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Testing of methods for reducing motivational bias in multi - criteria decision analysis problems

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The idea of multi-criteria decision making has been around for quite a while. All judgement tasks are potential points of bias introduction. Each judgement task was assessed to identify common biases introduced through an extensive literature review for each task and bias. In several other studies, the distinction is made between cognitive and motivational biases. Cognitive biases are widely studied and well known with mitigations that have been validated. Motivational biases are judgements influenced by the decision maker's desire for a specific outcome, also referred to as intentional bias, that are hard to correct and received very little testing and exploration. This study tested the techniques that are identified for reducing motivational bias and tested an instrument to identify characteristics within a decision maker that would increase the likelihood that they would be motivationally biased. The results of this study provide a methodology for assessing the susceptibility to motivational biases of the decision makers and provides a framework for reducing the motivational bias within the multi-criteria decision making (MCDM) process using the general steps applicable to all multi-criteria decision analyses. Given that the general steps are used, this methodology is generalizable to any MCDM problem or domain and was found to be reliable and consistent with previous instruments and tools. A summary of the future research

to further the explore the methodology and additional techniques for reducing motivational bias is proposed.

DEDICATION

This dissertation and completion of a Doctoral degree is dedicated to family. All the hard work and time spent was for both my own goals and aspirations, but also to show my family that you can achieve anything. I hope this achievement, my actions, and the lessons that I teach my kids instill life-long learning and exploring the world to further the human condition and solve problems that are challenging.

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INTRODUCTION

All decisions require judgements based on the experience, knowledge, and preferences of the decision makers. Decision makers are stakeholders in the development of the system such as customers, engineers, program managers, and system end-users. Each decision includes the development of a mathematical representation of the system value as a function of the attributes, referred to as the utility function. The utility function is a combination of knowing which decision maker's judgments of system value will have priority and the evaluation criteria (Maier, et al., 2009). If there is only a single criterion, the decision is very simple. The chosen alternative is simply the alterative with the best outcome based on the specified single criterion. Often there are multiple criteria, which are conflicting, assigned decision maker weightings, and preference dependencies (Hwang, et al., 1981). When decisions become complex, the decision maker becomes uncertain of their preferences. This leads to random errors or systemic biases in the value or utility assessment supporting the decision (Winterfeldt, et al., 1986). Multi-Criteria Decision Making (MCDM) techniques have been developed to aid decision analysis by providing a quantitative framework supporting the decision-making process.

1.1 Multi-Criteria Decision Making

The idea of multi-criteria decision making has been around for quite a while. In 1772, Benjamin Franklin proposed a "moral or prudential algebra" for making decisions (Koehler, 2004). Although it has taken some time to become more widely used, it now permeates many facets of study. In a study of 393 research articles related to MCDM techniques published between the year 2000 and 2014, the top three most widely used, unique, techniques were Analytic Hierarchy Process (AHP) at 32.57%, Technique for Order of Preference by Similarity to the Ideal Solution (TOPSIS) at 11.4%, and ELECTRE at 8.65% (Mardani, et al., 2015). Among the other techniques listed were PROMETHEE, VIKOR, and Analytic Network Process (ANP). There were significant uses of hybrid MCDM at 16.28%, which includes use of multiple techniques together, and aggregation decision making methods at 11.70%. Additionally, it was found that research in the MCDM domain is growing rapidly. While there were 3 articles published in 2000, there were 75 published in 2014. The growing research in MCDM techniques and their application shows a significant increase in utilization and importance for this domain.

As found in the environmental planning domain, the introduction of bias can lead to distrust and ultimately disregard for the results of the MCDM process by decision makers (Hajkowicz, 2007). When this distrust is propagated, the decision makers will often ignore the outcome of the analysis and make their own final judgement based on their own experiences and biases. The application of MCDM is far reaching, including all facets of business, from economics, engineering, construction, environmental, and management; the applications are endless (Hwang, et al., 1981). The wide utilization of MCDM provides justification for the importance for improving objectivity and confidence in the analysis outcome.

A 2015 study identified the general process for MCDM (Montibeller & Winterfeldt, 2015). There are 5 judgement-based tasks and a single aggregation task for any decision made. These steps include:

1. Generating the alternatives [judgement]
2. Developing the attributes/criteria [judgement]

3. Assessing the performance of the alternatives against the attributes [judgement]
4. Eliciting the utility function over attribute levels [judgement]
5. Eliciting the weights of each attribute [judgement]
6. Aggregating the data [aggregation]

For all MCDM problems, these steps apply. To guide thought, the purchase of a new vehicle for your family is used as an example. First, you must identify the alternatives that you wish to decide among. For a vehicle purchase, this includes many different options, we use sports utility vehicle (SUV), standard sedan, and sports car in this example for simplicity. Next, you must identify the attributes, or evaluation criteria, that you will use to aid in your decision. These are the critical characteristics of the alternatives that allow you to evaluate each one. For instance, number of passengers, gas mileage, safety rating, top speed, cost, and comfort of passengers. Next, you must complete a decision matrix with rows for alternatives and columns for the evaluation criteria. For each pairing an assessment of the alternative for that criterion is performed. The top speed of a SUV may be 120 miles per hour (mph), while the top speed of a sports car could be 180 mph. The gas mileage of a sedan could be 30 miles per gallon, while that of an SUV is 18 mpg. Lastly, the evaluation criteria are assessed for relative weighted importance. For the purchase of a vehicle for a family, the highest weighted criteria could be number of passengers, to ensure your entire family can fit in the vehicle, followed by comfort of passengers, to ensure they are all comfortable for the family road trips.

There are often conflicting criteria. In the vehicle purchasing example, the sedan may have a max number of passengers of 5 (2 in the front and 3 in the back), but the comfort of those passengers is diminished. The comfort for the passengers in a SUV may be better, but the cost is much higher than that of a standard sedan. The MCDM framework support these tradeoffs and provides a rigorous and structured approach to make these decisions.

1.2 Problem and Research Questions

All judgement tasks are potential points of bias introduction. Each judgement task was assessed to identify common biases introduced through an extensive literature review for each task and bias. In several other studies, the distinction is made between cognitive and motivational bias (Dolinaski, et al., 1987) (Finucane, et al., 2000). Cognitive bias is defined as systematic errors in judgment that conflict with the axioms of expected utility theory (Kahneman & Tversky, 1979). There are many sources in literature for defining, reviewing, and identifying mitigation practices for the cognitive biases (Montibeller & Winterfeldt, 2015) (Tversky & Kahneman, 1974). On the other hand, motivational biases are judgements influenced by the decision maker's desire for a specific outcome, also referred to as intentional bias. A general example of motivational bias is the underestimation of complexity for a project proposal, resulting in lower cost and shorter schedules to become more competitive to win a contract or grant (Montibeller & Winterfeldt, 2015). This is often intentional to reach the desired result, winning the bid for a new project.

As described in the literature, motivational biases are hard to detect and mitigate (Montibeller & Winterfeldt, 2015). Therefore, the research questions that will guide this study are:

- Are there methods for measuring motivational bias, or likelihood of motivational bias, within a multi-criteria decision making (MCDM) framework?
- Do the identified de-biasing techniques have any impact on reducing the motivational bias within a multi-criteria decision making (MCDM) framework?

1.3 Research Approach

To test the research questions, a quantitative experimental methodology was chosen. As related to the first question on measuring likelihood of motivational bias, a study of the participants and their probability of susceptibility to the identified biases will be conducted. For the de-biasing techniques, the experiment will contain a control group, without treatment, and treatment groups. The treatments will test the de-biasing techniques individually and compare to the control group that has no treatment. The experiment design will be a between-subjects, deductive, quantitative research design, which is fully detailed in CHAPTER III.

I

LITERATURE REVIEW

2.1 Motivational Biases

Among the literature there are five motivational biases in decision analyses which are "hard to correct" (Montibeller & Winterfeldt, 2015). Additionally, unlike the identified cognitive biases, all motivational biases identified are relevant to decision analysis. The five identified motivational biases are affect-influenced, confirmation, desirability of a positive outcome, undesirability of a negative outcome, and desirability of an option/choice bias.

2.1.1 Affect influenced bias

This bias is an emotionally driven bias called "affect," which is often thought of as a "first instinct." When faced with a decision your first instinct, or "gut feeling," will provide a basis for the judgement based on past experiences (Finucane, et al., 2000). This motivational bias is deeply internal, and many studies are working to determine the mechanisms behind the feeling of "goodness" or "badness" of a decision (Slovic, et al., 2004). Affect bias distorts decisions based on outcome probabilities according to what outcome they are attached and the emotional state of the decision maker (Rottenstreich & Hsee, 2001). Said another way, the outcome probabilities for options in the decision space are influenced by the decision maker's emotional connection with that specific option. As an example, it was shown that people assess the severity of a disaster caused by humans much higher than one caused by nature, even given the exact same outcome (Siegrist & Sutterlin, 2014). In the political domain, it was found that once voters became attached, affect influenced, to a candidate they tend to only search out information on that candidate and disregard information for the opposing candidate (Redlawsk, 2002). Even when faced with incongruent information on the affect generated candidate, it is posited that the voters were internally counter arguing the information, developing reasons why it would be incorrect or should be ignored. Another example is what is known as the endowment effect (Kahneman, 2011). This experiment randomly distributed a coffee mug to half of the participants. The participants with the mug were asked to identify a value at which they would trade the mug for cash ("Seller"). The participants without a mug were asked to identify a cash value that they would trade for the mug ("Buyer"). The result of the experiment showed the Seller's value was double that of the Buyer's value. The simulated "ownership" of the item alone, increased its value.

2.1.2 Confirmation bias

When a decision maker "cherry-picks" information that confirms their own preferences or beliefs is known as confirmation bias. Confirmation bias has been known for quite a while in the cognitive bias domain. In 1620, Philosopher Francis Bacon wrote of the desire of one to confirm their own beliefs in his work *Novum Organum*. This bias is particularly dangerous since it is often unconscious. People will often search for information that confirms their belief and discount information that supports the opposing view (Nickerson, 1998). This bias can also have a motivational side to it. When the decision maker is motivated for a specific outcome, they may intentionally disregard information or intentionally seek information to confirm, or support, their desired outcome.

2.1.3 Desirability of a positive event or consequence bias

Decisions can often have various outcomes that either provide a benefit or cost to the decision maker. This “wishful thinking” or optimism for an outcome that benefits the decision maker leading to an increase in the expected probability, is known as the desired outcome bias (Neumann, et al., 2014). This bias is also shown to be contagious (Seybert & Bloomfield, 2009). In a group decision making environment, once decision makers assert a desire for a specific outcome, their desires infect others in the group amplifying the bias throughout the entire group.

2.1.4 Undesirability of a negative event or consequence bias

Undesirability of a negative event or consequence bias is the opposite of the desired outcome bias. This is a cautious, prudent, and conservative approach to information gathering and analysis due to the desire to avoid the negative outcome of the decision. This is also referred to as pessimism bias, where the negative outcome likelihood decreases unrealistically (Dolinski & Gromski, 1987).

2.1.5 Desirability of options/choice bias

When a specific outcome is desired, not only is the judged probability higher, as shown in the two previous biases, but the decision makers will often leave out information, construe values, weights, and assessments, and even disregard relevant alternatives. This is known as desirability of options/choice bias. This form of bias is the most conscious form of motivational bias. Each decision maker has their own desires and agendas, often leading to the desire for a specific outcome. This intentional introduction of bias undermines the goal of decision analysis as a structured, logical, mathematical tool supporting objective decision making.

2.2 De-biasing Techniques

There have been many studies into mitigating biases in decision making. Across the literature there have been studies that attempt to identify potential solutions. The first step is defining what is known "not to work." Fischhoff found in reviewing solutions for biases that warning decision makers about biases, describing the direction of the bias, providing feedback to decision makers, and offering training/coaching on decision making did not dramatically reduce the biases introduced (Milkman, et al., 2009). This shows that simply providing information to the decision makers about their bias will not significantly reduce the bias that is introduced.

Within the literature there are discussions of different potential mitigations for motivational biases. The high-level classes of mitigations are: 1) group decision making, 2) critical analysis of data, 3) perspective/viewpoint, 4) data presentation, and 5) justification. The following paragraphs will provide an overview of these techniques, their use in de-biasing, and any potential pitfalls of using the method. One area that has shown promise for mitigating cognitive biases is what is described as the distinction between System 1 and System 2 cognitive functions (Stanovich & West, 2000). System 1 is the intuitive, first instinct, survival nature of humans. This is fraught with cognitive biases. System 2 is the deliberate, critical, and logical cognitive functions. The key here is to force decision makers into using System 2 where logic and reason become more salient. Where cognitive biases are unintentional and related to the subconscious, motivational biases are intentional, although it may not be apparent, and require more deliberate removal from the decision-making process. Most often techniques to reduce cognitive biases can be subtle, motivational bias reduction could take more drastic approaches to mitigate.

2.2.1 Group Decision Making

Group decision making was the most widely used and discussed mitigation for biases within the literature. There are both pros and cons when using group decision making. Groups can combine several different perspectives of a decision. Working together the group can come to a consensus on which alternative is best. While it sounds like a very good method, human interactions and behaviors are very complex and differ between members. The focus in the next few paragraphs are the pitfalls for the group decision making technique.

Groups are often unable to define the full range of objectives and have difficulty making choices to address their preferences (Wilson & Aryai, 2006). Group decision making can also be affected by informational influence and social influence, where the individuals with weaker resilience to bias, or persuasion, will "join the group" without the need for external sources of information (Del Vicario, et al., 2016) (Seybert & Bloomfield, 2009). It has also been found that groups tend to be more confident than individuals (Kerr, et al., 1996) and often show overconfidence (Kerr, et al., 2011). This can compound the issues with biases in decision making (Montibeller & Winterfeldt, 2015).

In the group setting, a strong opinion by one, or a few, members of the group will become the group majority opinion. A method to combat some of the group decision making pitfalls is the Delphi Process. This process "uses a panel of experts and repeated measurement and controlled feedback and replaces direct confrontation and debate with a planned program of sequential, individual interrogations usually conducted by questionnaire" (Jolson & Rossow, 1971). This process can significantly increase the time required for decision making.

2.2.2 Critical Analysis

Critical analysis of data was referenced in three of the biases, namely confirmation, desirability of positive outcome, and undesirability of negative outcome. This mitigation technique forces the decision maker to analyze the data logically, thoughtfully, and deliberately for the decision. One method involves forcefully slowing the reader/decision maker down using disfluency. For example, given confirmation bias, when individuals assume their hypothesis is true, they tend to interpret data and outcomes quicker (Hernandez & Preston, 2013). This could lead to disregard, or simply overlooking, relevant data against the hypothesis. Disfluency is the process making it more difficult to process the data provided by either adjusting the font size or type to make it harder to read. In a study where simple questions were asked, but where the intuitive response (System 1) was incorrect, the participants with the degraded font gave significantly more correct responses. The degraded font slowed the reader and engaged the logical, critical cognitive functions (System 2) (Oppenheimer, 2008). The second method, and partnered with disfluency, for critical analysis of data is providing the information directly to the decision maker. Although this must be carefully curated to avoid bias introduction, this is the most straightforward approach to ensure the data is considered (Finucane, et al., 2000). An example of this is used in the group decision making method, Delphi process, where the results are iteratively provided to the participants. Given the results of the entire group, the participants can review the data and change their responses in a feedback-type scenario.

2.2.3 Perspective and Viewpoint

Perspective and viewpoint were discussed as related to affect influenced biases. This mitigation involves putting the participant "in someone else's shoes." The decision maker can relate and utilizes their emotional response to the decision which then allows them to take on the persona of the stakeholder. An example of this is the "outsider's perspective." The decision maker can remove themselves mentally from the situation and consider the decision from outside the current problem. This has shown to reduce the overconfidence bias (Milkman, et al., 2009). Additionally, one can improve their decision making by asking a real outsider their view on the decision.

2.2.4 Data Presentation

Data presentation is only discussed regarding affect influenced and confirmation bias within the literature. This mitigation deals with how data is presented to the decision maker. This includes disfluency, as discussed in the critical analysis of data, but the primary concern is how the data is presented with regards to language used. A study looked at how clinicians assess the risk of mentally ill patients to become violent on a low, medium, and high scale (Rottenstreich & Hsee, 2001). The risk was assessed to be higher when the probability of violent activity for a patient was 10%, rather than when presented as a frequency of 10 in 100 encounters. In another study, college students were more strongly supportive of airport safety measures that would save "98% of 150 lives," than a measure that would save "150 lives" (Slovic & Peters, 2006). It was concluded that for humans, absolute numbers are harder to interpret than probabilities or percentages of a whole, resulting in reduced consideration/understanding of the data.

2.2.5 Justification

Justification requires the participants to justify their choices within the decision-making process. The action of providing a justification holds the decision maker accountable for the choices that were made. When people are required to justify their decision with others, they are less influenced by affect biases (Siergrist & Sutterlin, 2014). Justification forces the decision maker to provide a basis for their decision. This also slows down the decision and forces the decision maker to engage the more logical System 2 thought processes. This can lead to acknowledgement, or reversal, or their own motivational bias. In the policymaking domain, people are worried they will need to justify a decision in the event of a failure of the policy (Rothstein & Downer, 2012). Justification implicitly holds the decision maker accountable for their choice. This accountability causes a "pre-emptive self-criticism" within the decision maker in preparation for justifying their decisions to others (Koehler, 2004). This can often cause the decision makers to see their own biases and improve the decision making.

2.2.6 Summary

A summary of the motivational biases and corresponding mitigation techniques found throughout the literature is provided in Table 2.1.

Table 2.1 Motivational biases and de-biasing techniques

Mitigation / Bias	Group Decision Making	Critical Analysis of Data	Perspective/View	Data Presentation	Justification
Affect Influenced	●		●	●	●
Confirmation	●	●		●	
Desirability of Positive	●	●			
Undesirability of Negative	●	●			
Desirability of Options	●				●

In 2016, Ferretti tested best practices to reduce overconfidence bias, a cognitive bias, in MCDM (Ferretti, et al., 2016). Overconfidence bias is a cognitive bias where participants are overly confident that their decision is the right one. The participants were provided a questionnaire.

The questionnaire elicited probability and values for simple scenarios. After the initial estimates were provided, de-biasing techniques were applied. Finally, the participants were asked if they would like to revise their estimates. This process provided quantifiable data on when a participant would change their answer given the de-biasing technique applied.

The researchers employed two mitigation techniques to the questionnaires: hypothetical bets and counterfactuals. Hypothetical bets tell the participants to imagine they were betting on whether their choice was correct or not. Counterfactuals is a "what if?" scenario thinking about the other choice(s) within the decision. Both techniques slow the participants down to consider the decisions being made. The participants answered the questions, a technique was applied, then they were asked if they want to revise their responses. The analysis consisted of measuring the number of times the participants changed their answers due to a de-biasing technique being applied, which implied that the technique influenced the decision makers judgments.

2.3 Gaps

A gap within the research, also identified by others, is the exploration and testing of best practices for reducing motivational bias in MCDM (Montibeller & Winterfeldt, 2015). One study explicitly concluded with "Researchers need to identify strategies that will result in less biased decisions" (Slovic, et al., 2006). The few studies available provide some techniques that analysts use for reducing motivational biases, but these are untested in practice. In conclusion of another paper, a research agenda is proposed to further explore motivational biases and techniques for reducing these biases in decision analysis problems (Montibeller & Winterfeldt, 2015).

Given the gap identified and possible mitigations for the motivational bias introduced, the question remains: Where could motivational bias be introduced into our decision making? Breaking this down even further, you want to know the motivational bias susceptibility of your decision, degree to which the decision was influenced by bias, and best practices to avoid the introduction of biases.

I

RESEARCH DESIGN

Research design can be broken down into three categories, quantitative, qualitative, and mixed methods (Geoffrey, 2019). Quantitative research deals with numerical data and utilizes statistical methods to evaluate, analyze, and draw conclusions about the data. Qualitative research focuses on descriptive data like interviews or long-form responses on questionnaires where the researcher is often attempting to describe some phenomena or develop hypotheses for testing in another study. A mixed methods research design includes a combination of the two, both numerical analysis and long-form response data. As for inductive and deductive approaches, deductive is the process that transitions from theory to data while inductive is the process of taking data and deriving theories. The literature contains many theories and techniques for mitigation of motivational bias with very little data. Quantitative methods are typical for deductive approaches which is why it was chosen to guide this research.

To test the hypothesis, a quantitative experimental methodology was chosen. The experiment will contain a control group, without treatment, and three treatment groups, namely critical analysis, justification, and perspective/view. The treatments will test the de-biasing techniques individually and compare to the control group that has no treatment.

For this study, the group decision and data presentation techniques are not tested. Group decision making was not tested primarily due to COVID-19 restrictions and complexities involved with group decision making during the pandemic. Data presentation is primarily used for quantitative data interpretation. Although data presentation is not tested, all data presented to the participants is closely curated as to ensure consistency of the data among the alternative and evaluation criteria. The Reference Dataset provided to the participants is also included in the Appendix. Therefore, this study will focus on the three remaining debiasing techniques: critical analysis of data, justification, and perspective/view.

The flow of the research is provided in Figure 3.1. The study will take the literature review and develop a questionnaire to test the de-biasing techniques identified. The data will be analyzed to identify statistically significant impacts to reducing motivational biases. A framework will be developed to help reduce motivational biases in MCDM problems.

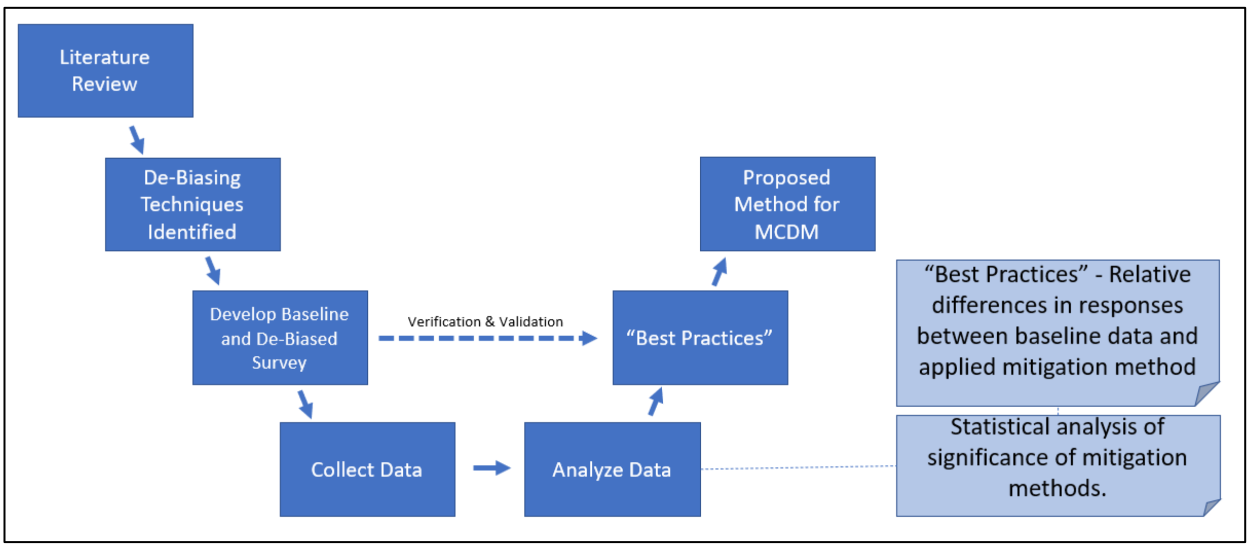

Figure 3.1 Research design overview

3.2 Data collection

The data collection will consist of a questionnaire distributed via broadcast email asking participants to voluntarily complete the questionnaire for primary data collection. The target participant pool is undergraduate engineering students. The first part of the questionnaire will gather inputs to the MCDM problem. The second part of the questionnaire will assess each participant for susceptibility to motivational bias by measuring characteristics that are known to correlate with the identified biases. The participants will provide inputs to an MCDM problem and susceptibility, which will be quantitatively assessed.

