The effect of COVID-19 on the behavioural profiles of university website visitors

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UNIVERSITY OF TWENTE.

Preface

Currently, you have my Master thesis “The effect of COVID-19 on the online behavioural profiles of university website visitors” in front of you. In this research we have taken a look into COVID-19 and the possible effects on the online website behaviour of potential new Master students. We used the Master of Business Administration at the University of Twente as a case study to draw a conclusion for the general population (Dutch universities).

The reason I started this research was because I wanted to get more experienced with marketing analytics. I preferred to use SPSS as well, since I did not only wanted to do qualitative, but also quantitative data analytics. Reaching out to Dr. A. Leszkiewicz at the University of Twente eventually led me to this specific assignment.

I want to thank Dr. Agata Leszkiewicz for her guidance, feedback and support during this process. We sometimes had to go back and forth and adjust several goals, but with help of her advice, we could make it work. I also want to thank Floris Metzner for providing me with data via Google Analytics and also guiding me in the start-up phase of the thesis. I would like to thank the University of Twente as well, for giving me the chance to do research at this university and sharing data with me. Lastly, I would like to thank Dr. Efthymios Constantinides for being my second supervisor.

Rebecca van Dapperen, 2021

Summary

This thesis is a research on the effects of COVID-19 on the online behaviour of potential university students. A case study was performed at the University of Twente in Enschede, the Netherlands. Data of the Master of Business Administration was used to draw a general conclusion about the impact of the pandemic.

COVID-19, also known as the coronavirus, is a new virus discovered in China in December 2019. The virus quickly spread all over the world, hitting the Netherlands in February 2020. Governments announced several safety measurements and some countries introduced a complete lockdown. The Netherlands eventually also shut down public locations and schools and universities were only allowed to teach online. Since the University of Twente is an internationalized university, many foreign students come from abroad to follow a programme there. However, in the start-up of the pandemic it was unsure how the virus would evolve and influence the future. Therefore, it is interesting to analyze how the pandemic affected the choice of a Dutch student whether or not to choose for a Master programme and a foreign study to choose whether or not to study abroad.

First, we collected data using Google Analytics. We distinguished between two time periods: the period before the pandemic (December 1, 2019 – February 29, 2020) and the period during the pandemic (March 1, 2020 – June 30, 2020). For both periods the collected data included the total amount of visitors, the conversions per goal, descriptive statistics, and four variables: bounce rate, pages per session, average session duration and affinity category. The most important analyzed goals were the following: downloading the brochure, visiting 3 or more pages, checking the admission requirements page and doing an eligibility e-check.

In this research we use Cluster Analysis, a technique whose primary goal is to group objects based on the possessed characteristics. By means of performing the six steps in Cluster Analysis using SPSS, we could create clusters in order to answer the following research question:

"How did the pandemic of COVID-19 change and/or affect the different online behavioural profiles of students visiting the website of Business Administration (MSc)?"

The created clusters were eventually turned into personas, semi-fictive persons with certain demographic and psychographic characteristics. These are also the behavioural profiles. In these profiles also an AIDA stage (Attention, Interest, Desire, Action) was included and the goal conversions of the four bigger goals were analyzed per persona. The personas in the first period showed international characters, from Europe, Asia and America, whereas the personas in the second period only showed one Asian characters and four European characters. Also, the personas in both periods were in the first two stages of AIDA, while we would have expected a shift from attention and interest to desire and action. Furthermore, the variables "pages per session" and "average session duration" scored very low in the second period compared to the first period. The same applies to the goals four bigger goals, especially doing the e-check and checking the admission requirements. These two goals seemed to be important in this period, but the results showed otherwise. Abovementioned conclusions are an indication that COVID-19 did affect the online behaviour of people. However, we will have to analyze more detailed and more universities to draw a definite conclusion about this.

Table of Contents

Chapter 1. Introduction

1.1 Situation and complication

On December 31, 2019 the Health Commission in Wuhan, China identified a new virus: COVID-19, also known as the coronavirus. A month later already 7736 cases were registered in China with 170 deaths.

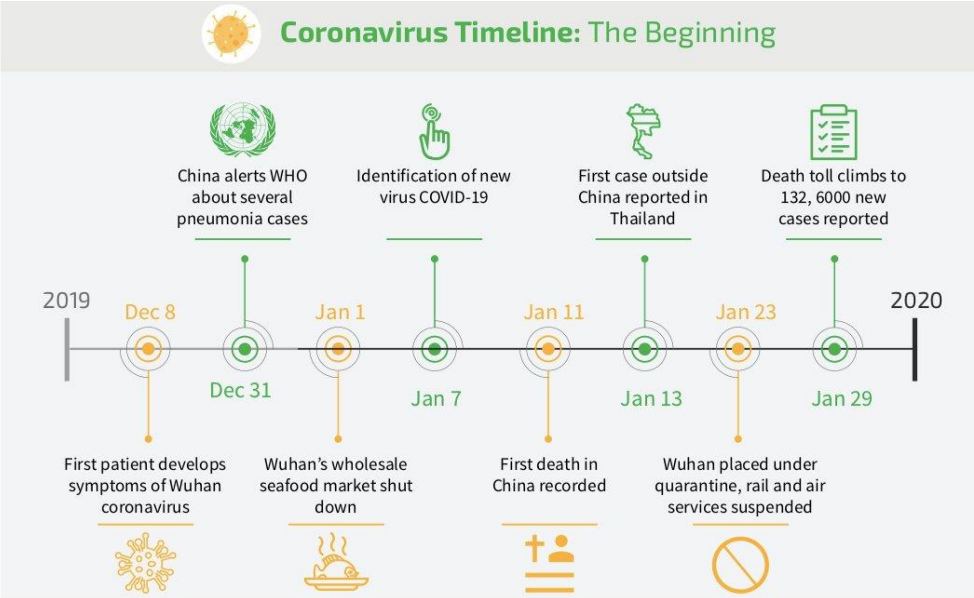


Figure 1. Timeline COVID-19 December 2019 – January 2020 (World Economic Forum, 2020).

Not only China was a high-risk country. In February also Italy was highly affected and the virus quickly spread around the country. With 9172 confirmed cases and 97 deaths on March 10, 2020, Italy became one of the highest affected countries in Europe (World Health Organization, 2020). After Italy, the virus also spread in other European countries. The Netherlands got hit by the virus at the end of February. COVID-19 began its growth in the United States (US) mid-March. During the first period of the virus, countries shut down most public spaces (such as shops and restaurants) and schools, cancelled sports events and training, and some countries even introduced a complete lockdown. It was advised not to travel abroad and to work from home. In June 2020 some countries began to relax their restrictions by for example opening borders and public spaces (Kantis et al., 2020).

In Figure 2 it can be seen that Europe, China and North America are the most infected areas in the world by March 31, 2020. This is spread out to almost the whole world by July 1 (Figure 3). For the sake of this research, the world map is not further shown since we analyse the period from March until June 2020. Figures 4 and 5 show the course of new COVID-19 cases and deaths worldwide.

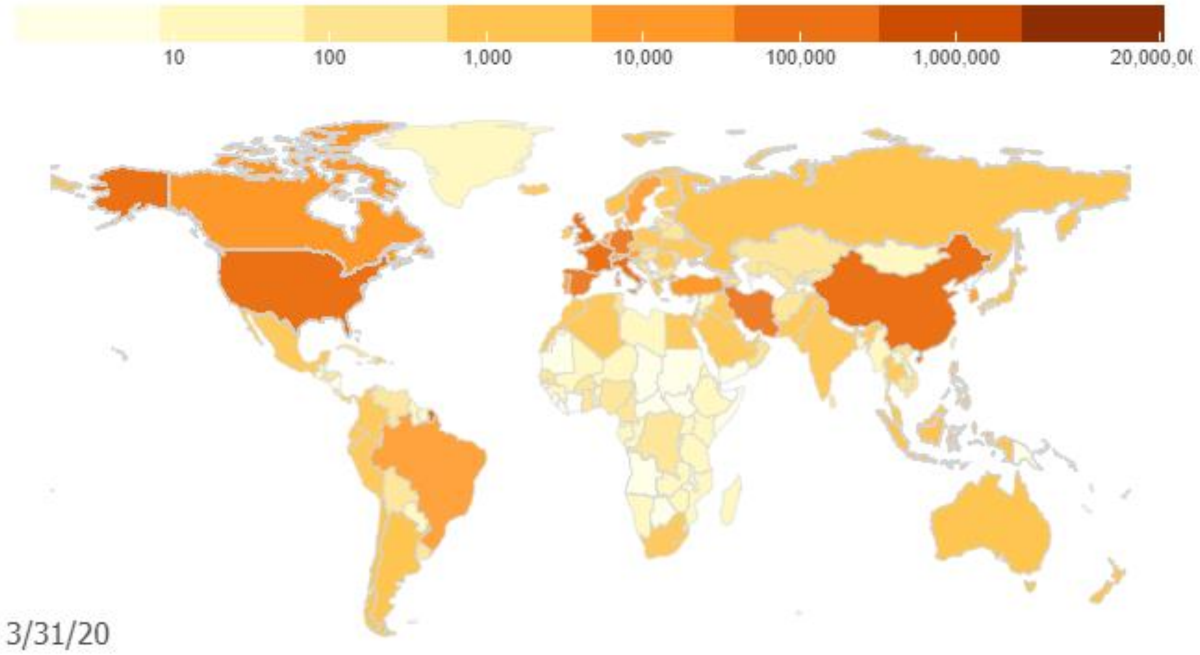


Figure 2. World Map COVID-19 cases until March 31, 2020 (Johns Hopkins Coronavirus Resource Centre, 2021).

