Improving Personnel Selection Through Value Focused Thinking

THESIS

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Abstract

Personnel selection has always and will continue to be a challenging endeavor for the military special operations. They want to select the best out of a number of qualified applicants. How an organization determines what makes a successful candidate and how to compare candidates against each other are some of the difficulties that top tier organizations like the special operations face. Value focused thinking (VFT) places criteria in a hierarchal structure and quantifies the values with criteria measurements, known as a decision model. The selection process can be similar to a college selecting their students. This research used college student entry data and strategic goals as a proxy for special operations applicants and standards. It compared two case studies of college admissions selection criteria. A sample pool of 8,000 select and 24,000 non-select candidates was generated from real world datasets. VFT was applied to develop a valid admissions selection process model. The schools admissions documentation was used to build the hierarchies, single attribute value functions (SAVF), multi-attribute value functions (MAVF), and weights. A Monte Carlo simulation was used to sample applicants from the generated pool and examined how accurately the models were able to select the correct applicants.

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This work is dedicated to my wife, who is the most supportive, caring, and hard working person I know.

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IMPROVING PERSONNEL SELECTION THROUGH VALUE FOCUSED THINKING

I. Introduction

When I find an employee who turns out to be wrong for a job, I feel it is my fault because I made the decision to hire him.

–Akio Morita

Co-Founder of Sony (Heller, 1997)

1.1 Motivation

Personnel selection has always and will continue to be a challenging endeavor. Recruiting the right person who will stay with and improve the organization is a complex problem. Additionally, how an organization determine what makes a successful candidate and how they compare to a set of candidates can be a daunting task. These are just some of the difficulties that all top tier organizations face. Decision analysis can be used to aid organizations with these difficult decisions.

Decision analysis is a philosophy and a social-technical process to create value for decision makers (DMs) and stakeholders facing difficult decisions involving multiple stakeholders, multiple (possibly conflicting) objectives, complex alternatives, important uncertainties, and significant consequences. Decision analysis is founded on an axiomatic decision theory and uses insights from the study of decision making (Parnell *et al.* , 2013). In general, the availability of means and the individual preferences of the DMs, is a highly complex problem. The multi-criteria nature of the problem makes multi-criteria decision making (MCDM) methods ideal to cope with this, given that they consider many criteria at the same time, with various weights and thresholds, having the potential to reflect at a very satisfactory degree the vague most of the times preferences of the DMs (Kelemenis & Askounis, 2010).

One form of MCDM is Multi-Objective Decision Analysis (MODA), which is the process for making decisions when there are very complex issues involving multiple criteria and groups who may be affected from the outcome of the decision. MODA allows for the selection of a best solution amongst a pool of available alternatives through value trade-off and factor weighting. When used for group decision making, MODA helps groups discuss the problem in a way that allows them to consider the values that each group views as important to the decision.

1.2 Contribution

The first contribution of this research is an examination of the ability for multi-objective decision analysis to codify an organization's selection process and the ability to return alternatives that successfully inform the decision makers. That is to show what organizations need to do to successfully implement a decision analysis approach to personnel selection.

The second contribution is an assessment of some common techniques used to determine the rank of alternatives, specifically value focus thinking, the MULTIMOORA method, and response surface methodology. Two case studies are used to demonstrate the ability to successfully rank alternatives, using the most effective technique, and to provide additional analysis that helped determine the alternative's strength.

The third contribution is to show how the use of statistical software can aid decision analysis calculations and visualizations. For this **R** was used to create a fully functioning decision analysis package that assist in solving the multi-objective decision analysis problem.

1.3 Assumptions

In many decision problems the evaluation of alternatives is complicated by alternative performance on uncertain attributes. This uncertainty is intuitively recognizable as a distinct "lack" of complete knowledge or certainty but can derive from many sources and thus assume multiple forms. We use the term "uncertainty" primarily for uncertainty arising when the consequences of an action are unknown because they depend on future events (Durbach & Stewart, 2012). Since this was the first venture into this model, this research will not capture uncertainty.

1.4 Organization

This chapter highlights the goal of this analysis, which was to validate the selection techniques with historical data and generated objectives. This will demonstrate the hypothesis that the selection process can be improved using decision analysis.

The following chapter highlights the existing literature relevant to personnel selection and the multi-criteria decision making models that are necessary to inform the analysis. Chapter III provides the formulation of the model and justification by looking at three different MODA methods. The analysis of two separate case studies, their models, and results are presented in Chapter IV. Finally, Chapter V presents significant insights and areas for future research.

II. Literature Review

2.1 Overview

This research defines a methodology for the use of decision analysis, specifically value focus thinking (VFT), in the prediction of personnel selection. This chapter reviews previously published literature on the validity of personnel selection in industry, current selection techniques used in the military, previous studies into the use of decision analysis (DA) for personnel selection, and finally the use of the VFT method of personnel selection.

2.2 Personnel Selection

Human capital is one of the core competences all companies must maintain to keep their competitive advantages in the knowledge economy. Personnel recruitment and selection directly affect the quality of employees. Hence, various studies have been conducted on resumes, interviews, assessment centers, job knowledge tests, work sample tests, cognitive tests, and personality tests in human resource management to help organizations make better personnel selection decisions. Indeed, the existing selection approaches focus on work and job analysis that are defined via specific tasks and duties based on their static properties (Chien & Chen, 2008).

For more than half a century, data collected utilizing the assessment center (AC) method has been used to make valid predictions of managerial and executive job performance. Typically, the AC method is a set of simulations, including paper and pencil tests, of job-related tasks to evaluate a candidates performance potential and needs for development. In conjunction with a resume and structured job interview, the information gained from the AC method assists organizational leaders in making better selection decisions than decisions based solely on a resume and interview. The assimilation of technology into the AC method reduces costs, time to administer, and time to score (Papadopoulos, 2012).

Today, however, with all of the advances in technology there is so much information available that organizations can easily be overwhelmed or unable to process it all by normal means. Countless books, journals, newspapers, and social media sites exist that can offer profound insights into potential candidates beyond that of a normal resume and reference point of contacts. Over the last few years new means of filtering this immense amount of data has emerged under the title of data mining. Data mining uses various algorithms and techniques to isolate useful information from a mass amount of data and make personalized suggestions of a small subset of them which a user can examine in a reasonable amount of time. Data mining allows recruiters or interviewers to quickly filter, organize, and rank candidates skills based on the organizations required qualifications. If the qualification values of a candidate are closer or even higher than the respective values of the specific job requirements, the candidate has a higher probability of being hired. Optimization can be utilized to calculate the smallest distance between the values of the preferences of an employer and the values of the characteristics of a group of available candidates in order to find the best matches and consequently to make recommendations (Almalis *et al.* , 2014).

Analytic thinking approaches are another set of suitable methods to address the problem of personnel selection. Analytic thinking systematically breaks down a 'system' into even smaller clusters. The resulting hierarchy provides large amounts of information integrated into the structure of a problem and forms a more complete picture of the whole system. The Analytic Hierarchy Process (AHP) is a suitable approach when the hierarchical levels are independent of each other and the Analytic Network Process (ANP) is used when factors are dependent. ANP allows for dealing with imprecise and uncertain human comparison judgments by allowing fuzzy value, and the decision capability of the decision maker by structuring the complex problem into hierarchical structure with dependencies and feedback system.

Multiple criteria decision making (MCDM) is generally described as the process of selecting from a set of available alternatives, or ranking the alternatives, based on a set of criteria, which usually vary in significance. Because of this MCDM can be used to solve a multitude of problems including personnel selection.

2.3 Selection in the Military

Predictors to determine a soldier's outcome during special forces (SF) training has been used for decades. Traits of predictors typically fall into three categories: physical ability, mental fortitude, and technical expertise.

The Australian Army conducted a study of their SF selection data to try to predict a candidate's pass/fail outcome based on their physical capability standards. Since the outcome of a failure carries a logistical and financial burden, it was determined that minimum performance standards possess a high sensitivity and high degree of specificity (Hunt *et al.* , 2013). This work was done to reduce the number of candidates at the selection course that would be more likely to fail. The conclusion was the Australian Army was unable to pre-predict pass/fail outcomes, but could determine a combination of standards that when applied together helped predict which candidates could successfully complete the course. For example, the pass rates for the selection course ranges from 18% to 70%, where most of the candidates fail from being physically prepared, specifically for the 20-km march. The study found that those candidates who completed the 5-km march in less than 45:45 minutes, achieved greater than level five on the sit-up test, and completed over 66 push-ups were statistically more likely to pass the course than those who were unable to meet these standards.

The Norwegian Naval Special Forces (NSF) evaluated the validity of psychological testing for predicting pass/fails results of their candidates (Hartmann *et al.* , 2003). Previous analysis on pilots suggested that cognitive and psycho-motor abilities were a better predictor of performance than intelligence and personality attributes. This testing looked at candidates scores on a Norwegian version of the Minnesota Multiphasic Personality Inventory's (MMPI) Big Five and the Rorschach Inkblot test. Multivariate analysis showed there was significant correlation between variables of the Rorschach test and some minor correlation between variables of the Big five. A 75% classification accuracy was achieved.

The United States Army had the Army Research Institute create a new screening criteria based on spatial recognition due to the large number of candidates that were failing the land navigation course. The goal was to predict if a candidate possessed the skills necessary to pass the Qualification Course (Bus, 1991). Potential candidates were given a map, orientation, and maze test. In addition to these three tests, the candidates cognitive and physical fitness scores were recorded. The correlation was able to predict pass/fails at 67%, which was just slightly higher than the actual pass/fail rate of 60%. It was noted, however, that the orienteering portion of Special Forces Assessment and Selection (SFAS) was considered a "stress test" and there were potentially outside variables not measured.

Duckworth (Duckworth, 2016), maintains that one's ability to succeed in SF training be based on their "grit". She defined grit as a combination of passion and perseverance for a singularly important goal. For this testing SF candidates were evaluated on grit, intelligence, fitness and years of schooling. The resulting linear regression model showed that grit contributed significantly to the model. Additionally, individuals who scored one standard deviation from the mean grit were 32% more likely to complete SFAS training.

Another approach to predicting personnel likely to qualify for SF is to build personality profiles to determine an ideal candidate. Along this avenue, the average SEAL's psychological profile was compared to that of the "normal" adult male. SEALs scored lower in Neuroticism and Agreeableness, average in Openness, and higher in Extroversion and Conscientiousness compared that of the normal male. Extroversion and conscientiousness scores have been shown to predict job performance in other high performance professions. This follows with SEALs who typically seek exciting and dangerous environments, but are otherwise stable, calm, and rarely impulsive. While this case does not capture the traits of each individual SEAL it does provide a good baseline profile of the SEALs as a whole for the US Navy (Braun *et al.* , 1994).

Finally, Diemer (2001) provides an in depth look at predicting selects or non-selects. He was determined that the most productive and relevant recruitment approaches were those that emphasize quality over quantity. Targeted recruiting of fewer higher quality soldiers as the main effort while increasing the pool of eligible candidates by tapping into several low number, high-yield, and high-payoff supporting efforts would be the most successful. Additionally, striking a balance between highly trainable physical attributes, such as the need for "moving in excess of 180 kilometers with a (45-65 lbs) rucksack," with the attributes that SF has determined as more difficult to train, yet just as important to success in SF operational units, will provide the biggest bang for the buck and insure that the best soldiers will attend the training phases of Special Forces Qualification Course (SFQC) (Diemer, 2001).

2.4 Previous Applications of Decision Analysis in Selection

During the second half of the 20th century, MCDM was one of the fastest growing areas of operational research (Stanujkic *et al.* , 2013). Because of this many different MCDM methods have been proposed. Among the MCDM application problems that are encountered in real life is the personnel selection problem. This problem, from the multi-criteria perspective, has attracted the interest of many scholars.

TOPSIS

A common MCDM method is the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS), originally developed by Hwang and Yoon in 1981. Like all MCDM approaches, TOPSIS follows the general path of establishing an evaluation criteria, generating alternatives, evaluating the alternatives, applying a MCDM method, and find optimal alternative (Opricovic & Tzeng, 2004).

Using TOPSIS for personnel selection is not a new concept. Recruitment activities are processes aimed at singling out applicants with the required qualifications. Substantial research has been conducted on recruitment due to its critical role in bringing human capital into organizations. In a research study that occurred in 2013, TOPSIS was applied to the selection of an academic of staff. It used the opinions of experts applied to TOPSIS to successfully model the group decision making process. There were ten qualitative criteria for selecting the best candidate amongst five prospective applications. A framework was developed based on the concepts of ideal and anti-ideal solution for selecting the most appropriate candidate from the short-listed applicants. The method enables users to incorporate data in the forms of linguistic variables (Safari *et al.* , 2014).

Organizations have also used TOPSIS to measure not only qualifications, but performance as well. A combination of Fuzzy TOPSIS and data envelopment analysis (DEA) was used to select the highest performers among 13 departments at a university based on 10 criteria (number of PhDs, associate professors, assistant professors, instructors, budget of departments, number of credit hours taught, number of alumni, instructor evaluation scores, number of academic categories, and number of academic papers). The alternatives were scored by the DEA approach, then the opinion of experts group DM, called the intuitionistic Fuzzy TOPSIS (IFT) method, was applied. The results of both methods were multiplied to obtain the final ranking. The combination of DEA and IFS does not replace DEA, instead it provided further analysis into the ranking the departments by combining the individual opinions of DMs (Rouyendegh, 2011).

