Identifying markets for customized bicycles using data and business analytics

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List of Abreviations

Table 1: List of Abreviations

Abbreviation	**Explanation**
CTCT	The Cape Town Cycle Tour
ABSA	Amalgamated Banks of South Africa
UCI	Union Cycliste Internationale
UK	United Kingdom
US	United States
LBPP	Lower Back and Pelvis Pain
PFP	Patellofemoral Pain
BAGB	Bicycle Association of Great Britain
AHP	Analytic Hierarchy Process
3D	Three Dimensional
MIT	Massachusetts Institute of Technology
SIQR	Semi-Interquartile Range
RMB	Ren min Bi ("money of the people")
GPS	Global Positioning System
MAS	Multi-media Authorizing System
MOLP	Multi Objective Linear Programming
PCS	ProCyclingStats
ZAR	South African Rand
ITA	Italy
BEL	Belgium
FRA	France
NED	Netherlands
ESP	Spain
AUS	Australia
GER	Germany
GBR	Great Britain
COL	Colombia
DNS	Did Not Start
DNF	Did Not Finish
OTL	Over Time Limit
BNG	Belgium, Netherlands and Germany

Chapter 1

Introduction

Calculus Bikes is a start-up company that designs and builds customized bicycles for their clients based on their specified requirements and bio-metrics. They want to identify their niche clients and use a data driven entrance strategy to enter the relevant, identified markets with the most client potential.

Each person is different, has unique bio-metrics and no-one rides in the same manner. Calculus Bikes believes that riders should not be limited to a choice of only three frame sizes when choosing a bicycle (CALCULUS BIKES, 2018). The core team currently consists of a mechanical engineer and an industrial engineer and their office is situated in Hermanus, South Africa. To design and manufacture each bike according to unique specifications is costly and more time consuming than buying a standard bicycle from larger manufacturers; thus they have a very specific group of clients that have to be identified and targeted in order for them to have a competitive edge. These clients can possibly be identified by analyzing relevant open-source data from the cycling community and area demographics along with micro- and macroeconomics whilst considering relevant trade-offs and barriers to entry.

1.1 The Business Opportunity

At Calculus Bikes they pride themselves in building long term relationships with their clients. The design process is kicked off with a personal meeting with the client to confirm their riding style and bike expectations. The client is then measured and also undergoes a biometric fitment to determine their ideal position on the bike. The frame is designed and manufactured accordingly. Thereafter, the bike is fitted with components as discussed in the first meeting, followed by a bike setup to ensure that the client is satisfied with the final product.

1.1.1 Local and International Growth of Cycling as a Sport

According to industry specialists, the South African cycling industry has been growing at least 25% a year between 2004 and 2008 (Fin24, 2008) and according to Cycling South Africa there were 526 000 active cyclists in South Africa in 2009. Major cycling events hosted in South Africa include the 94.7 Cycle Challenge, The Cape Town Cycle Tour (CTCT), The ABSA Cape Epic and a leg of the Union Cycliste Internationale (UCI) World Cup was hosted in Stellenbosch on 10 March 2018 (Into Cycling Newspaper, 2017).

The CTCT became the Golden Bike Series' opening event in 2002 and consequently received international recognition from UCI. In the 2003 event, this series attracted cyclists from 44 countries (Brand South Africa, 2002). The CTCT also has an undeniable positive effect on the city's economy with an estimated amount of R500 million rolling into the Western Cape economy during the week of the CTCT (Capetowncycletour.com, 2018).

When the 94.7 Cycle Challenge was established in 1997, the event attracted about 4 000 cyclists, which increased to more than 22 000 cyclists in the 2002 event (Brand South Africa, 2002). The Cycle Challenge is currently the second largest timed cycle-race in the world and raised over R15.2 million for charity in 2017 with 25 300 riders finishing the race (Brand South Africa, 2002).

In the United Kingdom (UK), more than two million people rode their bikes at least once a week in 2016. British Cycling - UK cycling's governing body - stated that this was the highest this number has ever been (BBC News, 2016). Halfords, at the time responsible for 33% of bikes sold in the UK, experienced an 11% increase in sales in 2016 compared to 2015. In 2014, the Office for National Statistics confirmed that the sales of bicycles manufactured in the UK improved by 69%, while the London-based business, Rapha, experienced a 30% increase in sales for cycling apparel annually for 11 years in a row (BBC News, 2016). In 2015 in the United States (US), approximately 17.4 million bicycles were sold where mountain bikes were the top sellers in 2012, with a quarter of all specialty bike sales falling within the mountain biking category (Statista, 2016).

1.1.2 Bicycle Prices

Santam, one of South Africa's top short-term insurers, insured over 34 000 bicycles across the country in 2014. This makes perfectly sense since investing in a bicycle can cost a rider anywhere between R 8, 000.00 - R 80, 000.00 depending on the purpose intended (Santam, 2014).

According to the annual Cape Epic rider survey in 2017, the average bike value at the race increased to more than R90 000 - to be more precise, the exact estimated value was R95 662. Out of the 1332 entrants, 1141 (86%) took the optional survey, making it a relatively good sample size. In 2015 only 59% of the riders stated that their bikes cost more than R50 000, which increased to 89% in 2017. Of that 89%, 44% said their bike cost them more than R100 000. Not a single bike included in the survey cost less than R30 000 and 17.44% of the bikes cost over R130 000 (Lloyd and Lloyd, 2017). These statistics from the ABSA Cape Epic show that local and international riders are willing to pay large amounts of money for a proper bicycle, since not a single bike – from the survey – cost less than R30 000.

1.1.3 Choosing the Right Bicycle

How well a bicycle fits a cyclist's proportions inarguably and directly affects the rider's endurance, performance and overall comfort on a bicycle. According to recent studies published in The South African Journal of Sports Medicine, of the estimated 80 million cyclists in the US in 2016, nearly half of them suffered from neck related problems, 42% from knee related injuries, 31% hurt their back while 31% complained from sore and damaged hands (Byrnes, 2016).

Cycling injuries can mainly be grouped into direct trauma injuries (crashing) and overuse injuries. Overuse injuries in cyclists are as high as 85%, with lower back and pelvis pain (LBPP) and Patellofemoral pain (PFP) being the most common overuse injuries in recreational cyclists (Rodseth and Stewart, 2017) (Van Zyl, Schwellnus and Noakes, 2001). The most common of these injuries is Patellofemoral pain, which is largely associated with incorrect patellar alignment during the flexion to extension knee movement. Factors in the biomechanics of PFP in cyclists include incorrect training methods, incorrect bicycle and equipment setting and abnormal lower-limb biomechanics (Van Zyl, Schwellnus and Noakes, 2001). Besides the position of the cyclist, the bicycle may also influence the development of lumbo-pelvic pain. The lower back and pelvis are essential to driving and guiding the bicycle and vital for optimal performance and comfort. Cyclists spend long, uninterrupted hours in sustained forward flexion, which is regarded as a main contributor to lumbo-pelvic pain. A proper bicycle set-up is essential for injury prevention, safety, comfort, and peak performance (Rodseth and Stewart, 2017).

1.1.4 Barriers to Market Entry

The benefits of increased efficiency and decreased production costs often resulting from large, growing companies are referred to as economies of scale (Study.com, 2018). Larger established bicycle manufacturers (Specialized, Scott, Trek, Cannondale etc.) have the advantage of producing bicycles in high quantities limited to a few predetermined frame sizes and components; saving them time and money while excluding any relationship with the client whatsoever or “product as a service” that Calculus Bikes offers. The client is thus limited to readily built bikes which may not offer the exact comfort and requirements to assure the best possible riding experience. Fortunately for popular manufacturers, yet unfortunately for start-up companies, the value of a product or service increases the more popular it becomes among people. This concept is often referred to as the network effect. The network effect, brand recognition and exceptional service can altogether establish and improve product differentiation. New companies will have to invest extra time and money to enter desired markets and persuade potential customers with clear communication concerning unique product benefits and qualities; stressing the importance of targeting the most desirable, optimum local and foreign markets (Study.com, 2018).

In 2016, the Bicycle Association of Great Britain (BAGB) estimated that 50% of turnover in the bicycle industry was accounted for by bicycle retail sales with the remaining turnover being generated from bicycle accessories, parts and apparel sold. The BAGB also estimated that approximately 95% of bicycles bought by U.K. users were imported, meaning only the remaining 5% was locally manufactured (Frearson, 2017).

Since Calculus Bikes’ frames are not manufactured locally, it is desirable for the company to not only target local markets, but also focus on potential international markets since cycling is a more popular and well established sport in e.g. most European countries than in South Africa.

1.2 Research Design

Ultimately the most attractive markets for customized bicycles (road- and mountain biking) should be identified and a data driven entrance strategy suggested. A comprehensive market analysis will be necessary to identify both the presence and location of possible customers. An expected deliverable would thus include a heat map of where the most desirable markets for the customized bicycles are. A heat map (also choropleth map) is typically described as a map displaying mean values of a particular quantity in corresponding areas by using variances in shading and colouring. These average values can include different metrics of attractiveness to determine the optimum markets. These metrics can be used along with the Analytic Hierarchy Process (AHP) to determine a score for all prospective market candidates - these scores can then be visually represented in a heat map. The market climate of the potential identified areas will also be investigated, considered and discussed in the light of business engineering. The competitive market climate includes macro- and micro economics, barriers to entry and other trade-offs that should be considered before deciding to enter a new market.

1.3 Research Method

1.3.1 Data Analytics

Since it is desirable to know exactly who to target, a thorough customer identification analysis for Calculus Bikes’ target customers was considered an appropriate starting point. The data used to obtain information regarding who these customers might be, included statistics from top level races to determine where cycling was considered to be a popular or growing sport. Race statistics of events such as The ABSA Cape Epic, The Cape Town Cycle Tour, The Tour de France and the UCI (road and cross-country) championships were used to identify where exactly cycling was a popular sport and where the most riders that participate in these large events were coming from. The availability of data greatly determined the length and depth of the data analytics processes followed and iterations necessary to identify a few core countries for further in depth investigation. Factors of consideration typically started with nationality, age and performance and was used as a guide to investigate the cycling communities in certain areas showing potential as a desirable market. It was expected that the data could yield results that propose other factors or trigger the consideration of factors that were not considered in first iterations of analysis.

1.3.2 Business Engineering

Considering business engineering, barriers to enter potential markets need to be identified and quantified along with the potential gains of entering those markets. Macro- and microeconomics of the cycling industry consequently also play an important role in determining which markets will be worth entering.

After taking both data analytics and business engineering research results into consideration, the most important factors will be reconsidered and the Calculus Bikes team can assign a weight to each to construct a more accurate heat map of the countries that show the most client potential for customized bicycles. Ideally the objective would be to identify at least 3 optimum markets for possible entry.

