Implications

Does Rank Information Help or Hurt Making the Best Choices?

The presence of rank information increases preference for the option that is rated highest on the ranked attribute. In this section, we discuss the pros and cons of being influenced in this way.

We first consider Study 1, which analyzed historical data that included not only rank information (within specific performance categories) but also overall performance information (as calculated by weighting a variety of performance categories). Figure 1 shows

Table 9
Mean Perceived Importance of Attributes in Study 7: Hiring Condition

Attribute	Ranking based on expertise in computer science ($n = 101$)	Ranking based on negotiation skills ($n = 99$)	Total ($n = 200$)
Expertise in computer science	5.95 (1.02)	5.42 (1.19)	5.69 (1.14)
Negotiation skills	5.52 (1.25)	5.93 (1.17)	5.72 (1.22)
Years of managerial experiences	4.84 (1.54)	4.71 (1.66)	4.78 (1.60)

Note. Numbers in parentheses are standard deviations.

Table 10
Mean Perceived Importance of Attributes in Study 7: No Hiring Condition

Attribute	Ranking based on expertise in computer science (n = 101)	Ranking based on negotiation skills (n = 101)	Total (n = 202)
Expertise in computer science	5.84 (1.11)	5.81 (1.05)	5.83 (1.08)
Negotiation skills	5.74 (1.03)	5.78 (1.18)	5.76 (1.10)
Years of managerial experiences	4.38 (1.54)	4.45 (1.66)	4.41 (1.69)

Note. Numbers in parentheses are standard deviations.

that overall performance was highly predictive of the likelihood of being voted onto the All-NBA Team. Importantly, being ranked number one in a performance category significantly weakened this relationship. As a result, a number of players with the highest overall performance were not chosen for the award when they were not top ranked within the performance category. When those players were omitted for the award, the chosen players were often top ranked players who did *not* demonstrate the highest overall performance. These findings illustrate how decision makers may focus on rank information and prefer the top ranked options, overlooking other equally strong or perhaps stronger options.

Throughout the remaining studies, we found that decisions were significantly affected by rank information even when it was presented with the underlying attributes, adding no new information regarding the options' characteristics. One could argue that information conveying no new knowledge should be ignored and thus exert no influence on preference. This view, however, may assume an unrealistic level of information processing capability. Multiattribute choice is often cognitively demanding because of the sheer amount of information and the need to make tradeoffs; some use of simplifying strategies may be optimal in a full analysis of the tradeoff between effort and accuracy (Payne et al., 1993). In this spirit, we reflect on some of the factors that may make ranks more or less helpful in achieving effective decisions. We first consider the ranks based on individual attributes and then the ranks based on aggregate ratings (such as average ratings).

When ranks are put on individual attributes, we believe one important problem can arise if options differ from one another only slightly on the ranked attribute but more substantially on non-ranked attributes. In this case of small differences on the ranked attribute, the presence of rank information might prevent decision makers from noticing the options' characteristics in the non-ranked attributes and thus making their preferred trade off—giving up a small difference on the ranked attribute to achieve a sizeable gain on other attributes. As a result, rank information could worsen decision outcomes.

To explore the effectiveness of putting ranks on aggregate ratings (e.g., average scores across multiple attributes), we should first examine decision makers' baseline tendencies in choice. In Study 3, without rank information, 60% of participants chose the options that rated highest in the attributes they considered to be most important (when they were given the average ratings of the options as well). This may be explained by the operation of a fast and frugal strategy in multiple-attribute choice (Payne et al., 1993) such as the lexicographic heuristic (Fishburn, 1974) or the take-the-best strategy (Gigerenzer & Goldstein, 1996). Similarly, in Studies 4 and 6 (where the options had identical sum totals), 65% of participants without rank information chose the candidate that had the highest rating in one of the three attributes. Again, this pattern suggests that without rank information people may attempt to simplify their decisions based on the attribute they considered to be most important.

In this situation, information providers can help decision makers incorporate more attributes by presenting rankings based on aggregate ratings. However, to properly understand the implication of such strategies, we should recognize that while creating the aggregate ratings, information providers also make choices about how to weight the attributes. One weighting scheme, for example, could be a simple equal-weighted averaging (as in the weighting of facilities, staff, and vibe in the gym decision in Study 3). Decision makers themselves, however, may have good reasons to want to put more weight on one attribute (such as facilities) and less on another (such as vibe). Therefore, rankings based on aggregate ratings may create (or worsen) a misalignment between the decision makers' original preferences and the weights assigned by information providers. The risk of misalignment can be compounded in many popular rankings offered by magazines and websites that are opaque regarding the weights used to calculate the aggregate ratings (Monks & Ehrenberg, 1999).