Game Theory

Game theory has been applied in conjunction with MCDM to aid in personnel selection. A method based on combining of Game Theory and MCDM concepts was developed where the MCDM framework is applied for evaluating strategies and weighting the criteria and Game Theory was used for the final evaluating of applicants. Some instances of personnel selection are more complicated and important because some positions are so critical and important for all sections of a company or organization. This method was applied to selecting between two final CEO applicants with different strategies and ideas. The methodology was devised to help in top-level of human resource management field where selecting the best applicant can totally change the future of organizations and companies. This methodology accommodates the dynamic process of decision making. Decision makers make different decisions with more depth in issues regarding the situation of alternatives (players) and also strategies (Zolfani1 & Banihashemi, 2014).

Simple Additive Weighting

Simple Additive Weighting (SAW) is the simplest and therefore most often used multi attribute decision method (Podvezko, 2011). An evaluation score is calculated by summing the values, associated with each evaluation criterion, and weighting them according to the relative importance of each criterion as determined by the DM. The advantage of this method is that it is a proportional linear transformation of the raw data therefore the order of magnitude of the standardized scores remains equal (Afshari *et al.* , 2010a).

Analytic Hierarchy Process

Analytic Hierarchy Process (AHP) is a multiple criteria decision-making tool that uses the attributes eigenvalues for pair-wise comparison (Saaty, 1980). AHP allows for the problem to be laid out in different levels, or hierarchies, that outline the goals, criteria, necessary sub-criteria and alternatives. The different criteria maximum eigenvalues, consistency index (CI), consistency ratio (CR), and normalized values for each alternative are tested until these values lie in a desired range.

Tam and Tummala (2001) used AHP in the vendor selection for a telecommunication system, which was a complex, multi-person, multi-criteria decision problem. They found AHP to be very useful in involving several decision makers with different conflicting objectives to arrive at a consensus decision. Their proposed model was applied to two case studies. In both, the decisions reached using AHP agreed with those obtained using the pre-existing selection process. However, for the AHP model, the selection criteria were clearly identified and the problem was structured systematically. This enabled the DM to better examine the strengths and weaknesses of each alternative (Tam & Tummala, 2001).

VIKOR

Opricovic (1998) developed the VIKOR method for optimization of complex systems. VIKOR ranks alternatives by looking at a set of alternatives and determines a compromised solutions. It determines the ranking list and the optimal solution by introducing the multi-criteria ranking index based on a measure of closeness to the ideal solution. The VIKOR method provides a maximum group utility for the majority and a minimum of an individual regret for the opponent. The VIKOR method was used to select of personnel in hospital tertiary care. The results showed that the VIKOR method can successfully order personnel with uncertain and incomplete information (Liu *et al.* , 2015).

ELECTRE

The ELECTRE method by Roy (1991), is widely it ability to handle both qualitative and quantitative data. A study was done were a telecommunications company in Iran applied ELECTRE to their personnel selection process. While it was able to rank order candidates there was concern over its ability to properly account for the qualitative criteria as their structure did not allow or precise measurements (Afshari *et al.* , 2010b).

PROMETHEE

Preference Ranking Organization Method for Enrichment Evaluation (PROMETHEE) is designed to solve problems where alternatives are ranked by considering multiple, sometimes conflicting, criteria. There are six types of preference functions in PROMETHEE method, so decision makers can develop flexible scoring criteria according to the requirement of particular need. PROMETHEE was used for a transnational enterprise's desires to select an overseas marketing manager. Where a board of directors want to choose the best of five candidates based on four criteria. PROMETHEE presented a flexible method to deal with the personnel selection problem based on different evaluation information which included quantitative and qualitative information (Chen *et al.* , 2009).

MOORA

Brauers and Zavadskas (2006) developed the Multi-Objective Optimization on the basis of Ratio Analysis (MOORA) method. This method is the process of optimizing two or more conflicting objectives subject to certain constraints. It is composed of two parts. First is the ratio analysis, where each criteria of an alternative is compared to the square root of the sum of squares of the responses and the sum of beneficial criteria is subtracted from the sum of non-beneficial criteria. Finally, all alternatives are ranked, according to the obtained ratios. Second is the reference point theory which chooses for maximization a reference point, that has the highest value per objective and for minimization, the lowest value. The distance between this optimal point and all points of that objective are calculated and the highest value for each alternative is recorded as the furthest point from optimal. This values are rank ordered from smallest to largest. Finally the average rankings of the ratio analysis and reference point theory determine the final alternative rankings (Brauers & Zavadskas, 2006).

Table 1 compares of some of the most widely used MODA methods by their computational time, simplicity, mathematical calculations involved, stability, and type of the information it can process. From this, MOORA clearly outperformed the other MODA methods in terms of its universal applicability and flexibility as an effective method in solving complex decision-making problems (Chakraborty, 2011).

MULTIMOORA

MULTIMOORA is composed of two parts, MOORA (ratio analysis and reference point theory) and of the Full Multiplicative Form of Multiple Objectives. Developed by Miller and Starr (1969), the full multiplicative form consists both maximization and minimization of a purely multiplicative utility function. The overall utilities

Table 1. Comparative performance of some popular MODA methods

Method	Computational Time	Simplicity	Calculations Involved	Stability	Information Type
MOORA	Very less	Very simple	Minimum	Good	Quantitative
AHP	Very high	Very critical	Maximum	Poor	Mixed
TOPSIS	Moderate	Moderate	Moderate	Medium	Quantitative
VIKOR	Less	Simple	Moderate	Medium	Quantitative
ELECTRE	High	Moderate	Moderate	Medium	Mixed
PROMETHEE	High	Moderate	Moderate	Medium	Mixed

are obtained by the multiplication of different units of measurement and become dimensionless.

The MULTIMOORA method has been applied in various studies to solve a wide range of problems including economics/regional development, mining, prioritization of energy crops, construction, and personnel selection. Dumlupinar University, in Turkey, applied the MULTIMOORA method to it's Erasmus student selection process, which determines which students are admitted into the University's study abroad program. The students were evaluated to determine their foreign language competency through written and oral exams. Then, they were ranked ordered using the MULTIMOORA method. The MULTIMOORA method was also extended into the fuzzy environment, meaning that the constraint boundaries are not sharply defined, to allow for even more flexibility. It was determined that in many real-life situations, both quantitative and qualitative criteria should be considered to accurately rank candidates and select the most suitable ones. DMs often use uncertain judgments and it was necessary to convert these judgments to numerical values. Therefore, MULTIMOORA was an effective method to determine an unbiased ranking of students (Deliktas & Ustun, 2017).

Response Surface Methodology

When optimization involves more than one response, it is not possible to optimize each one individually. In cases like these the solution process must look for an optimal region, that is a compromise solution must be found (Derringer & Suich, 1980). Derringer and Suich (1980) were able to optimize multiple responses by developing a desirability function. This functions goal is to find conditions that ensure compliance with the criteria of all the involved responses. This is done by converting the different responses into a single scale, and combining the individual responses into a single function. Once the variables are converted into desirability functions, they are combined in the global desirability (D) to find out the best joint responses (VeraCandioti *et al.* , 2014).

2.5 Value Focused Thinking

Value focused thinking (VFT) is a strategic, quantitative approach to decision making that uses specified objectives, evaluation measures, and value hierarchies (Kirkwood, 1997). Because of this VFT is a useful method to use for problems that involve selection criteria or rank ordering of alternatives.

VFT is usually applied through a ten step model (see Figure 1). For Step 1, the problem is framed to ensure the purpose, perspective and scope are understood by all parties. In Step 2, objectives are found that represent the values of the DM. The primary means of doing this is to review organizational standards. There are four information standards: platinum, gold, silver, and combined. Platinum standard is from interviews with the DMs. The gold standard is from official documentation, while the silver standard is from interactions with the DMs representatives and unofficial documentation. The combined standard is a mix of any two or more of these. Objectives are then arranged in a hierarchal model that represents the organizational goals. Step 3 develops evaluation measures for each attribute, or a measuring scale for the degree of achievement. These can be either continuous or discrete sets. In Step 4, the evaluation measures are used to define single attribute value functions that convert the raw data into value scores. For Step 5, weights are determined for each attribute for the multi attribute value function. Step 6, alternatives are created and screened to ensure they are valid. For Step 7, value scores are multiplied by their respective attributes weight to determine each alternative's score. Steps 8 and 9, allow for deterministic and sensitivity analysis to gain additional insights and test the model's resiliency to changes. Finally, in Step 10, the results are communicated to the DM. This 10-step process is discussed in depth in Chapter III.

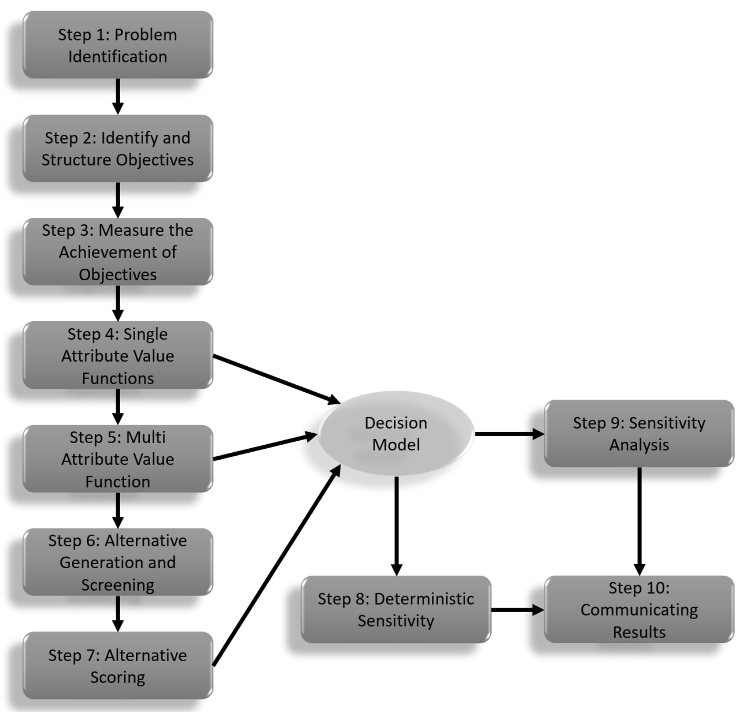


Figure 1. Steps of Value Focused Thinking (Shoviak, 2001)

In the early 2000s the Army applied VFT in its acquisition of infantry simulation tools (Boylan *et al.* , 2006). The Army looked to quickly field a system in order to keep up with growth in technology. To support the acquisition process, a multi-objective approach rooted in VFT was applied to the selection process. The selection process was broken into four phases: problem identification, model design and analysis, decision making, and implementation. The primary goal of the problem definition phase was to conduct a thorough investigation of the problem, achieved through DM interviews and systems analyses. This ensured the identification of critical inputs, outputs, and functions, as well as the conditions in which the system had to operate. Then the system requirements were combined with the DM objectives to create a value hierarchy used to evaluate and compare potential alternatives. Evaluation measure were determined as means of ranking alternatives. Weights were assigned to the criteria based on DM input. The design and analysis phase began with alternative generation and screening. Eleven different alternatives were generated. In the decision making phase the alternatives were scored according to the predetermined weights and the value hierarchy. Sensitivity analysis was conducted on the attributes weights and on the performance estimates used to convert the raw score to value scores. For implementation, it was determined that the best course of action was to combine three systems that were already in use to allow communication between them. This was also the highest scoring alternative (Boylan *et al.* , 2006).

The main objective of the selection process is to evaluate the differences among candidates, or alternatives, and determine which one is best meets the organization's goals, or criteria. VFT places criteria in a hierarchal structure and quantifies the values with criteria measurements, known as a decision model. Alternatives are scored by the value model, qualifying how well the criteria are achieved. Because of this VFT is well suited to solve the selection problem.

III. Methodology

3.1 Multi-Objective Decision Analysis Overview

Most complex decisions involve more than a single objective. Multi-objective decision analysis (MODA) is the process that allows for decision makers (DMs) to make trade-offs between different objectives. This allows for the ability to compare disparate alternatives by converting everything into common value scores. Too often decisions are solved by taking the problem's alternatives and then the objectives used for evaluation are determined. This is alternative focused thinking and it is reactive rather than pro-active (Keeney, 1994). Value focus thinking (VFT) defines values and objectives before identifying the alternatives. VFT is designed to focus the decision maker on the essential activities that must occur prior to solving a problem. VFT helps uncover hidden objectives and leads to more productive information collection (Keeney, 1994). This type of thinking is what makes using VFT for personnel selection so successful. It compels DMs to determine what characteristics they are looking for in candidates. Figure 2 from Keeney highlights some of the benefits of VFT.