Chapter 2

Literature Review

2.1 Prior Knowledge and Market Opportunity Identification

Gruber, MacMillan and Thompson (2013) studied the framework and composition of founders' of different start-up company's market choice sets. The founders in this case, refers to the entrepreneur or entrepreneurs who started a specific business. A market choice set can be defined as the final set of market opportunities that were identified after others have been considered, investigated and rejected. These sets were compiled prior to market entry by searching for relevant market opportunities in which the founders' product or service could be commercialized. The general approach followed in search for these market opportunities was studied along with the analysis of data collected from 469 ventures. The authors documented how the initial limitations from the aforementioned choice sets could impact the company's growth potential and overall likelihood of expansion over time. These initial limitations or constraints in potential markets can include barriers to entry such as economies of scale, brand recognition and access to distribution channels.

One of the two perspectives considered while theoretically developing the study were the inuence of founders' knowledge on the identication of market opportunities. In Shane's (2000) study regarding the commercialization of three-dimensional (3D) printing – which was developed at The Massachusetts Institute of Technology (MIT)- not one out of 8 entrepreneurs managed to identify more than one potential market opportunity for three-dimensional (3D) printing due to their restricted prior knowledge of customer requirements in other markets. For example, the entrepreneur with an architectural background proposed an opportunity for architects to print their models, while the entrepreneur who specialized in orthopaedics suggested an opportunity in custom-tted orthopaedic devices for the medical market. Thus relying only on prior knowledge to identify market opportunities results in smaller and less varied potential opportunities to choose from.

Prior knowledge due to individual life experience can be limiting and it may be a good idea to source innovative knowledge from beyond the company's boundaries to ensure a qualitatively rich strategic option between the identified potential market entry choices.

2.2 Gaining Wisdom from Knowledge through Data Analytics

A possible way of addressing a research question and gaining innovative knowledge could be to evaluate existing data concerning different aspects of the involved research topic. The process of data mining includes the translation of raw data into useful information by carefully analysing and interpreting its patterns. This process will most likely involve statistical or mathematical modelling, mostly including some kind of prediction (Passfield and Hopker, 2016). Data analytics' main advantage is to enable manufacturers to gain valuable, innovative information from the extracted data. Based on this information, forecasts can be generated for making important decisions (Wang et al, 2015). To gain wisdom, rather than just information from data, knowledge needs to be converted to wisdom. Knowledge is gained from information, and information is gained directly from raw data. This wisdom hierarchy of data processing can prove to be challenging, but could lead to a ground-breaking discipline in the sports sciences, namely sports analytics (Passfield and Hopker, 2016).

Passfield and Hopker (2016) used web-crawler or web-spider software to mine data for successive analysis and examined the development and success of elite cyclists' careers. A reflective analysis of race results was constructed.

To explore whether the success of senior elite athletes is dependent on their performance in junior competitions, race results from 1980-2014 were extracted for elite cycling races (both junior and senior) from an online database procyclingstats.com. They focussed on 25 races, obtaining data for more than 5000 cyclists from 75 countries. These data sets included the name, date of birth, nationality, race, and finishing position. The average career duration was established from the data and proved to be three seasons of level competing on average. From the results it was evident that a few highly prolific cyclists caused the data to be heavily skewed, thus a semi-interquartile range (SIQR) was used as an alternative way of illustrating the typical length of cyclists' careers. The SIQR was made up of half of the data between the 25th and 75th percentile and it was evident that half of all cyclists' careers ranged from one to seven years. Remarkably, 86% of cyclists didn't achieve a top 10 placing in the major races that were studied in their career at all (Passfield and Hopker, 2016).

Typically when a country performs well in a certain sport (or has many top athletes in certain sport disciplines), it implies that there is room for development of the sport along with favourable conditions, opportunities and facilities to practice the sport in that particular country. Similarly from Passfield and Hopker's (2016) study, elite race results over a few years can be used to determine where exactly most of the riders in top level teams come from - creating a framework of where to consider further investigation for attractive market prospects.

Passfield and Hopker (2016) also concluded that specified research questions could be answered using innovative results and findings by means of analysing large data sets. It does however require time-consuming and careful work to ensure such accurate and meaningful results. Some problems in the data such as changed race names or information recorded in both English and native languages were present. In some cases, results were missing and it was required to confirm whether a race took place or not. Similarly, misspelt names needed to be corrected before the analysis was conducted to ensure that results were assigned correctly (Passfield and Hopker, 2016). A sensitivity analysis can prove useful to determine how sensitive the data is to small errors or changes. In the prospective analysis for Calculus Bikes, expected errors included the exclusion of countries that are hyphenated (e.g. South-Africa) or written as two or more words (e.g. Czech Republic, United Arab Emirates or Hong Kong) from results. In certain instances the program used for data-analysis (R Studio) will most likely only pick abovementioned names up when written in inverted commas, which is not how it would typically appear in the raw data. This along with other minor, yet error-causing details is expected to be fixed before any final conclusions are made from the respective data analyses. Unfortunately, it is most likely that these errors will only be picked up during the prospective analyses and would have to be fixed or updated as they are noticed.

2.3 Data Visualization through Heat Maps

Wang et al. (2015) aimed their research towards the development of data-driven demand models for customer preference analysis and prediction under a competitive market environment - the Chinese auto market. Firstly, a regional analysis was conducted to understand the impact of geographical factors on customer preference. Usually when displaying regional variables, heat maps are used by generating nearly continuous shades in proportion to the extent or measurement of the observed variable. This technique allows the visualization of how a group measurement varies across a geographic area along with the corresponding level of variability within a particular region (Wang et al, 2015).

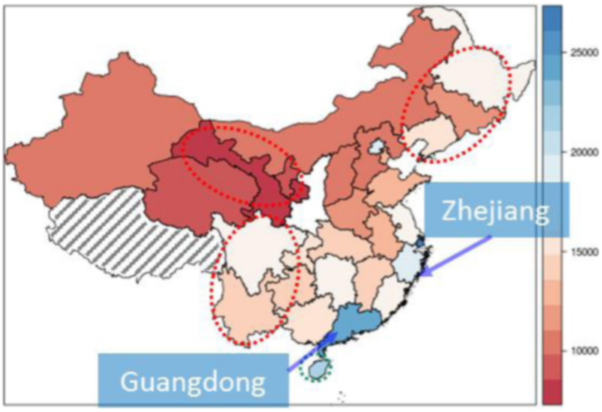

Figure 2.1: Monthly Household Income (in RMB) (Wang et al., 2015)

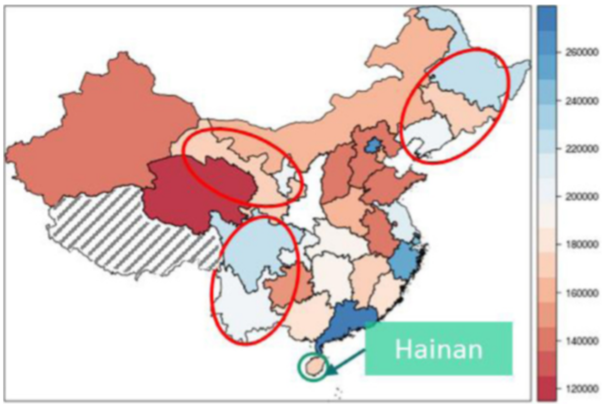

Figure 2.2: Vehicle Purchase Price (in RMB) (Wang et al., 2015)

The heat maps in Figure 1 and Figure 2 above demonstrate the comparison between household income and vehicle price respectively (Data: NCBS 2013), where RMB is an abbreviation for Ren min Bi, meaning "money of the people" or in simpler terms the currency of China. Customers' salaries are compared alongside purchased automobile prices in these figures, where approximations are based on the number of buyers per province. With the application of bi-polar colour progressions, the amount of buyers per province is then visualized within the heat map. The absolute value of the amount of interest is used to determine the shades of the colours with red and blue representing a low and high range respectively. An observation made from these maps was that the usage trends of a driver's vehicle is very different from region to region due to geographical circumstances and infrastructure (Wang et al, 2015).

Although the above-mentioned study demonstrates the basic idea of data visualization through heat maps, it does not directly correspond to the type of data to be used and results required from the heat maps desired for Calculus Bikes. The data used in Calculus Bikes' case cannot, unlike in Wang et al. (2015)'s study, be based on previous customer's data since they are looking to enter a new market. However, a national analysis along with aforementioned race statistics could prove useful to identify attractive markets in a similar way.

By collecting human mobility data from Global Positioning System (GPS) equipped smartphones, Sainio, Westerholm and Oksanen (2015) presented a map server with the ability to generate and visualize heat maps. These maps then display popular routes based on client preference, obtained from sports track data.

Figure 2.3: Popular Cycling Routes in Helsinki displayed in a Heat Map (Sainio, Westerholm and Oksanen, 2015)

In Figure 3, cycling routes and their corresponding popularity was plotted using more than 2.8 billion GPS data points. In Calculus Bikes' case, it would however be most useful to plot data from the cycling community along with area demographics using packages such as rworldmap and colorbrewer in R Studio. Since the aim is to determine the most desirable markets for their product as a service, these demographic factors can include, but are not limited to: age, gender, geographical location, household income, occupation status, and race. As previously discussed, data obtained from race statistics should be a good starting point to determine potential countries and later more specified areas for drawing up these maps as a visual representation of optimum markets.

2.4 The Analytic Hierarchy Process

A multi-objective decision making technique Calculus Bikes could consider is Thomas Saaty's Analytic Hierarchy Process (AHP). When the decision maker is confronted with multiple important objectives influencing the decision, it can prove difficult to say with certainty which decision is best. AHP can be used in such situations where multiple objectives are involved (Winston, 2004).

To illustrate how AHP works, suppose a person is considering a few possible job alternatives. In determining which job offer would be the overall best choice, it can be measured how well each of them meets the following objectives that are important to the decision-maker:

Table 2.1: Example Objectives for AHP (Winston, 2004)

Objective	**Description**
Objective 1	High starting salary (SAL)
Objective 2	Quality of life in city where job is located (QL)
Objective 3	Interest in work (IW)
Objective 4	Job location near family and relatives (NF)

2.4.1 Obtaining Weights for each Objective

Assuming that there are three attractive job offers to choose from. Let i = 1,2,3,4 be objective i. The objectives listed in table 2.1 are all important to consider for this particular decision, but all objectives may not be equally important. The AHP can generate a weight w_i for the i^{th} objective. These weights will (for convenience) always sum to 1.

Let there be n objectives. To obtain these weights, a $n \times n$ pairwise comparison matrix A can be written down with the entry in row i and column j (a_{ij}) indicating how much more important objective i is than objective j. This degree of importance can be measured on a integer-valued scale of 1-9, with each integer having an interpretation shown in table 2.2.

Table 2.2: Interpretation of Entries in Pairwise Comparison Matrix (Winston, 2004)

Value of a_{ij}	**Interpretation**
1	Objective i and j are equally important.
3	Objective i is slightly more important than j.
5	Objective i is strongly more important than j.
7	Objective i is very strongly more important than j.
9	Objective i is absolutely more important than j.
2,4,6,8	Intermediate values e.g. 2 falls between equally important and slightly more important.