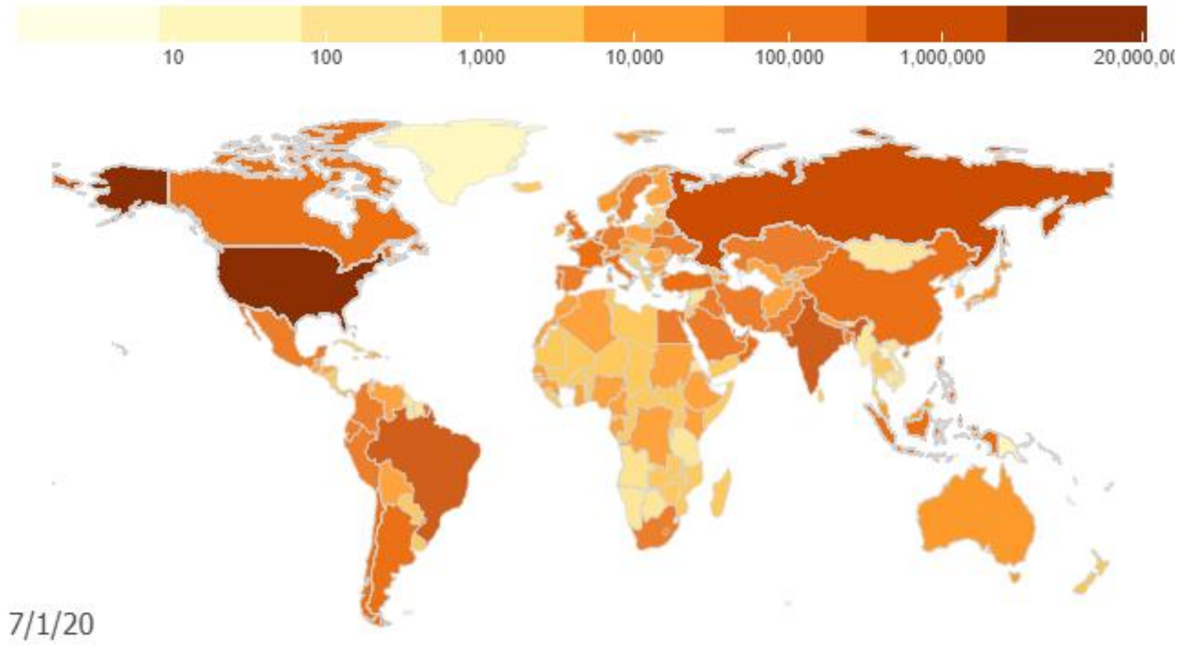


Figure 3. World Map COVID-19 cases until July 1, 2020 (Johns Hopkins Coronavirus Resource Centre, 2021).

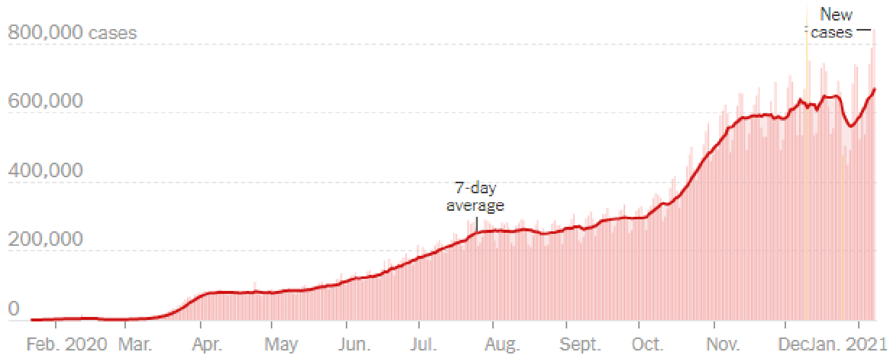


Figure 4. Global Graph COVID-19 cases (New York Times, 2021)

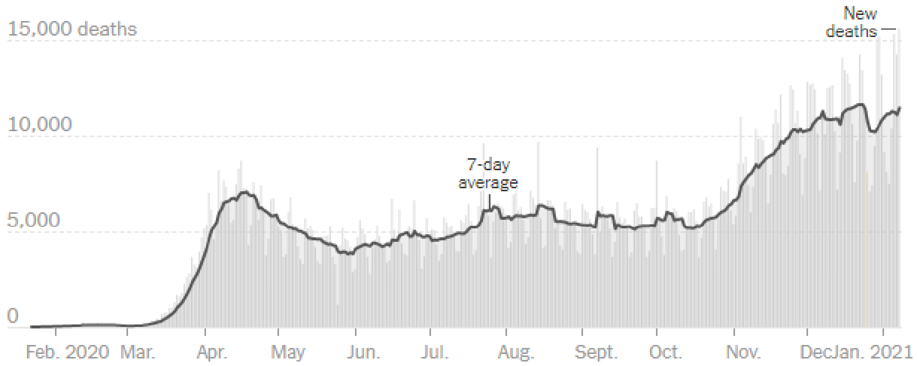


Figure 5. Global Graph COVID-19 deaths (New York Times, 2021)

Because of the virus and the many measurements the government has taken, many people were affected financially and socially. Shutting down restaurant and shops caused several people to become unemployed, temporarily or not. Between March and August 2020 approximately 150,000 Dutch employees became unemployed (CBS, n.d.). Employees working at offices had to work from home and discuss with their colleagues via video conferencing programs, such as Zoom and Skype. Therefore, being socially distanced. Furthermore, consumers shifted from shopping in stores to shopping online, not only retail shopping, but grocery shopping as well. Also, in 2019 firms already spent more money on digital advertising, which strengthens a consumer's online shopping behaviour (Gupta et al., 2020). The increase in online shopping eventually increased virtual contact of shops with customers by means of chatbots or livestreams. It is expected that this online shopping behaviour will continue after the pandemic (Grewal et al., 2021).

Not only firms and employees suffer consequences from COVID-19, but also schools and universities and its students. Since lessons have to be given online students are almost completely socially distanced from their classmates. Also, not all home environments are appropriate for online education, thinking of domestic violence – and therefore not being able to "run away" from home –, not being able to focus because of roommates, etc. Research has already shown that universities are concerned about possible decreases in percentages of foreign students (Keystone Academic Solutions, n.d.). By giving online classes universities try to maintain interest in the programmes. Holmes (2020) adds to this that with less (international) students applying for higher education, the universities could get into financial troubles. Furthermore, online teaching will not always work for everyone which could cause many failures or drop-outs.

Since it is not researched yet, we are interested in the response of students to COVID-19. There has been done research to the motives of students for deciding not to apply for a programme because of COVID-19. This research can be found in Section 2.3. However, online website behaviour of potential students interested in following a programme at a Dutch university has not been studied yet. By analyzing this behaviour, we can see whether these times of crises have an influence on the decision whether or not to start a university programme. Due to limited time we are not able to study all Dutch universities. Therefore, we will specifically focus on the MSc programme in Business Administration (BA) at the University of Twente in Enschede. BA is a large programme both Dutch and foreign students follow. In 2019 a total of 348 students enrolled in the first year of the Master of Business Administration. To compare: this is more than twice the amount of students enrolled in the Master of Communication Studies and almost 7 times as much as the amount in the Master of European Studies (University of Twente, n.d.). In 2018 the University of Twente had students of 85 different nationalities. Almost 30% of all students were non-Dutch (University of Twente, 2019).

The University of Twente has some ambitions in the field of internationalization. Their vision of 2020 is “Educating the Global Citizen”. The goal of the University is to accept more international students (University of Twente, n.d.). One way to achieve this is by switching several Dutch-taught Bachelor (BSc) programmes into English-taught ones, so that these programmes are also attractive to international students (University of Twente, 2015). Furthermore, all Master (MSc) programmes are already English-taught and because of this, these programmes are already attractive to foreign students. COVID-19 could stand in the way of this internationalization. Therefore, we will also focus on the geographical characteristics of the website users.

The research problem for this research is that it is unknown how the online behavioural profiles of the students applying for this specific programme look like. A behavioural profile can be described as an outline of the characteristics and the behaviour of an individual (Pam, 2013). For this research, we focus on the online behavioural profiles: how does an individual behave online and what characteristic traits do they show? It is very important we analyse the online behaviour, since the website is where currently all information about a programme can be found. By means of data of every individual which is saved online we can create an online behavioural profile in the form of a persona. Since COVID-19 was introduced, it is unknown how such a pandemic could influence the online behavioural profiles of applying students. Therefore, we study online behavioural profiles before and during the pandemic, to see the impact.

1.2 Research goal

For this research, we are interested in finding out the impact of COVID-19 to online website behaviour. We specifically look at the MSc programme Business Administration at the University of Twente. This is our case study. The following goals will be explored:

- students downloading the brochure;
- students visiting 3 or more pages;
- students checking the admission requirements page and
- students doing an online check to see whether they are eligible;

We also take a look at two somewhat smaller goals. We will not explore the behavioural profiles of these students, but only perform a descriptive analysis.

- Students signing up for the open days and
- students applying for the programme.

We will take into account several user characteristics, such as geographics and interests. Also, we will create the behavioural profiles before and during the pandemic to identify to what extent the pandemic has influence on the choice of a student to study at a university. For this latter part, it is especially very interesting to check whether there are changes in the decision of foreign students to or not to study abroad.

1.3 Research questions

The main research question for this research is:

"How did the pandemic of COVID-19 change and/or affect the different online behavioural profiles of students visiting the website of Business Administration (MSc)?"

In order to answer this research questions, a few sub-questions must be answered:

1. What is behavioural profiling?
2. What is Cluster Analysis?
3. What do the behavioural profiles look like before the pandemic?
4. What do the behavioural profiles look like after the pandemic?

By "before the pandemic" we mean the period before the virus hit the Netherlands, so between December 2019 and February 2020. By "during the pandemic" we mean the period when the virus hit the Netherlands, taking into account the application deadline, so between March 2020 and June 2020 (Figure 6).

Figure 6. Timeline research

The first two sub-questions will be answered in Chapter 2: Theoretical Framework. Questions 3 and 4 will be answered in Chapter 4: Results. A discussion and conclusion of the results can be found in Chapter 5.

1.4 Academic and practical contribution

The outcome of this research will be mostly beneficial for Dutch universities. Section 2.3 discusses the motives why the pandemic would have an impact on the online behaviour of people. Study shows that for Dutch students the main motives for deciding not to start at a university is because of absence of physical Open Days, Student-for-a-Day days or proper guidance. Also, diminished social contacts because of online lessons also plays a role in this decision. This last reason could also be a reason for foreign students. It would be hard for them to adjust to the culture without being able to make new social contacts or explore the country due to travel restrictions. Section 2.3 will discuss the motives more detailed. When knowing what the motives are for not applying for a university programme, the universities could already anticipate to this. The same applies to the outcome of this research. Knowing what impact COVID-19 could have on website behaviour could be a possibility for higher education to anticipate to this in the future when a crisis happens again. Things can already be changed such as website design or possible advertisements to make the university or specific programme somewhat more attractive. Procedures on how to act during a crisis could be created as well.

This thesis will also contribute to the knowledge of the University of Twente about its (potential) students and the website of the MSc of BA. By means of this research, the University will know what students visit the websites of the programme and how a pandemic such as the coronavirus pandemic could change the online behavioural profiles of the visitors. Furthermore, this latter information could be used to act better and faster when something severe as a pandemic happens again.