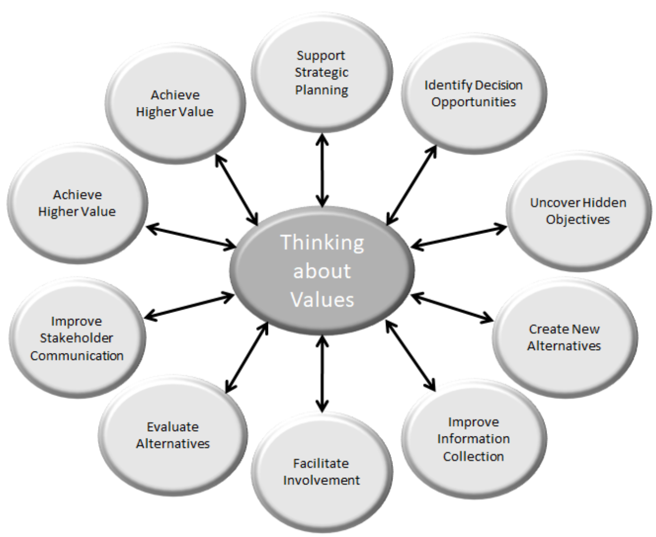


Figure 2. Benefits of Value Focused Thinking (Keeney, 1994)

This chapter examines three well respected MODA methods to determine which is the most effective for personnel selection. To do this a demonstration case is used. For the case, the overall goal is to win the World Series. Throughout this scenario a combination of silver and gold standard documents are used. Data for ten teams were created using random numbers generated from the average high/low scores of the ten post season teams over the last five years (see Table 2). The data categories were:

- Slugging percentage (SLG): The batting productivity of a team. SLG measures the number of bases a team has reached divided by the number of at bats (attempts).
- Runs (R): The number of runs (points) that a team scores during the season. This is a measure of their offensive performance.
- Stolen Bases (SB): The number of bases a team steals during the season. A stolen base advances the runner beyond their hitting, making it easier for them to score.
- Earned Run Average (ERA): The pitching performance of a team. This is measured by the number of number of earned runs scored against a team divided by the number of innings pitched.
- Saves (SV): The number of recorded saves the pitchers record for the season. This is a good measure of how teams perform in close games (under pressure).
- Strikeouts (SO): The number of strikeouts that a team induces in a season. This is considered to be a good measure of pitching efficiency.
- Fielding Percentage (FP): This measures the defensive strength of a team. It is the calculated by the number of times a team handles the ball properly divided

by the total number of times they handle the ball.

- Double Plays (DP): This is the number of times a team is able to get two outs on the same play. It is a good measure of how teams keep base runners from advancing.

Table 2. Demonstration Case Decision Matrix

	SLG	R	SB	ERA	SV	SO	FP	DP
Team 1	0.432	598	145	0.393	30	1109	0.986	134
Team 2	0.376	748	59	0.430	31	1316	0.989	134
Team 3	0.404	831	57	0.370	52	1026	0.990	159
Team 4	0.369	631	91	0.317	57	983	0.985	137
Team 5	0.372	625	161	0.431	49	1285	0.981	125
Team 6	0.358	672	113	0.311	54	1101	0.979	164
Team 7	0.389	690	53	0.367	32	1289	0.978	167
Team 8	0.432	796	147	0.406	38	1281	0.988	134
Team 9	0.421	656	52	0.347	27	1051	0.986	128
Team 10	0.470	618	94	0.383	51	1213	0.984	129

3.2 Response Surface Methodology

Response surface methodology allows examining an optimal solution by applying multiple response optimization, which is a form of multi-objective analysis. For this, the raw data is rescaled into a desirability score, $0 \leq d_i \leq 1$, where the target value is $d_i = 1$ and the bad value (base) is $d_i = 0$ (see Table 3). The desirability score was calculated as shown by Equation (1).

$$\frac{|Score - Base|}{Range} \tag{1}$$

The determined weights (w_i) are then applied to the desirability scores (d_i) and

Table 3. Demonstration Case Scaled Values

	SLG	R	SB	ERA	SV	SO	FP	DP
Team 1	0.661	0.000	0.853	0.317	0.100	0.378	0.667	0.214
Team 2	0.161	0.644	0.064	0.008	0.133	1.000	0.917	0.214
Team 3	0.411	1.000	0.046	0.508	0.833	0.129	1.000	0.810
Team 4	0.098	0.142	0.358	0.950	1.000	0.000	0.583	0.286
Team 5	0.125	0.116	1.000	0.000	0.733	0.907	0.250	0.000
Team 6	0.000	0.318	0.560	1.000	0.900	0.354	0.083	0.929
Team 7	0.277	0.395	0.009	0.533	0.167	0.919	0.000	1.000
Team 8	0.661	0.850	0.872	0.208	0.367	0.895	0.833	0.214
Team 9	0.563	0.249	0.000	0.700	0.000	0.204	0.667	0.071
Team 10	1.000	0.086	0.385	0.400	0.800	0.691	0.500	0.095

summed to calculate the final alternative's scores (D) using Equation (2).

$$D = \sum_{i=1}^{n} w_i d_i \tag{2}$$

Table 4 shows the final alternative scores. Team 8 was the highest ranked alternative.

Table 4. Demonstration Case RSM Rankings

	Score	Rank
Team 8	0.6345	1
Team 3	0.5874	2
Team 10	0.5352	3
Team 6	0.4649	4
Team 4	0.4064	5
Team 7	0.3995	6
Team 2	0.3855	7
Team 9	0.3675	8
Team 1	0.3486	9
Team 5	0.3368	10

3.3 The MULTIMOORA Method

Multi-objective optimization by ratio analysis (MOORA) composed of two methods: ratio analysis and reference point theory. When MOORA is combined with a full multiplicative form for multiple objectives, the three methods are joined under the name of MULTIMOORA. For the MULTIMOORA method, the demonstration case used the same decision matrix and weights as determined during the VFT approach.

The first step in using the MULTIMOORA method was to determine the performance goals (maximize or minimize) for each evaluation measure. Table 5 shows the performance goals for this scenario.

Table 5. Demonstration Case MULTIMOORA Evaluation Measures

Value Measure	Goal	Measurement
Slugging %	Maximize	Measure of the batting productivity of a hitter
Runs	Maximize	Number of runs scored
Stolen Bases	Maximize	Number of bases stolen
Earned Run Avg	Minimize	Mean of earned runs given up per nine innings
Saves	Maximize	Number of saves recorded
Strikeouts	Maximize	Number of strikeouts recorded
Fielding %	Maximize	Percentage of times player properly handles ball
Double Plays	Maximize	Number of double plays turned

For the ratio system of the MOORA method, the decision matrix was normalized by comparing each performance value of an alternative of a criterion against the other alternative performances on that criterion by:

$$x_{ij}^{*} = \frac{x_{ij}}{\sqrt{\sum_{j=1}^{m} x_{ij}^{2}}} \tag{3}$$

The weighted normalized performance values of beneficial criteria were added together, and then the same procedure was repeated for the non-beneficial criteria. The sums for non-beneficial criteria were subtracted from the sums for beneficial criteria using:

$$y_{i}^{*} = \sum_{i=1}^{g} w_j x_{ij}^{*} - \sum_{i=g+1}^{n} w_j x_{ij}^{*} \tag{4}$$

This produced the ratios, meaning how well the objectives scored compared to one another. See Table 6 for the ratio rankings.

Table 6. Demonstration Case MOORA Ratio Scores

	$\sum_{j=1}^{g} x_{ij}^{*}$	$\sum_{j=g+1}^{n} x_{ij}^{*}$	y_i^*	Rank
Team 8	0.279	0.065	0.214	1
Team 6	0.255	0.050	0.205	2
Team 3	0.264	0.059	0.204	3
Team 10	0.264	0.061	0.203	4
Team 4	0.246	0.051	0.195	5
Team 5	0.263	0.069	0.194	6
Team 1	0.245	0.063	0.182	7
Team 7	0.238	0.059	0.179	8
Team 2	0.243	0.069	0.174	9
Team 9	0.226	0.056	0.170	10

The reference point approach used the weighted normalized decision matrix. The maximal objective reference points (r_j) was the best attribute score for each objective (highest score for objectives maximized and the lowest score for those objectives minimized). The absolute value of the difference of each attribute score was subtracted from the maximal objective reference point, then the highest difference for all objectives was recorded as the alternative's score, as shown by:

$$\underset{i}{min}\{\underset{j}{max}|r_j - x_{ij}^{*}|\} \tag{5}$$

Equation (5 gives each alternatives maximum distance from optimal. The alternatives were then ranked lowest to highest and Table 7 is their reference point ranking.

The Multiplicative form for multi-objectives was introduced by Miller and Star (1969). It is nonlinear, non-additive and unweighted. The overall utility for each alternative was obtained by the multiplication of difference units of measurement, becoming dimensionless. In fact, in the full-multiplicative form the relation between the utilities does not change if more importance is given to an objective by multiplying it by a factor (weights). This was because all alternatives were multiplied by the same factors. To handle the combination of minimization and maximization goals,

Table 7. Demonstration Case Deviation from Reference Point

	SLG	R	SB	ERA	SV	SO	FP	DP	Max	Rank
Team 8	0.006	0.004	0.003	0.015	0.016	0.001	0.000	0.001	0.016	1
Team 6	0.018	0.017	0.010	0.000	0.003	0.008	0.000	0.000	0.018	2
Team 3	0.010	0.000	0.021	0.009	0.004	0.010	0.000	0.000	0.021	3
Team 4	0.016	0.021	0.014	0.001	0.000	0.012	0.000	0.001	0.021	3
Team 7	0.013	0.015	0.021	0.009	0.021	0.001	0.000	0.000	0.021	3
Team 2	0.015	0.009	0.020	0.019	0.022	0.000	0.000	0.001	0.022	4
Team 5	0.016	0.022	0.000	0.019	0.007	0.001	0.000	0.001	0.022	4
Team 10	0.000	0.023	0.013	0.012	0.005	0.004	0.000	0.001	0.023	5
Team 1	0.006	0.025	0.003	0.013	0.023	0.007	0.000	0.001	0.025	6
Team 9	0.008	0.019	0.022	0.006	0.025	0.010	0.000	0.001	0.025	6
r_j	0.074	0.088	0.032	0.050	0.048	0.047	0.017	0.003		

the objectives to be maximized were the numerators and those to be minimized were denominators, as shown by:

$$U_i = \frac{A_i}{B_i} \tag{6}$$

In this formula A_i and B_i were found as $A_i = \prod_{j=1}^{g} x_{ij}$ and $B_i = \prod_{j=g+1}^{n} x_{ij}$. Where g and (n - g) are the number of criteria to be maximized and minimized, respectively. Finally, the utility scores were ordered from highest to lowest and these became the multiplicative form's rankings (see Table 8).

Table 8. Demonstration Case Degree of Utilities

	A_i	B_i	U_i	Rank
Team 6	2.595E+11	3.11	8.344E+10	1
Team 8	3.257E+11	4.06	8.023E+10	2
Team 5	2.890E+11	4.31	6.705E+10	3
Team 10	2.144E+11	3.83	5.597E+10	4
Team 4	1.602E+11	3.17	5.053E+10	5
Team 3	1.607E+11	3.70	4.343E+10	6
Team 1	1.646E+11	3.93	4.189E+10	7
Team 7	9.583E+10	3.67	2.611E+10	8
Team 2	8.971E+10	4.30	2.086E+10	9
Team 9	5.143E+10	3.47	1.482E+10	10

The final step using the MULTIMOORA method was to take the average of the three ranks determined by the ratio analysis, reference point, and the multiplicative form, and determine the final rank order (see Table 9).

Table 9. Demonstration Case Rankings by the MULTIMOORA Method

	MOORA Ratio	MOORA Ref Pt	Multiplicative Form	MULTIMOORA
Team 8	1	1	2	1
Team 6	2	2	1	2
Team 3	3	3	6	3
Team 10	4	5	4	4
Team 4	5	3	5	5
Team 5	6	4	3	6
Team 1	7	6	7	7
Team 7	8	3	8	8
Team 2	9	4	9	9
Team 9	10	6	10	10

3.4 Value Focused Thinking

Value focus thinking (VFT) looks at the values and objectives and allows for the selection of a best solution amongst a pool of available alternatives through value trade-offs and factor weightings.

The first step necessary in helping the DM is to identify the problem, referred to as framing the problem. Improper framing can cause one to not fully understanding the problem, overlooking key objectives, or even not involving the right stakeholders, all of which can lead the failure of being able to make a good decision.

Once the decision frame is clear, objectives are identified and structured into the value hierarchy. An objective is the specific goal being sought. Appropriate structuring of objectives is critical to developing a successful value hierarchy. Stakeholders and DMs must accept the qualitative value model as a valid model so they will ultimately accept the quantitative analysis as rational.

Once the objectives are collected and a structure agreed upon, it is visualized through the value hierarchy. The value hierarchy places the overall, or strategic objective at the top with all of the lower-tiered, or fundamental objectives, below. The fundamental objectives are decomposed (if possible) until a single measurable objective remains.

For the Demonstration case, winning the World Series was the strategic objective. Most people agree that winning is commonly defined as scoring more runs than a team gives up. Arnold Soolman (1970), examined the winning percentages for 1166 team over multiple seasons, and determined that the winning percentage was based on batting (runs scored), pitching (earned runs allowed), and fielding (unearned runs allowed) (Thorn & Palmer, 1984). Using this and the seventeen key attributes determined by Wiley's (1976) analysis of how traditional baseball statistics were correlated, the value hierarchy was determined (see Figure 3).