It is necessary that for all i, a_{ii}=1, and if a_{ij}=k, then it is also necessary that a_{ji}=$\frac{1}{k}$ for consistency. Assuming the following pairwise comparison matrix was set up for the four objectives in table 2.1:

$$\mathbf{A} = \begin{array}{c} \\ SAL \\ QL \\ IW \\ NF \end{array} \begin{array}{c} \begin{array}{cccc} SAL & QL & IW & NF \end{array} \\ \begin{pmatrix} 1 & 5 & 2 & 4 \\ \frac{1}{5} & 1 & \frac{1}{2} & \frac{1}{2} \\ \frac{1}{2} & 2 & 1 & 2 \\ \frac{1}{4} & 2 & \frac{1}{2} & 1 \end{pmatrix} \end{array} \tag{2.1}$$

Note that there are slight inconsistencies in the pairwise comparison matrix. Since a_{13}=2, it implies that SAL is twice as important as IW. Since a_{32}=2, it then implies that IW is twice as important as QL, therefor it is expected for SAL to be 2×2 times more important than QL. Since a_{12}=5, the decision-maker decided that SAL is 5 (and not 4) times more important than QL. It is quite common for such inconsistencies to occur, although they do not cause any serious difficulties.

For each of A's columns, the entry in column i of A was divided by the sum of the entries in column i to yield a new, normalized matrix A_{norm}. The sum of the entries in each respective column sums to 1. From pairwise comparison matrix A, matrix A_{norm} was set up as follows:

$$\mathbf{A_{norm}} = \begin{array}{c} \\ SAL \\ QL \\ IW \\ NF \end{array} \begin{array}{c} \begin{array}{cccc} SAL & QL & IW & NF \end{array} \\ \begin{pmatrix} 0.5128 & 0.5000 & 0.5000 & 0.5333 \\ 0.5128 & 0.5000 & 0.5000 & 0.5333 \\ 0.2564 & 0.2000 & 0.2500 & 0.2667 \\ 0.1282 & 0.2000 & 0.1250 & 0.1333 \end{pmatrix} \end{array} \tag{2.2}$$

Finally, the weights carried by each of the objectives are determined from the normalized matrix by estimating W_i as the average of the entries in each of A_{norm}'s rows.

e.g,

$$w_1 = \frac{0.5128 + 0.5000 + 0.5000 + 0.5333}{4} = 0.5115 \quad (2.3)$$

thus,

$$w_1 = 0.5115,\ w_2 = 0.0986,\ w_3 = 0.2433,\ w_4 = 0.1466 \quad (2.4)$$

From these weights we can see that objective 1 has the highest weight, indicating that a high starting salary is the most important objective for the job seeker. This is followed by interest in work, nearness to relatives and quality of life. The next step would be to assign a score to every job based on how well it meets each of the previously stated objectives.

2.4.2 Finding the Score of an Alternative for an Objective

The next step is to determine how well each alternative satisfies each of the objectives listed in table 2.1. A pairwise comparison matrix is set up in a similar fashion as in section 2.4.1. Suppose that for SAL, the following matrix A is set up.

$$\mathbf{A} = \begin{array}{c} \\ Job_1 \\ Job_2 \\ Job_3 \end{array} \begin{array}{c} \begin{array}{ccc} Job_1 & Job_2 & Job_3 \end{array} \\ \begin{pmatrix} 1 & 2 & 4 \\ \frac{1}{2} & 1 & 2 \\ \frac{1}{4} & \frac{1}{2} & 1 \end{pmatrix} \end{array} \quad (2.5)$$

It is, for example, visible from matrix A that in terms of salary, Job_1 is a better option than Job_3. Normalizing matrix A by using the same procedure as in 2.4.1. yields:

$$\mathbf{A_{norm}} = \begin{array}{c} \\ Job_1 \\ Job_2 \\ Job_3 \end{array} \begin{array}{c} \begin{array}{ccc} Job_1 & Job_2 & Job_3 \end{array} \\ \begin{pmatrix} 0.571 & 0.571 & 0.571 \\ 0.286 & 0.286 & 0.286 \\ 0.143 & 0.143 & 0.143 \end{pmatrix} \end{array} \quad (2.6)$$

From A_{norm}, the average weights indicating how well each job scored on SAL was calculated as:

$$Job_1 \text{ SAL score} = 0.571,\ Job_2 \text{ SAL score} = 0.286,\ Job_3 \text{ SAL score} = 0.143$$

Repeating the process for QL, IW and NF respectively, yields the following weights indicating how well each job scored on each of the objectives:

Table 2.3: Job Seeker's Score for each Job and Objective (Winston, 2004)

Objective	**Job 1**	**Job 2**	**Job 3**
Salary	0.571	0.286	0.143
Quality of life	0.159	0.252	0.589
Interest in work	0.088	0.669	0.243
Proximity to Family	0.069	0.426	0.506

From table 2.3 and the weights assigned to each objective, the overall score for each job opportunity can be obtained. This is done by multiplying each job's score for a certain objective with the weight assigned to that objective.

Let j = 1,2,3 and s_j job offer j's score on objective i. For the j^{th} job offer the overall score for job offer j can be determined as follows:

$$h_j = \sum_{i=1}^{i=4} w_i s_j \tag{2.7}$$

After calculating each job's overall score, the job with the highest score will prove to be the optimal choice based on the identified objectives and the respective weights they carry.

Cheng and Li (2001) discussed AHP with regards to allocating weights to a group of elements. The elements that were chosen were derived from the most important business measures, and weights were assigned according to priority. AHP delivers a single experiential enquiry by combining a qualitative and quantitative research approach, and in Cheng and Li (2001)'s study they demonstrated how AHP could assist a selection panel in objective decision making concerning the best possible candidate for a job. The most important objectives that were identified for the abovementioned example included work experience, languages known, work experience and work performance. AHP was then used to allocate comparative weights for each of these dimensions (Cheng and Li, 2001).

Lai, Wong and Cheung (2002) reported on the results of how the AHP was used to assist with deciding-making in in a group decision environment. A multi-media authorizing system (MAS) had to be chosen and three potential MAS products were identified and eventually ranked using the AHP. The people participating in the study were six technically skilled and competent software engineers. They were taught how to use the AHP and asked to apply the technique to decide on the best MAS product for implementation. An interview along with a post-study survey were conducted with all of the participants to collect further feedback on the use of the technique, as compared to their regularly used Delphi technique, in supporting similar group decisions. The findings from the experiment results and survey showed that the AHP is more favourable compared to Delphi as the AHP helped the group members center their discussion around objectives, rather than alternatives. They also found the AHP to be more conducive to consensus building in group decision settings (Lai, Wong and Cheung, 2002).

In Calculus Bikes' case, AHP might be a better approach towards multi objective decision making than regression modelling or multi objective linear programming (MOLP). Regression modelling is a set of statistical processes for estimating the relationships among variables. To estimate these relationships, it is necessary to use paired data sets. Data sets are paired when each data set has the same number of data points and each data point in one data set is related to one, and only one, data point in the other data set. Linear programming is a mathematical technique for maximizing or minimizing a linear function of several variables, where MOLP has more than one objective. The tool is used to allocate values to resources to ensure that the desired outcome is met, thus finding the optimal solution. Constraints and variables can however not be prioritized by assigning weights like in the AHP.

Validating the model will prove to be quite challenging, as the data used is not paired, making it difficult to use techniques such as regression to verify and validate the results obtained. A possible method for validation is a Monte Carlo simulation - a computerized mathematical technique used to to account for risk in quantitative analysis and decision making. The decision-maker is provided with a variety of possible outcomes and the probabilities they will occur for any choice of action. The variety of outcomes can range from one extreme to the next and include everything in-between. Monte Carlo simulation makes use of random sampling and statistical modeling to estimate mathematical functions and imitate complex systems' operations (Harrison, Granja and Leroy, 2010).

Chapter 3

Methodology

3.1 Data Analytics

3.1.1 Popularity of Cycling as a Sport

To determine where exactly Calculus Bikes' potential customers are, data from top level cycling statistics were gathered from ProCyclingStats.com and uci.com. ProCyclingStats (PCS) is a large database with cycling statistics, race results, PCS and UCI rankings, starting lists and rider profiles. The Union Cycliste Internationale (UCI) is the world governing body for sports cycling and oversees international competitive cycling events. Data from The Tour de France (including only men) and La Course by Le Tour de France (including only women) were imported from uci.com and plotted in RStudio. The dataset included the name, age, position and nationality of all the riders that participated and was plotted in a scattergraph. From the scattergraph it was vaguely visible which countries yielded the most toplevel riders, and a trend concerning the age of female riders was also noted. To better illustrate this possible trend, the data from La Course and Le Tour was plotted on one density graph.

Datasets extracted from ProCyclingStats.com included the number of nationalities on toplevel teams from seasons 2016-2018. The data included statistics from both men and women toplevel cycling teams and the data were plotted in a heatmap in RStudio to obtain a rough idea of where the most cycling activity is. The heatmaps of the different seasons were compared to identify possible growing or stagnating markets.

3.1.2 Average Annual Income per Person

A customized bicycle is a quality product and can be quite expensive, ranging from R30 000 to R50 000 for the bike frame, without components. Adding components could easily cost an additional R10 000 - R30 000 or more, depending on what exactly the customer requirements are. An attractive market would thus not be an area where majority of the population receives a minimum loan per month, as it would just not be possible for the average person to afford the product. The next dataset collected was the average annual income per person in 2015. The data were collectted from WorldData.info and once again a heatmap was plotted in RStudio to visualy represent in which countries the average annual income per person was the highest and in which countries it was the lowest. The average annual income per person in Monaco and Liectenstein was R2 630 455 and R1 644 034 respectively. These figures were so high that it greatly influenced the spectrum of colors visible on the heatmap. The difference between these two countries' average annual incomes compared to the rest of the countries' annual incomes is of such a large magnitude that every country with an average annual income less than R1 000 000 appeared pale green or a light shade of blue. This caused the heatmaps to display a very limited color spectrum. After importing and working through many datasets concerning toplevel riders for previous research, it was noted that there were no toplevel riders from Monaco or Liechtenstein. Hence the decision to exclude these two countries from the average annual income heatmap.

3.1.3 Exchange Rate

The heatmaps from toplevel riders and average annual income can be compared with ease, showing that Europe, US and Australia might be the most attractive markets from both perspectives. This strategy however, then excludes countries like Spain and Colombia that yields quite a high number of toplevel riders each year, but have lower average incomes per year. It is also noted that the South African Rand (ZAR) is very strong compared to the Colombian peso, while the ZAR is very weak against the Euro (compared on 22 August 2018). This illustrates that comparing the heatmaps while only considering the countries that score the highest on one or two objectives might eliminate a few promising markets from the range of options. Furhermore, some of the objectives might be more important to the company than others, which is why it can prove usefull to prioritise these objectives by assigning weights to each of them.