3.2.1 MCDM inputs

Since this study measures motivational biases, the problem setup will encourage motivational bias to be present within the participants, if not already. To accomplish this, the introduction will provide reasons that students at a college/university would want their school to be recognized and gain reputation within the community. The participants will be presented the reasons for encouraging students to attend the university (i.e., funding, reputation, athletics, etc.) to encourage motivational bias for their current college/university being chosen at the end of the analysis. The participants are instructed that this analysis will be used to assess their home institution with other engineering universities. Below is the introductory paragraph that will be used to seed the motivational bias within the participant:

> “The US News College Ranking System has been used for over 40 years. The system ranks colleges and universities based on a set of criteria developed by experts and undergoes continuous improvements and refinement. These ranking systems are used by students globally to support their choice of higher education. Increasing enrollment at a university has many benefits for the institution. First, more students increase the revenue and therefore resources for student success. This not only includes materiel resources, but increased resources for recruiting top talent in both the student body and academic faculty.

> In several studies it was found that school ranking impacted both the early career advancement and opportunities (Hoxby, 1998), as well as higher salaries for graduates from top-ranked schools (Rindova, et al., 2005). This survey will gather inputs for a Multi-Criteria Decision Analysis (MCDA) comparing your current institution with others. You will be asked to select comparable schools for undergraduate engineering education, criteria for evaluation of those institutions, criteria weighting, and performance of each institution against those criteria. The results will be used by the researcher to evaluate the optimal choice for university based on your inputs."

Why will this seed motivational bias? The Institute for Higher Education Policy released a publication detailing the impacts of college and university rankings on student choice and outcomes (Sanoff, et al., 2007). They noted that students are aware that the rank of their school may affect their employment opportunities and students at less prestigious institutions (lower ranked) have tried to increase their standing by providing surprisingly upbeat survey responses.

For the questionnaire, the participants are undergraduate students in engineering programs at Mississippi State University. Using the testing of best practices of overconfidence bias reduction as a guide, questionnaires were developed to collect baseline data and data including a de-biasing technique (Ferretti, et al., 2016). The participants are presented with background information on decision making and the MCDM problem of interest for choosing the best university for engineering disciplines. The participant will provide inputs for the MCDM problem of choosing the best college/university for undergraduate engineering studies. The responses will correspond to each general step in the MCDM process. The questionnaire is estimated to take about 30 mins to complete, therefore participants were offered to be entered into a raffle for gift cards to encourage participation and reduce participation bias.

The questionnaire has four (4) unique formats, one for each of the de-biasing techniques being tested. Each format allows the participant to provide inputs to the same MCDM problem. The goal of this portion of the questionnaire is to allow the participants to make the decisions with the biases present. A de-biasing technique will then be applied to test the efficacy of the technique at mitigating the biases. Format 1 will include perspective/view de-biasing techniques, Format 2 will include the critical analysis of data techniques, Format 3 will include the justification technique, and Format 4 will include no de-biasing techniques and serve as the control group. Table 3.1 provides a summary of each format along with a description of the purpose for each.

Table 3.1 Questionnaire formats

Format	De-biasing technique	Purpose
1	Perspective/View	Testing of Perspective/View technique. This technique applies to Affect Influenced bias.
2	Critical Analysis	Testing of Critical Analysis technique. This technique applies to Confirmation, Desirability of Positive Outcome, and Undesirability of Negative Outcome biases.
3	Justification	Testing of Justification technique. This technique applies to Affect Influenced and Desirability of option/choice biases.
4	None	Baseline data collection; control group.

When testing the individual de-biasing techniques, particular attention can be given to the biases in which the technique is known, as well as not known, to be effective. This will support the literature and potentially show an effect of the technique in reducing biases. A detailed description of the judgment tasks in the MCDM process along with the implementation of the de-biasing techniques within the questionnaire is provided in the following sections.

3.2.1.2 Generating the alternatives

The participant will be asked to select from a list of schools to consider for comparison with respect to engineering disciplines. The participant will be asked to select three (3) schools for comparison to the participants current institution for a total of four (4) alternatives. The selection will be chosen from a predefined list. The list will be a mixture of moderately ranked schools and well-known, highly ranked schools (per US News rankings, 2020) as shown in Table 3.2.

Table 3.2 Alternatives for selection

Alternative	Ranking	Relevance
Mississippi State University	118	Home School
Georgia Institute of Technology	4	Comparison, higher ranking
University of Georgia	102	Comparison, near a home school
Tennessee Technological University	161	Comparison, near a home school
University of Mississippi	161	Comparison, near a home school
Massachusetts Institute of Technology	1	Comparison, higher ranking
University of California-Berkely	3	Comparison, higher ranking
Stanford University	2	Comparison, higher ranking

The selection of universities in the list contains universities in two primary categories: 1) universities that are ranked higher or lower than the home institution and 2) universities that are locally or nationally recognized. It is important to provide universities that the participants know well and may already have a strong feeling toward. This is particularly relevant for a rival school (either academically or athletically) that could cause a strong undesirable bias.

3.2.1.2.2 Format 1 – Perspective/View

The participant will be asked to take on the persona of a new incoming college student. They have done no initial analysis of universities and have no experience at their home institution. Throughout the questionnaire the participant will be reminded of this persona to ensure they do not forget or stray from the perspective.

3.2.1.2.3 Format 2 – Critical Analysis of Data

After making the initial selection, the participant would be shown the US News rankings of the universities in the list (US News, 2020). The participant would then be asked if they wish to update their chosen alternatives. A revision would represent a debiased answer.

3.2.1.2.4 Format 3 – Justification

After making the initial selection, the participant would be asked to justify why they chose the universities over the others in the list. The participant would need to be shown their choices and the available options (without data ranking the schools). The participant will be told before making their decision that a justification will be required. This is required to setup the "pre-emptive self-criticism" for accountability.

3.2.1.2.5 Format 4 – Control

No de-biasing techniques will be applied. The participants will simply provide inputs to each of the responses without intervention.

3.2.1.3 Developing evaluation attributes/criteria

The participant will be asked to provide a list of criteria to consider for their analysis, by selection from a predefined list. A brief description of the evaluation criteria and their purpose will be provided. The participant will be asked to choose four (4) evaluation criteria for this analysis. The selection list will include common vague criteria (Quality of Student Life, Quality of Food, Greek Life, # of Student Organizations) as well as the US News ranking criteria (US News, 2020).

Table 3.3 Evaluation criteria for selection

Criteria	Source	Description
Graduation Rate	US News	Percentage of first-year students who graduate within a six-year period
Reputation	US News	Measure of how a school is regarded by administrators at peer institutions
Class Size Index	US News	Assesses ability of students to engage with their instructors in class
Financial Resources	US News	Average spending per student on instruction, research, public service, academic support, and student services
Party Scene/Nightlife	Niche.Com	Access to venues and assessment of nightlife on campus
Athletics	Niche.Com	Number of national championships won and athletic department revenue
Campus Food	Niche.Com	Student survey on quality of campus food
Student Diversity	Niche.Com	Ethnic composition of the student body and proportion of international and out-of-state students

3.2.1.3.2 Format 1 – Perspective/View

The participant will be reminded of their persona of a new incoming college student. They have done no initial analysis of universities and have no experience at the participants home institution. Throughout the questionnaire the participant will be reminded of this persona to ensure they do not forget or stray from the perspective.

3.2.1.3.3 Format 2 – Critical Analysis of Data

After making the initial selection, the participant would be shown the US News evaluation criteria for ranking universities. The participant would then be asked if they wish to update their chosen alternatives. A revision would represent a debiased answer.

3.2.1.3.4 Format 3 – Justification

After making the initial selection, the participant would be asked to justify why they chose the criteria over the others in the list. The participant would need to be shown their choices and the available options. The participant will be told before making their decision that a justification will be required. This is required to setup the "pre-emptive self-criticism" for accountability.

3.2.1.3.5 Format 4 – Control

No de-biasing techniques will be applied. The participants will simply provide inputs to each of the responses without intervention.

3.2.1.4 Assessing the performance of the alternatives against the attributes

The participant will be asked to assess performance of colleges and universities against the evaluation criteria. Some data will be provided for the participants to review in making the assessments (US News, 2020). A brief description of the evaluation criteria will be provided. For each school and evaluation criteria (16 variables) the participant will use assess the performance of each school against each evaluation criteria on a scale of 1 to 10.

3.2.1.4.1 Format 1 – Perspective/View

The participant will be reminded of their persona of a new incoming college student. They have done no initial analysis of universities and have no experience at the participants home institution.

3.2.1.4.2 Format 2 – Critical Analysis of Data

After making the initial assessments, the participant would be shown the US News attribute values (performance against criteria). The participant would then be asked if they wish to update their assessments. A revision would represent a debiased answer.

3.2.1.4.3 Format 3 – Justification

After making the initial assessments, the participant would be asked to justify their assessment for the attribute values. The participant will be told before making their decision that a justification will be required. This is required to setup the "pre-emptive self-criticism" for accountability.

3.2.1.4.4 Format 4 – Control

No de-biasing techniques will be applied. The participants will simply provide inputs to each of the responses without intervention.

3.2.1.5 Eliciting the utility function over attribute levels

For this problem, the utility function over the attribute levels is generated by the MCDM techniques that will be analyzed in the analysis section. The participants will have no role in the selection of the MCDM technique. For the techniques identified, the value functions are purely linear functions given the scales provided.

3.2.1.6 Eliciting weights of each attribute

The participant will be asked to provide weighting of importance for the evaluation criteria. A brief description of the evaluation criteria will be provided. For each criterion, the participant will use slider bars to assign a weighted importance on a scale of 0 to 10, with zero being not important and 10 being extremely important.

3.2.1.6.1 Format 1 – Perspective/View

The participant will be reminded of their persona of a new incoming college student. They have done no initial analysis of universities and have no experience at the participants home institution.

3.2.1.6.2 Format 2 – Critical Analysis of Data

After making the initial assessments, the participant would be shown the US News criteria weighting (US News, 2020). The participant would then be asked if they wish to update their assessments. A revision would represent a debiased answer.

3.2.1.6.3 Format 3 – Justification

After making the initial assessments, the participant would be asked to justify their weighting for each criterion. The participant would be asked if they would like to update their assessments after providing justifications. A revision would represent a debiased answer.

3.2.1.6.4 Format 4 – Control

No de-biasing techniques will be applied. The participants will simply provide inputs to each of the responses without intervention.

3.2.1.7 Aggregating the data

The aggregation of data is not a judgmental task. This task will be completed in post processing once the participants have provided inputs. The aggregation of data will allow for data analysis as provided in the Data Analysis section of this chapter.

3.2.2 Susceptibility to Motivational Bias

After the MCDM inputs have been collected, the participants are assessed for susceptibility to the five biases identified in the literature. These five biases are 1) desirability of positive outcome, 2) undesirability of negative outcome, 3) desirability of option/choice, 4) affect-influenced, and 5) confirmation bias. The survey items are derived from literature reviews that relate to measuring each bias, or characteristics that correlate to bias susceptibility. The questions can be found in Appendix A containing the entire Qualtrics questionnaire provided to the participants. Within the questionnaire the questions are randomized to the participants. The following sections review where the measures were derived.

3.2.2.1 Desirability for Positive Outcome Bias & Undesirability of Negative Outcome Bias

Items 1 through 6 (Q6 through Q11 within the Qualtrics questionnaire) were derived from the Revised Life Orientation Test (LOT-R) (Scheier, et al., 1994). This test includes 10 questions in which six measure optimism and pessimism and four are filler. In the instrument presented to the participants, questions 1 through 3 measure optimism, while questions 4 through 6 measure pessimism within the participant. The filler questions are not included since the instrument used here contains additional questions for the remaining bias measurements.

It was found that one’s desires could increase focus on the entity involved in the desired outcome (Krizan & Windschitl, 2007). If that outcome was the focal entity in a comparative judgment, that would increase the optimism associated with that outcome. In the same study a decision strategy called differential scrutiny, which involves desires leading to quick acceptance of supporting information and scrutiny of unfavorable information, implies that desires lead to enhanced optimism (Krizan & Windschitl, 2007). Given that MCDM is inherently a comparative process this would mean an increase in optimism for the desired outcome. This optimism bias (desire for positive outcome) is the difference between one's expectation of an outcome and the actual likelihood of that outcome (Sharot, 2011). General optimism was positively correlated with increased attentional bias for positive stimuli (Segerstrom, 2001). Across the literature, optimism and pessimism are very often discussed in the same vein. In the same study, general pessimism was positively correlated with increased attentional bias for negative stimuli (Segerstrom, 2001). This provides the linkage between both desirability for positive outcome to optimism and undesirability of a negative outcome to pessimism.

3.2.2.2 Desirability of Option/Choice Bias

As for the desirability of option/choice, this bias is impossible to measure without explicitly asking for the desire from the participant. To use the same scale, the explicit statement of "Given an analysis of 4 engineering universities, including my own, it is highly desirable for my university to be highly ranked as compared to the other universities" was developed. While this is not an ideal measure for this bias because the participant could be hesitant to explicitly state they are biased, another option for measuring this is posited. Therefore, this bias was measured in two ways: 1) by asking at the beginning of the survey "How important is it for your home institution to have a high ranking among national universities?" and 2) combining the optimism and pessimism scores to form a desired option score.

Optimism and pessimism are not a single dichotomous trait, meaning one can be highly optimistic and highly pessimistic by nature depending on the situation (Hecht, 2013). In a study by Chen to account for optimism and pessimism in the MCDM calculation, optimism and pessimism were treated as two partially independent dimensions (Chen, 2016). Other studies also point to evidence that optimism and pessimism are two partially independent dimensions (Scheier, et al., 1994) (Chang, et al., 1997). It is posited that given moderate-to-high optimism and simultaneous moderate-to-high pessimism within a participant, which is a tendency to desire positive outcomes and not desire negative outcomes, implies a desire for a specific outcome. The aggregation of optimism and pessimism would be a measure of the desirability of option/choice bias.

3.2.2.3 Affect-Influenced Bias

Yip and Cote found that emotional intelligence translates to less affect influence on decision making (Lerner, 2015). In that study the authors used a subset of the Mayer-Salovey-Caruso Emotional Intelligence Test (MSCEIT), specifically the set of statements that assess emotional understanding. Ultimately concluding that a correlation exists between lower affect-influence on decision making with higher emotional intelligence scores. For this study, the 33-item Self-Report Emotional Intelligence Test (SREIT), which are statements 7 through 39 (Q12 through Q44 within the Qualtrics questionnaire), will be utilized to score the emotional intelligence of the participants to assess the susceptibility to the affect-influenced bias (Schutte, et al., 2007).

3.2.2.4 Confirmation Bias

Finally, confirmation bias will be assessed using the 10-item Confirmation Inventory (CI) instrument developed by Rassin (Rassin, 2008). Rassin developed the instrument by providing 14 statements to a group of participants and performing a Confirmatory Factor Analysis (CFA) on the items. There were 10 items with loadings greater than or equal to 0.4 and were thereby selected for the instrument as Q45 through Q54 within the Qualtrics questionnaire. Validation was confirmed by assessing a group of participants' CI score and then assessing their level of confirmation bias using a set of 5 Wason Selection Task-type scenarios.

In discussing the study with Rassin, two items were derived from Dutch expressions. These questions, namely questions 46 and 47, were adapted from their original versions for United States native English speakers. For item 46, the original statement was "The first blow is half the battle." The intent of this statement is fast action and not contemplating. This was adapted to be "Generally, getting that first win is half the battle." For item 47, the original statement was "Generally, half a word is enough for me." This relates to jumping to conclusions, meaning you know the answer before someone tells you (confirming your intuition). This was adapted to be "Generally, I know what someone is trying to say before they finish."

3.3 Population and Sample Size

Given the population for this study is undergraduate engineering students, the sample size for a given margin of error can be calculated. A simplified sample size calculation equation is provided, where *n* is the sample size, *N* is the population size, and *e* is the desired level of precision (Yamane, 1967).

$$n = \frac{N}{1 + N(e)^2} \tag{3.1}$$

According to the National Science Foundation there were 610,000 undergraduate engineering students in the United States in 2017 (National Science Foundation, 2018). Using that number as a baseline for the population and a 10% level of precision, this study aims to gather at least 100 participants' data.

3.4 Data Analysis

There are four (4) unique formats of the questionnaire that will provide 1) efficacy of the perspective/view technique against relevant and non-relevant biases, 2) efficacy of the critical analysis of data technique against relevant and non-relevant biases, and 3) efficacy of the justification technique against relevant and non-relevant biases 4) baseline data without de-biasing techniques applied.

Given the questionnaires are completed, all the required data will be present to execute one of the identified MCDM methods (AHP, TOPSIS, ELECTRE). The data will be used to complete a MCDM analysis using each participant's inputs. Custom data analysis software (Octave and R) will be developed to take the inputs of each participant and run it through the MCDM analysis method. The results of each of these analyses will provide a ranking of the alternatives for each participant. The primary data for analysis will be the ranking of the home institution by the participant given the inputs to the MCDM problem. The raw data from the questionnaire will need to be processed to generate a data format for processing. The variables produced from the raw data are provided in Appendix B.

Each participant's inputs will result in a ranking of four engineering universities. The initial analysis will identify incomplete responses and outliers. Outliers are defined as data points greater than 1.5 times the interquartile range (IQR) of the data set. Incomplete responses and outliers will be removed from this data set. Additionally, the data sets will be assessed for normality to support further statistical analyses. To check for normality, several tests are conducted including the Shapiro-Wilk, Pearson-Chi-square, and Kolmogorov-Smirnov tests.

In order to complete an analysis of variance (ANOVA), there are several assumptions that must be verified. The data will be random and independent, due to the distribution and single participant inputs. A Bartlett test, with alpha 0.10, will be conducted to test whether the population standard deviations are significantly different. Given that they are not, an ANOVA will be conducted to determine if there are statistically significant differences between the variances of the four levels (de-biasing techniques) in the single factor.

A Bonferroni procedure will be implemented to assess the difference of the means between the treatment groups. This will provide significant evidence that a treatment has an impact on the inputs of the participants and allow for simultaneous two-sample t-tests. Bonferroni procedures are used to adjust for simultaneous significance tests which can produce more Type I errors. This procedure lowers the significance level for the tests to limit the error likelihood. A Tukey's Honest Significant Difference (HSD) test will also be conducted to verify that the means of the treatments are significantly different.

I

RESEARCH FINDINGS

This chapter will provide the details analysis of the data from the online questionnaire. Once the analysis for the individual components is complete, the aggregated results will be presented.

4.1 Summary of data collected

The total number of participants that completed the online questionnaire this study was 68 undergraduate engineering students at Mississippi State University. There were 6 participants that completed everything except the last question for a raffle. Therefore, those 6 participant's data was manually recorded and included in the dataset for analysis. For the first step in the MCDM process, the participant is asked to select their home institution and 3 other universities for comparison. If the participant did not select their home institution, this invalidates their MCDM input responses. There were 8 participants that did not follow the instructions for the MCDM inputs portion of the questionnaire. The total number of participant responses that are analyzed for this study are 60.

Given the sample size calculation in Equation 3.1 and the total number of responses received the error level for this study is set to e = 0.129, or about 13% error is accepted. For the analyses going forward in the analysis, an alpha of 0.10 will be used for determination of significance.

The demographic information for the participants in the study is provided in Figure 4.1. As shown the participants included many engineering disciplines, both males and females, various academic years, and ethnicities. A key question for this sample is the representativeness of the data. Comparing the ethnicity and genders to published information on the Mississippi State University Bagley College of Engineering website and for the United States as a whole (National Science Foundation, 2018), the sample matches well with the student body for this population.

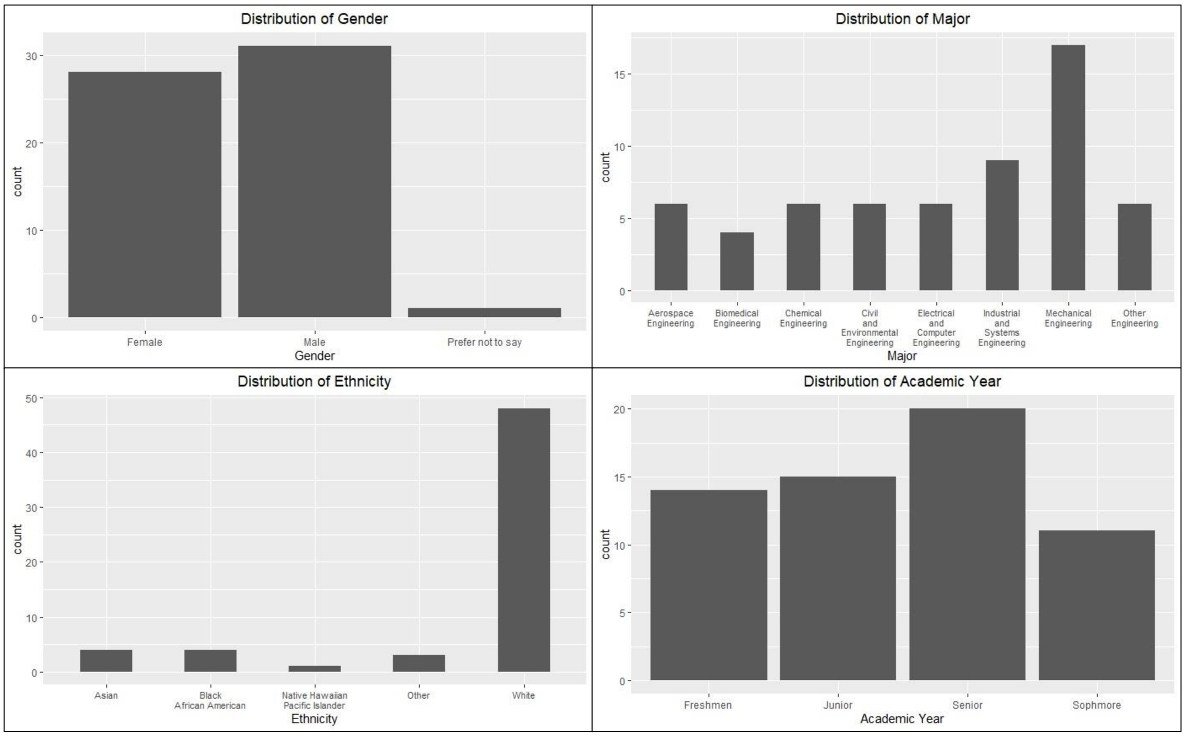

Figure 4.1 Demographic information for the participants in the study

The questionnaire was estimated to take the participants around 30 minutes to complete. The duration for the questionnaire was captured in the raw data with a median duration of 823 seconds, or 13.72 minutes.

4.1.1 Motivational bias setup

The first section of the questionnaire included a brief introduction to Multi-Criteria Decision Making, its purpose, and framework. The participants were asked, "How would you describe your familiarity with Multi-Criteria Decision Making processes and techniques?" The results show that very few participants were familiar with MCDM as shown in Figure 4.2.

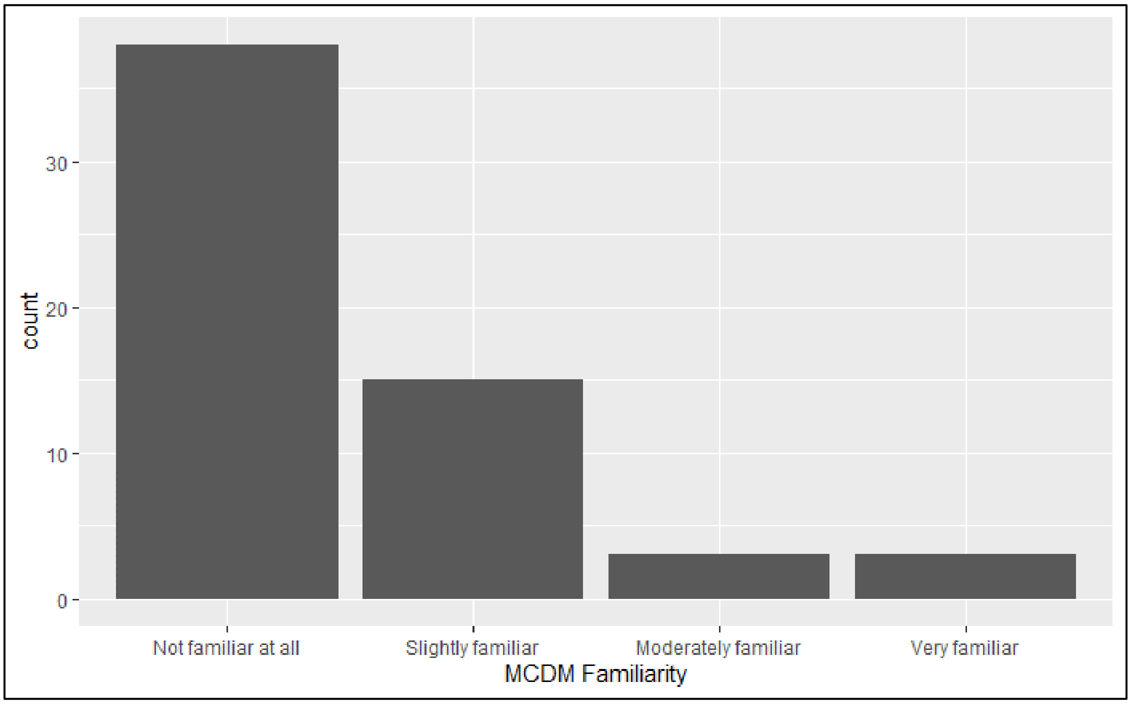

Figure 4.2 Familiarity with MCDM techniques and processes

The second portion of the setup was intended to setup the motivational bias within the participant. The questionnaire provided studies and data that should increase the motivation for an undergraduate student to want their university to rank highly in the analysis. These include job placement, career advancement, and salary. The participants were asked, "How important is it for your home institution to have a high ranking among national universities?" The results, as shown in Figure 4.3, show that a vast majority of participants stated that it was moderately to very important, with no participants responding as “Not important at all.”