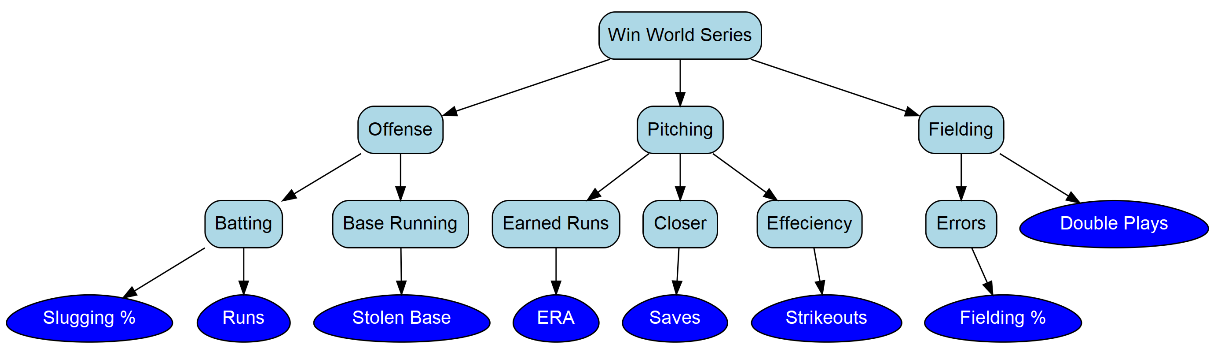


Figure 3. Demonstration Case Value Hierarchy

The attributes were reduced from seventeen to eight (see Table 10) to ensure that the fundamental properties of completeness, non-redundancy, independence, operational, and conciseness were met. For example instead of including the number of singles, doubles, triples, and home-runs by a team, the slugging percentage was used since it accounts for all of those and converts it into a percentage to the number of attempts.

The value hierarchy is a qualitative model. To conduct quantitative analysis,

Table 10. Wiley's Traditional Baseball Statistics (Thorn & Palmer, 1984)

Retained	Not Retained
Slugging Percentage	Batting Average
	Doubles
	Triples
	Home Runs
Runs Scored	
Stolen Bases	
Earned Run Average	Runs Allowed
	Shutouts
	Complete Games Pitched
Saves	
Pitcher's Strikeouts	Walks
Fielding Percentage	Errors
Double Plays	

attributes are assigned to each of the lowest level of objectives. Attributes, also called evaluation measures, are classified using a double dichotomy of natural or constructed and direct or proxy. A natural scale is one that is common and can be easily interpreted by everyone. While the constructed scale is developed to be measurement the degree of obtainment of a specific objective. A direct scale measures exactly the degree of obtainment of an objective, while a proxy scale reflects a degree of attainment of its associated objective, but is not a direct measure this (Kirkwood, 1997).

To measure the fundamental objectives for the demonstration case, evaluation measures were created (see Table 11) to determine the degree of achievement. For this, end point ranges were determined by considering the possible values deemed within the acceptable region. The ranges for the demonstration case were based on the highest and lowest values over the regular season the past five seasons. Evaluation measures allow for an unambiguous rating, that is if a person had infinite resources and instantaneous computational powers could they assign an accurate score.

Single Value Attribute Functions (SAVF) are used to calculate an individual cri-

Table 11. Demonstration Case VFT Evaluation Measures

Value Measure	Low	High	Measurement
Slugging %	0.350	0.460	Measure of the batting productivity of a hitter
Runs	550	875	Number of runs scored
Stolen Bases	50	170	Number of bases stolen
Earned Run Avg	3.00	4.90	Mean of earned runs given up per nine innings
Saves	25	60	Number of saves recorded
Strikeouts	950	1350	Number of strikeouts recorded
Fielding %	0.978	0.990	Percentage of times player properly handles ball
Double Plays	120	170	Number of double plays turned

teria score from the raw data. Using a custom function built in **R**, SAVF for the demonstration case were created (see Figure 4). The SAVFs were calculated using the bisection, or mid value method. Normally the DM is interviewed to determine the halfway mark for each value measurement, however for this mid points were calculated by using the mean values of the ten teams that made it to the post season (the playoffs) over the last five seasons. Exponential value functions were used for each attribute; ERA was the only decreasing value function.

Figure 4. Demonstration Case Single Attribute Value Functions

The final step in determining the alternatives score is to calculate the multi-attribute value function (MAVF) score. This was done by multiplying each attributes SAVFs ($v_i(x_i)$) by a vector of weights (w_i) corresponding to each criteria (x_i). The general form of the MAVF is:

$$V(x) = \sum_{i=1}^{n} w_i v_i(x_i) \tag{7}$$

The weights vector is normalized so that the sum of weights is equal to one:

$$\sum_{i=1}^{n} w_i = 1 \tag{8}$$

Typically the weights are determined by the DM, preferably by using the platinum or gold standard documents. For this demonstration case there were no platinum or gold standard documents that outlined what the weights for each attribute should be. However, Soolman's calculations were used as silver standard documentation. He determined that offense was approximately 50 percent of the game (because 88 percent of runs are earned), six percent was defense, and pitching 44 percent (Thorn & Palmer, 1984). These are the global weights. The ratio of Wiley's correlation coefficients were normalized to determine the local weights (see Figure 5).

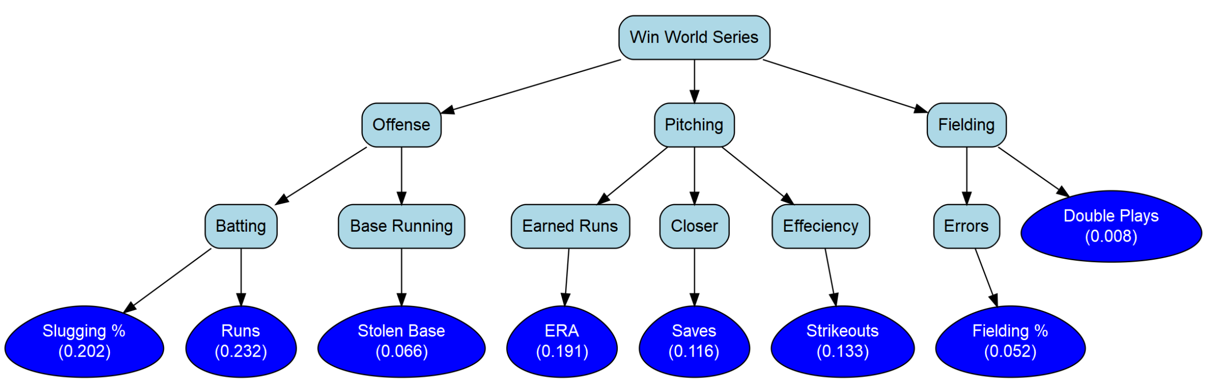


Figure 5. Demonstration Case Weighted Hierarchy

Using the decision matrix, each alternative's raw scores were converted to component value scores by applying the associated SAVFs to each. Finally, an overall score was found for each alternative by applying the weights developed in the MAVF to the component scores (see Table 12).

Table 12. Demonstration Case MAVF Scores

Name	Score
Team 8	0.5481
Team 10	0.5476
Team 3	0.4950
Team 6	0.4084
Team 4	0.3694
Team 2	0.3460
Team 1	0.3423
Team 7	0.3300
Team 5	0.3292
Team 9	0.3160

After the alternatives were scored, analysis was conducted to ensure the alternative rankings were easily understandable, not misleading, and to see if there were any insights or improvements that could be identified. This was done by looking at the deterministic sensitivity of each alternative. The value breakout graph (see Figure 6) allows for a quick and easy comparison of how each attribute affects the alternatives and how it can compare to the ideal, or Utopian, candidate.

Once the model was deemed acceptable, sensitivity analysis was conducted to determine the impact on the rankings of alternatives to changes in the various assumptions of the model, specifically the weights. The weights represent the relative importance attached to each evaluation measure. Figure 7 shows two of the attributes sensitivity analysis graphs. Team 8 and Team 10 are very similar and are resilient to changes in weighting as compared to the other eight teams. Teams 8 and 10 were so similar that their MAVF scores were only 0.0005 points apart which is why changes to the weighting will affect which of these two are the number one choice. In cases like

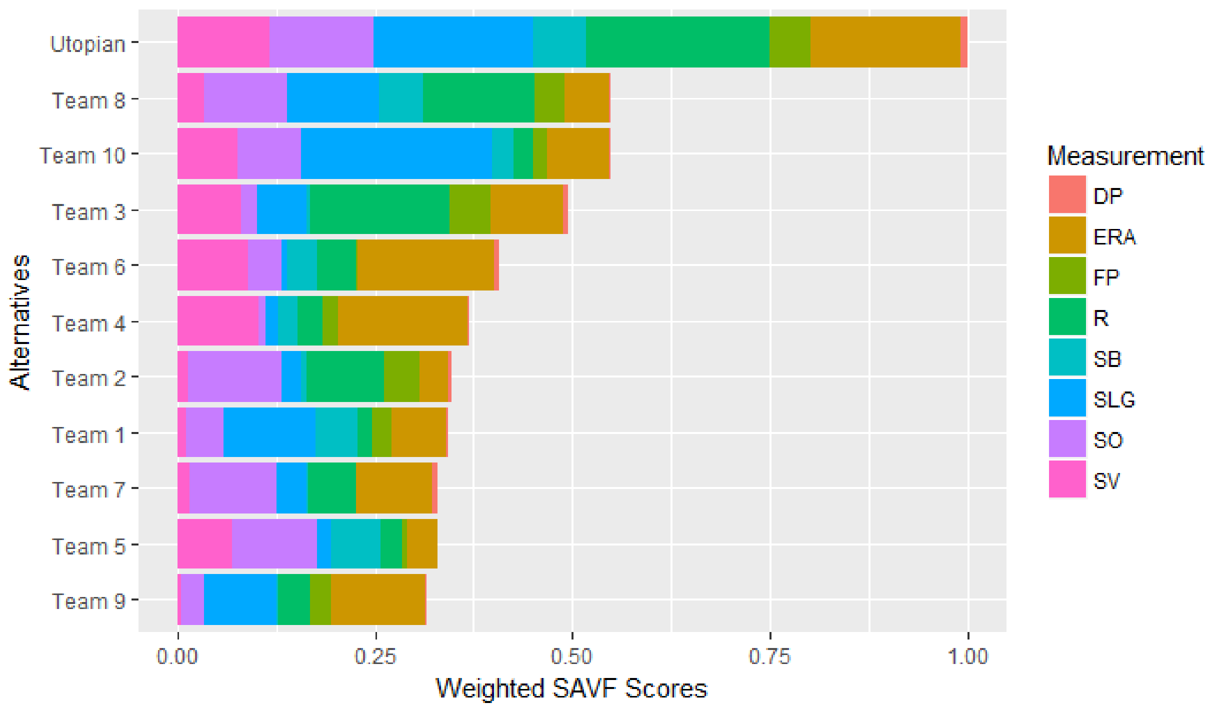
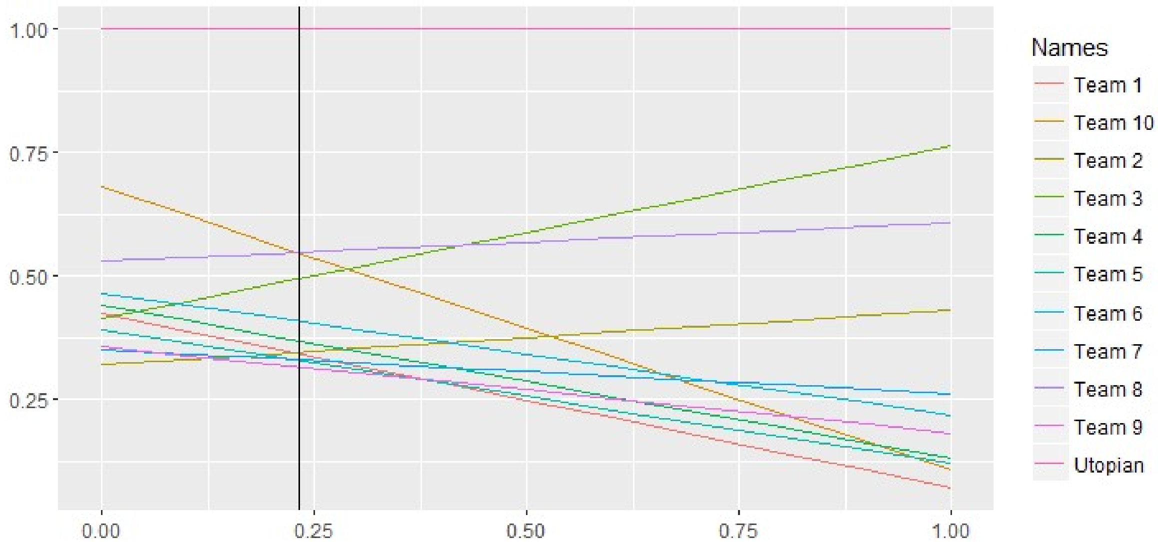


Figure 6. Demonstration Case Breakout Graph

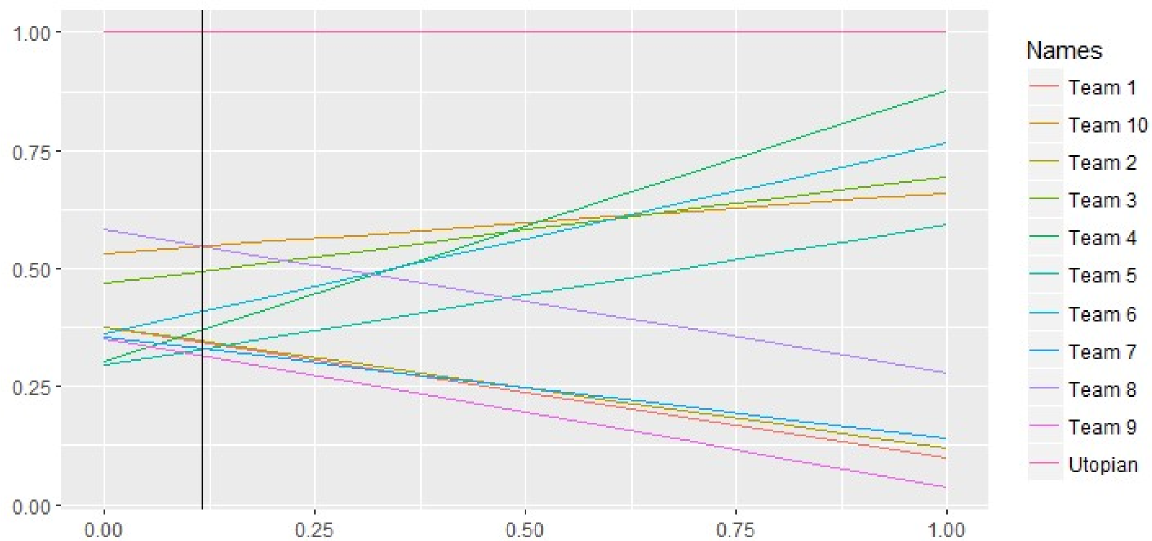
this additional analysis can be conducted to ensure the DM has the best information to make an informed decision.