3.2 The Analytic Hierarchy Process

Comparing the heatmaps of different objectives can be useful, although a final deliverable considering all the objectives in one heatmap would be the best visual representation of where the most attractive markets are. To determine a final score for the most attractive market opportunities, multiple iterations of AHP will be used to assign weights to the chosen objectives and score each market opportunity according to how well they meet each respective objective.

Objectives already discussed were the popularity of the sport in the country - derived from top level riders - and the wealth of the country - derived from average annual income per person. Since the bicycle frames are manufactured internationally and the head office is in South Africa, it might be a good idea to introduce exchange rate and the volatility of the exchange rate as objectives as well. These objectives will be considered in the first iteration of AHP.

Based on popularity of the sport over the past 3 years, the following 10 countries were identified as potential markets. The corresponding average annual income per person and the exchange rate compared to ZAR is also listed in the table.

Table 3.1: Potential Attractive Markets

Country	**Toplevel Riders**	**Annual Income**	**Exchange Rate**
Italy	61	\$37 700	0.060
Belgium	53	\$42 610	0.060
France	52	\$38 720	0.060
Netherlands	41	\$46 610	0.060
Spain	37	\$27 580	0.060
Australia	28	\$54 230	0.092
Germany	27	\$43 940	0.060
United States	19	\$56 850	0.070
Great Britain	18	\$42 370	0.055
Colombia	15	\$6 310	208.88

Let the top four potential markets j be Italy, Belgium, France and Netherlands, listed as j=1,2,3,4 respectively.

3.2.1 Obtaining Weights for each Objective

From table 3.1 the following preliminary objectives were identified:

All the objectives in table 3.2 are important to consider in deciding which market opportunities are the most attractive. For the above-mentioned objectives , let i= 1,2,3 be objective i. As previously

Table 3.2: Preliminary Objectives for Determining most Attractive Markets using AHP

Objective	**Description**
Objective 1	Popularity of Cycling as a Sport (PC)
Objective 2	Average Annual Income per Person (AAI)
Objective 3	Exchange Rate compared to ZAR (ER)

discussed, AHP generates a a weight wi for the ith objective and the chosen weights will sum to 1. Using the same interpretation of entries as listed in table 2.2, the pairwise comparison matrix A was set up as follows:

$$\mathbf{A} = \begin{array}{c} \\ PC \\ AAI \\ ER \end{array} \begin{array}{c} \begin{array}{ccc} PC & AAI & ER \end{array} \\ \begin{pmatrix} 1 & 5 & 4 \\ \frac{1}{5} & 1 & 6 \\ \frac{1}{4} & \frac{1}{6} & 1 \end{pmatrix} \end{array} \tag{3.1}$$

Matrix A from equation 3.1 indicates that the popularity of cycling as a sport (PC) is 5 times more important than the average annual income (AAI) of a country. Table 2.2 indicates that an a_{ij} value of 5 indicates that objective i is strongly more important than objective j - meaning that PC is strongly more important than AAI. PC was then chosen to be 4 times more important than the exchange rate (ER) of a country and since a_{23}=6, it also indicates that AAI is 6 times more important than ER. PC was chosen as the most important objective, because if there is no interest in cycling as a sport in a country, it would not matter how wealthy the average person in that country is since they would not be interested in the product. Similarly, the AAI is much more important than the ER, because even if the ZAR is strong compared to the other country's currency, it would mean nothing if the average person in that country could not possibly afford a custom-built bicycle. Normalizing matrix A yields:

$$\mathbf{A_{norm}} = \begin{array}{c} \\ PC \\ AAI \\ ER \end{array} \begin{array}{c} \begin{array}{ccc} PC & AAI & ER \end{array} \\ \begin{pmatrix} 0.6897 & 0.8108 & 0.3636 \\ 0.1379 & 0.1622 & 0.5454 \\ 0.1724 & 0.0270 & 0.0900 \end{pmatrix} \end{array} \tag{3.2}$$

From matrix A_{norm}, weights w_i were calculated as follows:

$$w_1 = \frac{0.6897 + 0.0.8108 + 0.3636}{3} = 0.6214 \tag{3.3}$$

$$w_2 = \frac{0.1379 + 0.1622 + 0.5454}{3} = 0.2818 \tag{3.4}$$

$$w_3 = \frac{0.1724 + 0.0270 + 0.0900}{3} = 0.0965 \tag{3.5}$$

It is evident from the assigned weights and equation 3.3 that objective 1 carries the most weight, indicating that the popularity of cycling as a sport is the most important objective in this case. This is followed by average annual income per person and the exchange rate compared to ZAR.

3.2.2 Finding the Score of an Alternative for an Objective - Iteration 1

Assigning a score to every prospective market opportunity based on how well it meets each of the previously stated objectives follows.

Suppose that for PC, the following matrix A was set up:

$$\mathbf{A} = \begin{array}{c} \\ ITA \\ BEL \\ FRA \\ NED \end{array} \begin{array}{c} \begin{array}{cccc} ITA & BEL & FRA & NED \end{array} \\ \begin{pmatrix} 1 & 3 & 3 & 6 \\ \frac{1}{3} & 1 & 2 & 3 \\ \frac{1}{3} & \frac{1}{2} & 1 & 3 \\ \frac{1}{6} & \frac{1}{3} & \frac{1}{3} & 1 \end{pmatrix} \end{array} \tag{3.6}$$

Normalizing matrix A yields:

$$\mathbf{A_{norm}} = \begin{array}{c} \\ ITA \\ BEL \\ FRA \\ NED \end{array} \begin{array}{c} \begin{array}{cccc} ITA & BEL & FRA & NED \end{array} \\ \begin{pmatrix} 0.5455 & 0.6207 & 0.4737 & 0.4615 \\ 0.1818 & 0.2069 & 0.3158 & 0.2308 \\ 0.1818 & 0.1034 & 0.1579 & 0.2308 \\ 0.0909 & 0.0690 & 0.0526 & 0.0769 \end{pmatrix} \end{array} \tag{3.7}$$

Suppose that for AAI, the following matrix A was set up:

$$\mathbf{A} = \begin{array}{c} \\ ITA \\ BEL \\ FRA \\ NED \end{array} \begin{array}{c} \begin{array}{cccc} ITA & BEL & FRA & NED \end{array} \\ \begin{pmatrix} 1 & \frac{1}{6} & \frac{1}{2} & \frac{1}{6} \\ 6 & 1 & 6 & \frac{1}{2} \\ 2 & \frac{1}{6} & 1 & \frac{1}{6} \\ 6 & 2 & 6 & 1 \end{pmatrix} \end{array} \tag{3.8}$$

Normalizing matrix A yields:

$$\mathbf{A_{norm}} = \begin{array}{c} \\ ITA \\ BEL \\ FRA \\ NED \end{array} \begin{array}{c} \begin{array}{cccc} ITA & BEL & FRA & NED \end{array} \\ \begin{pmatrix} 0.0667 & 0.0500 & 0.0370 & 0.0909 \\ 0.4 & 0.3 & 0.4444 & 0.2727 \\ 0.1333 & 0.0500 & 0.0741 & 0.0909 \\ 0.4 & 0.6 & 0.4444 & 0.5454 \end{pmatrix} \end{array} \tag{3.9}$$

Suppose that for ER, the following matrix A was set up:

$$\mathbf{A} = \begin{array}{c} \\ ITA \\ BEL \\ FRA \\ NED \end{array} \begin{array}{c} \begin{array}{cccc} ITA & BEL & FRA & NED \end{array} \\ \begin{pmatrix} 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 \end{pmatrix} \end{array} \tag{3.10}$$

Normalizing matrix A yields:

$$\mathbf{A_{norm}} = \begin{array}{c} \\ ITA \\ BEL \\ FRA \\ NED \end{array} \begin{array}{c} \begin{array}{cccc} ITA & BEL & FRA & NED \end{array} \\ \begin{pmatrix} 0.2500 & 0.2500 & 0.2500 & 0.2500 \\ 0.2500 & 0.2500 & 0.2500 & 0.2500 \\ 0.2500 & 0.2500 & 0.2500 & 0.2500 \\ 0.2500 & 0.2500 & 0.2500 & 0.2500 \end{pmatrix} \end{array} \tag{3.11}$$

Table 3.3: Potential Market Opportunities' Scores on each Objective

	PC	**AAI**	**ER**
ITA	0.5254	0.0662	0.2500
BEL	0.2338	0.3542	0.2500
FRA	0.1685	0.0871	0.2500
NED	0.0724	0.4925	0.2500

Let j = 1,2,3,4 and s_j country j's score on objective i. For the j^{th} country the overall score for country j can be determined as follows:

$$h_j = \sum_{i=1}^{i=3} w_i s_j \tag{3.12}$$

Consequently, the market with the highest score will prove to be the optimal choice based on the identified objectives and the respective weights they carry.

For the second iteration of AHP, the previously mentioned objectives were adjusted to conduct a sensitivity analysis. Since the alternative markets in the previous iteration were all located in Europe, the exchange rate made no difference in the decision making process as seen in equations 3.10 and 3.11. To include more alternatives without over-complicating the AHP process, some of the European countries was be grouped together geographically. Germany was added to the list of alternatives to be evaluated next, since it shows a high annual income and fairly high number of top-level riders. Belgium, Netherlands and Germany was then grouped together geographically since they are right next to each other on the world map. The United States and Australia was also added to the list of alternatives. To simplify the conduction of the pairwise comparison matrices, the annual income of each alternative was determined as a percentage from table 3.1 - making it easier to identify how alternatives score against each other. The objectives and their weights obtained from equations 3.1-3.5 in the first iteration was kept the same for the second iteration.

Let the alternative containing Belgium, Netherlands and France be BNG. The amount of top-level riders for this alternative was determined by calculating the group average of the top-level riders. The same was done for the average annual income, and since the exchange rate is the same for these three countries it remained unchanged for the geographical group.

Table 3.4: Potential Attractive Markets

Country	**Toplevel Riders**	**Annual Income (in %)**	**Exchange Rate**
Italy	61	9.4981	0.060
BNG	40	11.1828	0.060
France	52	9.7551	0.060
Australia	28	13.6627	0.092
United States	19	14.3228	0.070

3.2.3 Finding the Score of an Alternative for an Objective - Iteration 2

Assigning a score to each of the newly identified prospective market opportunities in table 3.3 based on how well it meets each of the previously stated objectives follows.