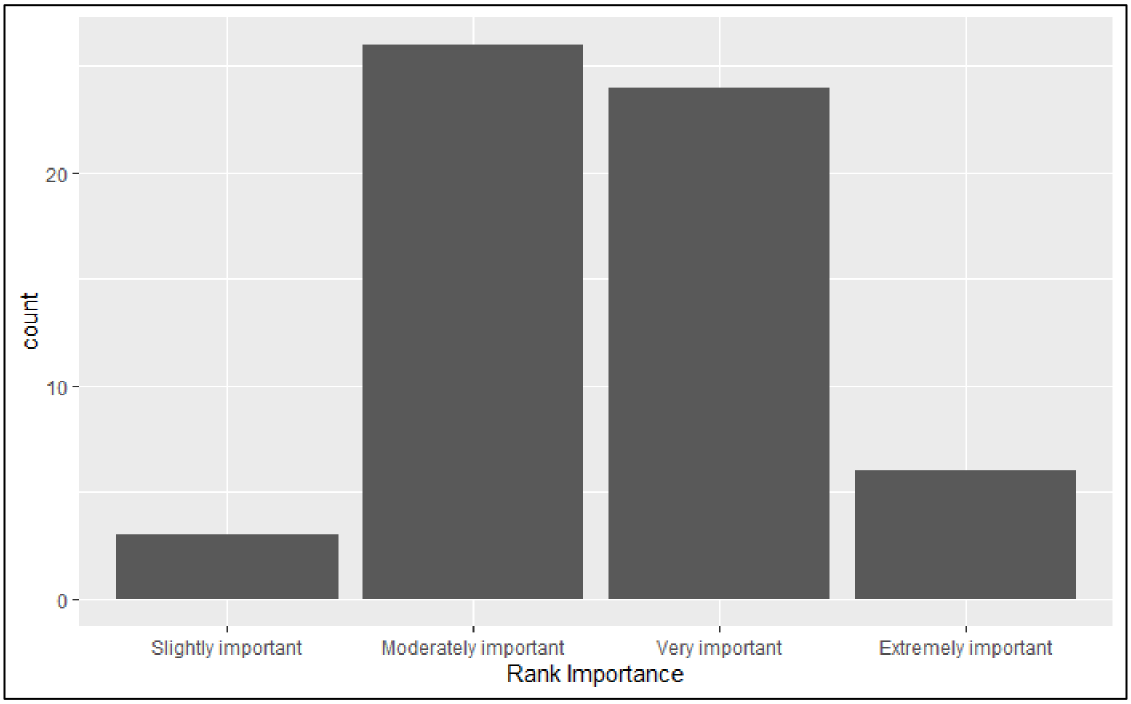

Figure 4.3 Home university rank importance

The results of the setup portion of the questionnaire show that the participants were not very familiar with MCDM. Analysis of the data shows that overall, the rank importance was consistent across genders, academic years, and treatments. The boxplots for rank importance measures across treatments is provided in Figure 4.4.

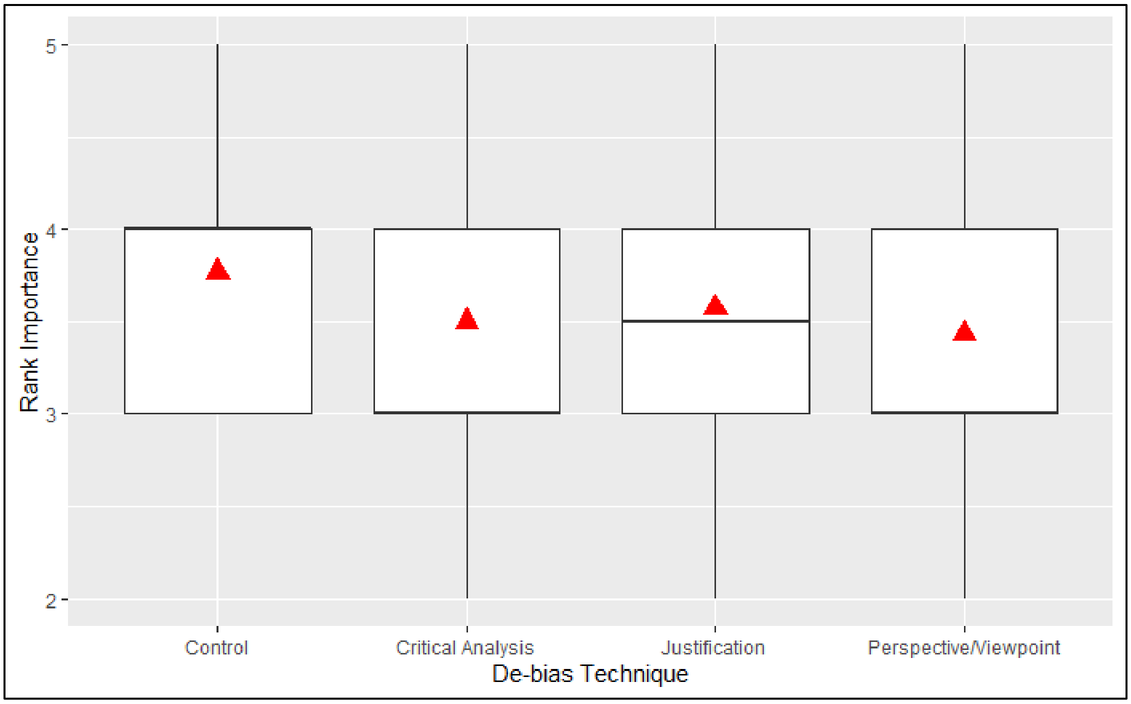

Figure 4.4 Rank importance measure across treatments

4.1.2 MCDM Inputs

The questionnaire asked the participants to select their home institution and three other universities for comparison, select evaluation criteria to compare the universities, assess each selected university against the selected criteria, then assess the relative importance weight for each criterion. These inputs were then subjected to a TOPSIS analysis to rank the universities selected by the participant based on their inputs. Each participant was either control or one of three treatments. The treatments were critical analysis, justification, and perspective, which were the three de-biasing techniques under test. The samples for each factor were control (n= 13), critical analysis (n=16), justification (n=14), and perspective/viewpoint (n=16).

4.1.2.1 Summaries

The following sections will provide a summary of the MCDM inputs by the participants for each treatment. The analysis will show the critical metrics that will be used for analysis and their distributions. These metrics allow for analyzing each step in the MCDM process to identify potential points of bias introduction. The metrics along with a description, unbiased target value, and interpretation are provided in Table 4.1

Table 4.1 Summary metrics and interpretations

Metric	Unbiased Target	Description	Interpretation
In-situ Rank	4	Ranking of home institution within the selected institutions per US News Rankings	Given there are 4 universities within the list that are higher rank (top engineering schools in the nation), this metric should be low.
Criteria Selected Ratio	1	Percentage of criteria selected that are valid US News criteria	Given that 4 criteria options are US News and 4 are non-relevant to academic success, this metric should be close to 1.
Home Performance Ratio	0.165 – 0.235	Relative proportion of assessment values given to home institution.	Given that there are 4 alternatives, this should be around 0.25. This means that the home institution received an appropriate proportion of the total assessment values given.
Criteria Weight Metric	0	Difference between ratio of weight given to US News criteria and the ratio of US News criteria selected.	Positive: Relatively more weight given to US News criteria Zero: Relatively equal weight given to US News criteria Negative: Relatively less weight given to US News criteria

The unbiased target values were created as a reference for each step in the MCDM process. In-situ Rank (home_insitu_rank) describes how the participant responded to step 1, generating alternatives. In an unbiased response, the participant is expected to select their home institution and nationally recognized, highly ranked universities for comparison to select the best undergraduate engineering university. Criteria selected ratio (criteria_selected) describes how the participant responded to step 2, developing attributes/criteria, as described in Equation 4.1. An unbiased response would be 1, selecting all 4 of the US News criteria from the choices.

$$\text{criteria\_selected} = \frac{Number\ of\ US\ News\ criteria\ selected}{4} \tag{4.1}$$

Home performance ratio (home_perform_ratio) is a measure related to step 3, assessing performance of alternatives, showing how much value the participant gave to the home institution relative to the sum of all assessments as evaluated in Equation 4.2. Analysis of the range of values for this metric shows a range from 0.165 to 0.235 would be appropriate. This range was derived by evaluating the full unbiased decision matrix that was developed for baseline data analysis. For example, Mississippi State University assessed alongside the top 3 universities in the list (Massachusetts Institute of Technology, University of California-Berkeley, and Stanford University) results in the lower bound, since the other universities assess higher relative to Mississippi State University.

$$\text{home\_perform\_ratio} = \frac{\sum Home\ perofrmance\ assessments}{\sum All\ performance\ assessments} \tag{4.2}$$

Criteria weight metric (criteria_weight_metric) describes how the participant responded to step 5, eliciting weights for each criterion, as described in Equation 4.3. This metric represents the difference in the ratios of the US News criteria weights to total weights and US News criteria selected to total number of criteria. Participants who give relatively equal weights to US News criteria would evaluate to a metric value of zero. Positive values indicate relatively more weight given to US News criteria, while negative values show relatively less weight given to US News criteria. For instance, if the participant chose 2 of the US News criteria and the proportion of weights given to those criteria was lower than 0.5, the criteria weight metric will be negative. This means the participant gave more weight to the vague criteria relative to the US News criteria.

$$\text{criteria\_weight\_metric} = \frac{\sum weights\ for\ US\ News\ criteria}{\sum all\ weights} - \text{criteria\_selected} \tag{4.3}$$

The unbiased targets were also compared against a subset of the participant responses where the home in-situ rank was 4 and home rank delta was 0. This subset indicates a group who chose highly ranked universities for comparison and provided inputs consistent with that as compared to US News ranking systems, resulting in a home rank delta of 0. The histograms of the metrics for that subset are provided in Figure 4.5. The results show that the unbiased targets are reasonable.

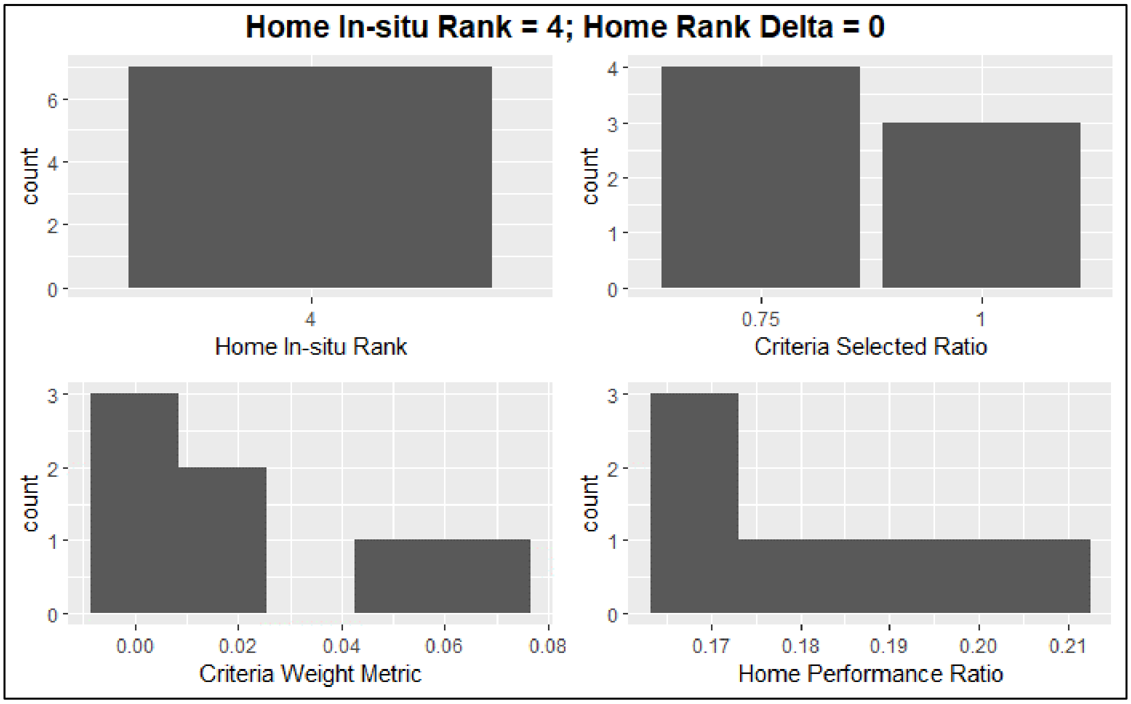

Figure 4.5 Metric target value validation within dataset

4.1.2.1.1 Control

The summary statistics for the metrics within the control group are provided in Table 4.2. The distributions for the metrics for the control group are provided in Figure 4.6.

Table 4.2 Summary statistics for control group metrics

Metric	Min	Max	Mean	SD	Median
Duration	387 sec	99,206 sec	9,674 sec	29,695 sec	780 sec
home_insitu_rank	2	4	3.462	0.660	4
criteria_selected	0.5	1	0.769	0.190	0.75
home_perform_ratio	0.165	0.284	0.228	0.051	0.244
criteria_weight_metric	-0.036	0.115	0.041	0.051	0.015

Place all detailed caption, notes, reference, legend information, etc here

For the control group, the Home In-situ Rank primarily ranges from 3 to 4, meaning the participants correctly selected the top-ranking universities for comparison. They also selected at least 2, majority selected 3 of the 4 US New criteria. The Criteria Weight Metric shows primarily positive values indicating proper weighting of the US News criteria. The Home Performance Ratio is within range but does show signs of higher values than anticipated.

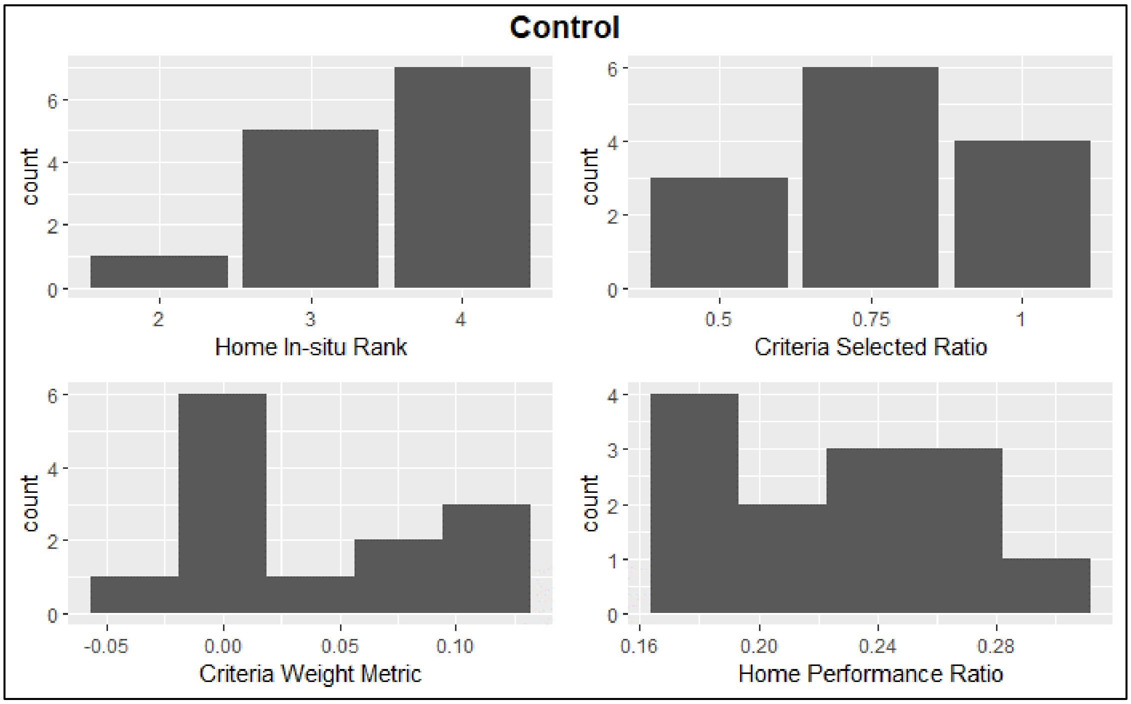

Figure 4.6 Summary histograms for the metrics in Control group

4.1.2.1.2 Critical Analysis

The summary statistics for the metrics within the critical analysis group are provided in Table 4.3. The distributions for the metrics for the critical analysis group are provided in Figure 4.7.

Table 4.3 Summary statistics for the critical analysis metrics

Metric	**Min**	**Max**	**Mean**	**SD**	**Median**
Duration	429 sec	2,713 sec	960 sec	566.91 sec	811 sec
home_insitu_rank	2	4	2.824	0.728	3
criteria_selected	0.5	1	0.706	0.202	0.75
home_perform_ratio	0.166	0.769	0.269	0.133	0.241
criteria_weight_metric	-0.083	0.133	0.022	0.051	0.014

For the Critical Analysis group, the Home In-situ Rank is concentrated between 2 and 3, meaning the participants chose one or two universities that were not higher ranking than Mississippi State University. The participants also selected at least 2, some all 4, of the 4 US New criteria. The Criteria Weight Metric shows primarily positive values indicating proper weighting of the US News criteria, but with some signs of highly negative values. The Home Performance Ratio tends to be high and out of the expected range of values, possibly indicating some bias. One outlier shows up around 0.8. Further investigation shows that this participant's assessments gave the home institution 10's across the board, and 1's to all other universities across all evaluation criteria. This outlier is removed from further analyses.

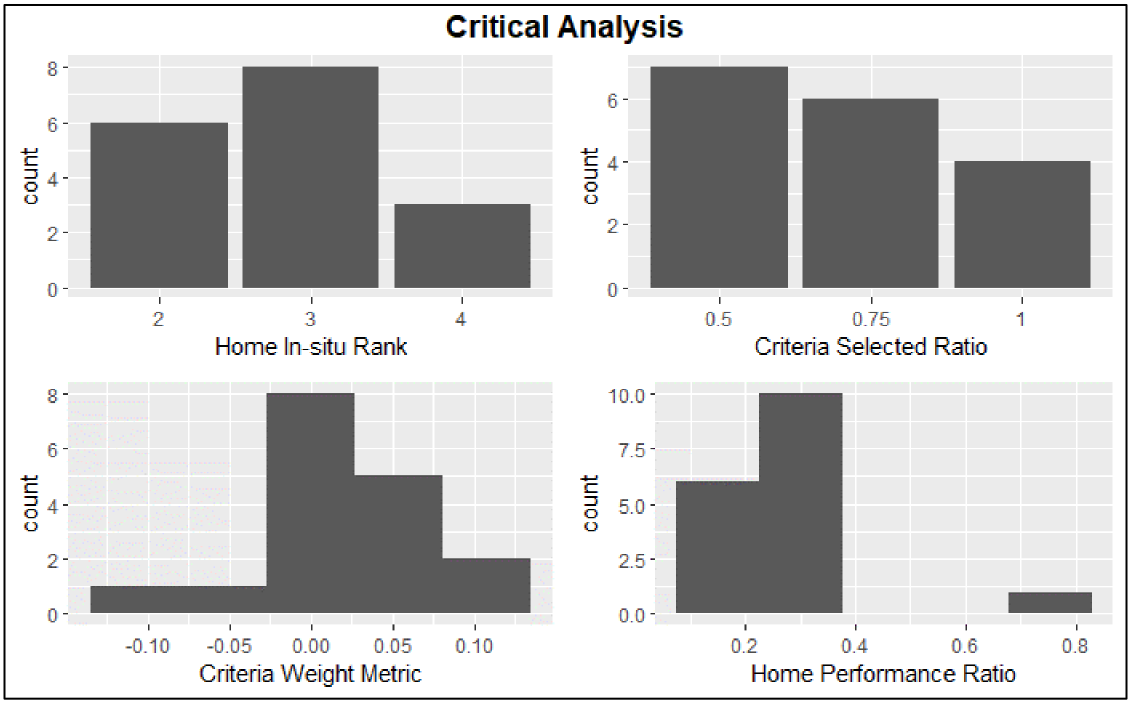

Figure 4.7 Summary histograms for the metrics in Critical Analysis group

At each step in the Critical Analysis treatment, the participants were allowed to provide inputs on their own. Once their inputs were provided, they were shown how US News Ranking systems would have responded. The participants were asked if they would like to change their answers based on this review and analysis of data provided.

Table 4.4 Revision counts in the Critical Analysis treatment

MCDM Step	Revised Responses	No Revisions
Step 1: Generating alternatives	0	16
Step 2: Developing attributes/criteria	2	14
Step 3: Assessing performance	1	15
Step 5: Eliciting weights of each attribute	2	14

Table 4.4 shows that providing additional details or data to the participants does not affect their responses in any significant way as very few participants revised their responses.

4.1.2.1.3 Justification

The summary statistics for the metrics within the justification group are provided in Table 4.5. The distributions for the metrics for the justification group are provided in Figure 4.8.

Table 4.5 Summary statistics for justification metrics

Metric	Min	Max	Mean	SD	Median
Duration	454 sec	5,064 sec	1,491 sec	1,171.5 sec	1,178 sec
home_insitu_rank	2	4	3.071	0.730	3
criteria_selected	0.5	1	0.714	0.193	0.75
home_perform_ratio	0.195	0.299	0.259	0.024	0.263
criteria_weight_metric	-0.071	0.250	0.046	0.073	0.040

For the Justification group, the Home In-situ Rank is concentrated around 3, meaning the participants chose at least one university that was not higher ranking than Mississippi State University. In this treatment group, the participants were instructed up-front that they would need to justify their answers. Therefore, this metric can be considered affected by the de-biasing treatment. They also selected at least 2 of the 4 US New criteria. The Criteria Weight Metric centers around zero showing that the criteria weights were properly applied. The Home Performance Ratio is concentrated outside the expected range.

Figure 4.8 Summary histograms for the metrics in Justification group

The participants were instructed at the beginning of this section that they would need to provide justifications for their responses. After each step in the MCDM inputs section, the participants briefly justified their inputs in long-form response text boxes. For this study, the long-form responses were not analyzed in detail. The requirement to provide a justification for responses was the technique being tested. A brief review of the responses finds evidence of motivational bias and non-biased answers. For instance, compare the two responses below for justification for selecting evaluation criteria:

"I think these are the top 4 ways Mississippi State could stand out from other schools."

"When you look for a school, you mainly look at these qualities of a school. Does the school have a good reputation, good althletics [sic], a high graduation rate, and a small class size index."

The first justification states that the evaluation criteria were strictly chosen so that the home institution would "stand out," or rank highly compared to the alternatives chosen. The second justification is based on what is important to a student making the decision, which is the use case for MCDM in this problem.

4.1.2.1.4 Perspective/Viewpoint

The summary statistics for the metrics within the perspective/viewpoint group are provided in Table 4.6. The distributions for the metrics for the perspective/viewpoint group are provided in Figure 4.9.