3.5 Conclusions

Table 13 shows the results of the three methods. Only two teams were ranked the same throughout the three methods. However, MULTIMOORA and VFT were the most similar with six teams matching. While the MULTIMOORA method was less computationally intensive and time consuming than VFT, it lacked the ability to show magnitude between different alternatives and lacked the ability to conduct sensitivity analysis. The RSM approach was simple computationally, however because the desirable attribute rescaled each group of attributes between zero and one the possibility of alternative scores being skewed existed. VFT allows for some insight into the selection process as apposed to a black box method style. Additionally, VFT



(a) Runs



(b) Saves

Figure 7. Demonstration Case Sensitivity Analysis

allows for easy adjustments to the hierarchy if an organization's focus ever changes. Since this research was to select the best group of personnel possible by a team, transparency and the ability to conduct sensitivity analysis are important. VFT appears to allow for the most robust overall analysis and was the method that was applied for the remainder of the research.

Table 13. Method's Results

	VFT	MULTIMOORA	RSM
Team 1	7	7	9
Team 2	6	9	7
Team 3	3	3	2
Team 4	5	5	5
Team 5	9	6	10
Team 6	4	2	4
Team 7	8	8	6
Team 8	1	1	1
Team 9	10	10	8
Team 10	2	4	3

IV. Analysis

4.1 Overview

Throughout this research the focus has been the ability to select personnel for top tier organizations such as military special operations units. Information for these types of organizations was not available in the required time frame so it was concluded that the selection process for admittance into college universities were an acceptable proxy. First, both are seeking high functioning individuals who share many of the same personality traits like hard-working, determined, goal focused, well organized, and many more. Additionally, the population that contains collegiate athletes are physically fit and competitive. While there are differences between these two groups, such as the technical and tactical skills required to be an SF operator, the process of selecting personnel is fundamentally the same. There is a quantifiable amount of known information for which is used to evaluate candidates, rank them, and to select the very best from among a group.

This research compared two case studies of college admissions selection criteria. The first school was non-competitive and the second was highly competitive. For the purpose of this research a non-competitive school was defined as one that admits greater than 90% of applicants, while a highly competitive school was defined as a university that admits less than 10% of applicants. A selection pool of 8,000 select and 24,000 non-select candidates was generated based off of the provided real world datasets. Value focused thinking (VFT) was then applied to show a valid admissions selection process model. The two schools admissions documentation were used to gather information on the hierarchies, single attribute value functions (SAVF), multi-attribute value functions (MAVF), and weights. Value hierarchies were determined based on the colleges admission requirements. SAVFs were created using the normalized exponential constant with the mean of selected candidates being the mid-value point. MAVFs and weights were determined by the ratio of the SAVFs correlation coefficients. Sample applicants were drawn from the generated pool and examined to see how accurately the models were able to select the correct applicants.

4.2 Case Study #1: Non-Competitive School

The first case study looked at the admission's data for a specific major from a large, non-competitive public university. This university had a lenient admissions policy, looking only at GPA and ACT scores. The university also tracked which high school the candidate attended to assess the quality of education the candidate potentially received. From this a simple value hierarchy was created (see Figure 8). The selection criteria was broken into four fundamental objectives, a candidates academic performance (GPA), mental capacity (ACT composite score), analytic capability (ACT math score), and the quality of their education (high school rank).

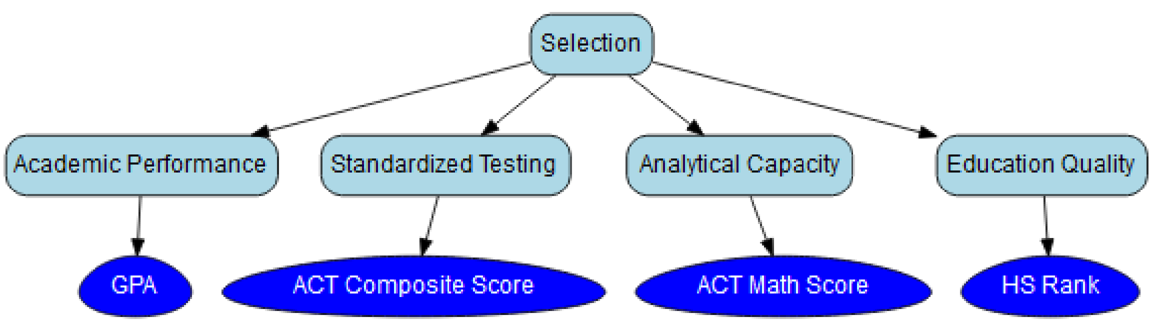


Figure 8. Non-Competitive Value Hierarchy

All evaluation measures (see Table 14) were based on constructed scales and for all measures a higher value was preferred. The grade point average (GPA) is the GPA at the time the candidate submitted their college application. It's range was from zero to five to cover those schools that used an extended grading scale. The ACT composite and math scores were the scores the candidate scored on the ACT test and had submitted to the university. The range of this attribute was from 10 to 36, which was deemed to be the feasible region of the scores. Finally, the high school rank score is the score the university determined for each school a candidate attended based on criteria such as student to teacher ratio, graduation rate, standardized test scores, etc.

Table 14. Non-Competitive Evaluation Measures

Value Measure	Low	High	Measurement
GPA	0.0	5.0	High School Grade Point Average
ACT Composite	10	36	ACT composite score
ACT Math	10	36	ACT math score
High School Rank	1	11	Assessed school score

Single attribute value functions (SAVF) were calculated for each of the four variables. Silver standards documentation showed that the university had no predetermined weighting. With this, and not having access to the actual decision maker (DM) exponential SAVFs were used where the attribute's mid-value was the mean of the respective attribute from the original dataset. All attributes were increasing SAVFs (see Figure 9).

To calculate the multi-attribute value function (MAVF) the same method from the demonstration case was used. Correlation coefficients were used to determine how much each attributes contributed to the model and weights were based on their ratios (see Figure 10). The global weights were 40.9%, 15.5%, 27.8%, and 15.8% for the fundamental objectives.

The dataset needed to be cleaned prior to being used. This dataset had approximately 3,4000 observations and nine variables. The observations represented the ad-

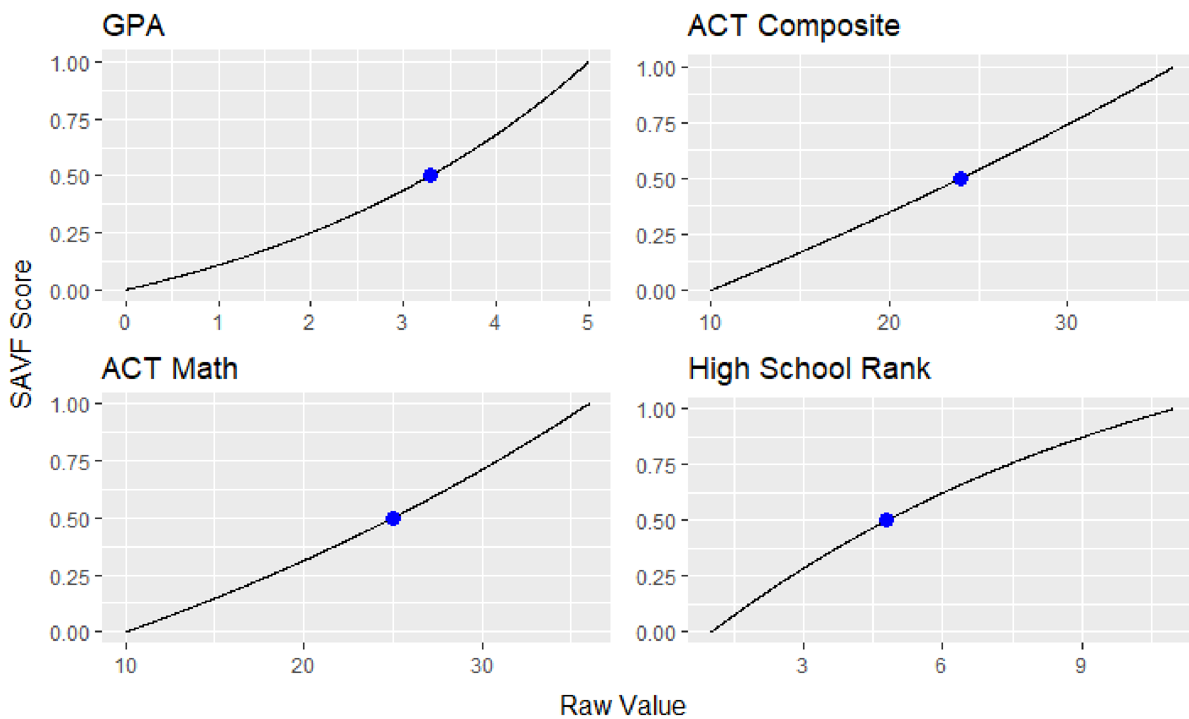


Figure 9. Non-Competitive Single Attribute Value Functions

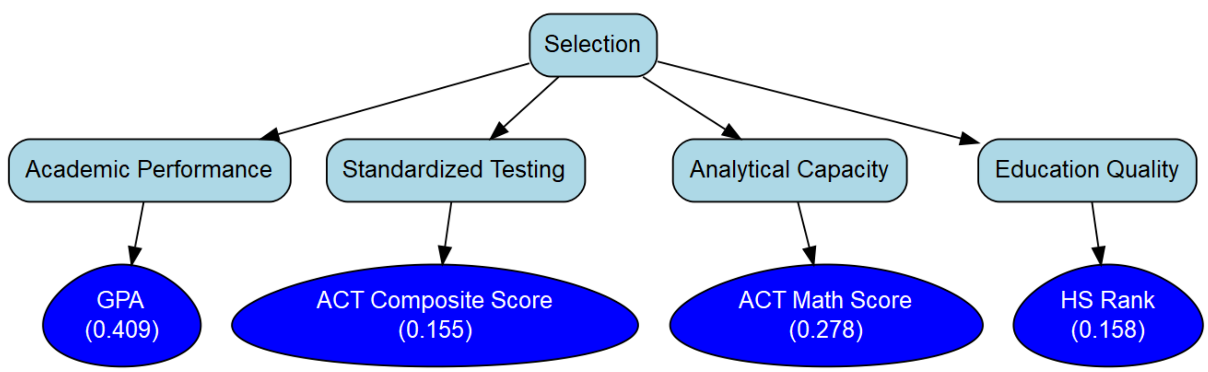


Figure 10. Non-Competitive Weighted Value Hierarchy

mitted students and the variables were the data points the admission's team tracked. All biographical information was removed, and variables were reduced to ensure independence. It was assumed that gender, race, and declared major had no significant impact to admittance. The final dataset had five variables (student number, high school GPA, ACT composite score, ACT math score, and high school quality score).

Additionally, 400 observations were removed due to missing data for their high school quality score, leaving the final dataset with approximately 3,000 observations.

A known distribution was fit to each of the variables to allow for the ability to easily generate new data points. A normal distribution was fit to each attribute to ensure it would be an acceptable distribution to use when generating data. Using **R**, 8,000 random "select" candidates were generated using the defined normal distribution. One issue with this dataset was that it only contained data from candidates already selected to attend the university. To address this, the means of the normal distributions used to generate the "selected" candidates was shifted approximately 15% to the left to create "non-selected" candidates that were just slightly worse than their counterparts. Again using **R**, 24,000 "non-select" candidates were generated. Figure 11 shows the histogram of the dataset with the solid blue line representing the normal distribution of "select" candidates and the dashed red line the "non-select" candidates.