Suppose that for PC, the following matrix A was set up:

$$\mathbf{A} = \begin{array}{c} \\ ITA \\ BNG \\ FRA \\ AUS \\ US \end{array} \begin{array}{c} \begin{array}{ccccc} ITA & BNG & FRA & AUS & US \end{array} \\ \begin{pmatrix} 1 & 6 & 3 & 8 & 9 \\ \frac{1}{6} & 1 & \frac{1}{3} & 3 & 6 \\ \frac{1}{3} & 3 & 1 & 7 & 8 \\ \frac{1}{8} & \frac{1}{3} & \frac{1}{7} & 1 & 3 \\ \frac{1}{9} & \frac{1}{6} & \frac{1}{8} & \frac{1}{3} & 1 \end{pmatrix} \end{array} \tag{3.13}$$

Normalizing matrix A yields:

$$\mathbf{A_{norm}} \begin{array}{c} \\ ITA \\ BNG \\ FRA \\ AUS \\ US \end{array} \begin{array}{c} \begin{array}{ccccc} ITA & BNG & FRA & AUS & US \end{array} \\ \begin{pmatrix} 0.5760 & 0.5714 & 0.6520 & 0.4138 & 0.3333 \\ 0.09602 & 0.0952 & 0.0724 & 0.1552 & 0.2222 \\ 0.1920 & 0.2857 & 0.2173 & 0.3621 & 0.2963 \\ 0.072 & 0.0317 & 0.0311 & 0.0517 & 0.1111 \\ 0.06400 & 0.0159 & 0.0272 & 0.0172 & 0.0370 \end{pmatrix} \end{array} \tag{3.14}$$

Suppose that for AAI, the following matrix A was set up:

$$\mathbf{A} = \begin{array}{c} \\ ITA \\ BNG \\ FRA \\ AUS \\ US \end{array} \begin{array}{c} \begin{array}{ccccc} ITA & BNG & FRA & AUS & US \end{array} \\ \begin{pmatrix} 1 & \frac{1}{4} & \frac{1}{2} & 7 & \frac{1}{8} \\ 4 & 1 & 4 & \frac{1}{5} & \frac{1}{6} \\ 2 & \frac{1}{4} & 1 & \frac{1}{7} & \frac{1}{8} \\ 7 & 5 & 7 & 1 & \frac{1}{3} \\ 8 & 6 & 8 & 3 & 1 \end{pmatrix} \end{array} \tag{3.15}$$

Normalizing matrix A yields:

$$\mathbf{A_{norm}} = \begin{array}{c} \\ ITA \\ BNG \\ FRA \\ AUS \\ US \end{array} \begin{array}{c} \begin{array}{ccccc} ITA & BNG & FRA & AUS & US \end{array} \\ \begin{pmatrix} 0.0455 & 0.02 & 0.0244 & 0.0319 & 0.0714 \\ 0.1818 & 0.08 & 0.1951 & 0.0446 & 0.0953 \\ 0.0909 & 0.02 & 0.0488 & 0.0319 & 0.0714 \\ 0.3182 & 0.4000 & 0.3415 & 0.2229 & 0.1905 \\ 0.3636 & 0.48 & 0.3902 & 0.6688 & 0.5714 \end{pmatrix} \end{array} \tag{3.16}$$

Suppose that for ER, the following matrix A was set up:

$$\mathbf{A} = \begin{array}{c} \\ ITA \\ BNG \\ FRA \\ AUS \\ US \end{array} \begin{array}{c} \begin{array}{ccccc} ITA & BNG & FRA & AUS & US \end{array} \\ \begin{pmatrix} 1 & 1 & 1 & \frac{1}{4} & \frac{1}{2} \\ 1 & 1 & 1 & \frac{1}{4} & \frac{1}{2} \\ 1 & 1 & 1 & \frac{1}{4} & \frac{1}{2} \\ 4 & 4 & 4 & 1 & 3 \\ 2 & 2 & 2 & \frac{1}{3} & 1 \end{pmatrix} \end{array} \tag{3.17}$$

Normalizing matrix A yields:

$$\mathbf{A_{norm}} = \begin{array}{c} \\ ITA \\ BNG \\ FRA \\ AUS \\ US \end{array} \begin{array}{c} \begin{array}{ccccc} ITA & BNG & FRA & AUS & US \end{array} \\ \begin{pmatrix} 0.1111 & 0.1111 & 0.1111 & 0.1200 & 0.0909 \\ 0.1111 & 0.1111 & 0.1111 & 0.1200 & 0.0909 \\ 0.1111 & 0.1111 & 0.1111 & 0.1200 & 0.0909 \\ 0.4444 & 0.4444 & 0.4444 & 0.4800 & 0.5455 \\ 0.2222 & 0.2222 & 0.2222 & 0.1600 & 0.1818 \end{pmatrix} \end{array} \tag{3.18}$$

From matrices 3.13-1.18, the average weights indicating how well each country scored on each of the objectives respectively was calculated as follows:

Table 3.5: Potential Market Opportunities' Scores on each Objective

	PC	**AAI**	**ER**
ITA	0.5093	0.0386	0.1088
BNG	0.1282	0.1194	0.1088
FRA	0.2707	0.0526	0.1088
AUS	0.0595	0.2946	0.4718
US	0.0323	0.4948	0.2017

As in iteration one, let j = 1,2,3,4,5 and s_j country j's score on objective i. For the j^{th} country the overall score for country j can be determined as follows:

$$h_j = \sum_{i=1}^{i=3} w_i s_j \tag{3.19}$$

Consequently, the market with the highest score will prove to be the optimal choice based on the identified objectives and the respective weights they carry.

Chapter 4

Results and Discussion

4.1 Data Analysis and Visualization

As a starting point to determine the popularity of the sport in different countries, race results from The Tour de France and La Course by Le Tour de France were analysed and the following graphs were plotted in RStudio. The two graphs show the nationality, age and position of each of the riders - men and women respectively - giving us a vague idea of where the most cyclists that participated in this top-level race came from. The grey dots indicate riders that did not start (DNS), did not finish (DNF) or went over the time limit (OTL).

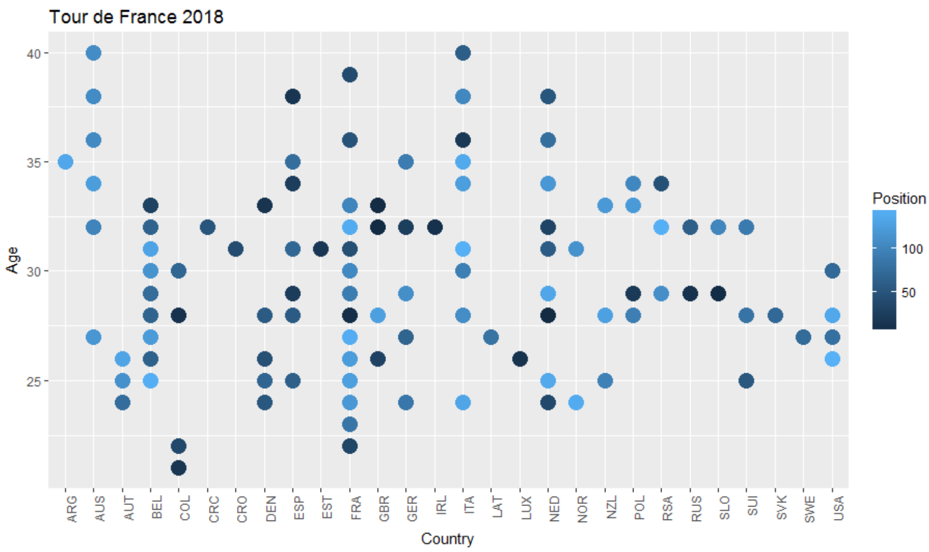

Figure 4.1: Country, Rank and Age of Top Riders (Elite Men) 2018

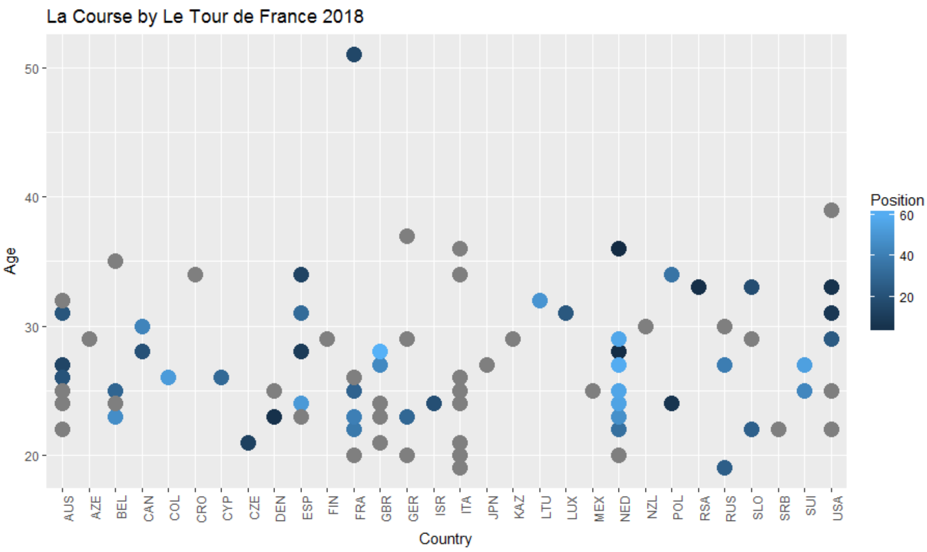

Figure 4.2: Country, Rank and Age of Top Riders (Elite Women) 2018

Figure 4.1 and Figure 4.2 illustrate that it is quite hard to make sense of data related to countries in a traditional scatter-graph. Although it was not explicitly investigated, certain trends concerning the age of male and female riders were vaguely identified. These trends might be useful for future marketing campaigns or further in depth customer research.

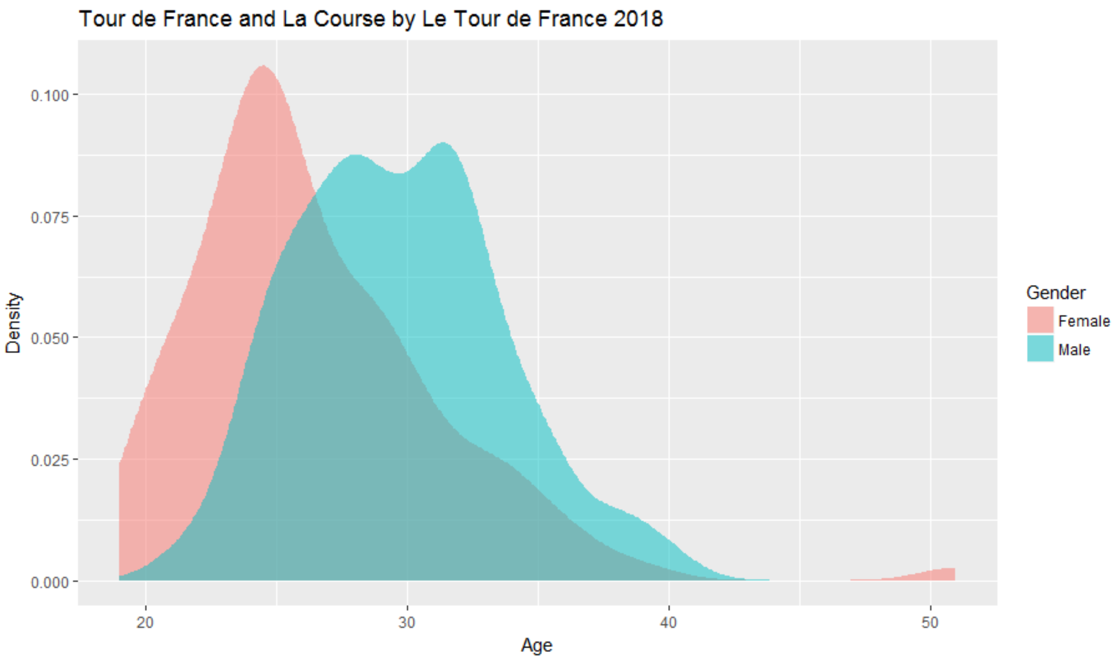

Figure 4.3: Age distribution of Le Tour de France and La Course by Le Tour de France 2018

Figure 4.3 illustrates this aforementioned age trend much better - it seems that women tend to peak in their cycling career at a much younger age and retire much sooner than men. The number of women competing in top level races between the age of 27 and 35 is significantly lower than the number of men competing at that age. Another interesting trend noted while extracting the data, was that the distribution of nationalities competing in a mens race were not as heavily affected by the location of the race than with the womens races. A race held in France would typically include much more entrants from France than from other countries. This could perhaps be due to women preferring local races due to family responsibilities. This trend is significant, because it may have an effect on the company's marketing approach towards men and women respectively.