Self-Reinforcement of Rank Order

The results from Study 7 revealed that participants used rank information to make their decisions, and then reported the importance of attributes that were consistent with the decisions (Bem, 1972; Brehm & Cohen, 1962). When such beliefs regarding attribute importance shape future decisions, decision makers' preference for the top ranked option can persist in the long run (Salganik et al., 2006). In other words, ranking could become self-reinforcing.

This possibility should be considered along with the fact that ranking is often used in combination with sorting in various settings. For example, when online platforms provide information about restaurants, they frequently rank the restaurants based on certain ratings (e.g., "Overall" or "Average") *and* sort them by the rankings. Previous research has shown that sorting can increase attention to the first-listed item (Dellaert & Häubl, 2012; Häubl & Trifts, 2000). It is possible that when sorting occurs based on ranking, sorting can further strengthen the effect of ranking (although we did not find such a pattern in our test of this possibility in Study 5).

Lastly, we revisit the Study 1 results that explored how rank information explained award decisions. Both conceptually and practically, awards and rankings are differentiated from each other. Conceptually, awards are given to a selected group of individuals, whereas rankings are assigned to all relevant options. Practically, awards are mostly given as a signal of appreciation and recognition, whereas rankings can be done for purely evaluative purposes.

However, rankings and awards can be meaningfully related. First, as our results suggested, rankings may influence award decisions. Conversely, decision makers may infer rank information from award decisions. For example, if they learn that a particular option received an award in the past, they may infer that the option could have been the top ranked one. Such a process can help the top ranked options dominate others even after their attributes have changed. This benefit may be related to the strong motivation that people demonstrate to win awards as discussed in the prior literature (Frey, 2007).

Alternative Processes

In Study 2, we considered whether a double-counting process (driven by rankings in addition to ratings) could explain the ranking effect. The results indicated that the effect of rankings in addition to ratings was not significantly different from rankings shown alone, providing no evidence for a double-counting explanation. Also, in Study 7, we evaluated the potential operation of conversational norms (Grice, 1975; Schwarz, 1994; Sher & McKenzie, 2006). Participants in the no hiring decision condition reported that the ranked attribute was no more important to consider than the non-ranked one. These findings indicate that rank information did not in itself affect participants' beliefs regarding the attribute importance; the perceived importance of the attributes was influenced by rank information indirectly via choice.

Another possibility that is not tested in the current work suggests that rank information may distort the way decision makers encode the options' characteristics (e.g., ratings; Monroe, 1973; Montgomery & Svenson, 1989; Russo et al., 1996; Tajfel, 1957; Veltkamp et al., 2008). This process may emerge particularly between the top ranked option and the rest. The perceptions formed during encoding could contribute to the advantage of the top-ranked option.

Directions for Future Research

We briefly consider some possible directions for future work. First, there are multiple stages at which individual decision makers use rank information. For example, people may screen their options in an initial stage to determine which ones they would consider for decisions (Shi et al., 2013). In a later stage, they may use the rankings to make decisions among the screened options (Häubl & Trifts, 2000). Our experiments may be more relevant to this second stage, because we asked participants to make their decisions among a limited set of options. Thus, future studies can illuminate the effect of rank information in the initial stage by examining how it influences the process in which decision makers select the options that they would further consider for decisions (Dellaert & Häubl, 2012).

Another issue that may be worth exploring is understanding the utility function involving rankings (Houthakker, 1950; Samuelson, 1937). Just as there are nonlinear utilities for money (e.g., psychologically, $10,000 is not worth 10 times as much as $1,000; Booij & van de Kuilen, 2009; Kahneman & Tversky, 1979), rankings may also produce nonlinear utility. Our results imply that the differences among the top ranked versus non-top ranked options' utility can be perceived to be greater when rank information is available. Future work can reveal the details of utility functions involved in rankings from the very top to the bottom.

Conclusion

Ranking is a widely popular approach that people use to assess various options they are considering. However, our findings suggest that there is a risk in relying on ranking to make decisions. Rank information can significantly shape decision makers' preference for the top ranked option, even when the ranking itself does not provide additional information regarding the options' characteristics. The effect of rank information is explained by the amount of attention that decision makers invest in the top ranked option (over other options), which leads them to recognize the top ranked option's strength while overlooking the other options. Overall, our evidence suggests that ranking can operate as a channel in which the top ranked option dominate the market over and above its merit.

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