1.5 Outline of the research

This research will start by explaining in detail the required theories. This can be found in Chapter 2. Then, the methods in Chapter 3 will be explained extensively. In Chapter 4 the results can be found. We start by analysing the Google Analytics page of the MSc of Business Administration in detail, at which we focus on the period before the pandemic hit the Netherlands (December 2019 – February 2020). With this information, behavioural profiles, in the form of a persona, of the website visitors are made. This is done by using Cluster Analysis in the statistical program SPSS. After this, the focus will lie on the period after the pandemic hit the Netherlands (March 2020 – June 2020), and with this information, new behavioural profiles will be made with Cluster Analysis. In the personas we included the geographic and demographic features of the cluster. We also tried to focus on the phase of a funnel the specific persona was in, using the AIDA stages. In the end, we will compare the created personas before and during the pandemic in order to conclude how the COVID-19 pandemic has an impact on the behaviour of potential students on their online behaviour and choice of study.

Chapter 2. Theoretical framework

In this chapter, two main concepts of the research will be explained: behavioural profiles and Cluster Analysis. This chapter gives an answer to the first two research questions:

1. What is behavioural profiling?
2. What is Cluster Analysis?

Furthermore, it is explained what the motives are for doing this research and why we should expect a change in the behavioural profiles.

2.1 (Behavioural) Profiling

In this section it is explained what we mean by "behavioural profiling". However, since there is a difference between profiling and behavioural profiling and it is important to notice the difference, we explain both.

2.1.1 Profiling

The term profiling can be described as a process of deducing a person's information based on their known characteristic traits, habits or behaviour (Nowek, 2019). Profiling is used a lot when wanting to identify a criminal. This is called criminal or offender profiling. Criminal profiling is the process of identifying distinctive characteristics, such as physics, habits, emotions and the voice of an offender responsible for a crime (Turvey, 1999). Nowek (2019) also mentions psychological profiling, which is the method of identifying a suspect based on emotional, mental and personality characteristics which can be deduced from the things left or done at the scene of crime.

2.1.2 Behavioural profiling

A behavioural profile is somewhat the same as regular profiling, but it is based on a user's online behaviour. According to Sachser et al. (2013) a behavioural profile is a composition of an individual's characteristics. It constitutes the behavioural traits, such as social behaviour, cognitive abilities, emotions and stress responses. Besides these traits, a behavioural profile also includes personality and temperament. Nowadays, such information can be deduced with help of artificial intelligence, data analysis via Google and Facebook, and machine learning. This way, profiles of a certain personality can be created very accurately. A behavioural profile is already shaped in the prenatal phase of a (human) life. Differences in behavioural profiles are a consequence of both genetic and environmental factors (Heiming & Sachser, 2010).

The goal of web user behavioural profiling is to summarize a large amount of user information. This way, product recommendations and personalized information could be given to the user. The user information can be gathered through online registrations and/or surveys and by using techniques such as cookies and logins. The web user profile can include several aspects, such as demographics (name, phone number, address, hobbies, etc.), which are often offered by the user itself. The profile can also include explicit information, such as the user's activity and transactions, and implicit information, which is gathered by analysing the user's activity using statistical or data mining methods (Yang, 2010). Web user profiling could be done just to identify users, but it could also be an intermediate step to achieve better personalization and targeting. This latter is called behavioural targeting. Tomšů et al. (2017) add to this that the behaviour of people does not change over time for various websites. However, the behaviour does differ amongst different users.

2.2 Cluster Analysis

In order to identify the behavioural profiles, we use a quantitative data analysis method in SPSS. There are several data analysis methods and in this section, we discuss the method we are going to use in this research: cluster analysis.

Hair et al. (2008) describes cluster analysis as a technique whose primary goal is to group objects based on the possessed characteristics. When grouping, each object is similar to other objects in the same cluster and different from the objects in the other clusters. A user profile contains several variables. Clustering can be used to generate aggregate user profiles so that recommendations and personalized information can be provided to the users (Mobasher et al., 2002). According to Hair (2008) there are several stages to follow when doing cluster analysis. We will explain them here and also apply this research to them.

Stage 1: Objectives of Cluster Analysis

The first step of the cluster analysis is to select one or more objectives and select variables which characterize the objects. There are several objectives to choose from:

- *Taxonomy description:* with this method, cluster analysis is used to explore and form an empirical classification of objects (taxonomy). Also, hypotheses about the structure of objects could be generated. Sometimes, a theoretical classification of objects (typology) is compared to the outcome of a cluster analysis for confirmatory purposes.

- *Data simplification:* data simplification defines dimensions and structure among the observations by grouping observations based on general characteristics. This creates a simplified perspective.

- *Relationship identification:* this last objective is used to reveal relationships among the observations. This is done by defining the clusters and its underlying structure.

The objective we will use in this research is taxonomy description. By clustering the individual users based on their online behaviour, we can attach a certain classification to each cluster to see what kind of users they are. The classifications are based on the stages of the AIDA (Awareness, Interest, Desire, Action) model.

When selecting the variables for the cluster analysis, we must keep theoretical, conceptual and practical considerations in mind. It is important only relevant variables are included and the variables must characterize the users being clustered. Therefore, we choose to study the variables of average time spent on the website, their bounce rates and the amount of pages visited per session. These all give an indication of what kind of users we are dealing with.

Stage 2: Research design in Cluster Analysis

In this stage a few questions must be answered:

1. *Is the sample size acceptable?*
   By sample size we mean the number of observations, in our case the number of website visitors/users. The criterion to check whether this sample size is acceptable is that it must be large enough to sufficiently represent small groups of a population. When samples are larger the chance increases that the small groups (the clusters) contain enough cases so that their presence can be easily identified.

2. *Are there any outliers. If so, should we delete them?*
   When performing cluster analysis it is important that irrelevant variables are excluded. Similarly, it is important that objects which are different from other objects (the outliers) are excluded. In most cases, outliers are observations which are not representative of the population or the observations only represent a very small segment of the population. Not deleting such outliers will decrease the accurateness, representativeness and the structure of the clusters. In our research, we detect outliers by performing a “Descriptive Statistics” analysis in SPSS and check which observations are outside the interval ([mean – standard deviation, mean + standard deviation]).

3. *How can we measure object similarity?*
   Object similarity, also interobject similarity, is the resemblance between the objects which will be clustered. Similarity is measured based on the observation’s characteristics. There are three measures for object similarity: correlational measures, distance measures and association measures. The first measure calculates the correlation coefficient between a pair

of observations. High coefficients indicate similarity. The second measure, which is most commonly used, focuses on the proximity of an object to another object. The larger the value, the less similarity. Also, there are different types of distance measures, such as Euclidean distance and City-block distance. The last object similarity measure, the association measure, is used to compare observations with nonmetric (nominal or ordinal) characteristics. This measure can be neglected in our research, since we only have metric variables.

4. *Should we standardize the data?*
   Variables can be standardized to make clustering easier. Most commonly used is converting the variables into standard scores, or *Z scores*. This is done by subtracting the mean from each variable and dividing it by the standard deviation. By doing this, the mean becomes 0 and the standard deviation 1, which in turn, eliminates bias caused by differences in scales of the variables.

We answer these questions elaborately in Chapter 4.

Stage 3: Assumptions in Cluster Analysis
When doing cluster analysis, we have to keep two assumptions in mind:

1. *Representativeness*
   It is important that the sample (the observations) used for the cluster analysis must be representative of the whole population. This can already be managed by deleting the outliers which cause bias in the structure of the clusters.

2. *Multicollinearity*
   Multicollinearity means that there is a high correlation between two or more variables. This could make clustering more difficult. When multicollinearity is found, we should reduce the amount of variables to an equal number. In our research, this would probably not be a problem, since we have very few variables.

Stage 4: Deriving clusters and assessing overall fit
In this stage we have to decide on which partitional procedure to use and the numbers of clusters we would like to form.

The partitional procedure consist of the rules we have to take to form the clusters. The procedure could be either hierarchical or non-hierarchical.

Hierarchical cluster procedures work with *n – 1* decisions, where *n* is the amount of observations. The procedure combines the observations into a hierarchical structure or tree form (dendrogram). There are different algorithms of hierarchical cluster procedures. Since we will perform cluster analysis via SPSS, we will not go in too much detail about the working of the algorithms. We will only describe them shortly:

- *Single-Linkage (nearest-neighbour):* this method creates clusters in which any object in a cluster has the shortest distance to any object in another cluster.

- *Complete-Linkage (farthest-neighbour):* this method is similar to the single-linkage method. However, the clusters are created based on the maximum distance between objects in each cluster. This method is found to be the most appropriate technique.
- *Average Linkage:* this technique creates clusters where the average similarity of the observations in one cluster are similar to those in another cluster.
- *Centroid Method:* the centroid method forms clusters with similar cluster centroid distances. The centroids are the mean values of the objects. This method has the advantage of being less affected by possible outliers.
- *Ward's Methods*: with the Ward's method the clusters are created based on the sum of squares of the variables of the clusters. This technique is useful when the number of observations is very small. However, it is easily affected by outliers.

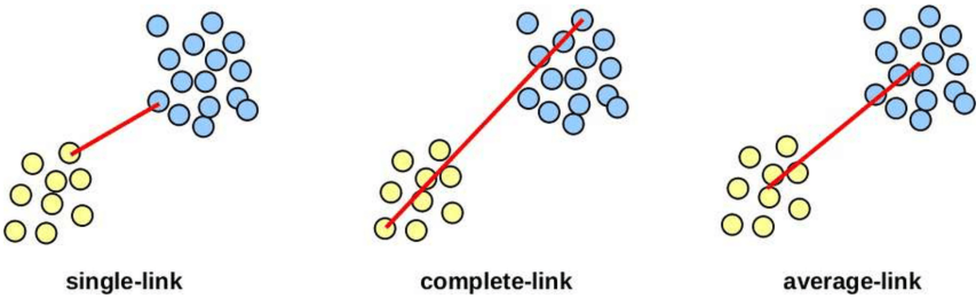


Figure 7. Linkages in cluster analysis (Guevara, 2011)

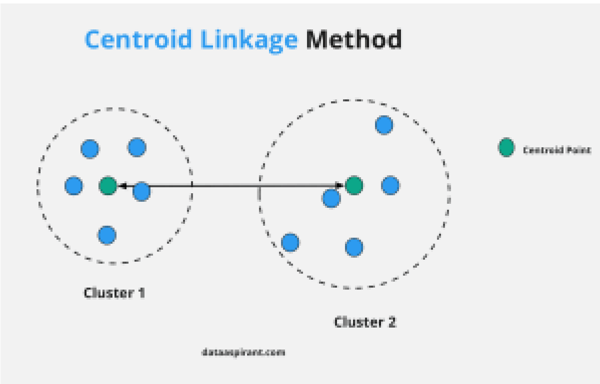


Figure 8. Centroid Method (Polamuri, 2020)

Non-hierarchical cluster procedures put observations in clusters once the number of clusters to be created is given. Since we do not use this method, we will not go into detail about it any further.