The following, simple heat maps were generated in RStudio using data obtained from ProCyclingStats.com. The packages rworldmap and colorbrewer were used along with the data containing the number of riders in top teams per country in the years 2016-2018. The colour scale at the bottom of each map represents the number of cyclists (men and women) from top level teams. Dark blue represents one rider and vibrant red represents the highest number of cyclists from the same country obtained from the corresponding year's dataset. The countries that appear grey did not deliver any riders in top level teams in that specific year.

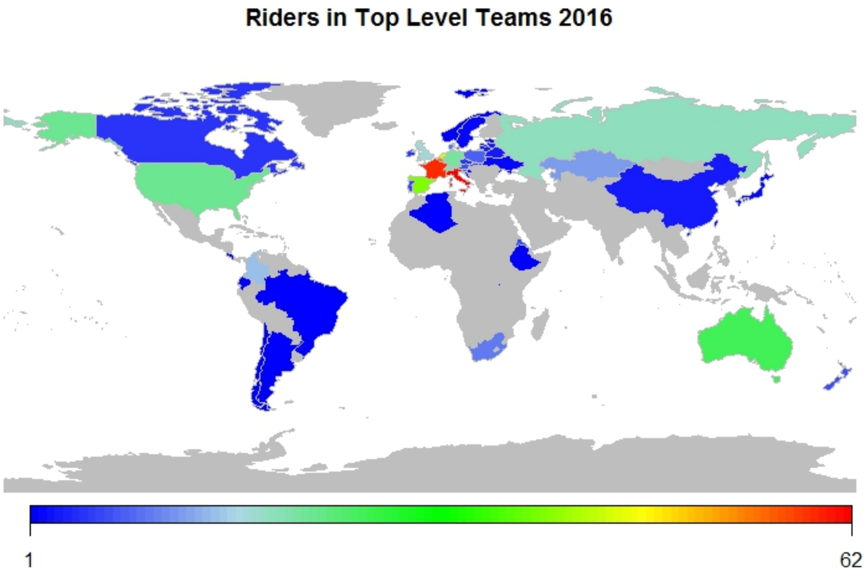

Figure 4.4: Riders in Top Level Teams 2016

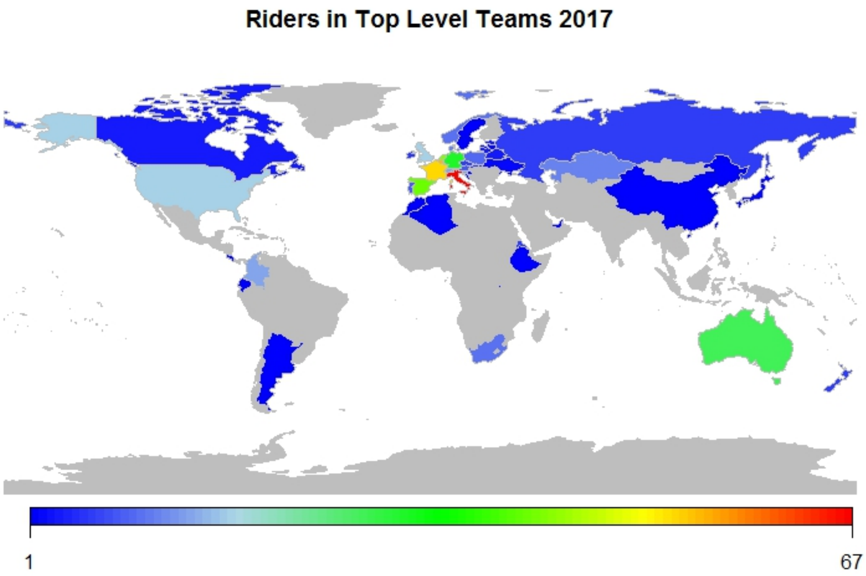

Figure 4.5: Riders in Top Level Teams 2017

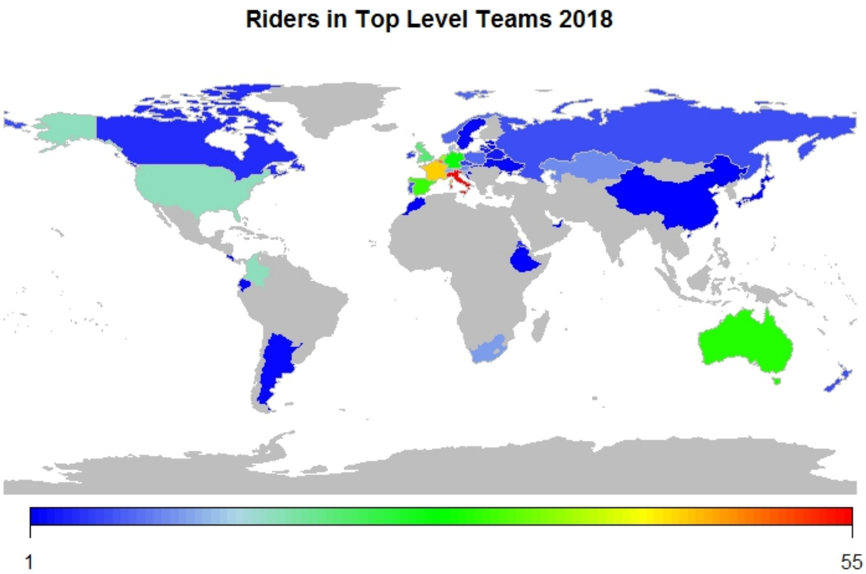

Figure 4.6: Riders in Top Level Teams 2018

It is clearly evident from these maps that European countries and Australia usually have the most professional cyclists in top level teams such as Astana, Sunweb, Hans Bora Grohe, Team Sky, Dimension Data etc. A notable change from 2016 to 2018 is that Australia seems to be getting warmer, while France got a little colder by going from red to yellow. The Us went from pale green to light blue from 2016-2017, but went from light blue to pale green again in 2018. By analysing data from professional cyclists, a basic framework of where there is a possible market opportunity for customized bicycles can be generated, although there are many other factors still to be considered to form a better idea of where the most attractive markets are.

The following map was drawn using data concerning the average annual income per person in 2015. As previously discussed, Monaco and Liechtenstein were excluded from the dataset as the average annual income was so high that it limited the color spectrum of the heatmap and since there are no top-riders from either countries.

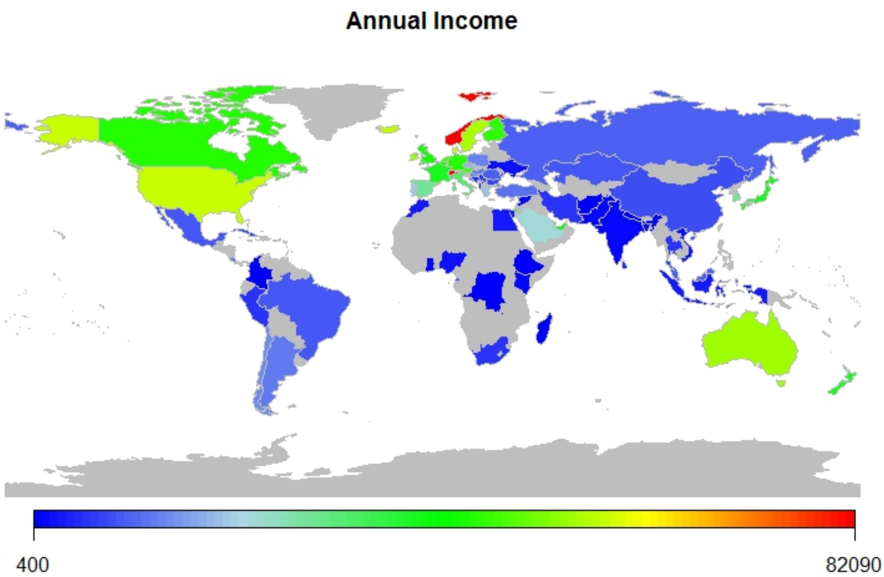

Figure 4.7: Average Annual Income per person over 76 Countries (2015)

It is notable from figure 4.7 that the European countries, the United States, Canada, Australia, Japan and New Zealand show a higher average income per person than most countries.

4.2 The Analytic Hierarchy Process

For the model to be more accurate, the discussed objectives were used in AHP and the following results were calculated.

Table 4.1: Overall AHP Score Obtained by Each Market - Iteration 1

Country	**AHP Score**
ITA	0,3679
BEL	0,2692
FRA	0,1534
NED	0,2093

The objectives, their weights, and how well each market opportunity adhered to these objectives influenced the attractiveness of each market by influencing the AHP score. The following heatmap containing these results was plotted in RStudio, and since all four countries are in Europe, the world map shown in figure 4.8 is zoomed in on Europe specifically.