Table 4.6 Summary statistics for the perspective/viewpoint metrics

Metric	Min	Max	Mean	SD	Median
Duration	323 sec	20,359 sec	2,319 sec	5,433.9 sec	672 sec
home_insitu_rank	2	4	3.125	0.806	3
criteria_selected	0.5	1	0.734	0.170	0.75
home_perform_ratio	0.193	0.343	0.248	0.035	0.237
criteria_weight_metric	-0.070	0.189	0.040	0.063	0.037

For the Justification group, the Home In-situ Rank is distributed around 3, meaning the participants chose at least one university that was not higher ranking than Mississippi State University. In this treatment group, before entering responses the participants were instructed to "imagine yourself as a new student looking for a university for undergraduate engineering studies. You have no preconceived notions or experience with a university or preference for a particular institution." Therefore, this metric can be considered affected by the de-biasing treatment. They also selected at least 2, many selected 3, of the 4 US New criteria. The Criteria Weight Metric shows a concentration around 0 primarily extending in the positive direction. This indicates properly weighted criteria. The Home Performance Ratio is concentrated in the upper range of expected values but extends far beyond showing some bias toward assessing the home institution higher than other alternatives.

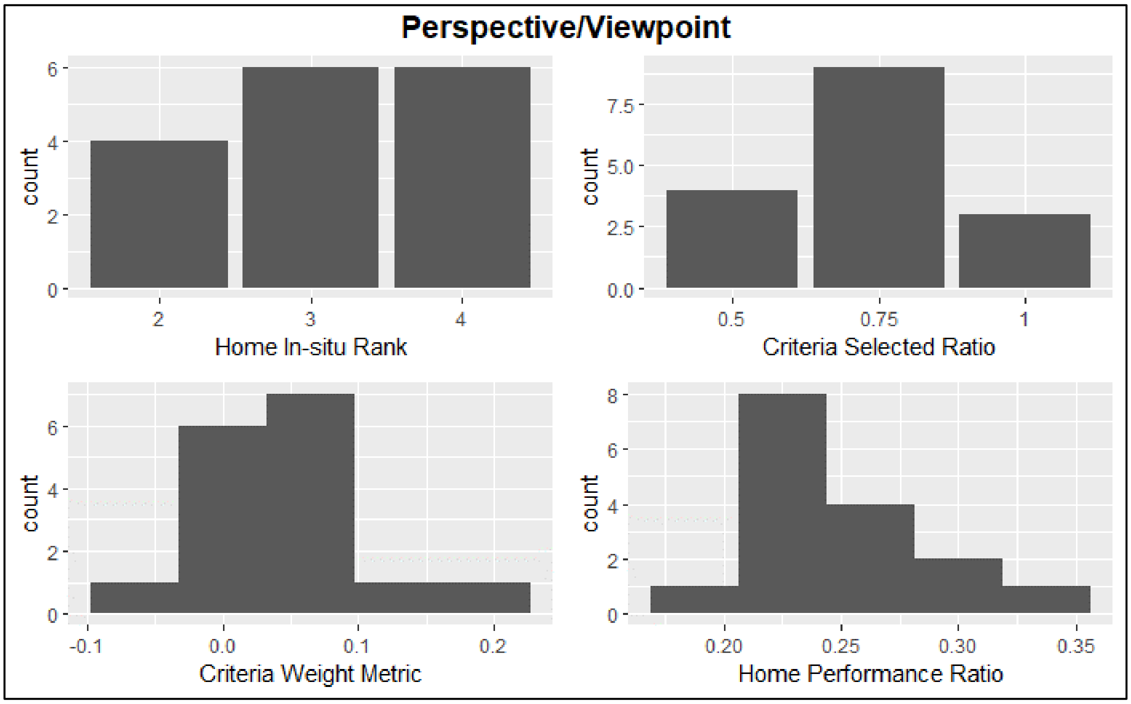

Figure 4.9 Summary histograms for the metrics in Perspective/Viewpoint group

4.1.2.2 Ranking Deltas

The inputs provided by the participants was subjected to a Technique for Order of Preference by Similarity to the Ideal Solution (TOPSIS) multi-criteria decision making framework. This function takes the responses provided by the participants and completes the TOPSIS analysis to rank the alternatives. The Home Final Rank metric was then recorded for analysis. The Home Final Rank for each treatment is shown in Figure 4.10.

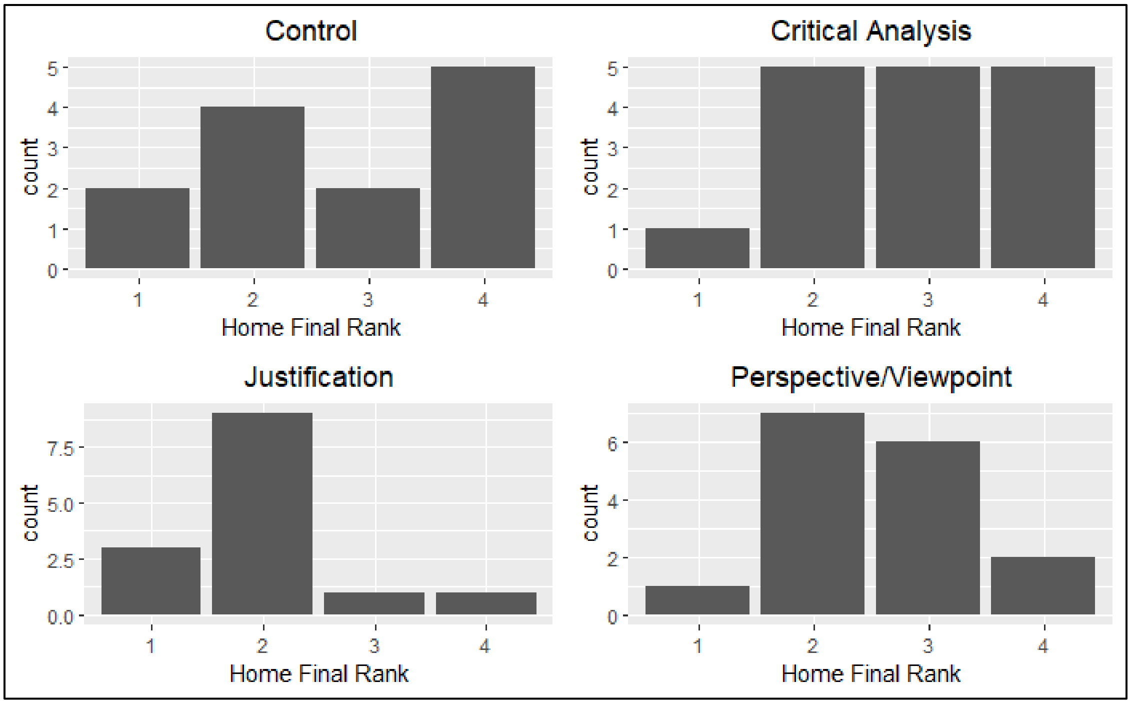

Figure 4.10 Summary histograms for the Home Final Rank across treatments

In evaluating the effects of the de-biasing techniques on the inputs to an MCDM analysis, it is important to analyze how the rank of the home institution changed before (home in-situ rank) and after (final ranking) the MCDM analysis is executed. The metric "home_rank_delta" was derived from the dataset to investigate this effect as evaluated by Equation 4.4.

$$\text{home\_rank\_delta} = \text{home\_insitu\_rank} - \text{home\_rank\_final} \tag{4.4}$$

This metric can be negative (ranking reduction), zero (no change in rank), or positive (rank improvement). There are four unique conditions where this number can be assessed as shown in Table 4.7.

Table 4.7 Home rank delta metric conditions

In-situ Rank	Final Rank	Home Rank Delta Value	Interpretation
Low	Low	Zero	No change in home institution ranking
Low	High	Positive	Improvement in home institution ranking
High	High	Zero	No change in home institution ranking
High	Low	Negative	Reduction in home institution ranking

The comparison of the Home Rank Delta metric is provided in Figure 4.11. The control group did not have significant deltas in the rank. Reviewing the Critical Analysis metric shows many participants did not drastically change the rank of home institution (+/- 1 rank) with a few exceptions. Negative rank deltas is particularly concerning, because any reduction in rank would be considered an over reduction of bias, resulting a negative bias in the opposite direction. Reviewing the Justification metric seems to confirm bias, where most of the participants increased their ranking by 2. Reviewing the Perspective/Viewpoint metric shows about half the participants improved the rank of the home institution (positive values).

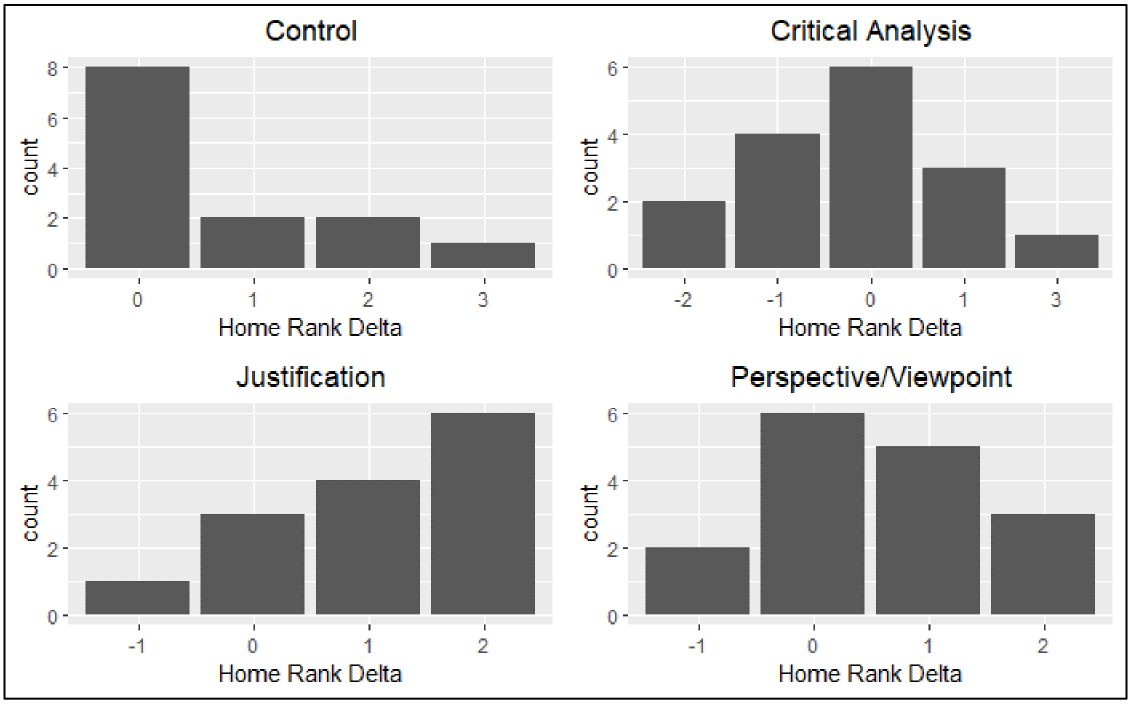

Figure 4.11 Home Rank Delta metric across treatments

4.1.2.3 Analysis

In order to test the effect of the treatments on the participant's responses several key assumptions must be tested in order to choose the right analysis to evaluate differences. The assumptions for analysis are that the samples are random and independent, normally distributed, and homogeneity of variances. The assumption for random and independent is satisfied by the data collection process. The questionnaires were sent to all undergraduate engineering students via email and participation was on an individual, voluntary basis. To reduce participation bias, a raffle for gift cards was included.

Next, testing whether the metrics' variances are significantly different. This was accomplished using a Bartlett's test for homogeneity of variances. Bartlett's tests were run on each metric across the de-bias technique factors. The resulting p-values for home_insitu_rank (p =

0.887), criteria_selected (p = 0.932), home_perform_ratio (p = 0.283), criteria_weight_metric (p = 0.555), home_final_rank (p = 0.468), and home_rank_delta (p = 0.792), lead to accepting the null hypothesis that the variances of these metrics between the treatments are equal.

Finally, using a Shapiro-Wilk test to check that the samples are normally distributed. The resulting p-values for the entire dataset metrics home_insitu_rank (p = 2.4 e-7), criteria_selected (p = 2.6 e-7), home_perform_ratio (p = 0.419), criteria_weight_metric (p = 0.003), home_final_rank (p = 7.2 e-6), and home_rank_delta (p = 0.001), lead to the rejection of the null hypothesis that all samples are normally distributed. While the total dataset analysis shows non-normality, investigating by treatment is necessary. Further investigation of the data using graphical methods, refer to Figure 4.6, Figure 4.7, Figure 4.8, and Figure 4.9 show that a few of the metrics appear to be normally distributed. The full results of the Shapiro-Wilk tests across metrics and treatments are shown in Table 4.8.

Table 4.8 Shapiro-Wilk Tests for normality

Metric	**Control**	**Critical Analysis**	**Justification**	**Perspective /Viewpoint**
home_insitu_rank	p = 0.002	p = 0.002	p = 0.009	p = 0.003
criteria_selected	p = 0.014	p = 0.003	p = 0.008	p = 0.003
home_perform_ratio	p = 0.193	p = 0.935	p = 0.089	p = 0.058
criteria_weight_metric	p = 0.087	p = 0.674	p = 0.015	p = 0.281
home_final_rank	p = 0.022	p = 0.026	p = 0.002	p = 0.030
home_rank_delta	p = 0.001	p = 0.269	p = 0.014	p = 0.061

Given that all metrics are not normally distributed, an analysis of variance (ANOVA) cannot be used to test for statistical differences between the treatments. Given the assumptions tested, we must use a non-parametric analysis. The appropriate test given the conditions is a

Kruskal-Wallis Rank Sum test which tests whether samples come from the same population. In this test, the null hypothesis is that the samples in each group come from the same population distribution. The resulting p-values for home_insitu_rank (p = 0.086), criteria_selected (p = 0.860), home_perform_ratio (p = 0.113), criteria_weight_metric (p = 0.893), home_final_rank (p = 0.065), and home_rank_delta (p = 0.029) across de-biasing techniques. Given an alpha = 0.10, this leads to rejecting the null hypothesis that the samples come from the same population and are significantly different for three of the six metrics.

Given that the dependent variables are not all normally distributed, in order to analyze where the specific differences are within the metrics across debiasing techniques, the pairwise Wilcoxon Signed Rank test was run. This is a non-parametric version of the repeated one-way ANOVAs to determine where the statistically significant differences are with respect to comparison to the control group. The results are summarized in Table 4.9.

Table 4.9 P-values for Wilcoxon Rank Sum tests

	De-biasing Techniques		
Metric	**Critical Analysis**	**Justification**	**Perspective/Viewpoint**
home_insitu_rank	p = 0.07	p = 0.32	p = 0.32
criteria_selected	p = 0.95	p = 0.95	p = 0.95
home_perform_ratio	p = 0.71	p = 0.13	p = 0.54
criteria_weight_metric	p = 0.92	p = 0.92	p = 0.92
home_final_rank	p = 0.86	p = 0.15	p = 0.72
home_rank_delta	p = 0.14	p = 0.29	p = 0.94

The Pairwise Wilcoxon tests shows a significant difference between the control group and Critical Analysis for the home_insitu_rank metric. Further investigation of home_insitu_rank using graphical analysis, Figure 4.12, shows that the box plots for Control and Critical Analysis do overlap but are not significantly different given the alpha. For this case, since the participants have not been exposed to any element of the Critical Analysis treatment prior to making the selections, this relationship is insignificant.

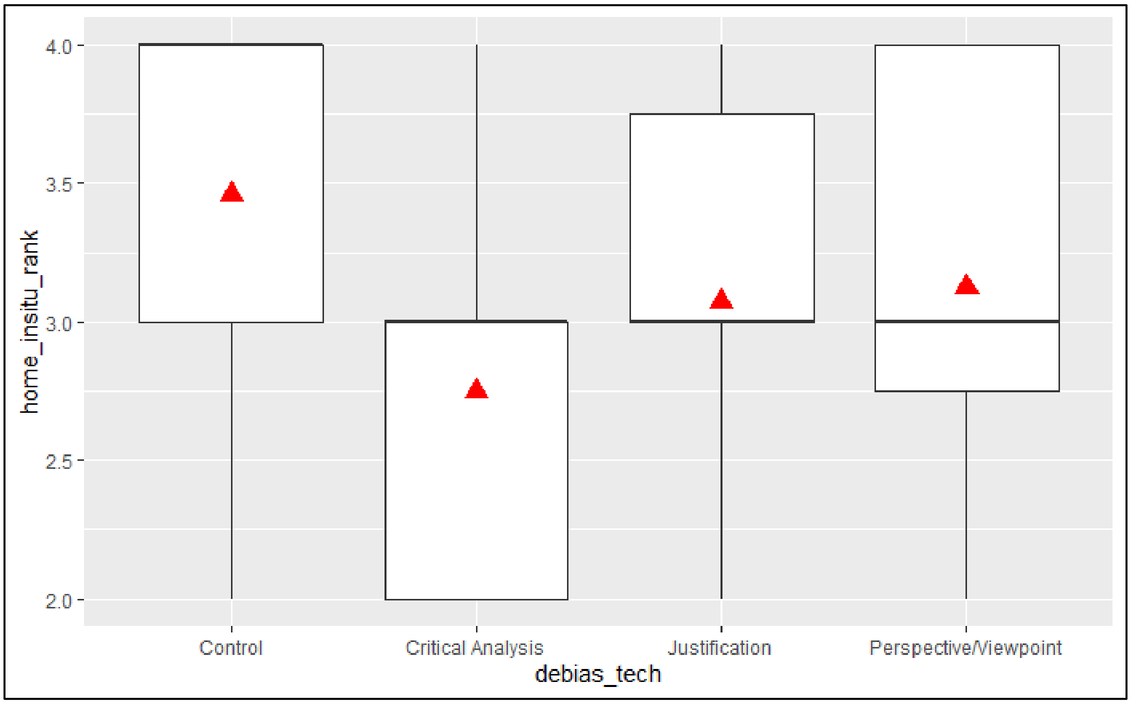

Figure 4.12 Boxplots of home_rank_delta across treatments

There were two metrics that were close to significance as compared to the Control. To assess the effect sizes of the lowest p-value metrics, 1) the Justification on home performance ratio as compared to the control and 2) the Critical Analysis on home rank delta as compared to the control, the effect size is computed. Since the sample size is relatively small, n = 13 for Control, n = 14 for Justification, and n = 17 for Critical Analysis, Hedges g is computed. The Hedges g, with a confidence level of 0.9 results in a g = -0.899 for home performance ratio in Justification and a g = -1.012 for home rank delta in Critical Analysis, meaning the difference between the two sample means in each case is estimated to be about one standard deviation away. This is considered a large effect size, given the rules of thumb are classified as small (g = 0.2), medium (g = 0.5) and large (g = 0.8).

Finally, the participants who increase the rank of their home institution by 2 or more are investigated. These participants selected highly ranked universities for comparison but provided MCDM input responses that increased the rank of their home institution from an in-situ rank of 3 or 4 to a final rank of 1 or 2. Since home rank delta is linearly dependent on the home in-situ rank and home final rank metrics, these metrics are not analyzed here. For example, if the home rank delta metric is +3, the home in-situ rank must be 1. Therefore, the extreme values do not provide additional information for analysis purposes.

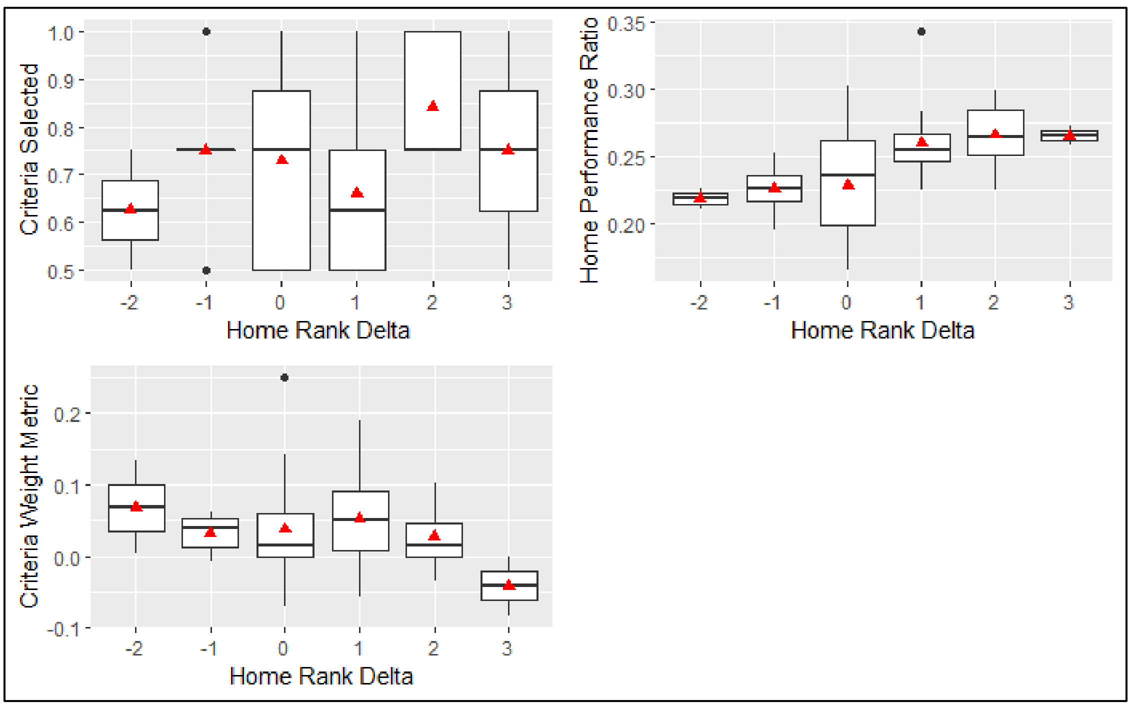

Figure 4.13 Boxplots of MCDM input metrics vs home rank delta values

In the boxplots for the metrics across home rank delta values, it is clear that there are significant differences, Figure 4.13. When home rank delta is high, rank increases of 2 or more, the home performance ratio is higher. Additionally, the criteria weight metric is lower for home rank delta of 3. This helps explain how participants used the MCDM inputs to improve the rank of their home institution using a combination of performance assessments and vague criteria.

4.1.2.3.1 Metric Correlations

The metrics were compared within the Control group to determine if there are any correlations among the metric. The correlation matrix is provided in Table 4.10.

Table 4.10 MCDM input correlation matrix

	home_insitu_rank	criteria_selected	home_perform_ratio	criteria_weight_metric	home_final_rank
home_insitu_rank					
criteria_selected	0.59				
home_perform_ratio	**-0.65**	-0.37			
criteria_weight_metric	**-0.68**	**-0.69**	0.39		
home_final_rank	0.47	0.30	**-0.94**	-0.35	

Identifying the strong correlations ($r \geq 0.6$) we analyze further to determine if the correlations are logical or lead to further findings. First, home performance ratio is negatively correlated with home in-situ rank ($r = -0.65$). This correlation is anticipated since a lower home in-situ rank results in lower ranked universities for comparison. Next, criteria weight metric is negatively correlated with home in-situ rank ($r = -0.68$). This correlation points to bias. When comparing against known, highly ranked universities, the participant is giving lower relative weight to the US News criteria. The participant seems to be using the vague criteria to improve the rank of the home institution. Next, criteria weight metric is negatively correlated with criteria selected ($r = -0.69$). This correlation is anticipated since a majority of these values are positive, see Figure 4.6, and given the participant selects all US News criteria this metric will be 0. Lastly, home final rank is very strongly negatively correlated to home performance ratio ($r = -0.94$). Again, this is anticipated, and interpretation depends highly on the home in-situ rank for the given response. Given a high home in-situ rank, highly ranked comparisons chosen, the home performance ratio will decrease.

4.1.3 Susceptibility to motivational bias

The second part of the questionnaire provided the participants a series of statements in a randomized order to assess characteristics that have shown to correlate with motivational biases, namely optimism, pessimism, optimism + pessimism, emotional intelligence quotient (EIQ), and confirmation inventory. The data collected consisted of 59 participants ($n = 59$).

4.1.3.1 Summaries

The summary statistics for the susceptibility scores is provided in Table 4.11.

Table 4.11 Summary statistics for susceptibility scores

Susceptibility Measure	**Associated Bias**	**Median**	**Mean**	**SD**	**IQR**
Optimism	Desirability of Positive Outcome	10	9.85	2.78	8 - 12
Pessimism	Undesirability of Negative Outcome	8.5	8.62	2.89	6 – 10.25
Optimism + Pessimism	Desirability of Option/Choice	19	18.47	2.86	17 - 20
Emotional IQ	Affect-influenced	124	123.50	15.52	113 - 135
Confirmation Inventory	Confirmation	37	36.32	4.83	33 – 40.25

Additionally, the data collected was plotted on histograms to show the approximate distributions, Figure 4.14. Since these scores are not affected by the treatments, the scores can be analyzed together.