The number of clusters to be created can be inserted in the SPSS clustering details. However, when one does not specify this number, the program will automatically calculate the optimal number of clusters.

Stage 5: Interpretation of the clusters
In this stage the clusters are examined and labelled based on the interpretations. The clusters could be useful to confirm or refute assumptions.

Stage 6: Validation and profiling of the clusters

When checking whether the cluster solution is valid, we must check whether it is representative of the population studied. This way, the clusters are generalizable and could be used in other research.

In this research, we will focus on profiling the clusters, which means describing each cluster's characteristics. We will study characteristics such as demographics and certain patterns.

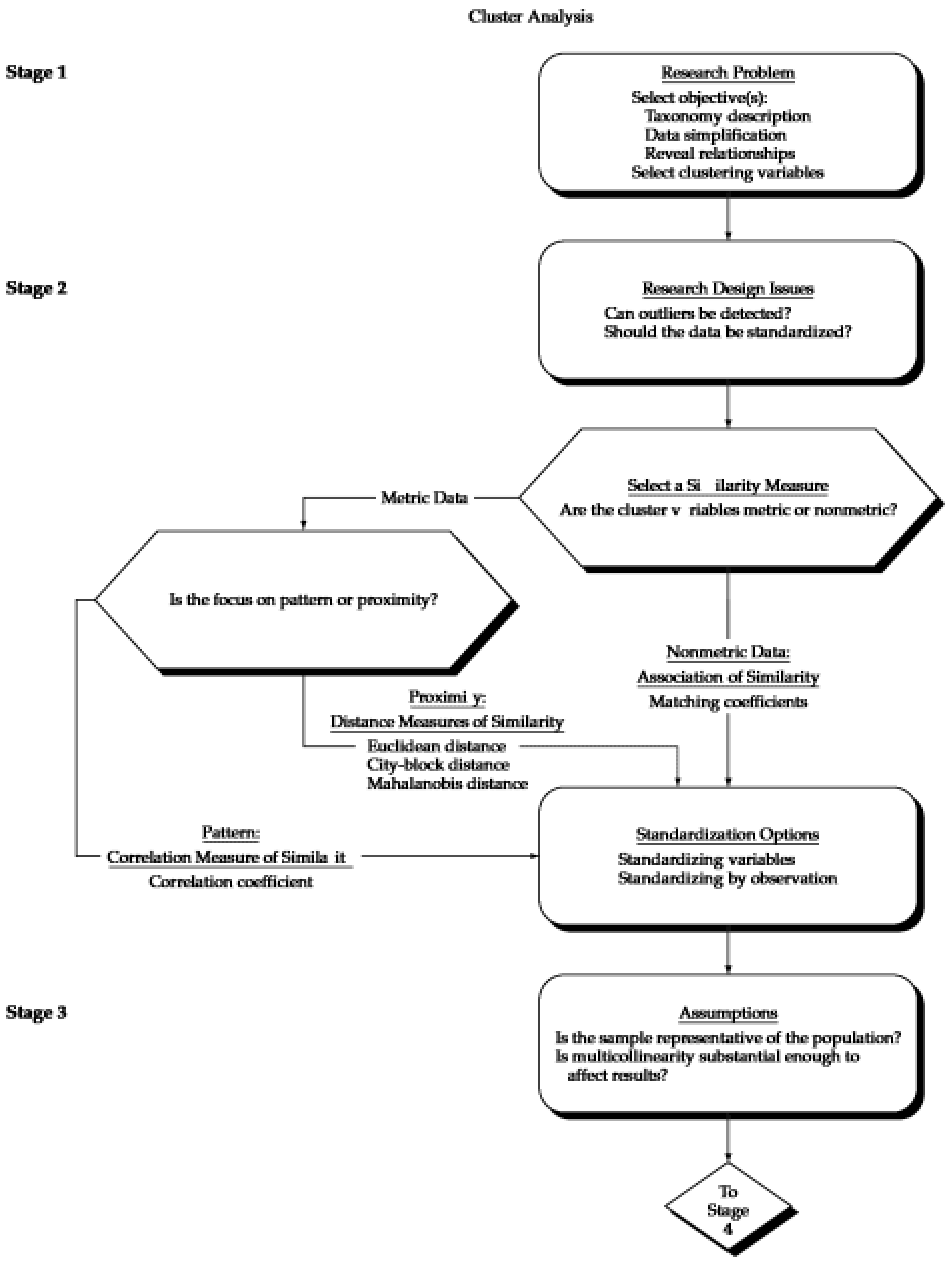


Figure 9.1. Stages 1 – 3 of Cluster Analysis (Hair et al., 2008)

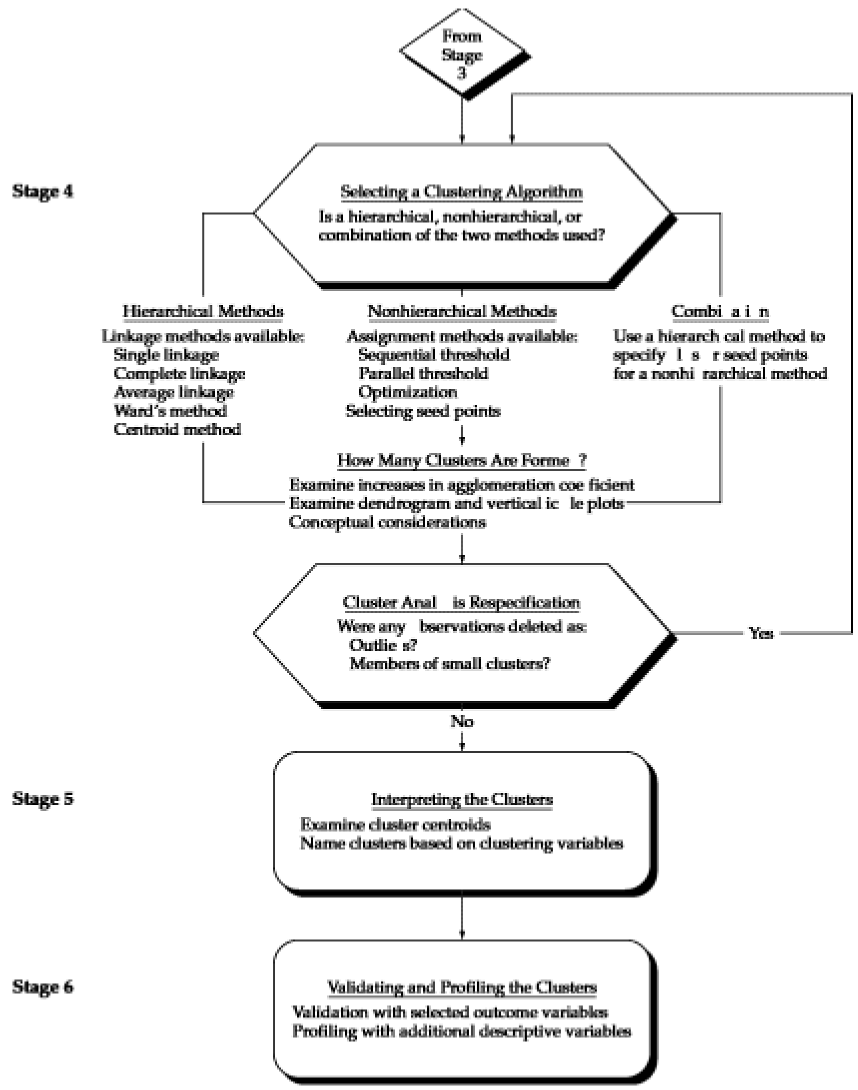


Figure 9.2. Stages 4 – 6 of Cluster Analysis (Hair et al., 2008)

2.3 Motives: why should we expect a change in profiles?

Since COVID-19 was introduced the world went upside down. Many measures were taken in order to hold back the growth of and eventually stop the virus. Not only shops and restaurants felt the impact of these measures, but also universities and its students. Students had to take classes online, work on group projects via Skype of Microsoft Teams, and even take tests online. This section describes to what extent Dutch and foreign students might doubt about following an education during the time of a pandemic. When in doubt, their online activity will probably diminish which is a prediction of less students registering for a certain programme.

2.3.1 Motives for Dutch students

The pandemic started in March, a month in which last-year students will orientate themselves about their further education since final exams are in May. However, classes are only given online and tuition fees stay the same, so some students might not want to start a university programme immediately. Research shows that 47% of all exam candidates are influenced by the virus in making their choice for further education. They are very aware about the consequences of such a crisis. The main reason that it is hard to make a decision is the cancellation of the open days and "Student for a Day" days (93% of the students). Because of this, they cannot get a full picture of the programme. Also, at high schools the dean is responsible for giving advice about study choices. However, because of the virus, schools are closed and 27% of the students find it hard that it is not possible to ask for this advice in real life. Another reason for struggling with making a decision is the fact that social contacts are diminished. 48% of the students think it is very important to talk about a study choice with friends in real life, which is not possible in this pandemic. Also, contacts with future new study friends cannot be established, since only online classes are available. Lastly, 67% of the students are insecure about their futures because of COVID which negatively influences their study choices. (Qompas, 2020).

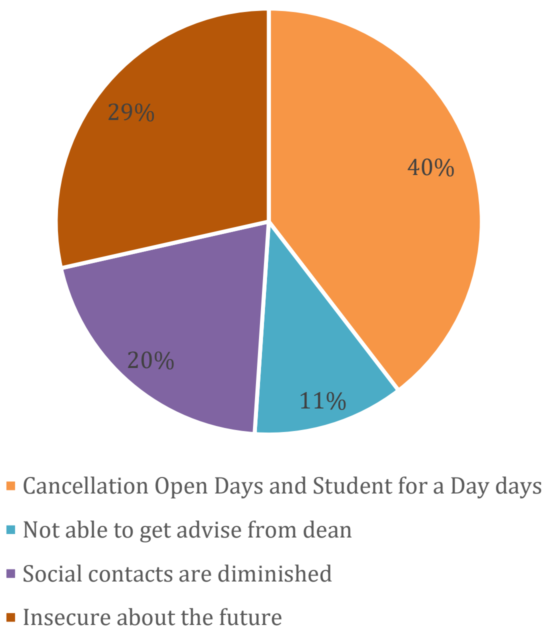


Figure 10. Motives for doubts about further education (Qompas, 2020)

The reasons mentioned in this section are all reasons why we can expect a difference in online behaviour between the period before COVID and during COVID. However, this difference can go two ways. First of all, students can decide not to start a university programme, because of aspects such as lack of open days and diminished social contacts. These students could choose the direction of a gap year: a year in which the student works or travels to develop themselves. Therefore, they will not visit the web pages of potential studies. This means that online behaviour and activity decrease. However, some students might take a quick look on some of the programme pages, just to get a picture of what they might like in the year after their gap year. This does influence the behavioural profiles, since they do not complete the funnel. The second route a student can take is the route of finding as much information as possible online. This means they visit al sub-pages of a programme page and possibly visit the online open days or download the brochure. Since most information pre-COVID is gathered through an open day or a Student for a Day day, it can be expected that online activity and behaviour will eventually increase with this route. Of course, it is also possible that online activity stays the same. We will find this out by means of this research.