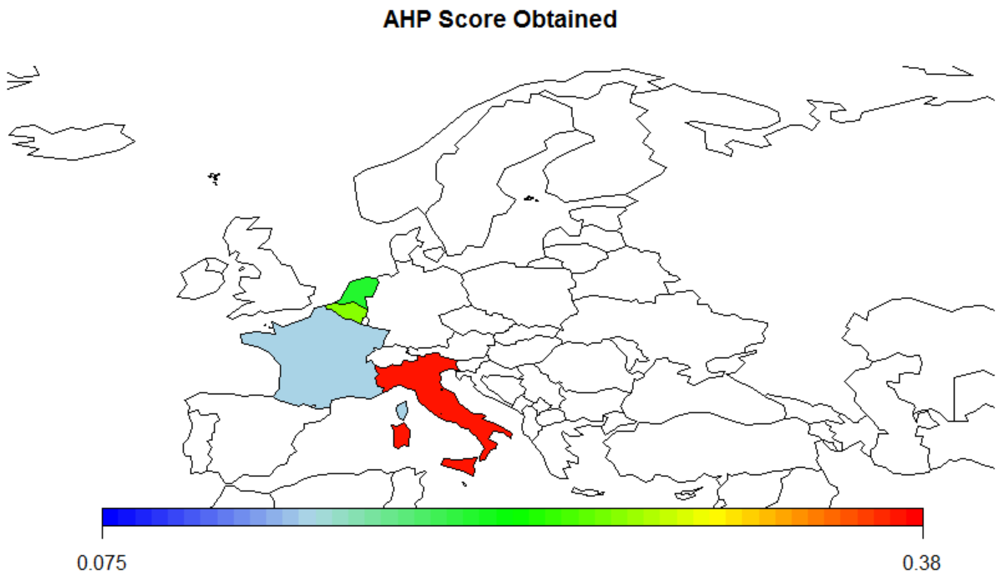

Figure 4.8: Results Obtained from AHP - Iteration 1

From the AHP results and figure 4.8 it is visible that Italy, Belgium and The Netherlands are the most attractive markets based on the popularity of cycling as a sport, the average annual income per person and the exchange rate compared to ZAR. Since these results were obtained by only looking at three objectives and comparing only four potential markets, the heatmap's accuracy can be improved by introducing more objectives into the AHP equation and comparing more potential markets. Since the exchange rate of all four countries' currency (Euro) was the same compared to ZAR, this objective did not influence the decision, meaning the decision was basically based on the popularity of the sport and the average annual income per person only. In the second iteration of AHP, three European countries within close proximity (Belgium, Netherlands, France) were grouped together geographically and Australia and the United States were also considered as potential markets. This iteration yielded the following results.

Table 4.2: Overall AHP Score Obtained by Each Market - Iteration 2

Country	**AHP Score**
ITA	0,34
FRA	0,19
US	0,18
AUS	0,17
BNG	0.12

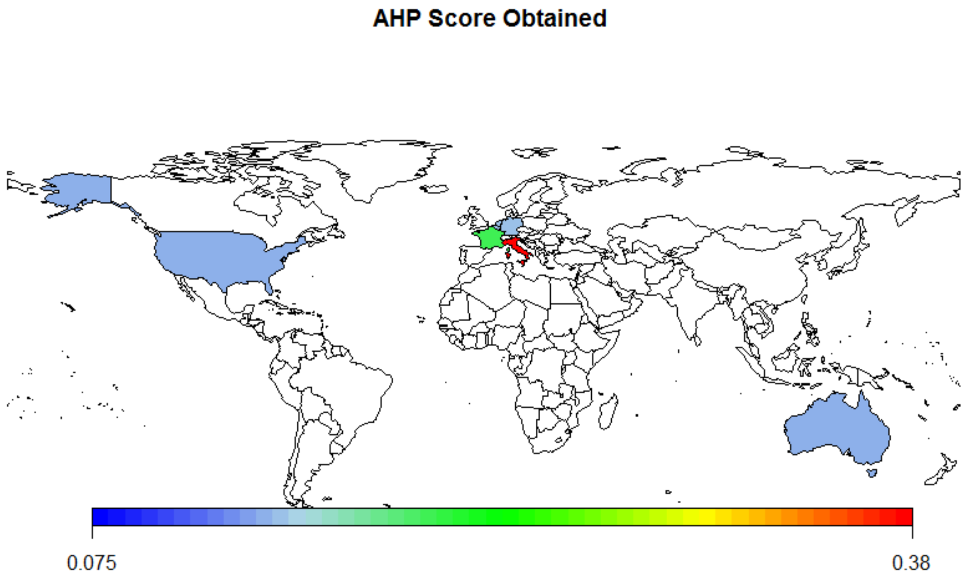

Figure 4.9: Results Obtained from AHP - Iteration 2

From figure 4.9 it is visible that Italy and France are considered the most attractive markets compared to the potential markets listed in table 4.2 after the second iteration of the AHP. The other markets' scores lie fairly close to each other.

Quite surprisingly, even though the BNG group had much more top-level riders than the US and AUS - the group still obtained the lowest score. This was most probably due to their higher annual incomes and better exchange rates. Germany's lower number of toplevel cyclists also seemed to have influenced the score of the geographical group BNG negatively. The AHP model seems to be very robust in a sense, meaning that the objectives that carry the highest weights will strongly influence the final score and outweigh other objectives, unless they score extremely high. It was found that the AHP model was quite sensitive to the AAI input specifically.

4.3 Validation and Verification

To validate the results obtained from the improved AHP iteration (iteration 2) - a Monte Carlo simulation was used to predict the growth of each market. Data from 1988-2018 was gathered from ProCyclingStats.com for each of the markets assesed in the second iteration of AHP. Since PC carried the most weight in the AHP, the datasets used in these simulations included the year and the number of cyclists from each nationality in toplevel teams. This was done to try and predict how many toplevel cyclists each market (country) would yield in the future and thus how the popularity of the sport would increase or decrease. Ten simulation runs were executed for each market to yield a variety of possible outcomes. The outcomes ranged between extremes and was plotted in separate graphs for each market in RStudio.

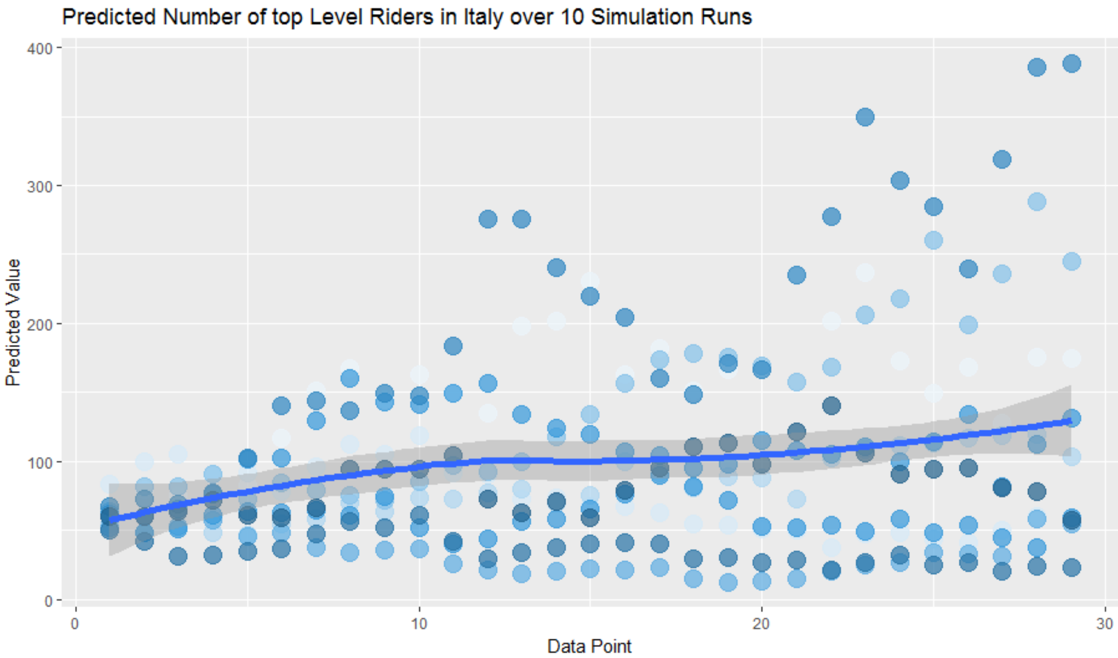

Figure 4.10: Predicted number of top-level riders - Italy

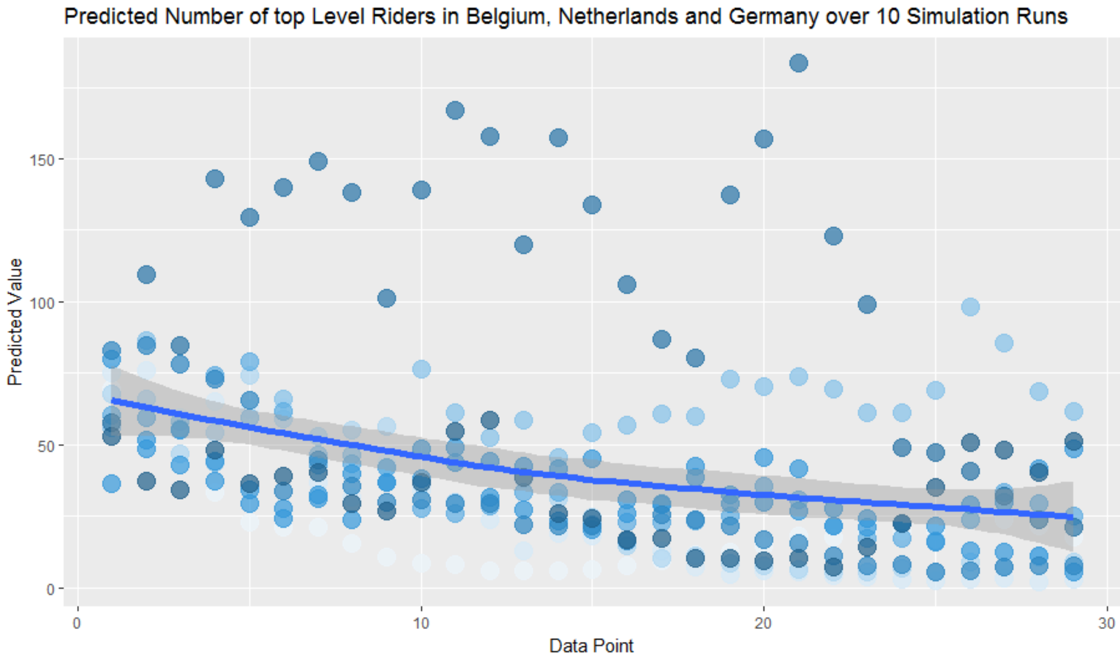

Figure 4.11: Predicted number of top-level riders - Belgium, Netherlands and Germany (BNG)