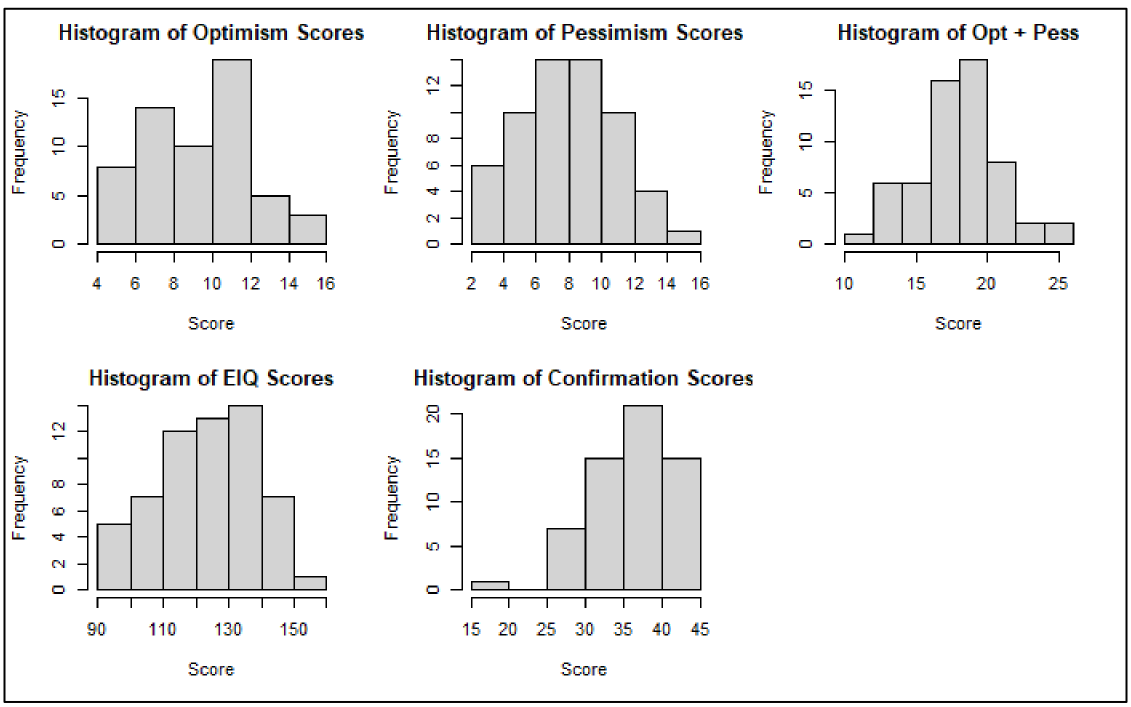

Figure 4.14 Susceptibility scores among participants

The statement responses range from Strongly Disagree (scored 1, or 5 for reverse scored items) to Strongly agree (scored 5, or 1 for reverse scored items). Responses of Neither agree nor disagree received a score of 3. Therefore, to declare a characteristic within the participant, the scores were evaluated using Neither agree nor disagree as a threshold.

The resulting scores for declaring a bias susceptibility within a participant for each bias are desirability of positive outcome (score ≥ 9), undesirability of negative outcome (score ≥ 9), affect-influenced (score ≤ 99), and confirmation (score ≥ 30). For the desirability of an option/choice bias, this was declared if the participant was declared for both desirability and undesirability biases. The sum of the optimism and pessimism scores are provided in Figure 4.14 for completeness. A summary of the biases declared are provided in Table 4.12.

Table 4.12 Summary of bias declarations

Bias	**Bias Declared**	**No Bias Declared**
Desirability of positive outcome	35	24
Undesirability of negative outcome	24	35
Desirability of option/choice	9	50
Affect-influence	3	56
Confirmation	51	8

4.1.3.2 Analysis

To test the effect of the scores on the participant's responses and de-biasing techniques (treatments), several key assumptions must be tested to choose the right analysis for effects. The assumptions for analysis are that the samples are random and independent, normally distributed, and homogeneity of variances. The assumption for random and independent is satisfied by the data collection process. The questionnaires were sent to all undergraduate engineering students via email and participation was on an individual, voluntary basis. To alleviate any bias in participation a raffle for gift cards was included.

Next, testing whether the metrics variances are significantly different. This was accomplished using a Bartlett's test for homogeneity of variances. Bartlett's tests were run on each metric across the de-bias technique treatment. Note that optimism + pessimism was not assessed since this bias is based on two other biases. The resulting p-values for the dataset are optimism ($p = 0.844$), pessimism ($p = 0.853$), optimism + pessimism ($p = 0.072$), EIQ ($p = 0.268$), and confirmation ($p = 0.560$), lead to rejecting the null hypothesis that all scores across all treatments have homogenous variances.

Finally, using a Shapiro-Wilk test to check that the samples are normally distributed. The resulting p-values for the dataset are optimism ($p = 0.077$), pessimism ($p = 0.343$), optimism + pessimism ($p = 0.105$), EIQ ($p = 0.948$), and confirmation ($p = 0.002$). These results state that the confirmation and optimism scores are not normally distributed, but the others are normally distributed.

The bias susceptibility measures were subjected to linear regressions to assess the relationship between the susceptibility scores and the MCDM input metrics. Only EIQ had a significant relationship with criteria_selected at $p = 0.029$, but the R^2 was 0.033 which means the model has high variability and not very useful. All other p-values were insignificant, with the lowest at $p = 0.176$. Although the distributions of the scores are not normally distributed, since there is a sufficiently large sample size for this analysis ($n = 59$) and the sample sizes are similar an ANOVA is robust to these conditions. Therefore, a standard analysis of variance (ANOVA) can be used. ANOVAs were examined to assess the differences between the MCDM input metrics based on declaration of susceptibility to each of the 5 identified biases. A single significant difference was identified. The means of home final rank between no declared affect bias and declared were found to be significantly different, as shown in Figure 4.15.

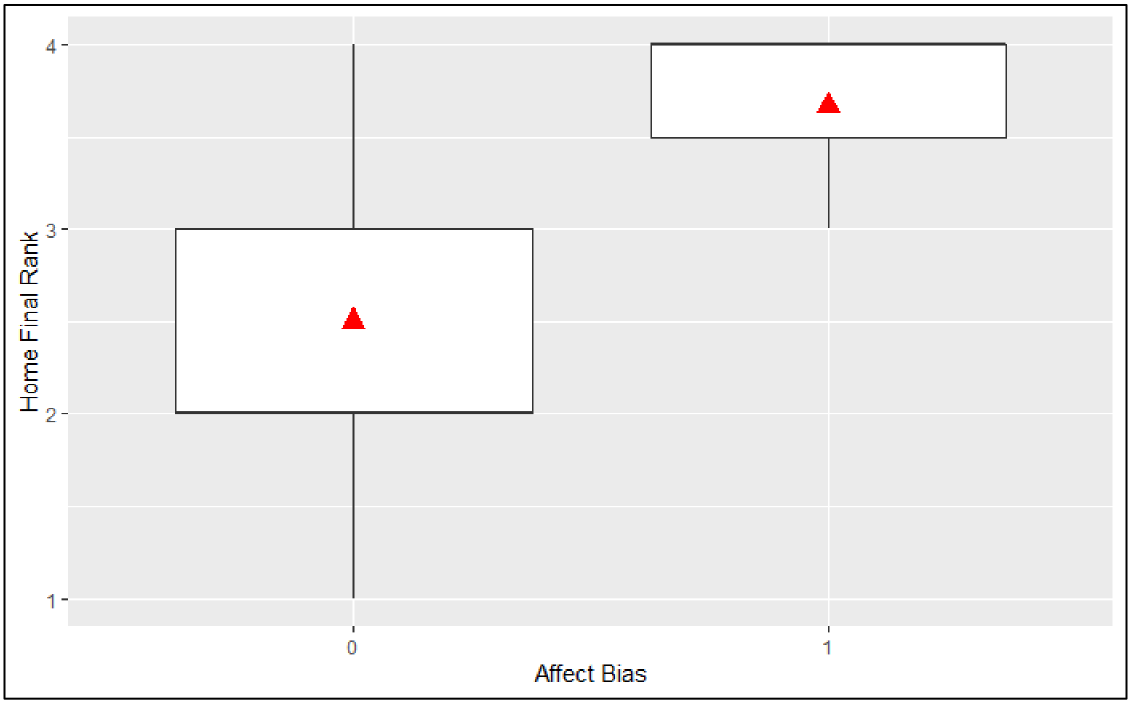

Figure 4.15 ANOVA significance: home final rank between affect bias declaration

This result seems to show that participants who had a higher emotional IQ (EIQ), and therefore not declared to be susceptible to affect bias were more likely to provide responses that ranked their home institution higher.

For the Option/Choice, Affect-influenced, and confirmation bias declarations, refer to Table 4.12, the sample size for one side of each is rather low. In order to properly evaluate the relationships within these factors, a bootstrap re-sampling was completed. There were 10,000 bootstrap samples created to assess significant differences between the means. The p-values were evaluated for each metric to determine if the difference between the bootstrap sample means and the observed sample means were significantly higher. The relationships that were identified for further investigation are: home in-situ rank between option bias declarations, home performance ratio between affect bias declarations, and home final rank between affect bias declarations. The box plots for the observed data are provided in Figure 4.16for graphical analysis.

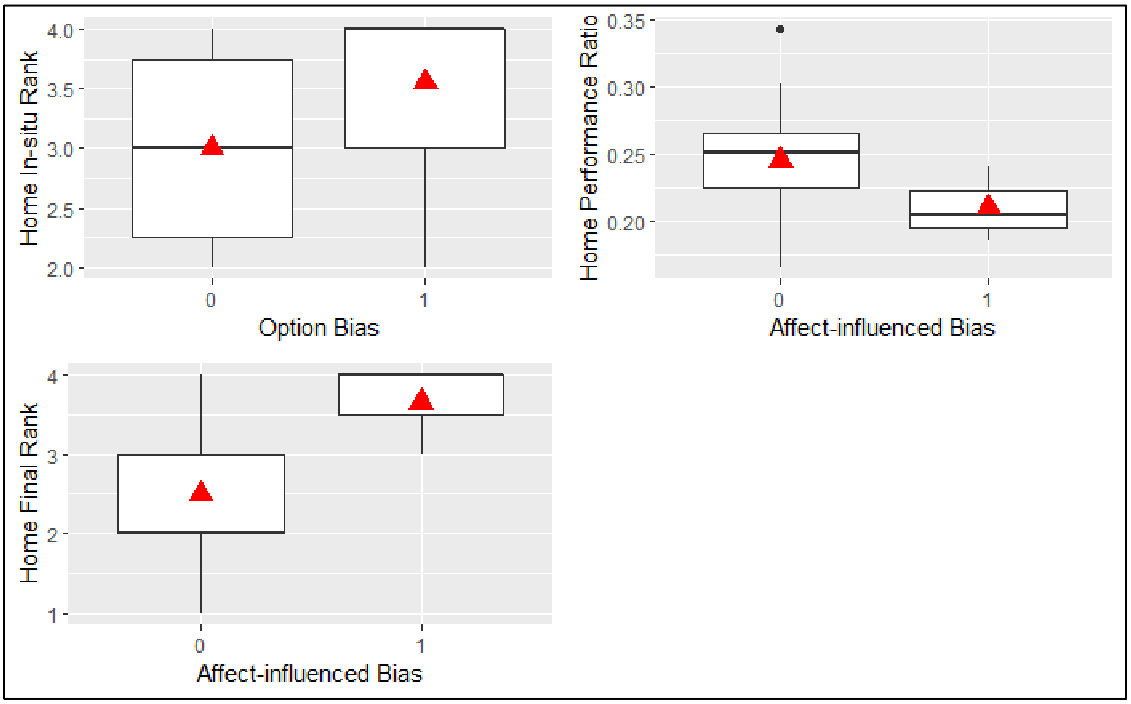

Figure 4.16 Boxplots from bootstrapping findings

First, the difference between the observed and bootstrap means for home in-situ rank were found to be significantly larger across the Option/Choice bias. Given a declared Option/Choice bias, the participants will select institutions that are higher ranking for comparison to the home institution, hence a higher home in-situ rank. Next, the difference between the observed and bootstrap means for home performance ratio were found to be significantly larger across the Affect-influenced bias. Given a declared Affect-influenced bias, the participant's responses will be relatively closer to the expected range of values for this metric. Finally, the difference between the observed and bootstrap means for home final rank were found to be significantly larger across the Affect-influenced bias. Given a declared Affect-influenced bias, the participants provide inputs to the MCDM problem that result in lower ranking for the home institution.

The susceptibility scores were assessed to determine if there were any correlations between the scores. The summary of the correlation matrix is shown in Table 4.13. The correlation matrix shows that there are no strong correlations between the variables.

Table 4.13 Susceptibility scores correlation matrix

	Optimism	**Pessimism**	**EIQ**	**Confirmation**
Optimism				
Pessimism	-0.49			
EIQ	0.56	-0.39		
Confirmation	0.25	-0.02	0.35	

4.2 Aggregated Results

Analyzing the entire dataset given the de-biasing techniques and susceptibility measures is now required to assess and interaction effects of the independent variables. Revisiting the research questions guiding this study, there are two questions:

- Are there methods for measuring motivational bias, or likelihood of motivational bias, within a multi-criteria decision making (MCDM) framework?
- Do the identified de-biasing techniques have any impact on reducing the motivational bias within a multi-criteria decision making (MCDM) framework?

The focus for this portion of the study is on the aggregated analysis of the susceptibility measures and the de-biasing techniques. Are there any de-biasing techniques that work particularly well for a given bias declaration? Interaction plots allow graphical analysis to investigate these relationships.

4.2.1 Interaction effects

This portion of the analysis will look at the interaction of susceptibility measures and de-biasing techniques. First, identifying the areas where there are significant interaction effects. To identify these interactions, a multivariate analysis of variance (MANOVA) was performed across all MCDM metrics, susceptibility declarations, and de-biasing techniques. The interactions with significant differences between the means are shown in Table 4.14.

Table 4.14 Significant interaction effects

MCDM Input Metric	Interaction	p-value
criteria_selected	De-biasing Technique: Confirmation Bias	0.055
home_perform_ratio	De-biasing Technique: Desirability Bias	0.047
home_perform_ratio	De-biasing Technique: Undesirability Bias	0.085
home_final_rank	De-biasing Technique: Desirability Bias	0.091
home_final_rank	De-biasing Technique: Undesirability Bias	0.077
home_final_rank	De-biasing Technique: Affect-influenced Bias	0.073
home_rank_delta	De-biasing Technique: Desirability Bias	0.047

To investigate the interactions graphically, interaction plots with means and standard errors are plotted for each of the relevant significant interactions. Again, the significance of the home final rank metric is not relevant without the home in-situ context. Therefore, those interactions will not be analyzed further.

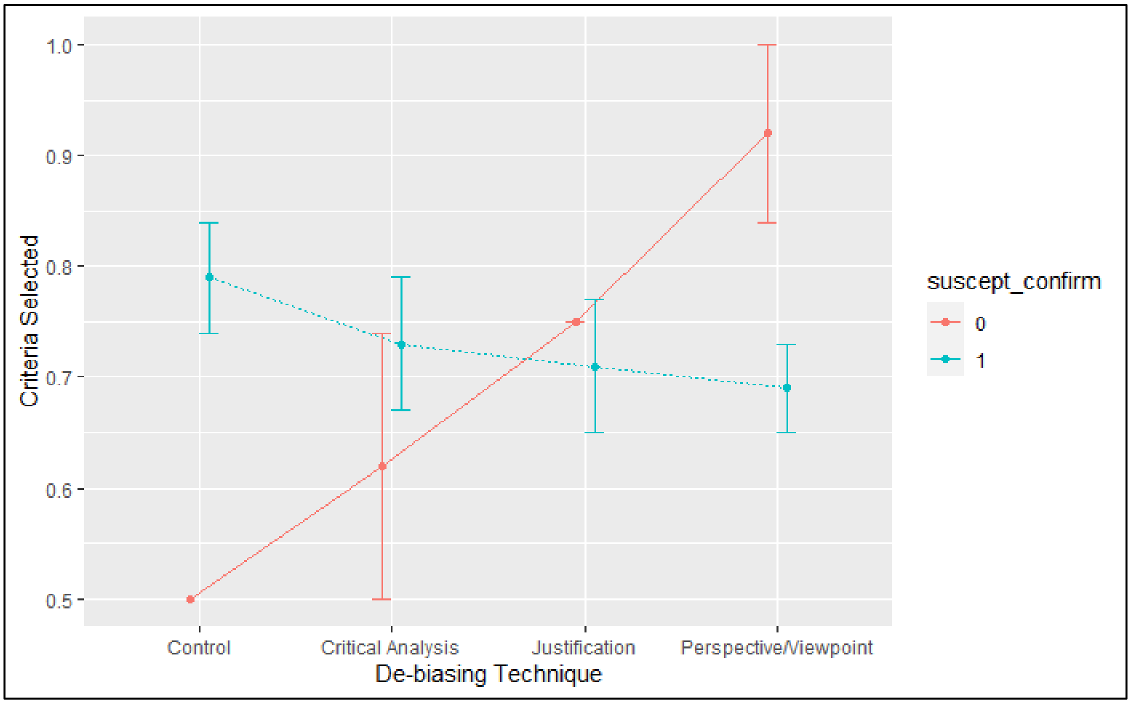

Figure 4.17 Interaction plot for criteria selected ratio across treatment and confirmation bias

The interaction plot for the criteria selected ratio across the de-biasing techniques and susceptibility to confirmation bias measures is provided in Figure 4.17. Given a declaration of susceptibility to the confirmation bias, the metric is stable across treatments. On the other hand, without confirmation bias, the metric differs across treatments.

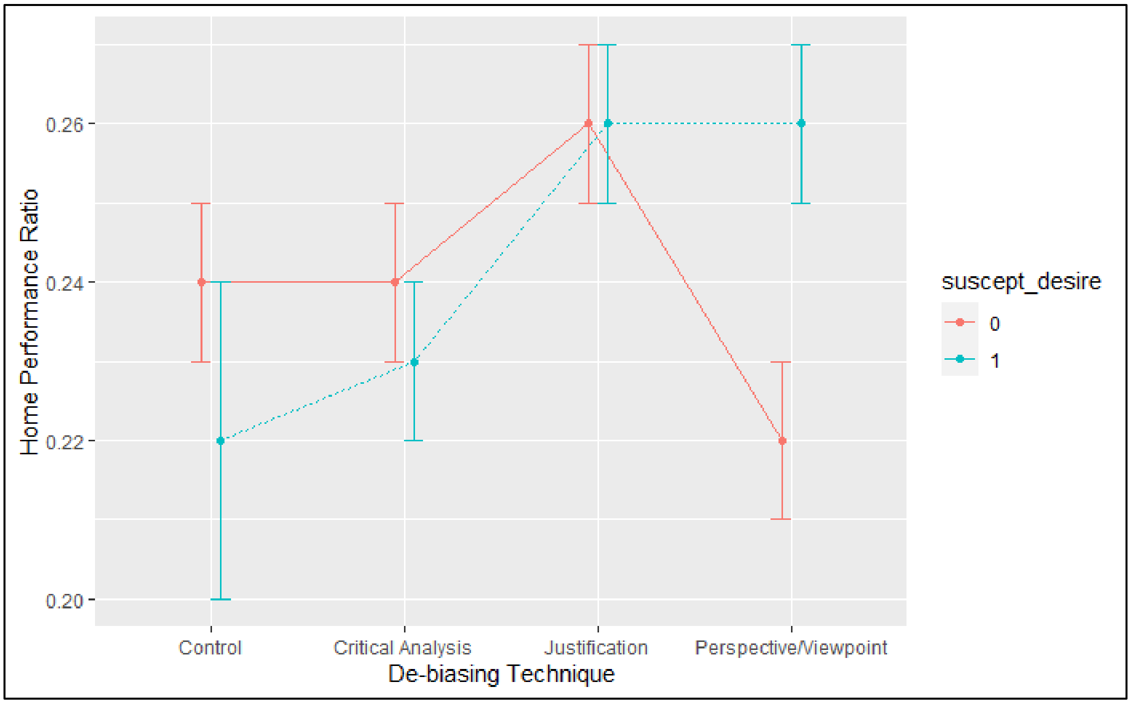

Figure 4.18 Interaction plot for home performance ratio across treatments and desirability bias

The interaction plot for the home performance ratio across the de-biasing techniques and susceptibility to desirability bias measures is provided in Figure 4.18. Given a declaration of susceptibility to the desirability bias, the metric is higher for all treatments. Without desirability bias declaration, the metric differs in two treatments (Justification and Perspective/Viewpoint) with respect to the control.

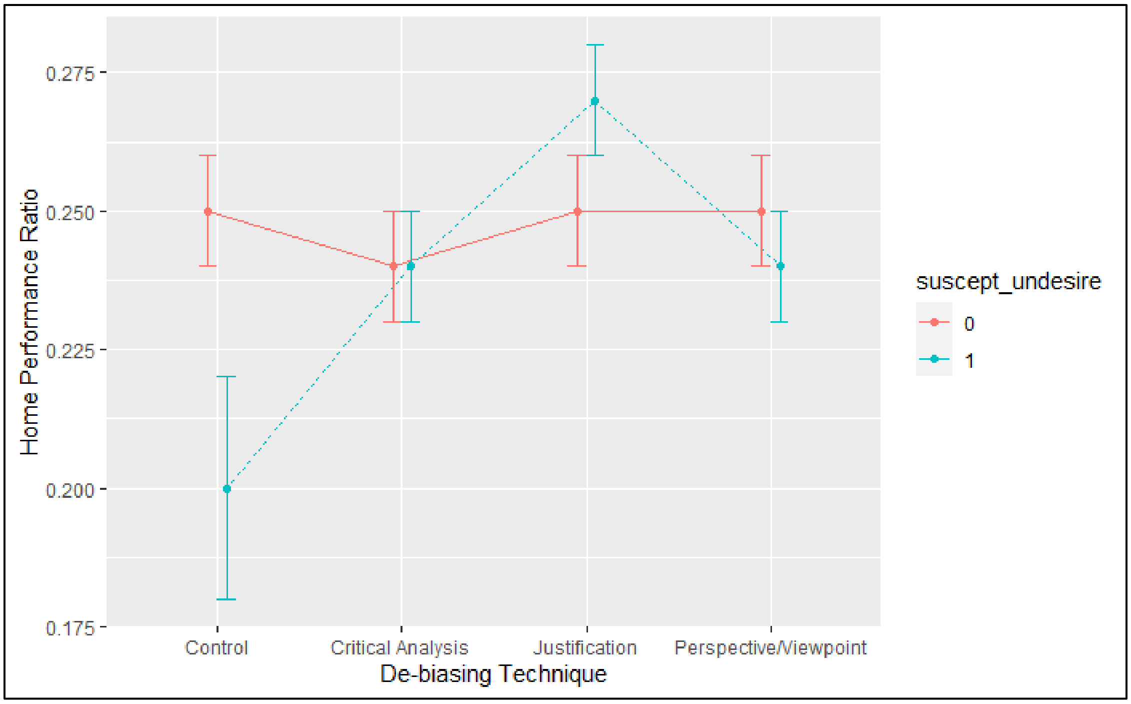

Figure 4.19 Interaction plot for home performance ratio across treatments and undesirability bias

The interaction plot for the home performance ratio across the de-biasing techniques and susceptibility to undesirability bias measures is provided in Figure 4.19. Given a declaration of susceptibility to the undesirability bias, the metric is higher for all treatments. Without undesirability bias declaration, the metric is stable across all treatments.