2.3.2 Motives for foreign students

It is not easy for foreign students to study abroad. First of all, they (often) do not speak the language and the culture is different. Furthermore, they are far from home and much has to be arranged (a residence, permits, etc.). Also, the grading systems are different which is sometimes hard to understand. Dutch education systems are created in such a way that independency and self-discipline is needed. There will be guidance, but students are responsible for their own work. Studying during a pandemic means online classes, online guidance, and less supervision. It could be hard for a foreign student to accomplish their goals without getting proper guidance. Also, contacts with other foreign students is little or not even present at all. With restaurants and cafes closed, these contacts cannot establish either. Furthermore, getting to know the culture is also hard with buildings such as museums being closed. Traveling inland is also discouraged, which means the students will not get to know the country as good as they would have liked. These aspects could all be possible reasons for foreign students not to study abroad. An even more discouraging aspect could be the fact that it is advised not to travel to other countries. It is also possible the country experiences a large COVID outbreak which means everyone has to stay in quarantine and is prohibited to travel abroad. This means the foreign students are not allowed to travel back home during holidays or when their education is finished. This is a risk some students might not want to take. Therefore, their online behaviour could be different from when things are normal. The activity will probably be less during the pandemic compared to the period before the pandemic.

Chapter 3. Methodology

3.1 Research design

The first step for this research is to know exactly what behavioural profiling and cluster analysis are. It is also useful to understand how cluster analysis can be applied. This information is all explained in the theoretical framework (Chapter 2) of this thesis. Then, data should be collected. The data needed for this thesis is data of students visiting the website of the MSc of Business Administration. We specifically focus on a few goals, which are mentioned in Section 1.2, and four variables: bounce rate, pages per session, average session duration and affinity category. We distinguish between two period: before the pandemic (December 2019 – February 2020) and during the pandemic (March 2020 – June 2020). After the data collection, all information will be put in two separate SPSS files to get a good overview of the different variables in the two time periods. By means of Cluster Analysis the data will be analysed and the profiles/personas for the two time periods will be made.

3.2 Selection and sample

The samples used for this research are the students that visit the website of the MSc programme Business Administration at the University of Twente. In the personas we focus on four goals: students downloading the brochure, visiting 3+ pages, checking the admission requirements page and doing the e-check.

3.3 Data collection

Data will be provided by the University of Twente. Access to the Google Analytics account is given, from which we could analyse the data.

3.5 Data analysis

The given data will be analysed using SPSS. With SPSS, many quantitative data analysis methods can be used. This way, we can easily find patterns in the data and make graphs and tables using the appropriate data analysis method. The quantitative method that is used in this research is hierarchical clustering. We will create behavioural profiles by this technique to the given data.

Chapter 4. Results

In this chapter, the results of the research are described. We especially look at the period before the pandemic hit the Netherlands (December 1, 2019 – February 29, 2020) and during the pandemic (March 1, 2020 – June 30, 2020).

4.1 General data overview

In this section the general data of the website visitors is analysed. We distinguish between the two time periods.

Beforehand, table 1 gives an operationalization of the used variables and tables 2 and 3 the descriptive statistics before and during the pandemic. Figures 11 until 16 show the graphs of the numerical variables in the two time periods.

Table 1 Variable Operationalization

Variable	***Operationalization***
Average Session Duration	Average time during which a user performs active interactions on a website
Bounce Rate (%)	The percentage of users that leave the website after visiting one page without checking other pages
Pages per Session	Number of pages a user visits on a website per session
Affinity Category	Passion, habits and interests of the users

Table 2 Descriptive Statistics before the Pandemic

Variable	***Mean***	***Standard Deviation***
Average Session Duration	00:04:42	00:01:46
Bounce Rate (%)	31,53%	10,81%
Pages per Session	3,28	0,69

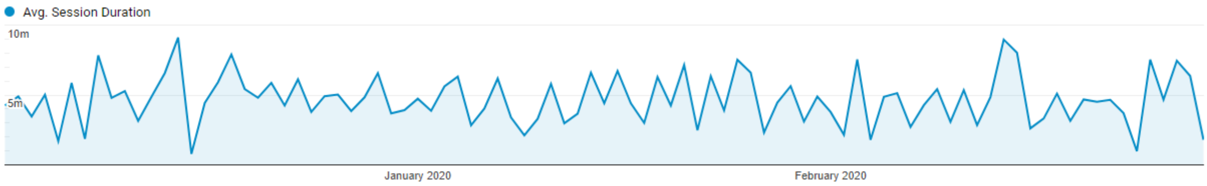


Figure 11. Graph Average Session Duration before the pandemic (Google Analytics, 2021)

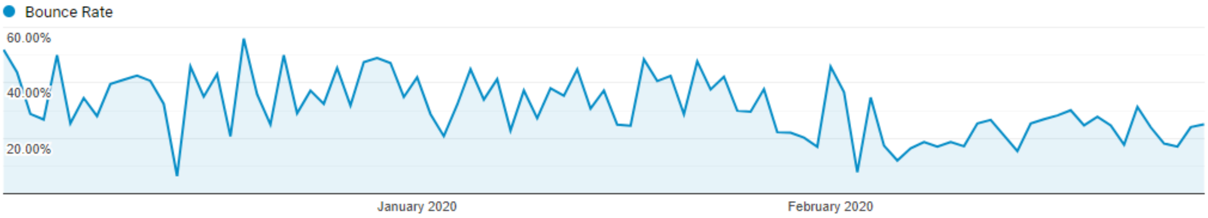


Figure 12. Graph Bounce Rate (%) before the pandemic (Google Analytics, 2021)

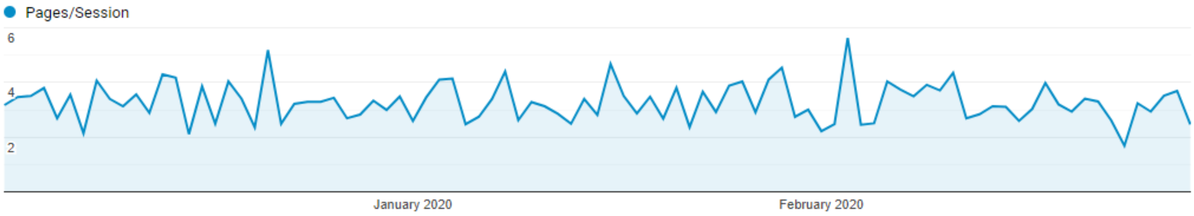


Figure 13. Graph Pages/Session before the pandemic (Google Analytics, 2021)

Table 3 Descriptive Statistics during the Pandemic

Variable	***Mean***	***Standard Deviation***
Average Session Duration	00:04:53	00:02:00
Bounce Rate (%)	20,93%	9,25%
Pages per Session	3,40	0,80

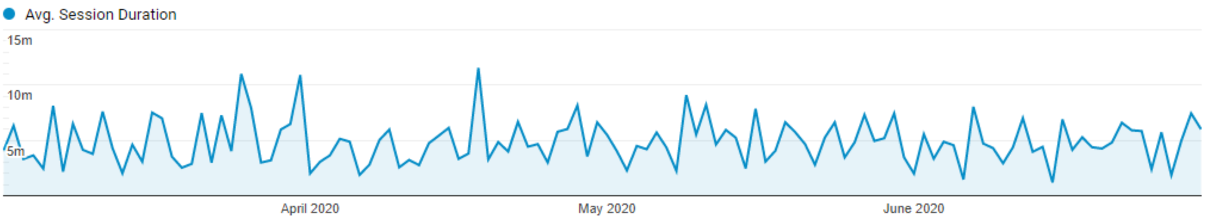


Figure 14. Graph Average Session Duration during the pandemic (Google Analytics, 2021)

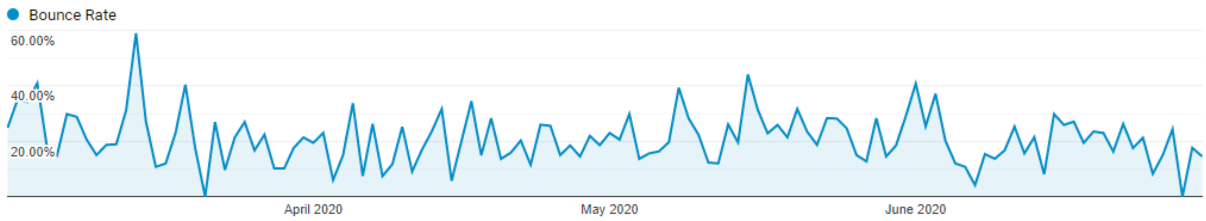


Figure 15. Graph Bounce Rate (%) during the pandemic (Google Analytics, 2021)

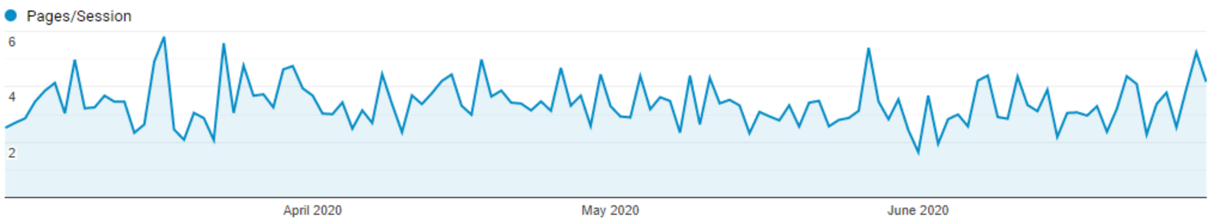


Figure 16. Graph Pages/Session during the pandemic (Google Analytics, 2021)

4.1.1 Before the pandemic (December 2019 – February 2020)

In the first time period a total of 10.636 people visited the website of the Master of Business Administration. Of all these people, 7.669 were new visitors, which is 72%. Mostly Dutch people visited the website, but it can also be seen that 134 other countries visited the website. The top 5 with corresponding visiting percentages can be listed as follows:

1. The Netherlands (26,96%)
2. Germany (6,47%)
3. India (4,91%)
4. Nigeria (4,06%)
5. Indonesia (3,43%)

When looking at the users flow (figure 17) of this specific period, we can clearly see that most visitors landed on the website via the main page of the programme. This page is called “Master Business Administration” and from here many other pages can be visited. Most visitors travelled to the admission page or the eligibility check page to see whether and how they can be admitted to the programme. The other part visited pages such as the programme overview and specialization pages. After going back and forth between different pages on the website, most visitors dropped off with on average 9 interactions.