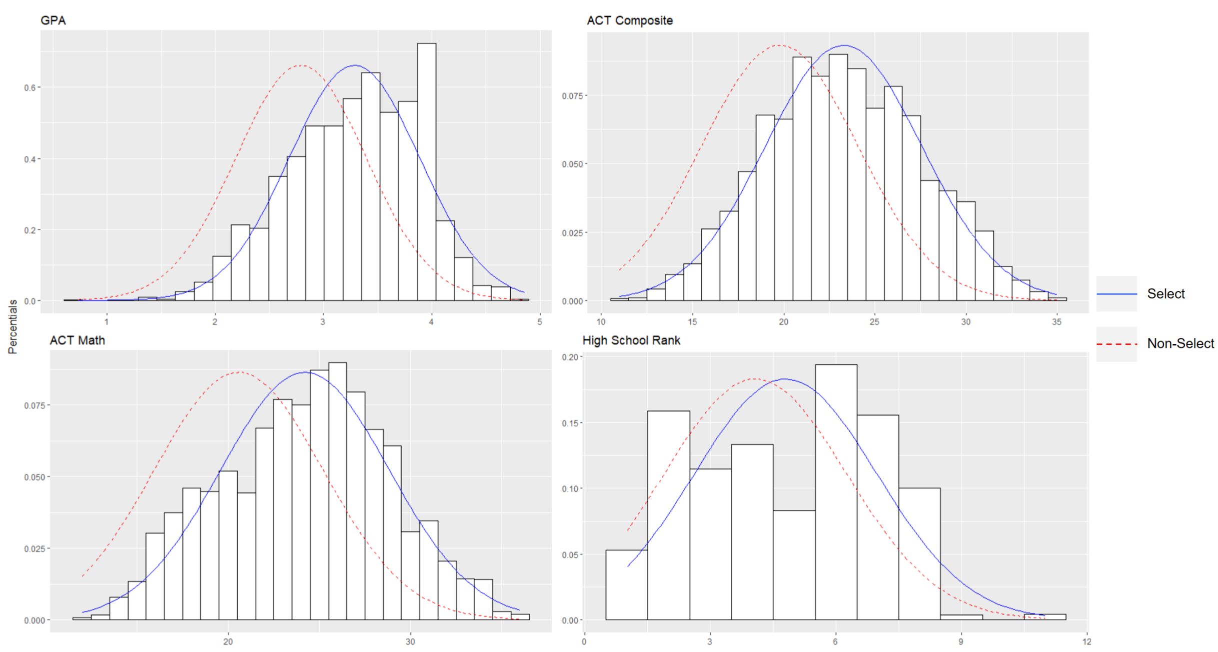


Figure 11. Non-Competitive Normal Distribution of Attributes

A simulation was developed where the 8,000 "select" and 24,000 "non-select" were combined, 4,000 candidates were randomly selected as a sample application year group. The MAVF scores were calculated and all of the candidates were rank ordered. The top 1,000 candidates were selected and compared to see how accurately the "selected" candidates were chosen. If candidates were picked completely at random to fill the 1,000 seat class the probability that candidates would all be chosen from the "selected" group was 1.56%. This was calculated using Equation (9).

$$P(t) = \frac{\binom{8000}{1000}\binom{24000}{3000}}{\binom{32000}{4000}} = 0.0156 \tag{9}$$

This model was repeated for 1,000 times in a Monte Carlo simulation. This model's selection accuracy rate was 55.16% (see Figure 12), just better that of flipping a coin, but still better than choosing completely at random which was 1.56%. No additional analysis was conducted to look at the potential for "non-selects" to be better than the "select" candidates as was done because it was determined that this decision model would not be able to yield any significant insights.

4.3 Case Study #2: Highly Selective School

For the second case study admission's data from a small, highly competitive, liberal arts university was used. Knowing that the school based the merits of a candidate on their scholastic, athletic, and leadership accolades the variables were arranged into an appropriate value hierarchy (see Figure 13). Scholastic ability was determined to measure a candidate's mental capacity through their standardized test scores (SAT verbal and math) and their academic performance (class rank constructed score). The athletic fundamental objective was determined by the candidate's athletic capability (athletic constructed score) and their fitness level (school administered physical fitness

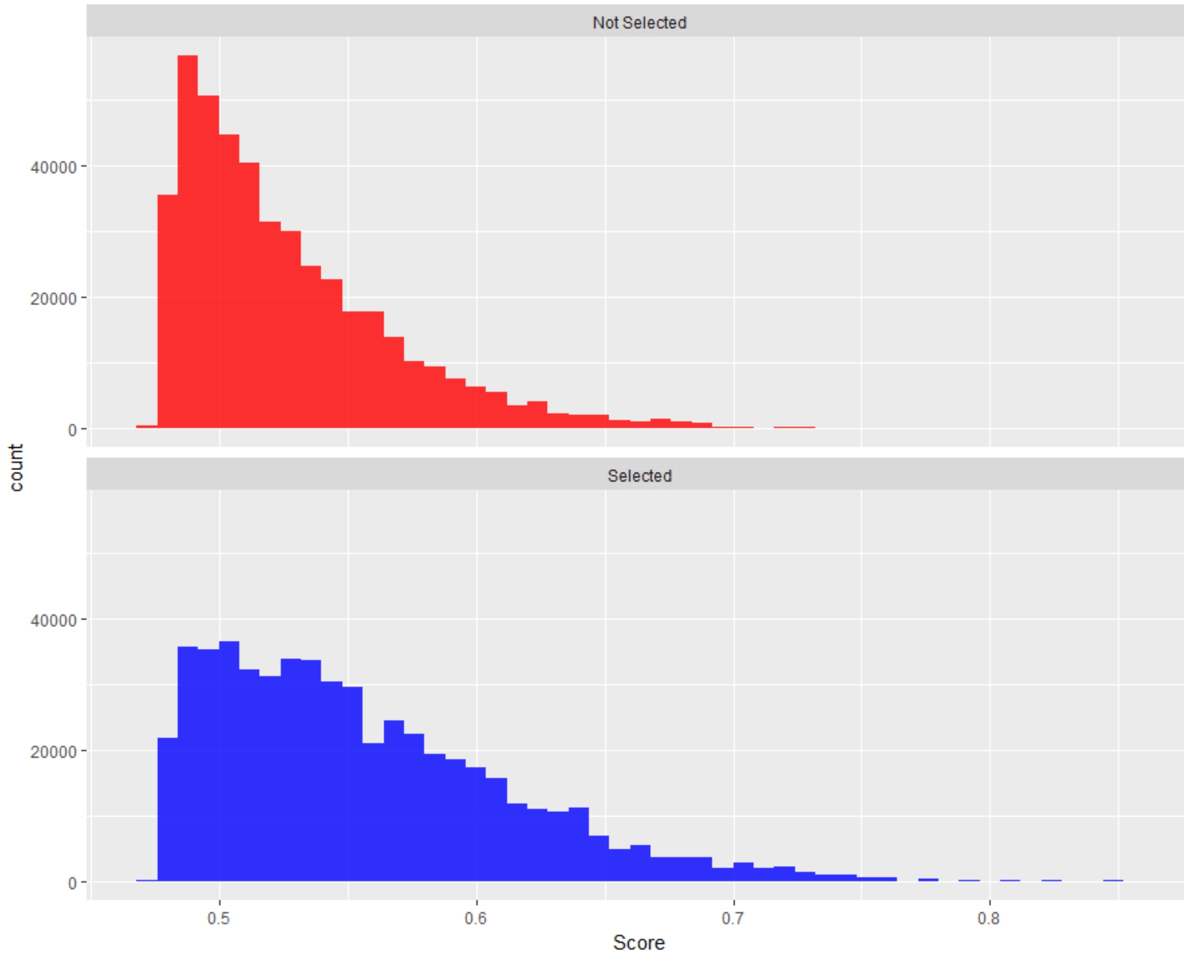


Figure 12. Non-Competitive Monte Carlo Simulation Results

test). Final, leadership was determined by their earned achievements (leadership constructed score) and the extracurricular activities the candidate participated in (extracurricular constructed score).

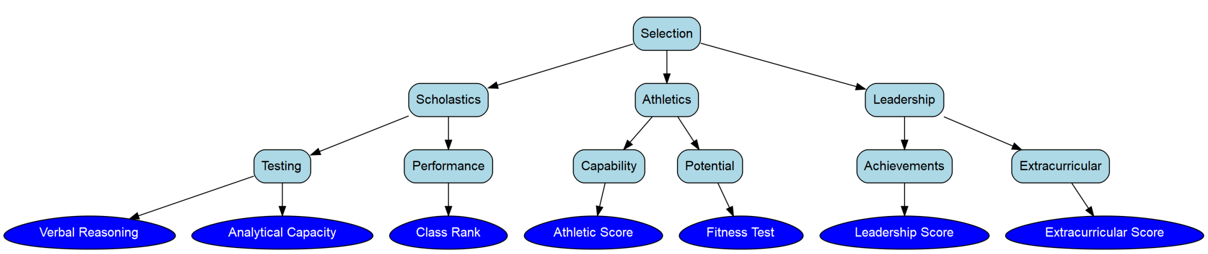


Figure 13. Competitive Value Hierarchy

All evaluation measures (see Table 15) were based on constructed scales, and for all measures a higher value was preferred. SAT Verbal and Math scores were the actual verbal and math scores the candidates received when they took the SATs. These scores range from a low of 400 to a high of 800. The remainder of the constructed scales had a low of 200 and a high value of 800. The class rank constructed score was a scale that was based on not only the candidates high school class rank and GPA, but the size of their graduating class as well. The athletic constructed score was based on how many sports a candidate participated in, for how many years, were they on the varsity team, and did they place at any regional, state, or national level events. The fitness test score was a constructed score based on how a candidate scored on six events (basketball throw, pull-up, shuttle run, sit-ups, push-ups, and one-mile run) during a school-administered test. The leadership score was a constructed score based on the candidate's leadership positions held in school and community organizations, while the extracurricular constructed score is based on the number of extracurricular events the candidate has participated in and the number of years they had participated in.

Table 15. Competitive Evaluation Measures

Value Measure	Low	High	Measurement
Verbal Reasoning	400	800	Verbal score of the SAT
Analytical Capacity	400	800	Math score of the SAT
Class Rank	200	800	High school rank constructed score
Athletic Score	200	800	Assessed athletic activities score
Physical Fitness Test	200	800	Physical fitness test score
Leadership Score	200	800	Assessed community leadership score
Extracurricular Score	200	800	Assessed extracurricular activities score

Single attribute value functions (SAVF) were calculated for each of the seven variables. Due using silver standard documentation, and not having access to the decision maker (DM) exponential SAVF were determined to be the best fit. All attributes were increasing SAVFs (see Figure 14). The mid-values used to calculate ρ were the mean value of each attribute from the original dataset.

To calculate the multi-attribute value function (MAVF) silver standard documents

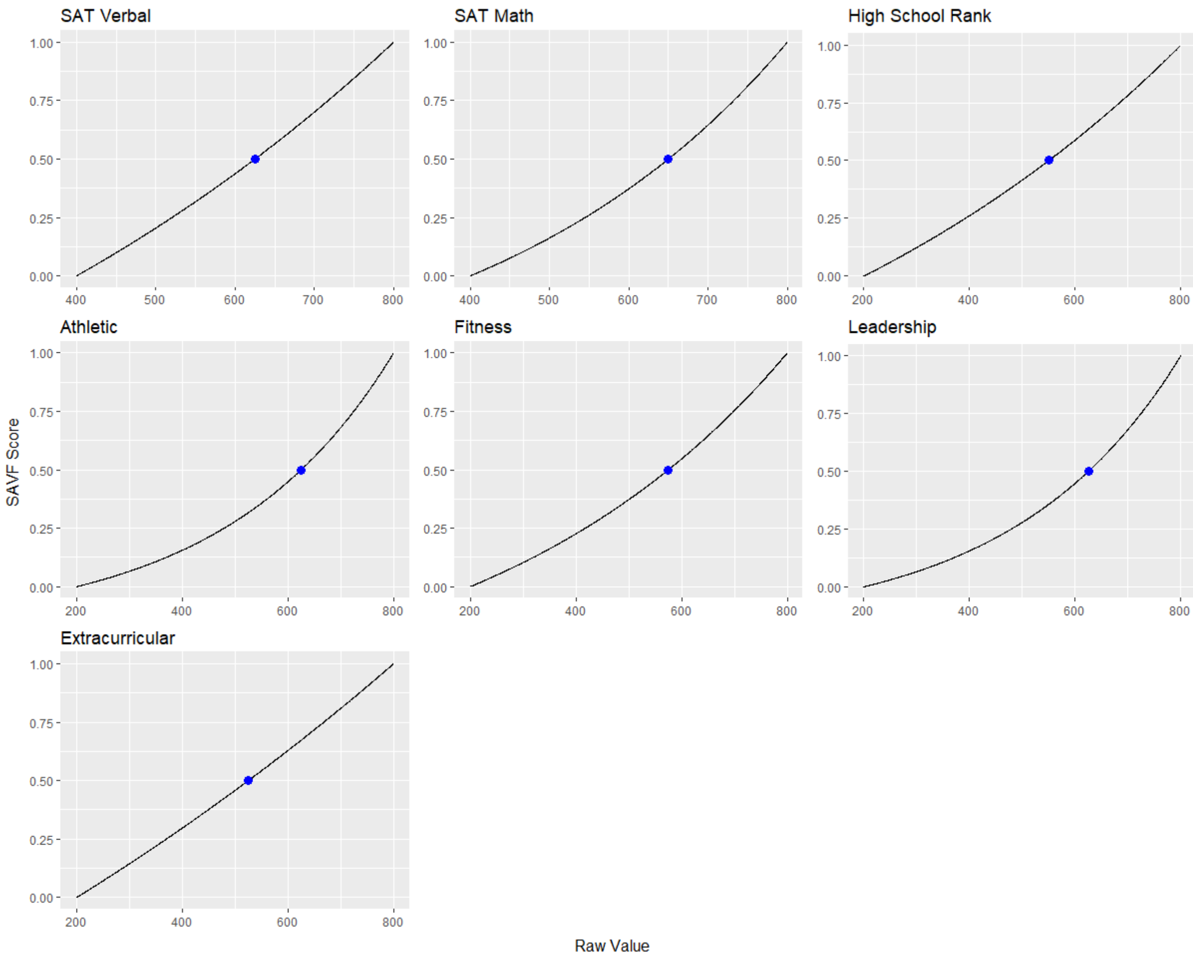


Figure 14. Competitive Single Attribute Value Functions

provided insight that the fundamental objective weights for scholastics, athletics, and leadership were 60%, 25%, and 15% respectively. Correlation coefficients were used to determine how each attribute contributed to the model and local weights were based on their ratios (see Figure 15).