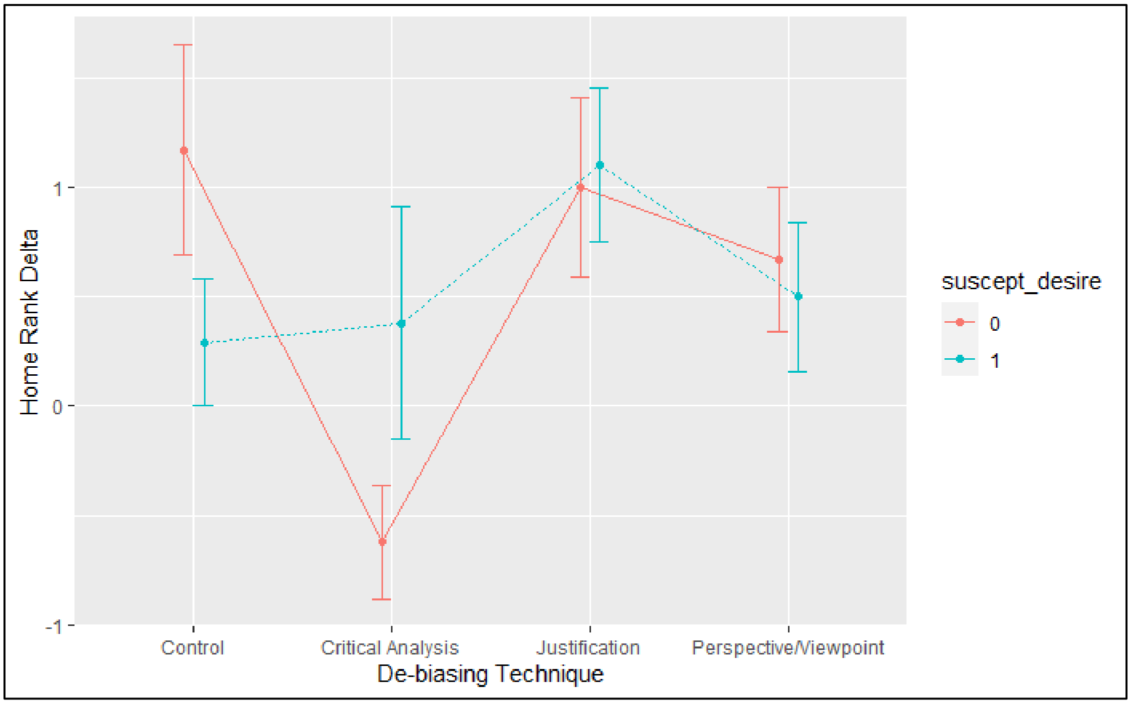

Figure 4.20 Interaction plot for home rank delta across treatments and desirability bias

The interaction plot for the home rank delta across the de-biasing techniques and susceptibility to desirability bias measures is provided in Figure 4.20. Given a declaration of susceptibility to the undesirability bias, the metric is higher for all treatments. Without undesirability bias declaration, the metric is stable across all treatments.

4.2.2 Correlation between MCDM metrics and susceptibility measures

Testing whether correlations exist between the susceptibility scores and MCDM input metrics will determine if a participant's susceptibility score has any relationship to their inputs across the metrics. For this analysis only the control group's data. The correlations are shown in Table 4.15.

Table 4.15 Correlation matrix for Control group MCDM input metrics and susceptibility scores

	home_insitu_rank	criteria_selected	home_perform_ratio	criteria_weight_metric	home_final_rank	home_rank_delta
suscept_desire_score	-0.09	0.02	**-0.42**	0.23	0.37	**-0.47**
suscept_undesire_score	0.30	0.09	-0.02	-0.39	0.04	0.15
suscept_option_score	0.30	0.16	**-0.60**	-0.24	**0.55**	**-0.43**
suscept_affect_score	-0.04	-0.16	-0.09	-0.08	0.02	-0.05
suscept_confirm_score	**0.40**	-0.19	-0.22	0.00	0.16	0.07

Among the correlations calculated, there are some moderate to strong associations ($r \geq 0.4$). This indicates that the participant's susceptibility measures for those metric/score combinations somewhat influence the responses.

4.3 Overall Findings

Aggregating the findings is crucial to understanding how the results of this study can be implemented to reduce the introduction of motivational bias in multi-criteria decision making. The following section will review each step of the MCDM process identifying the major findings from the analyses completed.

The bootstrap analysis completed on the susceptibility measures found that participants who were declared to have Option/Choice bias and Affected-influenced bias ranked their home institution lower and resulted in a lower home final rank. This suggests that someone who is declared for these two biases would provide unbiased responses. The home will have a low in-situ rank and a low final rank, resulting in a home rank delta near zero.

4.3.1 Step 1: Generating alternatives

Investigation of the first step in the MCDM process specifically evaluates the metric home_insitu_rank, which indicates how the participant chose alternatives. This analysis shows no significant effects among the MCDM metric across the de-biasing treatments. Given a target value of 4, from Table 4.1, Critical Analysis should be avoided for this step, see Figure 4.12. Neither Justification nor Perspective/Viewpoint significantly affect the participant's responses.

As for the susceptibility scores, there is a correlation between the home in-situ rank metric and Confirmation bias scoring (Table 4.10). This association is a moderate positive correlation. Given a low score in this measure, the participant is moderately likely to choose alternatives that are not as highly ranked as the home institution.

4.3.2 Step 2: Developing the attributes/criteria

Investigation of the second step in the MCDM process specifically evaluates the metric criteria_selected, which indicates how the participant chose attributes, or evaluation criteria. The ANOVAs determined no significant differences between the de-biasing techniques for this metric. Additionally, there were no correlations with the susceptibility scores.

Analysis of the interaction plots, Figure 4.17, did identify an interaction related to this step. Given a target value of 1.0 for this metric, see Table 4.1, the de-biasing techniques had different effects depending on a declaration of confirmation bias. Based on the analyses, if a confirmation bias is declared (suscept_confirm = 1), then no treatment should be used for this step. On the other hand, if a confirmation bias is not declared (suscept_confirm = 0), the a Perspective/Viewpoint treatment shows participants provided responses closest to the target value of 1.

4.3.3 Step 3: Assessing the performance of alternatives against attributes

Investigation of the third step in the MCDM process specifically evaluates the metric home_perform_ratio, which indicates how the participant assessed the performance of the home institution relative to the total of all assessments across the alternatives and criteria. Reviewing the analyses completed, there is a negative correlation with both Desirability of a Positive Outcome and Desirability of Option/Choice bias measures. Given that many of the responses in the Control group for this metric were high, see Figure 4.6, these characteristics improve the responses for this metric. Additionally, it was observed that participants who improved the rank of the home institution (home_rank_delta) had higher values for this metric.

Reviewing the interaction plots, if an Undesirability of a Negative Outcome bias is declared, the Control group had the values closest to the target range of 0.165 to 0.235, refer to Table 4.1. Given no declaration of this bias, there is no significant difference across the treatments. Therefore, for this bias, there are no recommendations for mitigation

The most significant finding for this step in the process involves the Desirability of a Positive Outcome bias. Given a declaration of this bias, the control group is within the anticipated range for this metric. Given no declaration of this bias, the Perspective/Viewpoint debiasing technique is the only treatment within the anticipated range. This is shown in the interaction plot in Figure 4.18.

4.3.4 Step 5: Eliciting weights for each attribute

Investigation of the fifth step in the MCDM process specifically evaluates the metric criteria_weight_metric, which relatively how much weight was given to the US News criteria. The target value for this metric is 0, refer to Table 4.1, therefore given a positive or negative value for this metric can signify biased responses. Specifically, as shown in Figure 4.13, participants who improved the rank of their home institution by 3 had only negative values for this metric. There are no strong correlations, interactions, or significant differences for this metric.

Analyzing Table 4.15 for the criteria weight metric shows a weak negative correlation between the susceptibility score for undesirability of a negative outcome bias. This means that given a higher score for this susceptibility measure the criteria weight metric decreases. As we saw in Figure 4.13, this can be an indicator of bias toward improving the rank of the home institution. Therefore, a lower score for the susceptibility to undesirability of a negative outcome bias is an indicator that this metric should be monitored and evaluated for bias.

4.4 Validity and Reliability

Validity and reliability are the most important aspects of any research design. You can have reliability without validity, but you cannot have validity without reliability (Kimberlin & Winterstein, 2008). Therefore, we will discuss and cover validity first and how it applies to this research study, then review reliability and how it applies.

It is important to note that both quantitative and qualitative designs contain validity and reliability considerations. Although the components of each are not the same, the measures are analogous between the two methods (Ihantola & Kihn, 2011). In quantitative designs, you have internal and external validity, where qualitative designs have contextual and generalizable aspects. In a qualitative design, procedural reliability is analogous with the quantitative reliability.

4.4.1 Validity

Validity is the extent to which a concept is accurately measured in a given study. Validity is composed of content, criterion, and construct validity (Heale & Twycross, 2015). Content validity determines if the study is measuring all the relevant aspects, or content, over the domain of the variables. If the content is not fully captured in the measurements, the content validity is not satisfied. Construct validity is the degree to which the study measures the construct that it set out to measure. This can be further separated into divergent and convergent constructs. Divergence relates to showing items that are not related are not correlated, or at most minimally correlated measurements. Convergence relates to measurement items that are related to a single construct being highly correlated. Constructs are abstract characteristics that cannot be directly measured. Therefore, many individual measures that are taken will be combined to an aggregate measure of the overarching construct. Criterion validity relates to how well the construct measurement correlates with other measures of latent constructs. The two types of criterion validity are predictive and concurrent. Predictive validity is how well the measures predict future results. Concurrent validity is compared to a similar instrument on how well it measures the construct in the present.

A final note on validity relates to external validity, or how generalizable the study is to other domains. The goal for this study is to develop a methodology that will be generalizable to a different problem or population. Therefore, the data collection will involve collecting data on the general steps of an MCDM problem. This allows for application to nearly any MCDM technique that will be used in practice. Additionally, researchers could leverage this methodology to explore other domains, such as engineering, economics, politics, or business.

4.4.2 Reliability

Reliability is how consistently, after repeated application, the study can replicate the results. There are three factors that need to be assessed for reliability: internal consistency, stability, and equivalence. Internal consistency assesses the items within the instrument to show that items measuring a single construct should correlate, while not correlating with other groups (constructs). Stability, or test-retest reliability, relates to how well the measurement remains consistent over time with the same participants. Lastly, equivalence shows that the instrument or study is consistent across researchers or alternate forms of the instrument.

4.4.3 Validity and Reliability Strategy

There are strategies that are employed to ensure validity and reliability. The primary issues that threaten these aspects are error and bias in both the participants and the researcher. First, the questionnaire for data collection will be completely reviewed by fellow researchers. This will help reduce the researcher bias and error as well as check for consistency and coherence to reduce participant error in providing inputs. A pilot study of the questionnaire will ask for feedback and address areas of misunderstanding or grammatical errors. This is also a form of face validity assessment. Participant bias, while motivational bias is sought, is not good for the validity of the questionnaire. A questionnaire sent out to students who respond voluntarily will attract a specific set of people. Those who are high achievers or enjoy taking part in research may be more likely to participate. Therefore, to ensure a larger sample size and encourage more participation the participants will be entered into a raffle for gift cards to an online marketplace. There will be offerings of three $50 gift cards to increase the chances of winning and encourage participation.

As for inductive and deductive approaches, deductive is the process from theory to data while inductive is the process of taking data and deriving theories. The literature contains many theories and techniques for mitigation of motivational bias with very little data. Quantitative methods are typical for deductive approaches which is why it was chosen to guide this research. The goal of this quantitative study is to gather data that will support, or deny, those theories. The bias measurement instrument and the MCDM inputs received by the participants will allow for mapping of biases to variations in the inputs, as well as de-biasing technique efficacy for reducing the motivational biases identified. Additionally, the data collected could derive additional theories or provide more insight into what steps in the MCDM process are more vulnerable to biases.

4.4.4 Framework

A framework for assessing the validity and reliability for questionnaires in research designs was published by Taherdoost (Taherdoost, 2016). Since this study is deductive and quantitative by design, the framework presented is a good framework for assessing this design.

For validity, the goal is to ensure that the study is measuring what it intends to measure. This includes face (optional), content, criterion, and construct validity as described above. With respect to reliability, the primary measure is internal consistency. Other measures that are not required are test-retest, interobserver, and split-half reliability (Del Greco, et al., 1987). An overview of the validities as adapted from Taherdoost is provide below.

Table 4.16 Validity and reliability assessments in research

Validity Component	**Definition**	**Requirement**
Content Validity	extent that items are relevant and all-inclusive to measure the target construct	Highly Recommended
Construct Discriminant Validity	extent that measures of different constructs diverge or minimally correlate	Required
Construct Convergent Validity	extent that measures of the same construct converge or strongly correlate	Required
Criterion Predictive Validity	extent that one measure predicts another	Required
Criterion Concurrent Validity	extent that a measure relates to another measure that it is supposed to relate	Required
Criterion Postdictive Validity	extent that a measure is related to an established instrument	Required
Reliability Internal Consistency	extent to which a measurement provides stable and repeatable results	Required

Adapted from (Taherdoost, 2016)

This study will evaluate the validity and reliability as described in the previous section as well as use this framework as a guide to ensure the results of the research are reliable, valid, and trusted. Given confirmation of the validities and reliability measures in Table 4.16, the research can be considered both reliable and valid.

Assessment of each validity type is unique. Here we will review the assessment tools and techniques for each validity and reliability measure.

Content validity requires review of the domain and questionnaire developed to ensure that all content within the domain is captured. This review should be completed by researchers in the field and a select set of participants. The participants will ensure that the questionnaire is easily read and understood. Any feedback during the review process should be evaluated and incorporated to fix any issues before proceeding to data collection.

Construct validity is the relationship, or correlation, between the explanatory variables and the response variable. The simplest way to assess this correlation is with a regression analysis and factor analysis. The confirmatory factor analysis (CFA) provides correlation loadings between measurement items within the questionnaire. This provides correlation of the items to both the construct being measured and between items. For items measuring the same construct, they should be highly correlated (≥ 0.4 loading). For items that measuring different constructs, they should be not correlated (or minimally correlated with loadings ≤ 0.4).

Criterion validity should be evaluated in both predictive and concurrent validity aspects, as applicable. This is a comparison between two measurements/instruments. For instance, a new instrument can be compared to an older instrument to ensure they are correlated or getting similar measures. Predictive criterion is similar to regression analysis where one criterion is assessed to predict another, which could be correlated with another set of criteria for further study.

For reliability, the internal consistency is a critical reliability measure. The standard measurement is Cronbach's alpha, which estimates the consistency of a participants' performance from item to item. This is a measure of how well the items measure a common construct. For Cronbach's alpha, an internal consistency of 0.7 or more is considered acceptable. If items are scored dichotomously, the Kuder-Richardson formula (K20) can be used to assess the internal consistency.

4.4.5 Validity & Reliability Assessment

We use the framework presented in the previous section to analyze the validity and reliability of the study. This assessment will be executed for both sections of the questionnaire, the MCDM inputs and the susceptibility to bias measurement.

4.4.5.1 MCDM inputs

In this research study, the content validity is accomplished in two ways, 1) an exhaustive literature review was conducted to aggregate de-biasing techniques to be tested and 2) the questionnaire will collect data on all steps in an MCDM problem framework. These two methods ensure that the content has been fully captured in both the theoretical and methodological aspects and the domain is fully addressed. Additionally, the content of the data collection and analysis received review from a panel of experts. In depth review occurred on two separate occasions with no major findings. For this study, an expert is defined by 3 primary categories: education, relevant experience, publications within the domain.

Table 4.17 Requirements defining "expert" for this study

Criteria	Minimum requirement
Education	Master of Science in Science, Technology, Engineering, or Mathematics field
Relevant experience	10 years of relevant experience in the decision analysis domain
Publications	3 peer-reviewed publications in decision analysis domain

The construct that is being measured and assessed in this study is motivational bias and de-biasing techniques. One popular way to validate the construct measurement is to compare the results to an established instrument. Motivational bias is very hard to measure because the participant is aware of this bias, it is not subconscious, and likely to shy away from admitting their bias. Additionally, no instrument is available to measure this bias. Comparison of results from the control groups where no bias is observed allows for identification of biased responses.

Criterion validity for this study will be aimed at predictive validity. The characteristics that are correlated with biases will be measured in the participants. Having the motivational bias construct measured by the MCDM inputs will allow for predictive validity to be assessed. The previous sections analyzing the responses show correlations, significant differences between means, and interaction effects between the de-biasing techniques and the susceptibility measures.

Given that this research area is somewhat uncharted territory, there are no instruments to compare against for reliability. Additionally, the participants will not be involved in multiple testing scenarios over time. The MCDM inputs portion of this questionnaire is heterogenous which eliminates the split-half reliability assessment.

Assessing the internal consistency of the MCDM portion requires some additional data manipulation. In order to use Cronbach's alpha, the metrics, which describe the participant's responses to each step in the MCDM process, were converted to a 5-point scale. For home insitu rank, a value of 4 was the highest (best) and mapped to a scaled value of 5, a value of 1 is the lowest (worst) and would map to a scaled value of 1. For criteria selected, higher numbers are better, therefore 0.25 to 1.00 was mapped to a scale of 1 to 5. For home performance ratio, this value is ideally 0, therefore these metrics were reverse scored to the 5-point scale. Lastly, criteria weight metric is a difference in ratios, ideally 0. Therefore, the absolute value was taken, then reversed scored to the 5-point scale. The metrics were then tested for internal consistency. The results show an alpha value of 0.67 and is summarized in Table 4.18. The results show that if any item is dropped the reliability decreases.

Table 4.18 Internal consistency for MDCM inputs

Item	**Reliability if item removed:**
home_insitu_rank	$\alpha = 0.59$
criteria_selected	$\alpha = 0.52$
home_perform_ratio	$\alpha = 0.66$
criteria_weight_metric	$\alpha = 0.58$

4.4.5.2 Susceptibility to bias measurement

The content validity of this portion of the study was heavily influenced by previously validated instruments and literature review. The biases identified and characteristics of a participant that correlate with those biases are taken from published, peer reviewed sources. Each source includes reliability and validity assessments for the individual measurement tools.

For the optimism and pessimism measures the Revised Life Orientation Test (LOT-R) was used. The study that developed the test has been sited over 8,000 times and is still being administered today for researching optimism and pessimism within groups of people from all over the world. The LOT-R has been converted to Spanish (Perczek, et al., 2000), French (Sultan &

Bureau, 1999), Japanese (Sakamoto & Tanaka, 2002), and Chinese (Lai, et al., 2002), all of which show convergence with the original English version.

The emotional intelligence quotient (EIQ) measurement is assessed using the Self-Report Emotional Intelligence Test (SREIT) developed by Schutte in 1998. This is one of the most widely used EIQ assessment tools, just behind the Mayer-Salovey-Caruso Emotional Intelligence Test (MSCEIT). The SREIT is a shorter version and has been validated and cited more than 5,000 times.

The confirmation assessment was completed using a Confirmation Inventory developed by Rassin in 2008. In this study the tool was developed, tested for temporal and test-retest reliability and validated by comparison to a set of Wason Selection tasks. The CI has been used on 29 studies ranging from political (Costello, et al., 2021), criminal investigations (Wastell, et al., 2012) and health research (Althebaiti, 2016).

Given that the instruments are validated, for this study we will look at the internal consistency of the combined susceptibility measurement tool. This includes 49 statements that the participants respond to on a Likert-scale. It is important to note that all original tools also used the same response type. The aggregated instrument internal consistency analysis resulted in a Cronbach's alpha of 0.866. Given that an alpha value of 0.7 or higher is acceptable this instrument shows good internal consistency. For each section, the internal consistency is compared to the original study. The comparisons are provided in Table 4.19.

Table 4.19 Comparison of internal consistency

Instrument	**Source study**	**Calculated**
LOT-R	$\alpha = 0.70 - 0.8$	$\alpha = 0.795$
EIQ	$\alpha = 0.87$	$\alpha = 0.883$
Confirmation	$\alpha = 0.65$	$\alpha = 0.659$

Additionally, a principal component analysis was conducted to analyze the scree plot for principal components. Reviewing the screen plot in Figure 4.21, after around 7 components the eigenvalues begin to taper off.

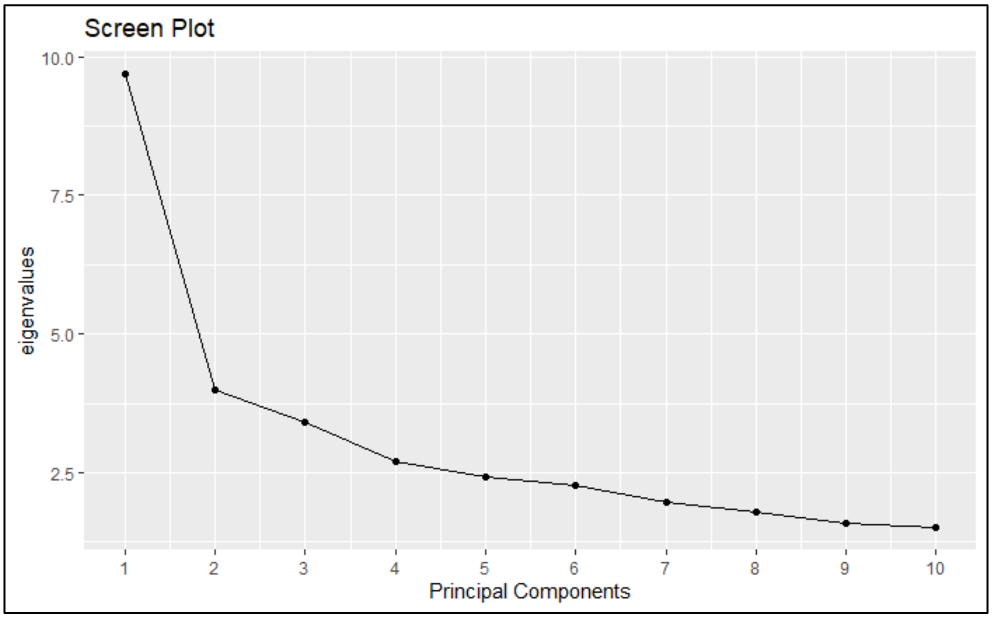

Figure 4.21 Scree plot of principal components

Plotting the proportion of variance explained by the principal components, Figure 4.22, also shows that the first seven components account for 54% of the variances in the model.

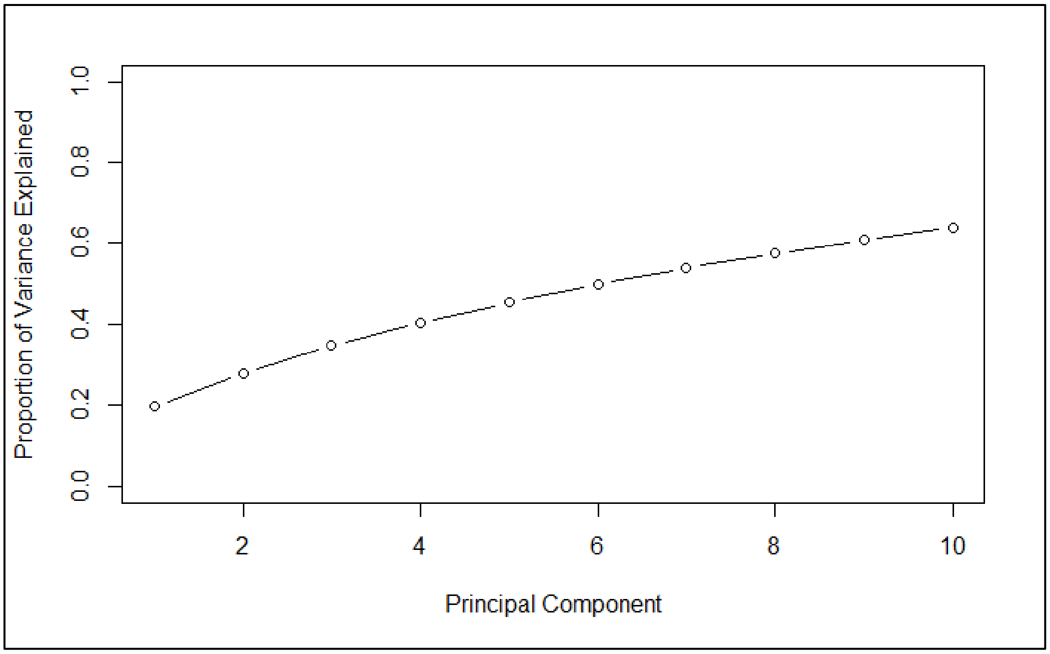

Figure 4.22 Proportion of variance explained for principal components

4.5 Implications

Given that the instrument and data is valid and reliable, the implications of this study result in a proposed methodology for reducing motivational bias in multi-criteria decision making (MCDM) problems.