Furthermore, approximately 10% of all visitors started on the “Entrepreneurship, Innovation & Strategy” page, which is a specialization of the programme. Another 10% started on the Dutch website of the Master programme. However, this page does not contain much information and directs the visitor to the English version of the page.

Figure 17. A small shot from the users flow before the pandemic (Google Analytics, 2021)

It is also interesting to look at the interests of the visitors. Most people visiting the website are interested in categories such as media & entertainment, jobs & education, sports, shopping, etcetera.

4.1.2 During the pandemic (March 2020 – June 2020)

From the beginning of March until the end of June the total amount of visitors slightly dropped to 10.158 of which 71% were new visitors. A total of 133 countries visited the web page and again, a top 5 can be made:

1. The Netherlands (36,28%)
2. Germany (10,30%)
3. India (4,14%)
4. Nigeria (3,22%)
5. Indonesia (2,94%)

The users flow (figure 18) in this period started again on the main page of the programme. Also, the route a visitor took in this period does not differ much from the route a visitor took in the first period. However, it appears to be somewhat harder to make a decision as the average interactions a visitor has to take before dropping off is now approximately 10 or 11 compared to 9 in the period before the pandemic.

Figure 18. A small shot from the users flow during the pandemic (Google Analytics, 2021)

The interests of the visitors have changed a lot. The percentages of categories such as jobs & education, internet & telecom, study-abroad programs and employment & resumes have increased. Thus, interests have shifted.

4.1.3 Intermediate analysis

From the number of total visitors before and during the pandemic, we can conclude that the total amount of visitors did not change much. However, we compared two different time periods: the first consisted of 3 months, while the second period consisted of 4 months. This means that the average amount of visitors per month decreased in the second period compared to the first period (3545 vs 2540). Since two different time periods are compared, we will use the average number per month in the remaining of this report.

When looking at the countries people came from, we can immediately see that there has not been any changes in the division of countries. The top 5 is exactly the same. This means that these countries did not see the virus as a cause to not study abroad. This can also be concluded from the fact that the percentages are also almost the same. Also the users flows were almost the same. However, the interests of the people visiting the web pages changed. This can be a consequence of them being more future-focused since economy has become very unstable because of the corona virus. The increase in the category internet & telecom can be a cause of the lockdown and therefore, people have to work and socialize online more than ever. This requires updated devices and software.

4.2 Goal conversions

First, we analyse the two smaller goals: signing up for the open days and applying for the programme. Even though this latter goal seems to be a big one, Google Analytics shows only few conversions. The amount of conversions for these two goals is not sufficient to create representative clusters. Therefore, we only perform a descriptive analysis. We do this for the two given time periods: before and during the pandemic.

In the first period, which we call "before the pandemic" and takes place between December 2019 and February 2020, the goal "Signing up for Open Days" had a conversion amount of only 21. Thus, 21 people signed up to attend the Open Days. This is actually explainable, since Open Days take place in March and therefore, not many potential students will already sign up in December or January. This can also be seen in figure 19.

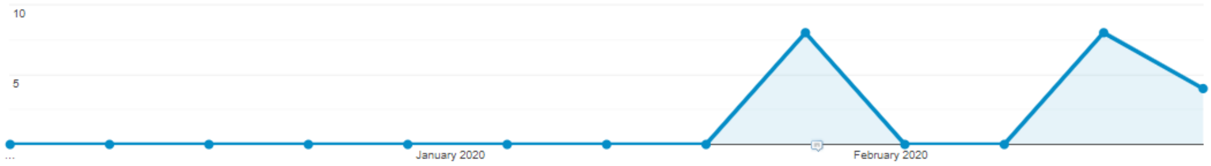


Figure 19. Conversions Open Days registration before the pandemic (Google Analytics, 2021)

In the second period ("during the pandemic") which starts in March 2020 and ends in June 2020, the number of conversions was only 19. All of the registrations took place in March (figure 20). However, when the coronavirus started to spread in The Netherlands, the Open Days were cancelled and alternated into online Open Days, of which we unfortunately do not have data.

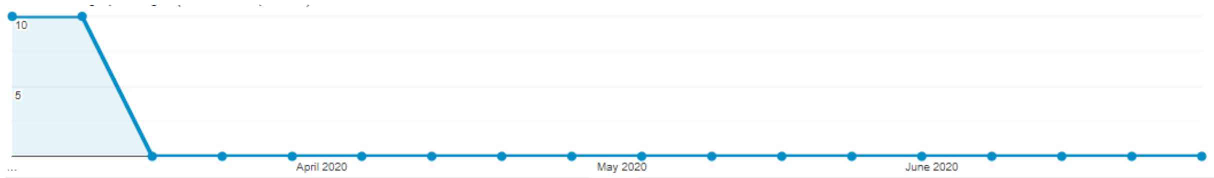


Figure 20. Conversions Open Days registration during the pandemic (Google Analytics, 2021)

Before the pandemic the goal "Studielink application submitted" had 58 completions, which means 58 students applied for the Master of Business Administration. This is not much, however, the period between December and February is still a period in which students need to orientate which programme and/or university they would like to choose. The new year only starts in September, which makes this number understandable. From figure 21 we see that at the start of the year the graph was stable, while at the end of January it started to fluctuate some more. This could be caused by the fact that foreign people were aware of the coronavirus existing in Asia and spreading around the world. Therefore, they were possibly already more careful in choosing to study abroad. Data also shows that from these 58 students, only 16 came from Europe (none of them from The Netherlands). The others came mostly from African and Asian countries.

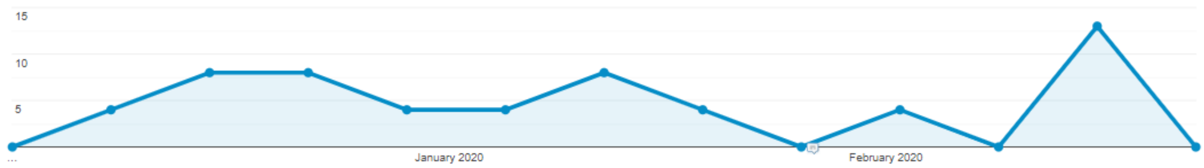


Figure 21. Conversions Studielink applications before the pandemic (Google Analytics, 2021)

The period between March and June used to be the period in which most of the students make a decision about their future study programme and therefore, we would expect this number to be higher compared to the first period. However, during the pandemic the amount of conversions was 48. This is on average a lot lower compared to the period before the pandemic, also considering the period during the pandemic contains 4 months instead of 3. In figure 22 we see that the conversion rates are fluctuating a lot. The graph has high peaks and low lows. The conversion rate at the end of May can be explained by the fact that the application deadline was delayed until June 1 instead of May 1 due to the coronavirus. From the 48 students almost 50% were European and the other half African, Asian and Southern American.

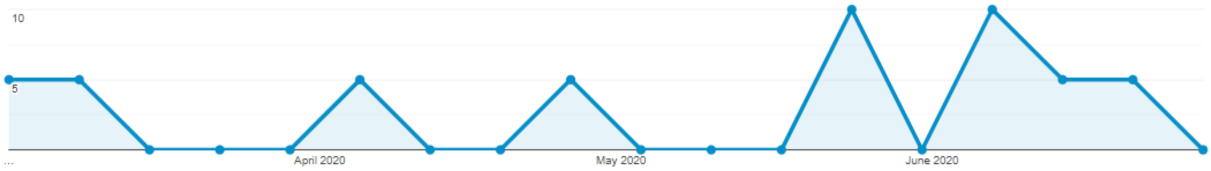


Figure 22. Conversions Studielink applications during the pandemic (Google Analytics, 2021)

Table 4 gives an overview of abovementioned and additional data. The numbers are displayed as “before” vs “during” the pandemic.

Table 4 Smaller goals with variable numbers before vs during the pandemic

Goal	***Completions***	***Average Session Duration***	***Bounce Rate (%)***	***Pages per Session***
Signing up for Open Days	21 *vs* 19	00:09:21 *vs* 00:10:44	17,66 *vs* 11,18	7,96 *vs* 8,53
Studielink application submitted	58 *vs* 48	00:09:51 *vs* 00:10:22	18,94 *vs* 13,34	8,30 *vs* 8,43

From table 4 we can conclude that the coronavirus did have an impact on the choice of students whether or not to start a study or study abroad. Especially the second goal (Studielink application) has less conversions and the variables have similar or lower scores, even though we would expect them to be higher. This could be explained by the fact that the virus made the future uncertain and therefore, some students, for example foreign students, are not willing to take the risk to study abroad.

For this research, there are also four big goals to look at which we link to the created clusters: downloading the brochure (“Goal 1: Brochure download”), visiting 3 or more pages (“Goal 5: Visited 3 or more pages”), checking the admission requirements page (“Goal 4: Toelatingseisen bekeken”) and doing an e-check (“Goal 2: E-check gestart”). The phrases between brackets are the names and numbers of the goals displayed in Google Analytics. The conversion rates for these goals will be used eventually for the personas created by the clusters. User personas will be explained in Section 4.5.

Table 5 Bigger goals with variable numbers before vs during the pandemic

Goal	***Conversions before the pandemic (avg/month)***	***Conversions during the pandemic (avg/month)***	***Monthly in/decrease***
Download the brochure	180 (60/month)	192 (48/month)	20% ↓
Visiting 3 or more pages	9047 (3015/month)	9601 (2400/month)	20% ↓
Visiting admission requirements page	5359 (1786/month)	5823 (1456/month)	19% ↓
Doing the e-check	2489 (830/month)	1762 (441/month)	47% ↓

4.3 Clustering: before the pandemic

In the created Excel file, to be used eventually in SPSS, all users are shown with corresponding regions/cities, average session durations, bounce rates, pages per session and affinity categories. Google Analytics unfortunately does not allow us to see the numbers per individual per region or city: it is very aggregated. Using the country as primary dimension and the affinity categories as secondary dimension we can see data as detailed as possible.