Cleaning of the original dataset was required to ensure it was usable for VFT. The original data consisted of approximately 13,000 observations and 26 variables. The observations represented the students who had been admitted to the university over the course of the last 10 years. The variables were all of the data points the admissions team recorded on candidates. The first step in cleaning the data was to reduce the variables to an independent set. For example, the data points for the high

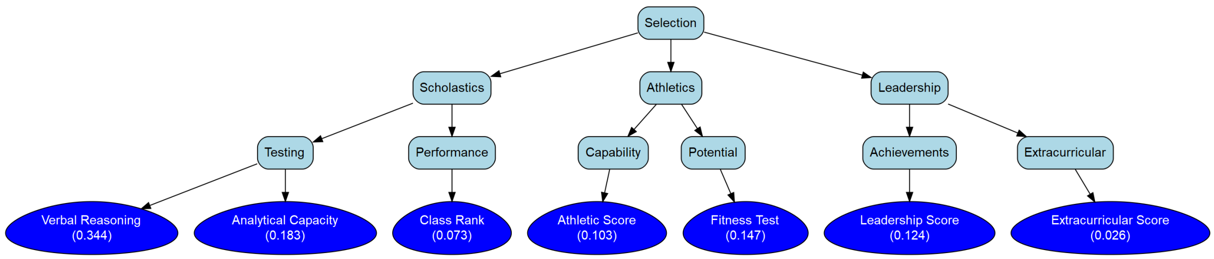


Figure 15. Competitive Weighted Value Hierarchy

school class rank constructed score was kept in favor of the raw overall class rank and the applicants high school class size since the constructed score was based off the other two. Additionally, all biographical data was removed along with gender and race. Finally, all students who only had ACT scores were removed (in favor of those who had SAT scores) to eliminate the need for designing a scale to relate ACT and SAT scores. This reduced the initial dataset from 26 variables to eight (Student number, SAT verbal score, SAT math score, class rank constructed score, athletic activity constructed score, fitness test score, leadership score, and extracurricular activity score). The final dataset contained approximately 7,800 observations.

A normal distribution was fit to each attribute to ensure it was an appropriate fit when generating additional data points. Using **R**, 8,000 "select" and 24,000 "non-select" candidates were generated to allow for the ability to compare the two case studies to one another. As in the first case study, the dataset only contained information about candidates already selected, so the "select" candidates were generated based on the 7,800 observations and the "non-select" candidates were generated by slightly adjusting the mean of the normal distributions during data generation (see Figure 16).

The same simulation developed for the non-competitive university was used to allow for the ability to compare the two models. For this, a sample application group of 4,000 candidates was again randomly selected from the pool of 32,000 (8,000 "select

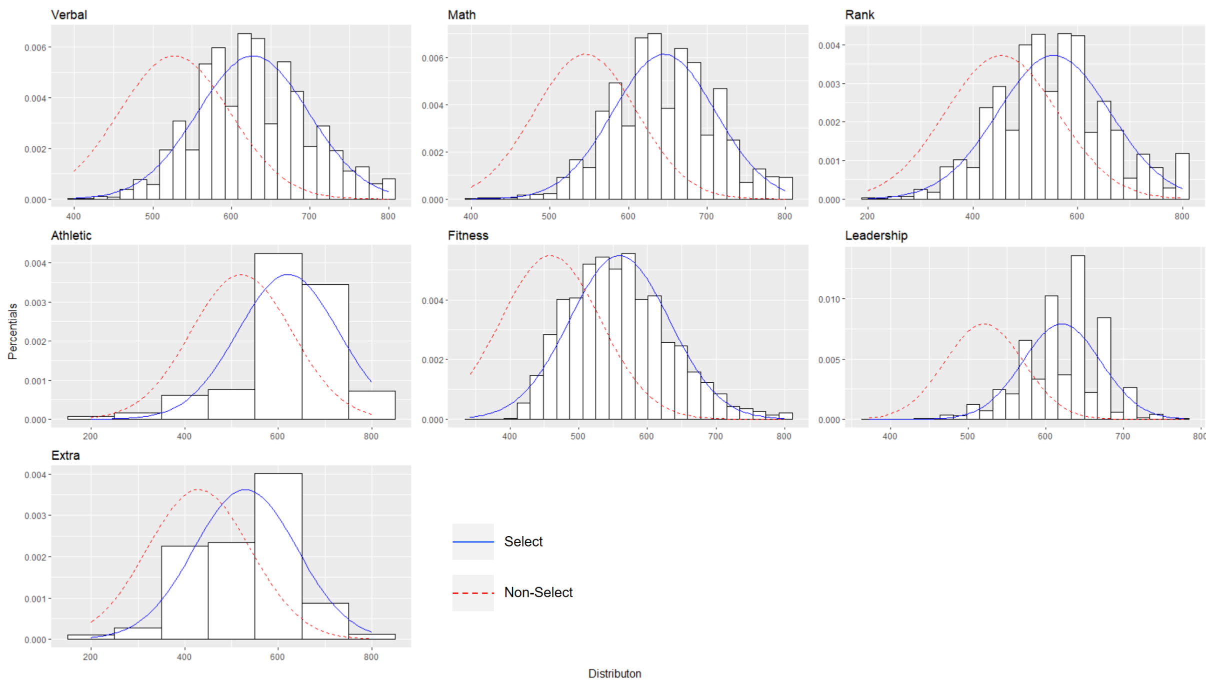


Figure 16. Competitive Normal Distributions of Attributes

and 24,000 "non-select) candidates, the MAVF scores were calculated, and the top 1,000 candidates were selected. This model was repeated for 1,000 times in a Monte Carlo simulation and compared to see how accurately the "selected candidates were chosen. This model correctly picked candidates from the "selected" pool 85.71% of the time (see Figure 17), which was a far better accuracy than the random selection probability of 1.56%.

Of note the 85.71% accuracy is likely a lower bound. This is due to the fact that at least some of the "non-selects" that were chosen were better candidates than those of the "selects" that were not chosen. The reason for this was the normal distribution that was used to create the "non-selects" can sometimes generate random values above those of the selects (see Figure 16). To illustrate this a single instance of the model was run and five "non-selects" chosen for the university were compared to five "selects" not chosen. Table 16 shows the MAVF score for each of the ten potential candidates. The "non-select" candidates clearly scored better than their counterparts

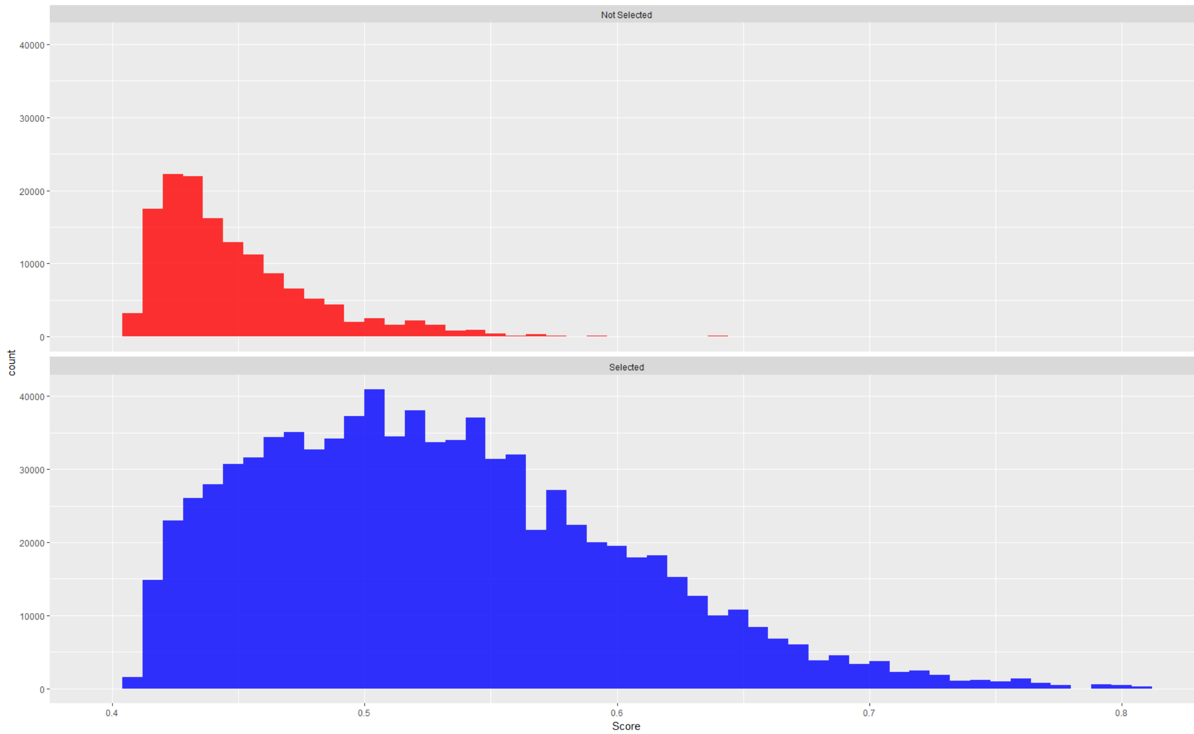


Figure 17. Competitive Monte Carlo Simulation Results

and therefore were better choices.

Table 16. Competitive Small Sample MAVF Scores

Student #	MAVF Score	Group
27890	0.6168	Non-Select
26452	0.5712	Non-Select
9977	0.5116	Non-Select
18696	0.4621	Non-Select
22349	0.4204	Non-Select
1608	0.3758	Select
2225	0.3621	Select
3921	0.3296	Select
2058	0.3021	Select
7986	0.2233	Select

This was further highlighted by using **R** to create a value breakout graph of the candidates MAVF scores (see Figure 18). This figure shows the deterministic sensitivity of each alternative. It allows for a quick and easy comparison of how each attribute affects the alternatives. All of the "non-selects" scored considerably higher in the most heavily weighted attribute, the SAT verbal score, than all of the candidates from the "select" population.

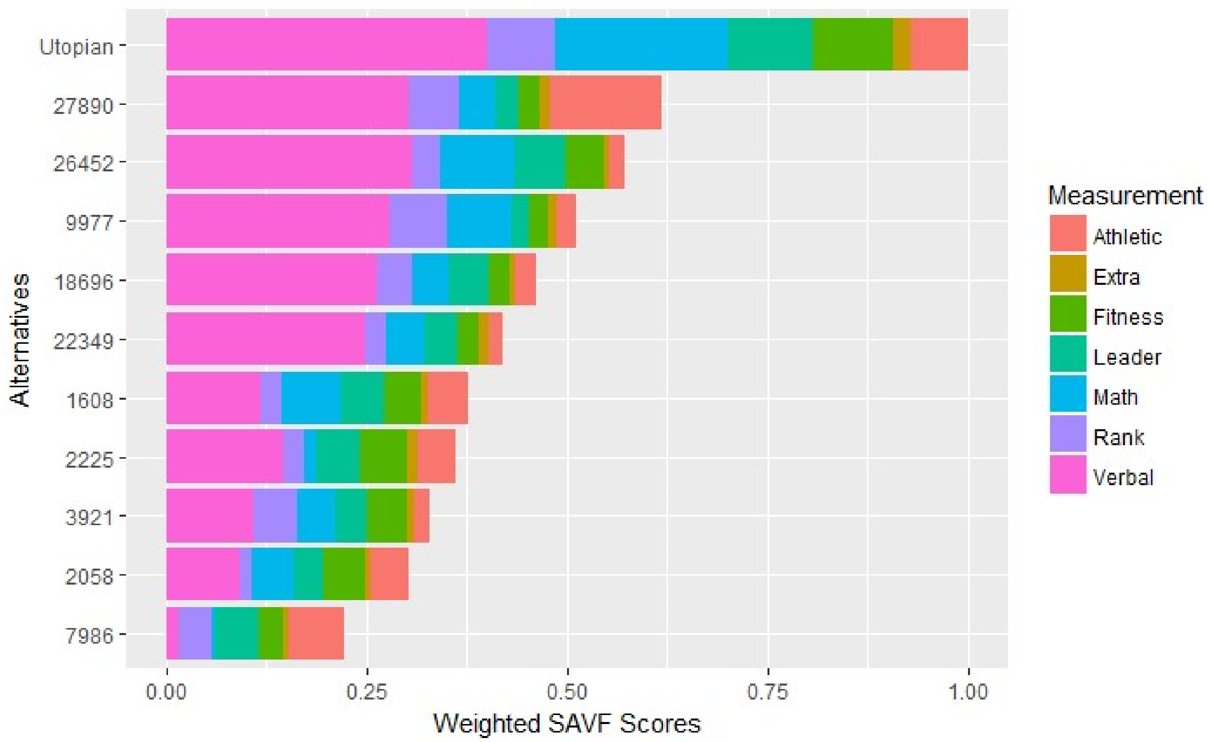


Figure 18. Competitive Small Sample Breakout Graph

Finally, sensitivity analysis was conducted to determine the impact on the rankings of alternatives to changes in the various assumptions of the model, specifically the weights (see Figure 19). The weights represent the relative importance attached to each evaluation measure. It was shown that the "non-selects" (shown by the solid lines) were resilient to changes in the weighting across all seven attributes. All attribute weights would have to be at least doubled (or halved in the case of the Verbal score) to have any impact on the "selects" overcoming the "non-selects".