Under the developed framework, the first step is assessing the participant for susceptibility to motivational biases. Based on the analyses of this study, if a participant is declared susceptible to Affect-influenced and Desirability of Option/Choice bias, the home rank delta is close to zero. This is graphically represented in Figure 4.16 by the combination of the home in-situ rank and home final rank boxplots. If this scenario is not satisfied, then a de-biasing decision tree is established. The methodology flow is presented in Figure 4.23.

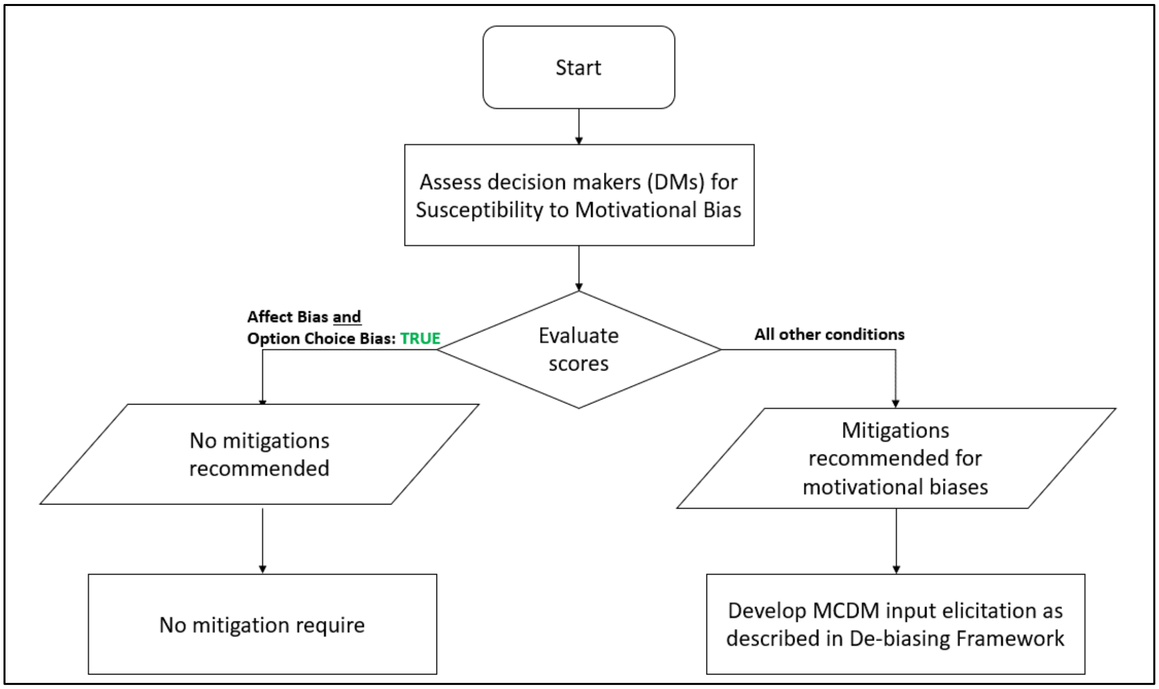

Figure 4.23 Methodology for reducing motivational biases

As shown in the methodology in Figure 4.23, if the decision makers are declared to be susceptible to Affect-influenced bias and Desirability of Option/Choice bias, no further mitigations are recommended. On the other hand, for any other conditions a De-biasing framework is proposed to reduce the motivational bias within that decision analysis. The framework is presented in Table 4.20.

Table 4.20 De-biasing framework

Step 1: Generating alternatives		
	Confirmation Bias Score	High: No mitigation recommended Low: Review alternatives, bias likely
Step 2: Developing criteria		
	Confirmation Bias	Present: No mitigation recommended Not Present: Perspective/Viewpoint
Step 3: Performance assessment		
	Affect Bias	Present: No mitigation recommended Not present: Perspective/Viewpoint
	Desirability of Positive Outcome	Present: No mitigation recommended Not present: Perspective/Viewpoint
	Desirability of Option/Choice Score	High: No mitigation recommended Low: Review assessments, bias likely
Step 5: Eliciting weights for criteria		
	Undesirability of Negative Outcome score	High: Review weights/metric, bias likely Low: No mitigation recommended

For each step in the MCDM problem, the framework in Table 4.20 provides recommended mitigations to reduce the impact of motivational bias. If a bias is not called out in the framework, it has no significant effect on the participant's responses and therefore no mitigations are recommended.

In the first step of generating the alternatives, if the participant has a low confirmation bias score, the alternatives should be reviewed. Based on a positive correlation between the home in-situ rank and confirmation bias scores, the participants who score lower on the confirmation bias measure will choose alternatives that are known to be lower ranking, resulting in a lower value for home in-situ rank.

In the second step of developing the attributes, or criteria, if Confirmation bias is declared, no mitigation steps are recommended as there are not significant differences. On the other hand, if the bias is not declared, the Perspective/Viewpoint technique is recommended. This is shown in the interaction plot of Figure 4.17 where many of the participants who were not declared to have confirmation bias under the Perspective/Viewpoint treatment chose a majority of the US News criteria. It is postulated that a participant who is not exhibiting confirmation bias uses the cues from the Perspective/Viewpoint treatment to assess the criteria and choose the relevant criteria while avoiding the vague criteria. While those with the bias are resistant to the treatments.

In the third step, assessing the performance of the alternatives against the criteria, there are multiple measures involved. First, if Affect-influenced bias is declared no mitigation is recommended. If the bias is not declared, the Perspective/Viewpoint treatment is recommended. As shown by the bootstrapping hypothesis testing, Figure 4.16, participants with a declared bias consistently provided responses within the anticipated range of values for the home performance ratio metric. Next, if a Desirability of a Positive Outcome bias is declared, the Perspective/Viewpoint treatment is recommended. If the bias is not declared, no mitigation is recommended. This is shown by the interaction plot, Figure 4.18, where the participant with no declared Desirability of a Positive Outcome bias in the Perspective/Viewpoint treatment group consistently provided responses within the anticipated range. Lastly, the Desirability of Option/Choice bias score was strongly, negatively correlated with the home performance ratio metric. Given higher scores, this metric was lower or within the anticipated range. The metric increased outside the anticipated range when this bias score was lower.

The final step of eliciting weights for the attributes/criteria, if the Undesirability of a Negative Outcome bias scores are high, the criteria weights should be reviewed. This is supported by the weak negative correlation between the Undesirability of a Negative Outcome bias score and the criteria weight metric, as shown in Table 4.15. Additionally, as shown in Figure 4.13, all participants who improved the rank of their home institution by 3 provided criteria weights that weighted the US News criteria relatively lower than vague criteria resulting in lower, often negative, criteria weight metric values. The participants seem to use the weighting to improve their home institutions ranking within the decision analysis.

4.5.1 Generalizability of the research

The data collection process focused on the general steps of an MCDM problem. This allows for application to nearly any MCDM technique that will be used in practice. The proposed framework adds little complexity to the already complex process of the decision analysis. The susceptibility measurement instrument only takes 5 minutes or so and the results can be used to apply additional measures to the decision process to help reduce motivational biases that may be present. Although this framework will not stop all motivational bias, it has shown to reduce the bias within the given study. As with any decision, the stakeholders for the decision should be involved in the process and monitor and review the decision makers for consistency and proper analytical decision making. Additionally, researchers could leverage this methodology to explore other domains, such as engineering, economics, politics, or business.

I

LIMITATIONS

It is important to note the assumptions and limitations of this study. These assumptions and limitations constrain the findings to a specific set of boundaries that properly scope the study. This section will discuss the assumptions and limitations and why they appear. After identifying the limitations, a discussion of the future research to resolve those limitations in additional studies will be provided.

5.1 Limitations of study

The first and most important assumption related to this study involves the motivational bias within the participants. The questionnaire used for data collection provided the reasons that a student would want to improve the rank of their home institution including career advancement, salary, and job opportunities. The participant was also asked how important they felt that university ranking was to them. The assumption here is that I properly “encouraged” or brought out that motivational bias within the participant if it did not already exist. Given that this is not a real-world decision, it is tough to ensure motivational bias is present.

As for the limitations of this study the first is that this is not a real-world motivationally biased decision. In order to collect data, the problem of choosing a university for engineering studies was selected. This provides a wider population to sample than a case study on a real problem. This also effects the sample size. The sample size was intended to be larger to achieve a

5% error, but given the time limitations and population, the sample size did not reach the levels to achieve this level of error. Therefore, the sample size is another limitation of this study.

The questionnaire within this study did not test two of the techniques mentioned in the literature. Group decision making was not tested, primarily due to the global pandemic. The intricacies of a group dynamic require in-person discussions and interactions to adequately evaluate the decision-making environment. Data presentation was not tested since it was not appropriate for the design of this study. Data presentation focuses on how the data is presented that could induce bias. For this study, the data was consistently presented for all alternatives, criteria, and treatments.

Lastly, the questionnaire design did not include Step 4 of the general MCDM process of eliciting the utility functions of the attributes. For this study, since the TOPSIS analysis and scales for assessment of performance were used, the utility functions were purely linear. Given a real-world scenario there are various utility functions that can be implemented. For this study, this function was outside the scope and not considered.

5.2 Future research

Given the limitations and findings of this study, there are several areas that require additional research. In order to further investigate the findings and address the limitations the following research agenda is proposed:

- Design of a study to test Group Decision making as a potential de-biasing technique
- Design of a study to test Data Presentation as a potential de-biasing technique
- Design of a study within a different population and problem domain

Outside of the limitations of this study, there are also several topics that require further exploration and testing. First, the aggregate susceptibility measures instrument needs a much larger sample size in order to properly validate and test reliability. Another study is proposed to collect an adequate sample size to further evaluate the reliability and perform a Confirmatory Factor Analysis (CFA) to ensure that the factors are being measured properly. Additional testing would also provide the data required to further evaluate the reliability within the stability and equivalency aspects of reliability testing.

The thresholds used to declare a bias should be tested to determine where the declaration point should be defined for this application. In this study, a mid-point was chosen to run the tests. Further evaluation and exploration of the biases and susceptibility scores should be completed. This will allow for proper thresholding on declaring a bias and mitigation within the methodology proposed.

Lastly, the full proposed methodology should be tested. In a similar method that was used in this study, the full methodology could be tested against a control group without any de-biasing techniques. This would provide the verification, validation, and reliability data needed for a full validation of the instrument. Given the need for expansion of the methodology to additional problem domains, this should be accomplished first on the same problem/domain, then expanded to another for full validation.

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QUESTIONNAIRE

Motivational De-biasing Techniques (Top)

Survey Flow

Standard: Informed Consent (1 Question)
Standard: Introduction to Multi-Criteria Decision Making (MCDM) (2 Questions)
Standard: Problem Overview (2 Questions)
Standard: Dataset (2 Questions)

BlockRandomizer: 1 - Evenly Present Elements

- **ReferenceSurvey: Inputs - Control**
- **ReferenceSurvey: Inputs - Critical Analysis**
- **ReferenceSurvey: Inputs - Justification**
- **ReferenceSurvey: Inputs - Perspective/View**

Standard: Bias Measurement Intro (1 Question)
Block: Bias Measurement (49 Questions)
Standard: Demographic (7 Questions)
Standard: Raffle Sign-Up (1 Question)
Standard: Redirect to Raffle Sign Up (1 Question)

Start of Block: Informed Consent

Informed Consent **Informed Consent Form**

Instructions: Please read the following informed consent form and if you would like to participate in this survey, indicate your consent by continuing with the survey.

Title of Study: University Selection and Multi-Criteria Decision Making

Researchers: Dr. Raed Jaradat as the PI and Mr. Chad S. Kerr as the Doctoral Student Researcher

Procedures: If you agree to participate, your participation will be for approximately 30-40 mins. You will be given a survey that will ask you provide inputs to a decision analysis, 49 personality-type questions, and 6 demographic questions.

Benefits: There will be no direct educational or health benefits to you for participating in this research.

Risks: This is a survey study. There are no possibilities for risk or harm to participants as a result of participation in the study.

Confidentiality: All the data collection process will be anonymous and all the data will be kept in PI’s possession.

Queries: If you have any questions about this research project, please feel free to contact Chad S. Kerr, PhD candidate, at csk171@msstate.edu and/or Dr. Raed Jaradat at jaradat@ise.msstate.edu.

Voluntary Participation: Please understand that your participation is voluntary. Your refusal to participate will involve no penalty or loss of benefits to which you are otherwise entitled. You may discontinue your participation at any time during the survey.

By entering the survey area, you indicate that you are at least 18 years old and are giving your informed consent to participate in this study.

○ I would like to participate in this survey

○ I am NOT interested in participating in this survey

Skip To: End of Survey If Informed Consent Form Instructions: Please read the following informed consent form and if you... = I am NOT interested in participating in this survey

End of Block: Informed Consent

Start of Block: Introduction to Multi-Criteria Decision Making (MCDM)

Q1

<u>Introduction</u>

In this survey, you will provide inputs to a Multi-Criteria Decision Making (MCDM) problem that will be used by the researcher to rank your home institution for undergraduate engineering studies relative to other universities. Multi-Criteria Decision Making is a quantitative framework for decision analysis that evaluates the options based on a set of criteria and their relative weighted importance. In decision making there are often conflicting criteria which adds difficulty in selecting the optimal choice. MCDM enables a structured, quantitative approach to decision making. Some MCDM techniques include Weighted Sum Model (WSM) and Technique for Order of Preference by Similarity to the Ideal Solution (TOPSIS).

Q108 How would you describe your familiarity with Multi-Criteria Decision Making processes and techniques?

- ○ Not familiar at all
- ○ Slightly familiar
- ○ Moderately familiar
- ○ Very familiar
- ○ Extremely familiar

End of Block: Introduction to Multi-Criteria Decision Making (MCDM)

Start of Block: Problem Overview

Q2 **Background**

The US News College Ranking System has been used for over 40 years. The system ranks colleges and universities based on a set of criteria developed by experts and undergoes continuous improvements and refinement. These ranking systems are used by students globally to support their choice of higher education. Highly ranked universities attract more talent and increase enrollment within the university. Increasing enrollment at a university has many benefits for the institution. Most importantly, higher student enrollment increases the revenue and therefore resources for student success. This not only includes materiel resources, but increased resources for recruiting top talent in both the student body and academic faculty. In several studies it was found that school ranking impacted both the career opportunities and early career advancement [13], as well as higher salaries for graduates from top-ranked schools [29]. This survey will gather inputs for a Multi-Criteria Decision Analysis (MCDA) comparing your current institution with others. You will be asked to select comparable schools for undergraduate engineering education, criteria for evaluation of those institutions, criteria weighting, and performance of each institution against those criteria. The results will be used by the researcher to evaluate the optimal choice for university based on your inputs.

[13]: Hoxby, C. (1998). The Return to Attending a More Selective College: 1960 to the Present. Retrieved September 6, 2006, from Harvard University Department of Economics Faculty.

[29]: Rindova, V., Williamson, I., & Petkova, A. (2005). Being Good or Being Known: An Empirical Examination of the Dimensions, Antecedents, and Consequences of Organizational Reputation. The Academy of Management Journal, 48(6), 1033-1049.

Q106 How important is it for your home institution to have a high ranking among national universities?

○ Not at all important

○ Slightly important

○ Moderately important

○ Very important

○ Extremely important

End of Block: Problem Overview

Start of Block: Dataset

Q3

Reference Data

Below is a dataset in pdf format that you can reference throughout the questionnaire. Each page will include a link to this pdf. Feel free to review this at any time.

Q4 Below is a dataset that will be available to you to support your inputs to the following questions.

End of Block: Dataset

Start of Block: MCDM_1_Control

MCDM_1_Control First, select your home institution.

Next, select three (3) universities that will be compared to your home institution.

(you should have 4 institutions for comparison in the box)

Universities for comparison to home institution
_______ University of Georgia
_______ Stanford University
_______ Tennessee Technological University
_______ Massachusetts Institute of Technology
_______ University of Mississippi
_______ University of California-Berkeley
_______ Mississippi State University
_______ Georgia Institute of Technology

Q8 Reference data

End of Block: MCDM_1_Control

Start of Block: MCDM_2_Control

MCDM_2_Control Please select four (4) criteria that will be used the evaluate each alternative.

Evaluation Criteria
______ Graduation Rate
______ Party Scene/Nightlife
______ Athletics
______ Reputation
______ Campus Food
______ Student Diversity
______ Financial Resources
______ Class Size Index

Q6 Reference data

End of Block: MCDM_2_Control

Start of Block: MCDM_3_Control

Carry Forward Selected Choices from "First, select your home institution.   Next, select three (3) universities that will be compared to your home institution. (you should have 4 institutions for comparison in the box)"

Carry Forward Selected Choices from "Please select four (4) criteria that will be used the evaluate each alternative."

MCDM_3_Control Please assess the performance of each selected university against the selected criteria.

On a scale of 1 to 10 with 1 being poor performance and 10 being excellent performance.

	Graduation Rate	Party Scene/Nightlife	Athletics	Reputation	Campus Food	Student Diversity	Financial Resources	Class Size Index
University of Georgia								
Stanford University								
Tennessee Technological University								
Massachusetts Institute of Technology								
University of Mississippi								
University of California-Berkeley								
Mississippi State University								
Georgia Institute of Technology								

Q7 Reference data

End of Block: MCDM_3_Control

Start of Block: MCDM_5_Control

Carry Forward Selected Choices from "Please select four (4) criteria that will be used the evaluate each alternative."

MCDM_5_Control For the evaluation criteria selected, please provide the weighted importance.

On a scale from 0 being not important at all to 10 being the most important.

	Not Important	Most Important
	0 1 2 3 4 5 6 7 8 9 10	
Graduation Rate		
Party Scene/Nightlife		
Athletics		
Reputation		
Campus Food		
Student Diversity		
Financial Resources		
Class Size Index		

End of Block: MCDM_5_Control

Start of Block: MCDM_1_Critical

MCDM_1_Critical First, select your home institution.

Next, select three (3) universities that will be compared to your home institution.

(you should have 4 institutions in the box)

Universities for comparison to home institution
______ University of Georgia
______ Stanford University
______ Tennessee Technological University
______ Massachusetts Institute of Technology
______ University of Mississippi
______ University of California-Berkeley
______ Georgia Institute of Technology
______ Mississippi State University

Dataset Reference data

End of Block: MCDM_1_Critical

Start of Block: 1_Critical_Review

MCDM_1_Critical_Revi The US News College Ranking for Engineering Programs ranked the universities in this order:

Massachusetts Institute of Technology

Stanford University

University of California - Berkeley

Georgia Institute of Technology

University of Georgia

Mississippi State University

University of Mississippi (tie)

Tennessee Technological University (tie)

1_Critical_Return Based on this information, would you like to revisit your selection of alternatives?
(${MCDM_1_Critical/ChoiceGroup/SelectedChoices})

○ Yes

○ No

End of Block: 1_Critical_Review

Start of Block: MCDM_2_Critical

MCDM_2_Critical Please select four (4) criteria that will be used the evaluate each alternative.

Evaluation Criteria
______ Graduation Rate
______ Party Scene/Nightlife
______ Athletics
______ Reputation
______ Campus Food
______ Student Diversity
______ Financial Resources
______ Class Size Index

dataset Reference data

End of Block: MCDM_2_Critical

Start of Block: 2_Critical_Review

2_Critical_Review The US News College Ranking for Engineering Programs uses the following criteria:

Graduation Rate

Reputation

Class Size Index

Financial Resources per Student

2_Critical_Return Based on this information, would you like to revisit your selection of criteria? (${MCDM_2_Critical/ChoiceGroup/SelectedChoices})

○ Yes

○ No

End of Block: 2_Critical_Review

Start of Block: MCDM_3_Critical

Carry Forward Selected Choices from "First, select your home institution.   Next, select three (3) universities that will be compared to your home institution.   (you should have 4 institutions in the box)"

Carry Forward Selected Choices from "Please select four (4) criteria that will be used the evaluate each alternative."

MCDM_3_Critical Please assess the performance of each selected university against the selected criteria.
On a scale of 1 to 10 with 1 being poor performance and 10 being excellent performance.

	Graduation Rate	Party Scene /Nightlife	Athletics	Reputation	Campus Food	Student Diversity	Financial Resources	Class Size Index
University of Georgia								
Stanford University								
Tennessee Technological University								
Massachusetts Institute of Technology								
University of Mississippi								
University of California-Berkeley								
Mississippi State University								
Georgia Institute of Technology								

dataset Reference data

End of Block: MCDM_3_Critical

Start of Block: MCDM_3_Critical_Review

MCDM_3_Critical_Revi The US News College Ranking for Engineering Programs assessed performance as shown in the table below:

Q17

-	Graduation Rate	Reputation	Class Size Index	Fin Resources per Student
Mississippi State University	6	6	5	6
Georgia Institute of Technology	10	9	5	6
University of Georgia	5	8	6	8
Tennessee Technological University	4	5	6	7
University of Mississippi	4	6	8	8
Massachusetts Institute of Technology	10	10	10	10
University of California-Berkeley	10	10	7	9
Stanford University	10	10	10	10

3_Critical_Return Based on this information, would you like to revisit your assessment of performance?

- ○ Yes
- ○ No

End of Block: MCDM_3_Critical_Review

Start of Block: MCDM_5_Critical

Carry Forward Selected Choices from "Please select four (4) criteria that will be used the evaluate each alternative."

MCDM_5_Critical For the evaluation criteria selected, please provide the weighted importance.

On a scale from 0 being not important at all to 10 being the most important.

	Not Important Most Important 0 1 1 2 2 3 3 4 4 5 5 6 6 7 7 8 8 9 9 10
Graduation Rate	
Party Scene/Nightlife	
Athletics	
Reputation	
Campus Food	
Student Diversity	
Financial Resources	
Class Size Index	

End of Block: MCDM_5_Critical

Start of Block: 5_Critical_Review

5_Critical_Review The US News College Ranking for Engineering Programs uses the following weights for the criteria:

Criteria	Weighting
Graduation Rate	3.67
Reputation	3.33
Class Size Index	1.33
Financial Resources per Student	1.67
Party Scene/Nightlife	NA
Athletics	NA
Campus Food	NA
Student Diversity	NA

5_Critical_Return Based on this information, would you like to revisit your assessment of criteria weighting?

- ◯ Yes
- ◯ No

End of Block: 5_Critical_Review

Start of Block: Justification Setup

Q8 For this portion of the questionnaire, you will be walked through the steps of the MCDM process and provide inputs. After each section that inputs are provided, you will be asked to provide a brief justification for your selections.

End of Block: Justification Setup

Start of Block: MCDM_1_Justification

MCDM_1_Justification First, select your home institution.

Next, select three (3) universities that will be compared to your home institution.

(you should have 4 institutions in the box)

Universities for comparison to home institution
______ University of Georgia
______ Stanford University
______ Tennessee Technological University
______ Massachusetts Institute of Technology
______ University of Mississippi
______ University of California-Berkeley
______ Mississippi State University
______ Georgia Institute of Technology

Data Reference data

End of Block: MCDM_1_Justification

Start of Block: MCDM_1_Justification_response

Q10_just **Your selections:** ${MCDM_1_Justification/ChoiceGroup/SelectedChoices}

From: ${MCDM_1_Justification/ChoiceGroup/AllChoices?displayLogic=0}

Q9_just Please provide a brief justification of why you made these selections.

____

____

____

____

____

End of Block: MCDM_1_Justification_response

Start of Block: MCDM_2_Justification

MCDM_2_Justification Please select four (4) criteria that will be used the evaluate each alternative.

Evaluation Criteria
_______ Graduation Rate
_______ Party Scene/Nightlife
_______ Athletics
_______ Reputation
_______ Campus Food
_______ Student Diversity
_______ Financial Resources
_______ Class Size Index

Q6_just Reference data

End of Block: MCDM_2_Justification

Start of Block: MCDM_2_Justification_repsonse

Q15_just **Your selections:** ${MCDM_2_Justification/ChoiceGroup/SelectedChoices}

From: ${MCDM_2_Justification/ChoiceGroup/AllChoices?displayLogic=0}

Q16_just Please provide a brief justification of why you made these selections.

____

____

____

____

____

End of Block: MCDM_2_Justification_repsonse

Carry Forward Selected Choices from "First, select your home institution.   Next, select three (3) universities that will be compared to your home institution.   (you should have 4 institutions in the box)"

Carry Forward Selected Choices from "Please select four (4) criteria that will be used the evaluate each alternative."