For the clustering analysis we use SPSS. By using the Ward's clustering method with Squared Euclidean distance, SPSS creates a dendrogram from which we can determine how many clusters are formed and which user belongs to which cluster. We use the stages described in Section 2.2.

Stage 1: Objectives of Cluster Analysis

We already described in Section 2.2 that the main objective of this research is taxonomy description: exploring and forming empirical classifications of objects (the taxonomies). Eventually, these taxonomies can be attached to one of the four stages of the AIDA (Awareness/Attention, Interest, Desire, Action) model to create a funnel. Also, personas will be created based on the clusters and the conversion rates for the four bigger goals can be attached to the personas.

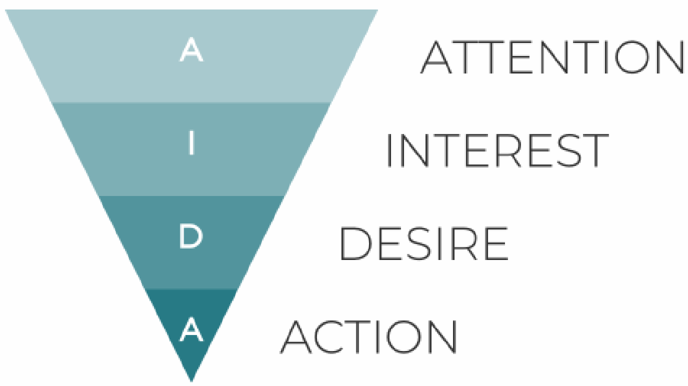


Figure 23. The AIDA model (Odekerken, 2018)

Stage 2: Research Design in Cluster Analysis

1. Is the sample size acceptable?

The sample size used for the first period is 326. This is a very acceptable sample size, since it could represent the whole population. When looking at the data, we can see there are many countries from all over the world involved. Therefore, the sample size is acceptable to use.

2. Are there any outliers?

When transforming the data in SPSS into a descriptive statistics table, the following results appear:

Table 6 Descriptive Statistics before the pandemic (SPSS, 2021)

Variable	***N (Total number)***	***Minimum***	***Maximum***	***Mean***	***Standard Deviation***
Bounce Rate	326	0,00%	100,00%	17,5336%	15,26709%
Pages/Session	326	1,00	17,70	8,7120	3,09855
Average Session Duration	326	00:00:02	00:28:47	00:09:28	00:04:36

From table 6 we can see there are a few outliers. First, the bounce rate has a minimum of 0,00% and a maximum of 100%. Based on the mean of 17,53% and the standard deviation of 15,26%, we can conclude the bounce rate must be in the interval of [2,27 ; 32,79]. This is calculated by the formula *mean ± standard deviation*. To make this interval somewhat bigger and changing it into round numbers, we turn it into [0 ; 35]. Applying this interval to the data, we can already delete 25 users.

Second, the pages/session variable has a minimum of 1 and a maximum of 17,7 pages. With a mean of 8,71 and a standard deviation of 3,09 we can establish an interval of [5 ; 15]. Then, we delete 24 outliers.

Third, the average session duration has a minimum of 0:00:02 and a maximum of 00:28:47. The mean is 00:09:28 and the standard deviation is 00:04:36. Therefore, the interval is [00:04:00 ; 00:15:00] and we can delete 39 outliers.

After deleting the outliers, the sample size is 251, which is still acceptable and representative.

3. How can we measure object similarity?

The object similarity will be measured by using the Squared Euclidean Distance interval measure. This measure is most commonly used in Centroid cluster analysis. With this measure the distance between observations is measured by taking the sum of the squared distances.

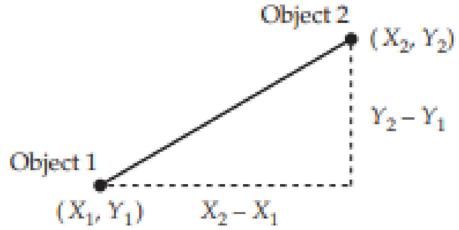


Figure 24. Example of Squared Euclidean Distance between objects 1 and 2 with variables X and Y (Hair et al., 2008).

The formula to calculate the distance between object 1 and 2 is then:
$(X_2 - X_1)^2 + (Y_2 - Y_1)^2$

4. Should we standardize the data?
The reason to use data standardization is to eliminate bias caused by differences in scales of the variables. This makes clustering easier. Therefore, we will standardize the data by using Z-scores.

Stage 3: Assumptions in Cluster Analysis
The two assumptions we have to take in mind are representativeness and multicollinearity. By deleting outliers, we already tacked the problem of representativeness: the observations used are possibly representative for the whole population. The assumption for multicollinearity can be calculated in SPSS. We do this by setting one variable as a dependent variable (DV) and the other two as independent variables (IV) to check whether they have a high correlation with each other. We do this for all three numerical variables. With a VIF (Variation Inflation Factor) threshold above 3 we can conclude there is multicollinearity. In this case, all VIF's are below 3 which indicates we do not have multicollinearity between the variables. Therefore, there is no need to change the amount of variables or search for different ones.

Table 7 VIF's of the numerical variables before the pandemic (SPSS, 2021)

DV / ***IV***	***Bounce Rate***	***Pages/Session***	***Average Session Duration***
Bounce rate	X	1,022	1,242
Pages/Session	1,304	X	1,242
Average Session Duration	1,304	1,022	X

Stage 4: Deriving clusters and assessing overall fit
In this research we use the hierarchical Ward's Method for the cluster analysis. This method tends to form equally-sized clusters with a small amount of observations (Hair, 2008), which could be beneficial for the analysis and creating the personas. The measure we use is the Squared Euclidean Distance. This method is most commonly used with the Ward's method.

From the dendrogram in Appendix A.2 we can see not all of the clusters are equally-sized. However, they do not differ very much and so, we can use these clusters for our analysis. Each small red line in the dendrogram is a cluster, connected to the users within that cluster.

Appendix A.3 shows us all of the created 14 clusters with the corresponding user ID's. The clusters with its corresponding observations can be found in Appendix B.

Stage 5: Interpretation of the clusters

If we look at the specific values of the variables in the clusters, we can see that certain clusters really have notable characteristics. The users in cluster 1 have mostly Media & Entertainment type of affinities and the other three variables are very fluctuating, while clusters 3 until 10 show relatively high bounce rates (almost all above 10%). Furthermore, all clusters have a comparable average amount of pages per session. Clusters 1 until 7 and 13 have relatively lower average session durations (below 00:10:00) compared to clusters 8 until 12 and 14 (above 00:10:00). To summarize all of the characteristics, we created a table (table 8). The amount of pages per session is called "low" when most numbers are below 10 and "high" when they are above 10. Sometimes the affinity categories were mentioned equally and not one specific affinity stands out. In this case, we write "Not Available (N/A)".

Table 8 Summary of the cluster characteristics before the pandemic

Cluster number	***Bounce Rate***	***Pages/Session***	***Average Session Duration***	***Most common Affinity Category***	***Most mentioned country***
1	Low	Low	Low	Media & Entertainment	Indonesia
2	Low	Low	Low	Media & Entertainment	Germany
3	High	High	Low	N/A	Indonesia
4	High	Low	Low	Lifestyles & Hobbies	The Netherlands
5	High	Low	Low	Lifestyles & Hobbies	The Netherlands
6	High	Low	Low	N/A	India
7	High	Low	Low	Food & Dining Media & Entertainment	The Netherlands
8	High	Low	High	N/A	Ghana
9	High	Low	High	Lifestyles & Hobbies	The Netherlands
10	High	High	High	N/A	India
11	Low	Low	High	N/A	Brazil
12	Low	High	High	Lifestyles & Hobbies	Germany
13	Low	High	Low	N/A	Turkey
14	Low	High	High	N/A	Germany

Stage 6: Validation and profiling of the clusters
In this stage, we must check whether the clusters are representative of the population studied. When looking at the affinity categories, we do not see much variation. There are many more categories than the ones mentioned in the table. Therefore, this variable does not really represent the population, but does add a little more detail. On the contrary, the countries do represent the population very well. There are several countries mentioned from different continents. Also, the Netherlands and Germany are mostly mentioned, which makes sense, because most students come from The Netherlands and nearby countries.

When creating the personas, we can combine clusters so we do not have to create 14 personas. Combining will also make analyzing easier. Therefore, based on the same level in bounce rate, pages/session and average session duration, we will merge the following clusters into one persona:

- 1 and 2
- 4, 5, 6 and 7
- 8 and 9
- 12 and 14

4.4 Clustering: during the pandemic

Stage 2: Research Design in Cluster Analysis

1. Is the sample size acceptable?
With a sample size of 264 and a variation of countries all over the worlds, we can conclude that the sample size is very acceptable and representable for the whole population.

2. Are there any outliers?
To detect outliers we must first create a Descriptive Statistics table. We create one in SPSS. With help of Table 9 we can easily detect these outliers.

Table 9 Descriptive Statistics during the pandemic (SPSS, 2021)

Variable	***N (Total number)***	***Minimum***	***Maximum***	***Mean***	***Standard Deviation***
Bounce Rate	264	0,00%	42,11%	10,3212%	7,46612%
Pages/Session	264	1,67	21,77	8,1871	2,79083
Average Session Duration	264	00:00:35	00:17:55	00:08:50	00:02:49

The variable Bounce Rate has a minimum of 0,00% and a maximum of 42,11. According to the mean of 10,32% and the standard deviation of 7,46% the bounce rate must lie in the rounded off interval [2 ; 20]. The 48 users who are not within this interval, will be deleted.

When looking at the variable Pages/Session we see a minimum of 1,67 and a maximum of 21,77. The mean is 8,18 and the standard deviation 2,79. The interval will then become [5 ; 12] and 34 outliers are deleted.

The third variable, Average Session Duration, has a minimum of 00:00:35 and a maximum of 00:17:55. With a mean of 00:08:50 and a standard deviation of 00:02:49 the interval becomes [00:05:00 ; 00:12:00]. We will then remove 20 outliers.

After deleting these outliers, there are 163 users left, which is still representative for the whole population, since it is large enough.

3. How can we measure object similarity?
The object similarity will be measured by using the Squared Euclidean Distance interval measure.

4. Should we standardize the data?
The reason to use data standardization is to eliminate bias caused by differences in scales of the variables. This makes clustering easier. Therefore, we will standardize the data by using Z-scores.

<u>Stage 3: Assumptions in Cluster Analysis</u>
In this stage we tackle two assumptions: representativeness and multicollinearity. Representativeness is already treated in stage 2. Therefore, we only have to calculate multicollinearity using SPSS (Table 10).