4.4 Comparison

Analysis of the two case studies showed how a well defined value hierarchy and weighting can improve an organizations personnel selection. The less defined hierar-

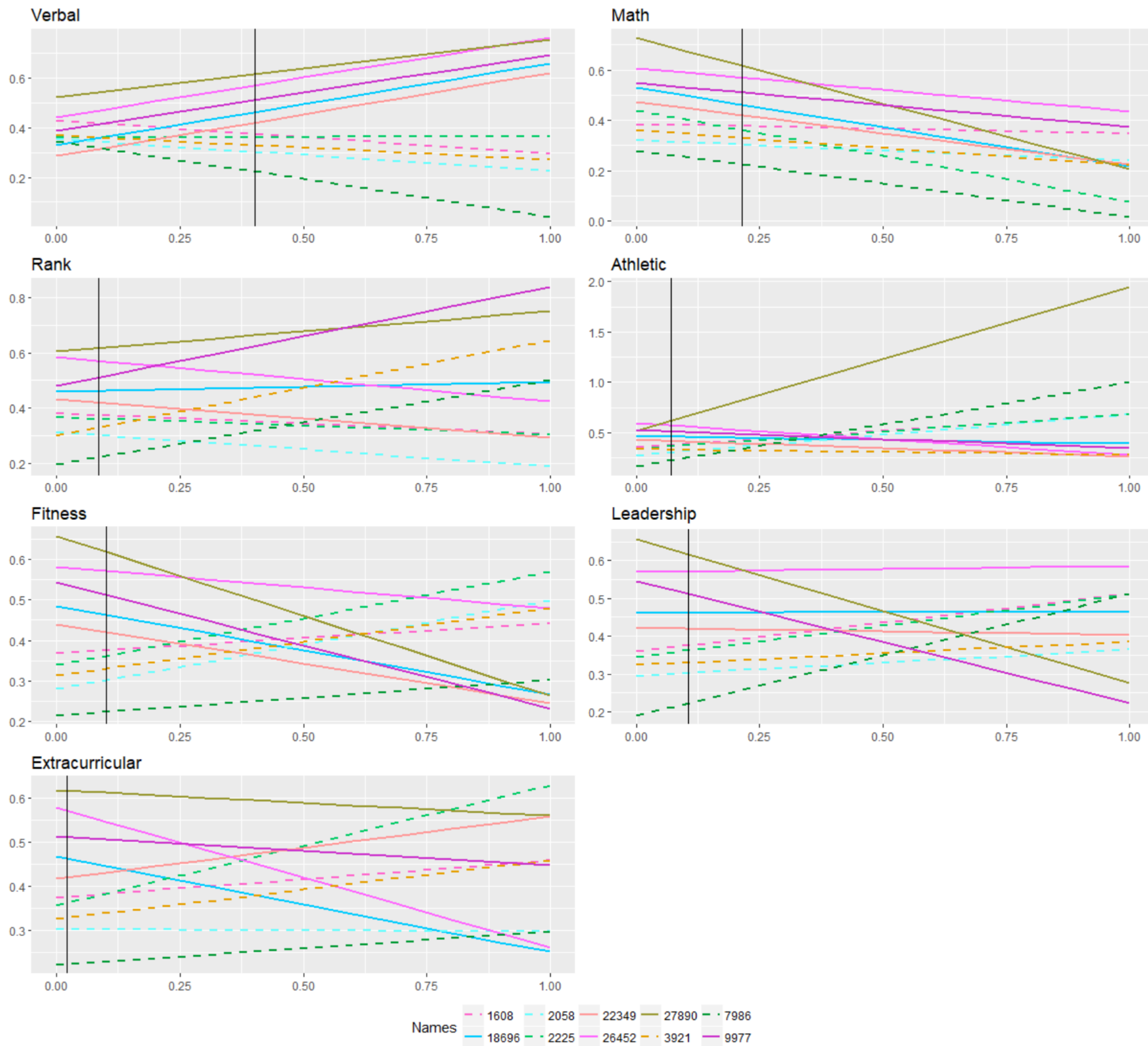


Figure 19. Case #2 Small Sample Sensitivity Analysis

chy from the first case study was only able to accurately place the "select" candidates just over half of the time, while the well defined hierarchy from the second case study was able to do so over 80% of the time. The transition from the hierarchy in the first case study to the hierarchy in the second is an example of how an organization can update their objectives to improve their quality of selection.

Additionally, the competitive university data allowed for additional analysis to be conducted if desired through deterministic and sensitivity analysis. This provided the

DM with more detailed information about how a candidate scored and how resilient those candidates were to changes in weighting, or value trade-offs. This transparency is beneficial to the selection process because it allows the choices to be debatable if necessary.

V. Conclusions and Future Research

5.1 Conclusion

This research showed how value focused thinking (VFT) could improve an organization's personnel selection process. First and foremost, VFT allows for organizations to codify their process so that it can be repeatable. The key to this is making sure an accurate picture of the organization's goals are captured through the value hierarchy. A well defined value hierarchy ensures that all objectives important to the organization are accounted for and that they have associated attributes for which to measure how successfully alternatives can meet these criteria. Our two case studies showed how a university with a well defined value hierarchy could successfully order alternatives at least 85% of the time while the university that lacked a well defined hierarchy was only accurate 55% of the time. Second, VFT allows for the ability to conduct deterministic sensitivity and sensitivity analysis on alternatives. This is particularly useful when working with a smaller group, when a smaller sample wants to be examined for additional consideration, or when there is a group of people selecting students because transparency leads to better discussion and coordination within the team. Finally, VFT provides a score for each alternative as opposed to simply rank ordering them. This provides decision makers (DM) the ability to examine the difference in magnitude between alternatives or students.

Throughout this research the statistical software **R** (Version 3.4.3) aided in calculations and visualizations. While there are several other programs that are designed specifically for VFT, **R** offers the distinct advantage that it is open source software and users can create and save programs to a global repository for anyone to use free of charge. The use of software assisted in solving calculations quickly and reduced chances of error by allowing for the ability to create custom functions that could be recalled. The same was done to aid in creating the visualization.

5.2 Recommendations for Future Work

Future work for this research could be to implement it in an organization's selection process and run it parallel to existing methods to compare results. It would be most successful for organizations that can create clear hierarchies based upon their requirements. This method could be successfully implemented in special operations units selection process, due to the challenges in selecting high performing individuals and the cost associated with accessing them.

A second area for future work would be to continue working with the two universities used in the case studies to build upon their selection process. These models can be further refined with platinum and gold standard documents to better replicate their criteria and weights associated with them. Uncertainty could also be added into the model to make it more robust.

Finally, the custom **R** functions that were used throughout this research can be packaged together and posted to the Comprehensive **R** Archive Network (CRAN). There is currently very few decision analysis packages in **R**, so this can help fill that void.

Appendix A. R Code

1.1 Calculating ρ

```
SAVF_calc_rho <- function(x_low , x_mid , x_high , increment = 1) {

 if (increment == 1) {
  z <- (x_mid - x_low) / (x_high - x_low)

   if (z <= 0.5) {
    f1 <- function (r) (-0.5 + (1 - exp(-z / r)) / (1 - exp(-1 / r)))
    value <- stats::uniroot(f1, interval = c(0,13))
   R <- value$root
    rho <- R * (x_high - x_low)
    return(rho)

   } else {
    z <- 1 - z
    f1 <- function (r) (-0.5 + (1 - exp(-z / r)) / (1 - exp(-1 / r)))
    value <-  stats::uniroot(f1, interval = c(0,13))
   R <- -value$root
    rho <- R * (x_high - x_low)
    return(rho)

 }} else {
  z <- (x_high - x_mid) / (x_high - x_low)
```

```
  if (z <= 0.5) {
   f1 <- function (r) (-0.5 + (1 - exp(-z / r )) / (1 - exp(-1 / r)))
   value <- stats::uniroot(f1, interval = c(0,13))
   R <- value$root
   rho <- R * (x_high - x_low)
   return(rho)

  } else {
   z <- 1 - z
   f1 <- function (r) (-0.5 + (1 - exp(-z / r)) / (1 - exp(-1 / r)))
   value <- stats::uniroot(f1, interval = c(0,13))
   R <- -value$root
   rho <- R * (x_high - x_low)
   return(rho)
   }
  }
}
```

1.2 Plotting Exponential SAVF

```
SAVF_exp_plot <- function (x, x_low, x_mid, x_high, increment = 1){

  if (increment == 1){
   rho <- SAVF_calc_rho(x_low, x_mid, x_high, increment = 1)
   x_desired <- x
   y_desired <- SAVF_exp_score(x, x_low, x_mid, x_high, increment = 1)
   x <- seq(x_low, x_high, by = (x_high - x_low)/1000)
```

```
    v <- SAVF_exp_score(x, x_low, x_mid, x_high, increment = 1)
    df <- data.frame(x = x, v = v)
    ggplot(df, aes(x, v)) +
      geom_line() +
      geom_point(aes(y = y_desired, x = x_desired), size = 3,
                                                    color = "blue") +
      xlab("Raw Value") + ylab("SAVF Score")

  } else {
    rho <- SAVF_calc_rho(x_low, x_mid, x_high, increment = 2)
    x_desired <- x
    y_desired <- SAVF_exp_score(x, x_low, x_mid, x_high, increment = 2)
    x <- seq(x_low, x_high, by = (x_high - x_low)/1000)
    v <- SAVF_exp_score(x, x_low, x_mid, x_high, increment = 2)
    df <- data.frame(x = x, v = v)
    ggplot(df, aes(x, v)) +
      geom_line() +
      geom_point(aes(y = y_desired, x = x_desired), size = 3,
                                                    color = "blue") +
      xlab("Raw Value") + ylab("SAVF Score")
  }
}
```

1.3 Exponential SAVF Score

```
SAVF_exp_score <- function(x, x_low, x_mid, x_high, increment = 1){
```

```
  if(increment == 1){
   rho <- SAVF_calc_rho(x_low, x_mid, x_high, increment = 1)
   value <- (1 - exp((x - x_low) / rho)) / (1 - exp((x_high - x_low) / rho)
   return (value)

  } else {
   rho <- SAVF_calc_rho(x_low, x_mid, x_high, increment = 2)
   value <- (1 - exp((x_high - x) / rho)) /(1 - exp((x_high - x_low) / rho)
   return (value)
  }
}
```

1.4 MAVF Score

```
MAVF_Scores <- function(SAVF_matrix, weights, names){

 SAVF_matrix[is.na(SAVF_matrix)] <- 0

 MAVF <- SAVF_matrix %*% weights
 value <- data.frame(names, MAVF)
 names(value) <- c("Name", "Score")
 value <- value [order(value$Score, decreasing = TRUE),]
 return (value)
}
```

1.5 MAVF Breakout Graph

```r
MAVF_breakout <- function(SAVF_matrix, weights, names){

 SAVF_matrix[is.na(SAVF_matrix)] <- 0

 SAVF <- t(SAVF_matrix) * weights
 MAVF <- SAVF_matrix %*% weights
 value <- data.frame(names, MAVF, t(SAVF))

 value %>%
  gather(Measurement, Value, -c(1,2)) %>%
   group_by(Measurement) %>%
   ggplot(aes(x = reorder(names, MAVF), y = Value, fill = Measurement)) +
   geom_bar(stat = "identity") +
   coord_flip() +
   ylab("Weighted SAVF Scores") + xlab("Alternatives") +
   ggtitle("Breakout of Weighted SAVF")
}
```

1.6 Sensitivity Analysis

```r
sensitivity_plot <- function(SAVF_matrix, weights, names, criteria){

 SAVF_matrix[is.na(SAVF_matrix)] <- 0

 i <- criteria
 x <- seq(0, 1, by = 0.1)
 m <- matrix(NA, nrow = length(weights), ncol = 11)
```

```
  for(j in 1:length(weights)){
   m[j,] <- (1 - x)(weights[j] / (1 - weights[i]))
   m[i,] <- x
   M <- data.frame(MAVF_Scores(SAVF_matrix, m, names))
   names(M) <- c("Names", x)}

 M %>%
   gather(Weight, Value, -c(1)) %>%
    ggplot(aes(x = as.numeric(Weight), y = Value,
                  group = Names, colour = Names)) +
     geom_line() + geom_vline(xintercept = weights[i]) +
     ylab("MAVF_Score") + xlab("Weight")
}
```

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14. ABSTRACT

Personnel selection has always and will continue to be a challenging endeavor for the military special operations. They want to select the best out of a number of qualified applicants. How an organization determines what makes a successful candidate and how to compare candidates against each other are some of the difficulties that top tier organizations like the special operations face. Value focused thinking (VFT) places criteria in a hierarchal structure and quantifies the values with criteria measurements, known as a decision model. The selection process can be similar to a college selecting their students. This research used college student entry data and strategic goals as a proxy for special operations applicants and standards. It compared two case studies of college admissions selection criteria. A sample pool of 8,000 select and 24,000 non-select candidates was generated from real world datasets. VFT was applied to develop a valid admissions selection process model. A Monte Carlo simulation was used to sample applicants from the generated pool and examined how accurately the models were able to select the correct applicants.

15. SUBJECT TERMS

Value Focused Thinking, Personnel Selection, Decision Analysis

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