MCDM_3_Justification Please assess the performance of each selected university against the selected criteria.
On a scale of 1 to 10 with 1 being poor performance and 10 being excellent performance.

	Graduation Rate	Party Scene/Nightlife	Athletics	Reputation	Campus Food	Student Diversity	Financial Resources	Class Size Index
University of Georgia								
Stanford University								
Tennessee Technological University								
Massachusetts Institute of Technology								
University of Mississippi								
University of California-Berkeley								
Mississippi State University								
Georgia Institute of Technology								

Q7_just Reference data

Q18_just Please provide a brief justification of why you made these performance assessments. Select one and briefly explain your rationale for the assessment.

____

____

____

____

____

End of Block: MCDM_3_Justification

Start of Block: MCDM_5_Justification

Carry Forward Selected Choices from "Please select four (4) criteria that will be used the evaluate each alternative."

MCDM_5_Justification For the evaluation criteria selected, please provide the weighted importance.

On a scale from 0 being not important at all to 10 being the most important.

	Not Important								Most Important		
	0	1	2	3	4	5	6	7	8	9	10
Graduation Rate											
Party Scene/Nightlife											
Athletics											
Reputation											
Campus Food											
Student Diversity											
Financial Resources											
Class Size Index											

Q15_just Please provide a brief justification of why you weighted the criteria this way. Select one and briefly explain your rationale for weighting.

____

____

____

____

____

End of Block: MCDM_5_Justification

Start of Block: Perspective Setup

Q8 For this portion of the questionnaire, imagine yourself as a new student looking for a university for undergraduate engineering studies. You have no preconceived notions or experience with a university or preference for a particular institution. Assume that you are not constrained by cost, location, or academic entry requirements.

End of Block: Perspective Setup

Start of Block: MCDM_1_Perspective

MCDM_1_Perspective First, select your home institution.

Next, select three (3) universities that will be compared to your home institution.

(you should have 4 institutions in the box)

Remember: You are a new incoming student with no college experience or preferences.

Universities for comparison to home institution
______ University of Georgia
______ Stanford University
______ Tennessee Technological University
______ Massachusetts Institute of Technology
______ University of Mississippi
______ University of California-Berkeley

______ Georgia Institute of Technology

______ Mississippi State University

Q8 Reference data

End of Block: MCDM_1_Perspective

Start of Block: MCDM_2_Perspective

MCDM_2_Perspective Please select four (4) criteria that will be used the evaluate each alternative.

Remember: You are a new incoming student with no college experience or preferences.

Evaluation Criteria

______ Graduation Rate

______ Party Scene/Nightlife

______ Athletics

______ Reputation

______ Campus Food

______ Student Diversity

______ Financial Resources

______ Class Size Index

Q6 Reference data

End of Block: MCDM_2_Perspective

Start of Block: MCDM_3_Perspective

Carry Forward Selected Choices from "First, select your home institution.   Next, select three (3) universities that will be compared to your home institution.   (you should have 4 institutions in the box)   Remember: You are a new incoming student with no college experience or preferences. "

Carry Forward Selected Choices from "Please select four (4) criteria that will be used the evaluate each alternative.Remember: You are a new incoming student with no college experience or preferences."

MCDM_3_Perspective Please assess the performance of each selected university against the selected criteria.

On a scale of 1 to 10 with 1 being poor performance and 10 being excellent performance.

Remember: You are a new incoming student with no college experience or preferences.

	Graduation Rate	Party Scene /Nightlife	Athletics	Reputation	Campus Food	Student Diversity	Financial Resources	Class Size Index
University of Georgia								
Stanford University								
Tennessee Technological University								
Massachusetts Institute of Technology								
University of Mississippi								
University of California-Berkeley								
Mississippi State University								
Georgia Institute of Technology								

Q7 Reference data

End of Block: MCDM_3_Perspective

Start of Block: MCDM_5_Perspective

Carry Forward Selected Choices from "Please select four (4) criteria that will be used the evaluate each alternative. Remember: You are a new incoming student with no college experience or preferences."

MCDM_5_Perspective For the evaluation criteria selected, please provide the weighted importance.

On a scale from 0 being not important at all to 10 being the most important.

Remember: You are a new incoming student with no college experience or preferences.

	Not Important									Most Important
	0	1	2	3	4	5	6	7	8	9	10
Graduation Rate											
Party Scene/Nightlife											
Athletics											
Reputation											
Campus Food											
Student Diversity											
Financial Resources											
Class Size Index											

End of Block: MCDM_5_Perspective

Start of Block: Bias Measurement Intro

Q5 The following survey includes statements for measuring how you have felt and acted during your everyday encounters over the past few months. There are no right or wrong answers.

For each statement below, decide which response best indicates your attitude or position - how much you agree or disagree with the statement.

End of Block: Bias Measurement Intro

Start of Block: Bias Measurement

Q6 **In uncertain times, I usually expect the best.**

- ○ Strongly agree
- ○ Somewhat agree
- ○ Neither agree nor disagree
- ○ Somewhat disagree
- ○ Strongly disagree

Q7 **I’m always optimistic about my future.**

- ○ Strongly agree
- ○ Somewhat agree
- ○ Neither agree nor disagree
- ○ Somewhat disagree
- ○ Strongly disagree

Q8 **Overall, I expect more good things to happen to me than bad**

- ○ Strongly agree
- ○ Somewhat agree
- ○ Neither agree nor disagree
- ○ Somewhat disagree
- ○ Strongly disagree

Q9 **If something can go wrong with me, it will.**

- ○ Strongly agree
- ○ Somewhat agree
- ○ Neither agree nor disagree
- ○ Somewhat disagree
- ○ Strongly disagree

Q10 **I hardly ever expect things to go my way.**

- ○ Strongly agree
- ○ Somewhat agree
- ○ Neither agree nor disagree
- ○ Somewhat disagree
- ○ Strongly disagree

Q11 **I rarely count on good things happening to me.**

- ○ Strongly agree
- ○ Somewhat agree
- ○ Neither agree nor disagree
- ○ Somewhat disagree
- ○ Strongly disagree

Q12 **I know when to speak about my personal problems with others.**

- ○ Strongly agree
- ○ Somewhat agree
- ○ Neither agree nor disagree
- ○ Somewhat disagree
- ○ Strongly disagree

Q13 **When I am faced with obstacles, I remember times I faced similar obstacles and overcame them.**

- ○ Strongly agree
- ○ Somewhat agree
- ○ Neither agree nor disagree
- ○ Somewhat disagree
- ○ Strongly disagree

Q14 **I expect that I will do well on most things I try.**

- Strongly agree
- Somewhat agree
- Neither agree nor disagree
- Somewhat disagree
- Strongly disagree

Q15 **Other people find it easy to confide in me.**

- Strongly agree
- Somewhat agree
- Neither agree nor disagree
- Somewhat disagree
- Strongly disagree

Q16 **I find it hard to understand the non-verbal messages of other people.**

- Strongly agree
- Somewhat agree
- Neither agree nor disagree
- Somewhat disagree
- Strongly disagree

Q17 **Some of the major events in my life have led me to re-evaluate what is important and not important.**

- Strongly agree
- Somewhat agree
- Neither agree nor disagree
- Somewhat disagree
- Strongly disagree

Q18 **When my mood changes, I see new possibilities.**

- Strongly agree
- Somewhat agree
- Neither agree nor disagree
- Somewhat disagree
- Strongly disagree

Q19 **Emotions are one of the things that make my life worth living.**

- Strongly agree
- Somewhat agree
- Neither agree nor disagree
- Somewhat disagree
- Strongly disagree

Q20 **I am aware of my emotions as I experience them.**

- ○ Strongly agree
- ○ Somewhat agree
- ○ Neither agree nor disagree
- ○ Somewhat disagree
- ○ Strongly disagree

Q21 **I expect good things to happen.**

- ○ Strongly agree
- ○ Somewhat agree
- ○ Neither agree nor disagree
- ○ Somewhat disagree
- ○ Strongly disagree

Q22 **I like to share my emotions with others.**

- Strongly agree
- Somewhat agree
- Neither agree nor disagree
- Somewhat disagree
- Strongly disagree

Q23 **When I experience a positive emotion, I know how to make it last.**

- Strongly agree
- Somewhat agree
- Neither agree nor disagree
- Somewhat disagree
- Strongly disagree

Q24 **I arrange events that others enjoy.**

- Strongly agree
- Somewhat agree
- Neither agree nor disagree
- Somewhat disagree
- Strongly disagree

Q25 **I seek out activities that make me happy.**

- Strongly agree
- Somewhat agree
- Neither agree nor disagree
- Somewhat disagree
- Strongly disagree

Q26 **I am aware of the non-verbal messages that I send to others.**

- ○ Strongly agree
- ○ Somewhat agree
- ○ Neither agree nor disagree
- ○ Somewhat disagree
- ○ Strongly disagree

Q27 **I present myself in a way that makes a good impression on others.**

- ○ Strongly agree
- ○ Somewhat agree
- ○ Neither agree nor disagree
- ○ Somewhat disagree
- ○ Strongly disagree

Q28 **When I am in a positive mood, solving problems is easy for me.**

- Strongly agree
- Somewhat agree
- Neither agree nor disagree
- Somewhat disagree
- Strongly disagree

Q29 **By looking at their facial expressions, I recognize the emotions people are experiencing.**

- Strongly agree
- Somewhat agree
- Neither agree nor disagree
- Somewhat disagree
- Strongly disagree

Q30 **I know why my emotions change.**

- ◯ Strongly agree
- ◯ Somewhat agree
- ◯ Neither agree nor disagree
- ◯ Somewhat disagree
- ◯ Strongly disagree

Q31 **When I am in a positive mood, I am able to come up with new ideas.**

- ◯ Strongly agree
- ◯ Somewhat agree
- ◯ Neither agree nor disagree
- ◯ Somewhat disagree
- ◯ Strongly disagree

Q32 **I have control over my emotions.**

- Strongly agree
- Somewhat agree
- Neither agree nor disagree
- Somewhat disagree
- Strongly disagree

Q33 **I easily recognize my emotions as I experience them.**

- Strongly agree
- Somewhat agree
- Neither agree nor disagree
- Somewhat disagree
- Strongly disagree

Q34 **I motivate myself by imagining a good outcome to tasks I take on.**

- Strongly agree
- Somewhat agree
- Neither agree nor disagree
- Somewhat disagree
- Strongly disagree

Q35 **I compliment others when they have done something well.**

- Strongly agree
- Somewhat agree
- Neither agree nor disagree
- Somewhat disagree
- Strongly disagree

Q36 **I am aware of the non-verbal messages other people send.**

- Strongly agree
- Somewhat agree
- Neither agree nor disagree
- Somewhat disagree
- Strongly disagree

Q37 **When another person tells me about an important event in his or her life, I almost feel as though I have experienced this event myself.**

- Strongly agree
- Somewhat agree
- Neither agree nor disagree
- Somewhat disagree
- Strongly disagree

Q38 **When I feel a change in emotions, I tend to come up with new ideas.**

- ○ Strongly agree
- ○ Somewhat agree
- ○ Neither agree nor disagree
- ○ Somewhat disagree
- ○ Strongly disagree

Q39 **When I am faced with a challenge, I give up because I believe I will fail.**

- ○ Strongly agree
- ○ Somewhat agree
- ○ Neither agree nor disagree
- ○ Somewhat disagree
- ○ Strongly disagree

Q40 **I know what other people are feeling just by looking at them.**

- Strongly agree
- Somewhat agree
- Neither agree nor disagree
- Somewhat disagree
- Strongly disagree

Q41 **I help other people feel better when they are down.**

- Strongly agree
- Somewhat agree
- Neither agree nor disagree
- Somewhat disagree
- Strongly disagree

Q42 **I use good moods to help myself keep trying in the face of obstacles.**

- Strongly agree
- Somewhat agree
- Neither agree nor disagree
- Somewhat disagree
- Strongly disagree

Q43 **I can tell how people are feeling by listening to the tone of their voice.**

- Strongly agree
- Somewhat agree
- Neither agree nor disagree
- Somewhat disagree
- Strongly disagree

Q44 **It is difficult for me to understand why people feel the way they do.**

- Strongly agree
- Somewhat agree
- Neither agree nor disagree
- Somewhat disagree
- Strongly disagree

Q45 **I only need a little information to reach a good decision.**

- Strongly agree
- Somewhat agree
- Neither agree nor disagree
- Somewhat disagree
- Strongly disagree

Q46 **My first impression usually seems to be correct.**

- Strongly agree
- Somewhat agree
- Neither agree nor disagree
- Somewhat disagree
- Strongly disagree

Q47 **I usually quickly know the ins and outs of the matter.**

- Strongly agree
- Somewhat agree
- Neither agree nor disagree
- Somewhat disagree
- Strongly disagree

Q48 **Some things are simply the way they are, regardless of other people's counterarguments.**

- Strongly agree
- Somewhat agree
- Neither agree nor disagree
- Somewhat disagree
- Strongly disagree

Q49 **Sometimes, I know things before there is actual proof of them.**

- Strongly agree
- Somewhat agree
- Neither agree nor disagree
- Somewhat disagree
- Strongly disagree

Q50 **I usually trust my intuition.**

- Strongly agree
- Somewhat agree
- Neither agree nor disagree
- Somewhat disagree
- Strongly disagree

Q51 **Generally, getting that first win is half the battle.**

- Strongly agree
- Somewhat agree
- Neither agree nor disagree
- Somewhat disagree
- Strongly disagree

Q52 **Generally, I know what someone is trying to say before they finish.**

- Strongly agree
- Somewhat agree
- Neither agree nor disagree
- Somewhat disagree
- Strongly disagree

Q53 **If my reasoning and the physical evidence are in contradiction, I tend to give more weight to my reasoning than to the evidence.**

- Strongly agree
- Somewhat agree
- Neither agree nor disagree
- Somewhat disagree
- Strongly disagree

Q54 **Once I have a certain idea, I can hardly be brought to change my mind.**

- ◯ Strongly agree
- ◯ Somewhat agree
- ◯ Neither agree nor disagree
- ◯ Somewhat disagree
- ◯ Strongly disagree

End of Block: Bias Measurement

Start of Block: Demographic

Q110 Now we would like to collect some additional information about you. Again, this will not be connected with your name or email address.

Q102 What is your age?

____

Q103 Please select your gender.

- ○ Male
- ○ Female
- ○ Prefer not to say

Q104 Where are you currently enrolled?

- ○ Mississippi State University
- ○ Georgia Institute of Technology
- ○ Kennesaw State University
- ○ University of Georgia
- ○ University of Mississippi

Q105 What is your major?

- Mechanical Engineering
- Electrical & Computer Engineering
- Industrial and Systems Engineering
- Chemical Engineering
- Biomedical Engineering
- Aerospace Engineering
- Civil and Environmental Engineering
- Other Engineering
- Not Engineering

Q109 What is your ethnicity?

- White
- Black or African American
- American Indian or Alaska Native
- Asian
- Native Hawaiian or Pacific Islander
- Other

Q113 Which most accurately describes your current academic year?

- ○ Freshmen
- ○ Sophmore
- ○ Junior
- ○ Senior

End of Block: Demographic

Start of Block: Raffle Sign-Up

Q55 Would you like to be entered into the raffle for one of three (3) $50 Amazon Gift Cards for you time participating in this survey?

- ○ No
- ○ Yes

Skip To: End of Survey If Would you like to be entered into the raffle for one of three (3) $50 Amazon Gift Cards for you t... = No

End of Block: Raffle Sign-Up

Start of Block: Redirect to Raffle Sign Up

Q112 To enter the Raffle for 1 of 3 $50 Amazon Gift Cards, please visit the link below.

https://msstate.co1.qualtrics.com/jfe/form/SV_cGRlwWp8xldQPPw

End of Block: Redirect to Raffle Sign Up

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REFERENCE DATA SET

Eval Criteria	Mississippi State University	Georgia Institute of Technology	University of Georgia	Tennessee Technological University	University of Mississippi	Massachusetts Institute of Technology	University of California-Berkely	Stanford Univeristy
Graduation Rate	59%	87%	85%	52%	62%	94%	92%	94%
Reputation	2.4 out of 5	4.6 out of 5	2.5 out of 5	2.1 out of 5	2.1 out of 5	4.9 out of 5	4.7 out of 5	4.7 out of 5
Class Size Index	**40%** of classes < 20 students **45%** of classes 20-49 students **15%** of classes > 50 students	**44%** of classes < 20 students **34%** of classes 20-49 students **22%** of classes > 50 students	**48%** of classes < 20 students **41%** of classes 20-49 students **11%** of classes > 50 students	**46%** of classes < 20 students **44%** of classes 20-49 students **10%** of classes > 50 students	**54%** of classes < 20 students **34%** of classes 20-49 students **12%** of classes > 50 students	**71%** of classes < 20 students **18%** of classes 20-49 students **11%** of classes > 50 students	**53%** of classes < 20 students **28%** of classes 20-49 students **19%** of classes > 50 students	**69%** of classes < 20 students **20%** of classes 20-49 students **11%** of classes > 50 students
Financial Resources per Student	**21%** of students covered financially **55%** of average student's need met	**19%** of students covered financially **56%** of average student's need met	**27%** of students covered financially **74%** of average student's need met	**16%** of students covered financially **68%** of average student's need met	**15%** of students covered financially **75%** of average student's need met	**100%** of students covered financially **100%** of average student's need met	**29%** of students covered financially **83%** of average student's need met	**91%** of students covered financially **100%** of average student's need met
Party Scene/Nightlife	**3%** say there are many of parties **45%** say lots of parties **27%** Say there are some parties **25%** says there are very few parties	**2%** say there are many of parties **23%** say lots of parties **51%** Say there are some parties **24%** says there are very few parties	**29%** say there are many of parties **55%** say lots of parties **8%** Say there are some parties **8%** says there are very few parties	**3%** say there are many of parties **16%** say lots of parties **39%** Say there are some parties **41%** says there are very few parties	**26%** say there are many of parties **47%** say lots of parties **14%** Say there are some parties **13%** says there are very few parties	**11%** say there are many of parties **26%** say lots of parties **54%** Say there are some parties **9%** says there are very few parties	**5%** say there are many of parties **35%** say lots of parties **44%** Say there are some parties **16%** says there are very few parties	**5%** say there are many of parties **41%** say lots of parties **43%** Say there are some parties **11%** says there are very few parties
Athletics	**34%** say everything revolves around varsity sports **64%** says varsity sports are a big part of campus life **3%** say varsity sports are not a huge part of campus life	**3%** say everything revolves around varsity sports **56%** says varsity sports are a big part of campus life **41%** say varsity sports are not a huge part of campus life	**43%** say everything revolves around varsity sports **52%** says varsity sports are a big part of campus life **5%** say varsity sports are not a huge part of campus life	**5%** say everything revolves around varsity sports **36%** says varsity sports are a big part of campus life **59%** say varsity sports are not a huge part of campus life	**46%** say everything revolves around varsity sports **49%** says varsity sports are a big part of campus life **5%** say varsity sports are not a huge part of campus life	**0%** say everything revolves around varsity sports **7%** says varsity sports are a big part of campus life **93%** say varsity sports are not a huge part of campus life	**5%** say everything revolves around varsity sports **58%** says varsity sports are a big part of campus life **37%** say varsity sports are not a huge part of campus life	**4%** say everything revolves around varsity sports **46%** says varsity sports are a big part of campus life **50%** say varsity sports are not a huge part of campus life
Campus Food	**Meal Plan Availability:** Yes **Avg Meal Plan Cost:** $4,038/yr 78% of students highly rate dining facilities	**Meal Plan Availability:** Yes **Avg Meal Plan Cost:** $5,172/yr 37% of students highly rate dining facilities	**Meal Plan Availability:** Yes **Avg Meal Plan Cost:** $4,036/yr 89% of students highly rate dining facilities	**Meal Plan Availability:** Yes **Avg Meal Plan Cost:** $4,954/yr 56% of students highly rate dining facilities	**Meal Plan Availability:** Yes **Avg Meal Plan Cost:** $4,470/yr 66% of students highly rate dining facilities	**Meal Plan Availability:** Yes **Avg Meal Plan Cost:** $5,960/yr 42% of students highly rate dining facilities	**Meal Plan Availability:** Yes **Avg Meal Plan Cost:** $2,500/yr 54% of students highly rate dining facilities	**Meal Plan Availability:** Yes **Avg Meal Plan Cost:** $6,323/yr 83% of students highly rate dining facilities
Student Diversity	**Female to Male:** 50% / 50% **In-state to Out-of-State:** 58% / 42% 56% say the student body is ethnically diverse	**Female to Male:** 39% / 61% **In-state to Out-of-State:** 51% / 49% 80% say the student body is ethnically diverse	**Female to Male:** 57% / 43% **In-state to Out-of-State:** 84% / 16% 44% say the student body is ethnically diverse	**Female to Male:** 45% / 55% **In-state to Out-of-State:** 95% / 5% 51% say the student body is ethnically diverse	**Female to Male:** 57% / 43% **In-state to Out-of-State:** 43% / 56% 38% say the student body is ethnically diverse	**Female to Male:** 47% / 53% **In-state to Out-of-State:** 7% / 93% 86% say the student body is ethnically diverse	**Female to Male:** 53% / 47% **In-state to Out-of-State:** 72% / 28% 66% say the student body is ethnically diverse	**Female to Male:** 50% / 50% **In-state to Out-of-State:** 33% / 67% 66% say the student body is ethnically diverse

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DATASET DEFINITION

Table 5.1 Dataset description

Data Item	Description	Scale/Units	Application
Duration	Number of seconds it took the participant to complete the questionnaire	sec	
RecordedDate	Date the questionnaire was completed	date and time	
ResponseId	Unique identifier for the participant's responses		
MCDM_Fam	Familiarly of the participant with MCDM processes	5-point scale	
rank_importance	How important university ranking is to the participant	5-point scale	
home_institution	Participant's home institution	character	Home institution
technique	De-biasing technique applied 0: Control, no technique 1: critical analysis 2: justification 3: perspective/view	0, 1, 2, 3	De-biasing technique label
home_insitu_rank	Ranking of the participant's home institution relative to the chosen alternatives per the US News Ranking scheme	1, 2, 3, 4	MCDM Step 1
criteria_selected	Percentage of US News Ranking criteria	0 to 1	MCDM Step 2
home_avg_perform	Normalized average performance for all criteria of the home institution relative to alternatives	0 to 1	MCDM Step 3
criteria_avg_weight	Normalized average weight for US News criteria relative to vague criteria	0 to 1	MCDM Step 5
home_final_rank	Ranking of the participant's home institution given the inputs and MCDM analysis	1, 2, 3, 4	MCDM Result
home_rank_delta	The relative movement in rank from the insitu rank to final rank once the MCDM is completed.	-3 to +3 integer	MCDM Result
revisions_stepX	Revisions made at each step after the de-biasing techniques was applied	TRUE/FALSE	De-biasing impact, where applicable

Table 5.1 (continued)

suscept_desire_score	Susceptibility to desirability of positive outcome bias	0 to 15 (integer)	Bias susceptibility
suscept_undesire_score	Susceptibility to undesirability of negative outcome bias	0 to 15 (integer)	Bias susceptibility
suscept_option_score	Susceptibility to desirability of option/choice bias	0 to 30 (integer)	Bias susceptibility
suscept_affect_score	Susceptibility to affect-influenced bias	0 to 165 (integer)	Bias susceptibility
suscept_confirm_score	Susceptibility to confirmation bias	0 to 50 (integer)	Bias susceptibility
suscept_desire	Susceptibility to desirability of positive outcome bias	TRUE/FALSE	Bias susceptibility
suscept_undesire	Susceptibility to undesirability of negative outcome bias	TRUE/FALSE	Bias susceptibility
suscept_option	Susceptibility to desirability of option/choice bias	TRUE/FALSE	Bias susceptibility
suscept_affect	Susceptibility to affect-influenced bias	TRUE/FALSE	Bias susceptibility
suscept_confirm	Susceptibility to confirmation bias	TRUE/FALSE	Bias susceptibility
age	Age of the participant	integer	demographic
gender	Gender of the participant	Male/Female	demographic
major	Major in undergraduate studies	character	demographic
ethnicity	Ethnicity of the participant	character	demographic
academic_year	Academic year standing of the participant	character	demographic