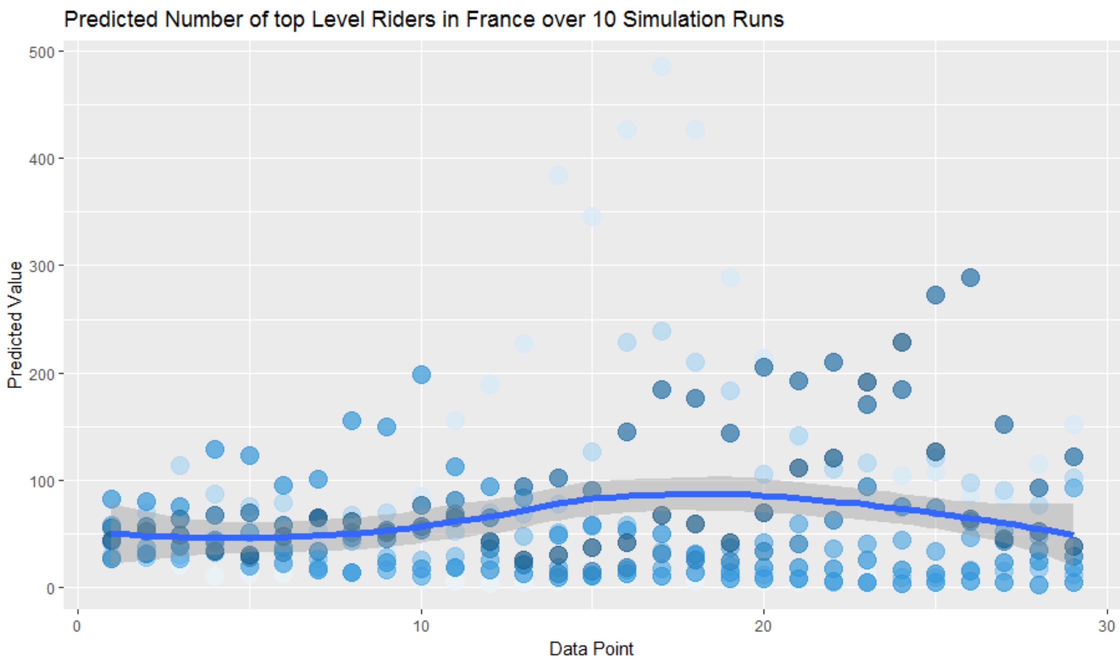

Figure 4.12: Predicted number of top-level riders - France

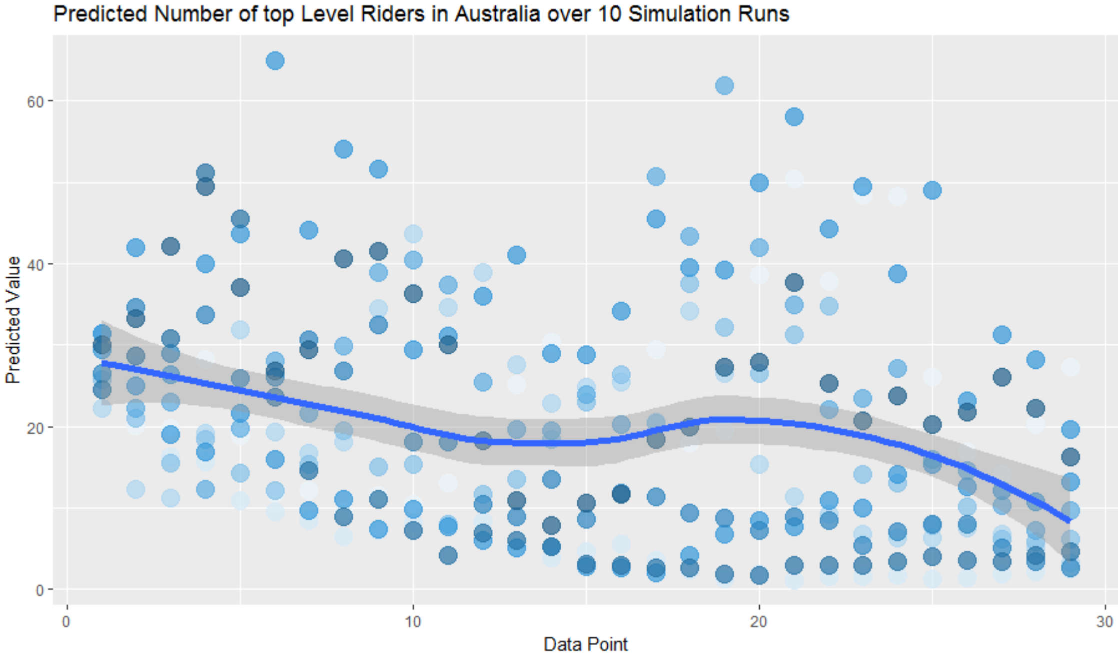

Figure 4.13: Predicted number of top-level riders - Australia

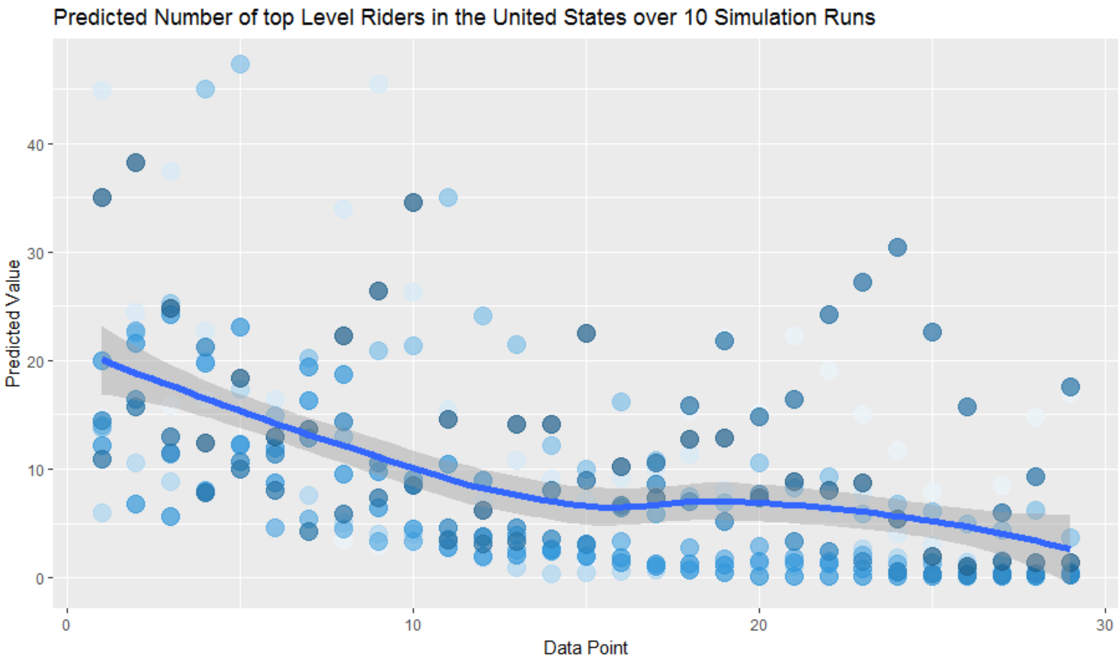

Figure 4.14: Predicted number of top-level riders - United States

From the predictions in figures 4.10-4.14, the following mean values were calculated for each market assessed in AHP iteration 2:

From table 4.3 it is visible that Italy will have the most top-level riders in future, followed by France and the geographically grouped market consisting of Belgium, Netherlands and Germany. To compare these results with the number of top-level riders from table 3.1 and the results obtained from AHP iteration 2, the following table can prove useful:

Table 4.3: Mean Value for Predictions of top-level Riders in Future

Country	**Mean of Predictions**
ITA	98
BNG	41
FRA	65
AUS	20
US	9

Table 4.4: AHP Scores Compared to Predicted Potential Market Growth

Country	**AHP Score**	**Top-level Riders**	**Predicted Top-level Riders**
ITA	0.3760	61	98
FRA	0.2028	52	65
BNG	0.1431	40	41
AUS	0.1411	28	20
US	0.1367	19	9

Prom table 4.4 it is visible that the top three markets identified in the second iteration of AHP corresponds with the markets showing possible growth according to the Monte Carlo simulations. Thus, the three most attractive markets are Italy, France, and the geographically grouped market consisting of Belgium, Netherlands and Germany.

4.4 Conclusion and Recommendations

To further improve the results obtained from the AHP, the popularity of cycling as a sport can be determined on an amateur level as well. The data sets used in the study consisted exclusively of top-level racing statistics and results. It could be interesting to see how considering races from local racing calenders could influence the results. Now that the three most attractive markets were identified, it is known which markets are favourable for the product. A useful evaluation to consider next would be to determine if the product is in fact favourable for the market - meaning, what barriers to entry are there that would prevent cyclists from buying a Calculus bike. A further in-depth customer and market analysis can be conducted to determine how big of an effect the network effect has on customers or how economies of scale would influence the sales of customized bicycles in a specified area.

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Project Plan

Table 4.5: Detailed Project Plan

Estimated Date	**Duties**
6-8 Feb	Email companies and enquire about possible projects
13 Feb	Confirm a project topic
23 Feb	Submit project topic
24-27 Feb	In depth research about project background
1-25 Mar	Report writing (proposal)
24 Mar	Submit project proposal
25 - 30 Mar	Gathering and cleaning data
1-10 May	Extensive research for literature review
10-12 May	Data analysis and visualization in RStudio
15 May	Submit preliminary report
18-23 May	Making of powerpoint presentation slides
23-28 May	Presentation
1-10 Jun	Convert work done so far to a report in LaTex
15-20	Further in depth data gathering and analysis
4-10 Jul	Extensive research about the AHP
15-25 Jul	Working through feedback from the preliminary report
26-30 Jul	Finalizing literature review for interim report
1-10 Aug	Methodology and calculations concerning AHP
15-25 Aug	Results and Discussion
26-27 Aug	Preliminary research about monte carlo simulations for validation and verification
30 Aug	Submit interim report
7-10 Sep	Work through feedback from interim report
10-15 Sep	Do a second iteration of AHP
16-19 Sep	Conducting monte carlo simulations for validation and verification
20-16 Sep	Report writing and finalization
27 Sep	Submit final report
16 Oct	Submit electronic copy of project poster
22-24 Oct	Final project presentation

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Faculty of Engineering, Built Environment and Information Technology

Fakulteit Ingenieurswese, Bou-omgewing en Inligtingtegnologie / Lefapha la Boetšenere, Tikologo ya Kago le Theknolotši ya Tshedimošo

1956 – 2016 60 years of Engineering Education

Final Year Project Mentorship Form
2018

Introduction

An industry mentor is the key contact person within a company for a final year project student. The mentor should be the person that could provide the best guidance on the project to the student and is most likely to gain from the success of the project.

The project mentor has the following important responsibilities:

1. To select a suitable student/candidate to conduct the project.
2. To confirm his/her role as project mentor, duly authorised by the company by signing this **Project Mentor Form**. Multiple mentors can be appointed, but is not advised.
3. To ensure that the **Project Definition** adequately describes the project.
4. To review and approve the **Project Proposal**, ensuring that it clearly defines the problem to be investigated and that the project aim, scope, deliverables and approach is acceptable.
5. To review and approve all subsequent project reports, particularly the **Final Project Report** at the end of the second semester, thereby ensuring that information is accurate and the solution addresses the problems and/or design requirements of the defined project.
6. Ensure that sensitive confidential information or intellectual property of the company is not disclosed in the document and/or that the necessary arrangements are made with the Department regarding the handling of the reports.

Project Mentor Details

Company:	**CALCULUS BIKES**
Project Description:	**Design of a national and international expansion strategy**
Student Name:	**Christelle Els**
Student number:	**14170991**
Student Signature:	*C. Els*
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