Table 10 VIF's of the numerical variables during the pandemic (SPSS, 2021)

DV / ***IV***	***Bounce Rate***	***Pages/Session***	***Average Session Duration***
Bounce rate	X	1,029	1,180
Pages/Session	1,255	X	1,180
Average Session Duration	1,255	1,029	X

Just like in the period before the pandemic the VIF's of the variables are below 3, which means there is no multicollinearity present and so, we do not need to change the (amount of the) variables.

<u>Stage 4: Deriving clusters and assessing overall fit</u>
In this research we use the hierarchical Ward's Method with Squared Euclidean Distance for the cluster analysis.

The first thing we notice from the dendrogram (Appendix A.4) and the table with clusters (Appendix A.5) are the small amount of observations in the first 9 clusters and the very long 10th cluster. Still, the first nine clusters are on average equally divided, which makes the analysis easier. Appendix C includes a list of the clusters with corresponding observations.

<u>Stage 5: Interpretation of the clusters</u>

Just like for the period before the pandemic we create a table with the characteristics of the different clusters (Table 11). In this table the bounce rate is called "low" when most of the values are below 10% and "high" when it is above 10%. The amount of pages per session is called "low" when they are mostly below 10 and "high" when they are above 10. The average session duration is "low" when the time is below 00:10:00 and "high" when the time is above 00:10:00. If the affinity categories are fluctuating, we write "N/A" which means not available.

Table 11 Summary of the cluster characteristics during the pandemic

Cluster number	***Bounce Rate***	***Pages/Session***	***Average Session Duration***	***Most common Affinity Category***	***Most mentioned country***
1	Low	Low	High	Lifestyles & Hobbies Shoppers	The Netherlands
2	High	Low	High	Media & Entertainment	Italy
3	Low	Low	High	N/A	The Netherlands
4	Low	High	Low	Lifestyles & Hobbies	Germany and Indonesia
5	High	Low	Low	N/A	India
6	High	Low	Low	Media & Entertainment	The Netherlands
7	Low	Low	Low	Media & Entertainment	Germany
8	Low	Low	Low	Lifestyles & Hobbies	Germany and India
9	Low	Low	Low	N/A	India
10	Low	Low	Low	Media & Entertainment	The Netherlands

Stage 6: Validation and profiling of the clusters

What we can already notice from the table above is the variation in countries. In the period before the pandemic the most mentioned countries were worldwide countries, whereas in this period, they are mostly European countries. This could already be an indication of the consequence of the pandemic to a foreign student's choice to study abroad. Indonesia and India are both mentioned. However, they are both once mentioned together with another most-mentioned country, which is a European country (Germany).

Another thing we noticed are the low bounce rates and pages per session compared to the previous period. Also the amount of low average session duration is higher than in the period before the pandemic. The low bounce rates are an indication that people still have the intention to study (abroad), because less people leave the website after visiting one page. On the contrary, the low pages per session could be an indication that potential students only look broadly at the programme and do not want to check out information in detail. Furthermore, the average session durations are low, which adds to previous perception. When looking at the affinity categories, the variation is again very low. So this variable is only a detail to the personas we will create in the next section.

For the personas we can combine the following clusters, because of their same level in variables:

- 1 and 3
- 5 and 6
- 7, 8, 9 and 10

To create the behavioural profiles, the clusters found in sections 4.3 and 4.4 are used. The profiles are divided according to the different stages in the AIDA model (Awareness, Interest, Desire, Action), certain characteristics are mentioned and personas are built. Also, average conversion rates for the goals are displayed in the personas.

4.5 Behavioural profiles and user personas

For this research we would like to analyze the behavioural profiles of the website users. We do this by creating user personas. A user persona is a semi-fictive person with certain demographic and psychographic characteristics (Grenier, n.d.). The user persona will include the demographics, geographics and affinities of the user based on the clusters created in Section 4.3 and 4.4. Also, we will make an indication in which stage of the AIDA model the user is in. To include the bigger goals discussed in Section 4.2, we will check the specific goal conversions of a similar user in Google Analytics and include this in the browsing behaviour of the persona.

We also included archetypes in the personas. Archetypes are characters within our unconscious mind. Based on a person's characteristics and motivations, the archetypes can be determined. We will explain the used ones here shortly (Neill, 2018):

- *Sage:* a person who wants to find the truth by looking for information and knowledge.
- *Explorer*: wants to be free to find out one's self and the world and likes to experience new things in life.
- *Jester:* someone who lives in the moment and wants to enjoy life .
- *Caregiver:* a person who likes to help others and desires to protect and do things for others.
- *Lover*: one who is very intimate and wants to be in a good relationship with people, work and the environment.

- *Innocent:* someone who is optimistic and whose goal is to be happy and do everything right
- *Hero*: a person who wants to improve the world and tries to do courageous things
- *Creator*: also known as "Artist", someone who likes to create things and thinks everything can be realized if you can imagine it

4.5.1 Behavioural profiles and user personas before the pandemic

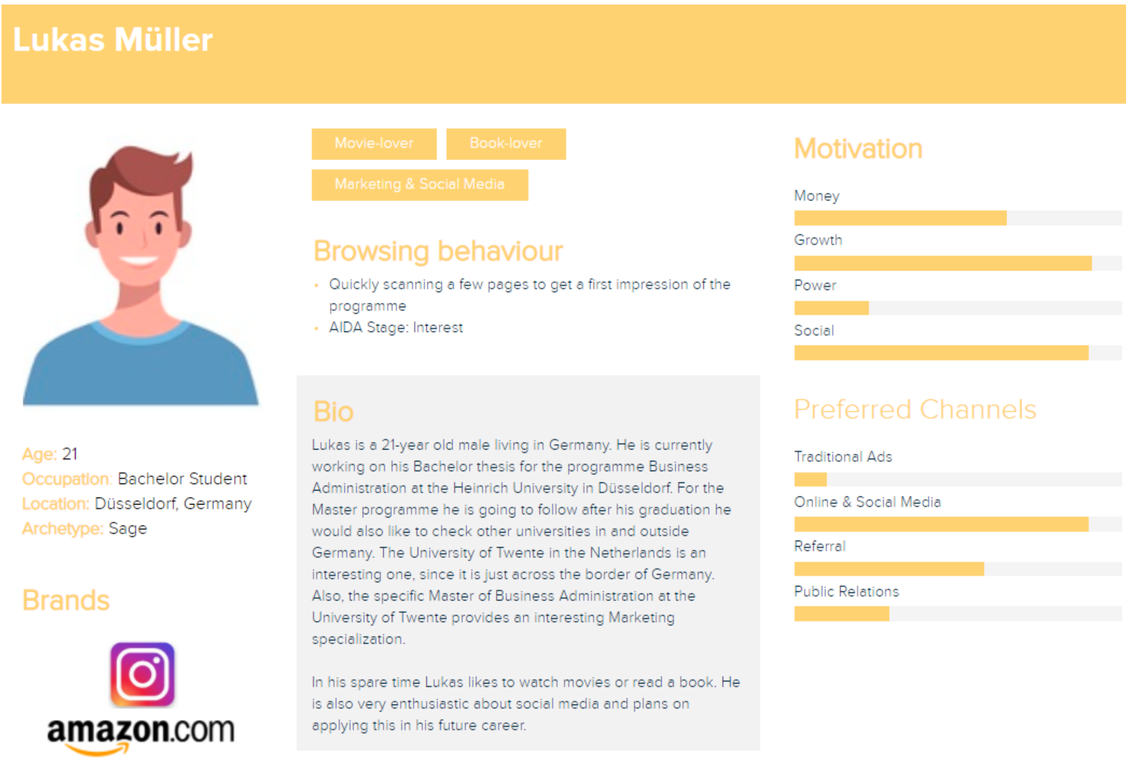
For the user personas we already concluded that some cluster could be combined in one user persona. We will combine the following clusters into one user persona:

- 1 and 2
- 4, 5, 6 and 7
- 8 and 9
- 12 and 14

Therefore, we have to create 8 personas. The user personas are created using a standard template on Xtensio.com.

As can be seen from the AIDA stages of the personas, most of them are in the first two stages: attention or interest. This is explainable, since we study the period from December until February which is the exploring phase of choosing a (follow-up) programme.

<u>Persona 1 (Clusters 1 and 2)</u>



<u>Persona 2 (Cluster 3)</u>

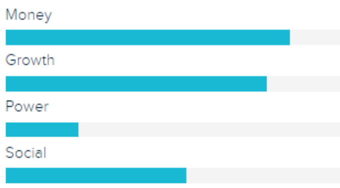
Maria Soeharto

Travelling | Food | Shopping | Fitness | Finance & Economics

Browsing Behaviour

- Visits many pages in a small amount of time
- Checks admission requirements
- AIDA Stage: Interest

Motivation

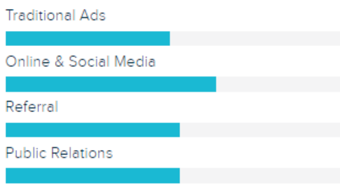


Age: 24
Occupation: Working part-time jobs and travelling
Location: Jakarta, Indonesia
Archetype: Jester

Bio

Maria Soeharto is a eager 24-year old female who likes to travel the world. She finished her Bachelor of Economics at the State University of Jakarta and took a few years off to travel the world and work part-time jobs in beauty salons. During her trip she was very enthusiastic about the Netherlands and its broad education programmes. Therefore, she decided to do a Master in Finance somewhere in the Netherlands. The University of Twente really speaks to her because of its internationalized culture and the choice between multiple Finance programmes.
While not working, studying or travelling, Maria likes to go outside to go shopping, do fitness or eat at a local restaurant.

Preferred Channels



Brands

<u>Persona 3 (Clusters 4 – 7)</u>

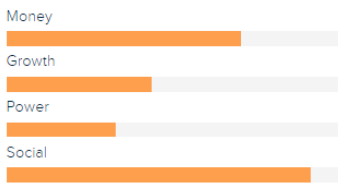
Rik Jansen

Outgoing | Concerts | Cooking | Games | Purchasing

Browsing behaviour

- Visits very few pages in a short amount of time to get a first impression of the programme
- Is not interested in an e-check or brochure
- AIDA Stage: Attention

Motivation



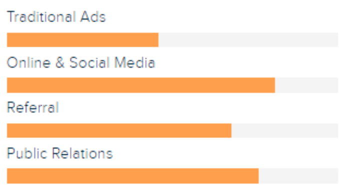
Age: 22
Occupation: Bachelor Student
Location: Enschede, The Netherlands
Archetype: Explorer

Bio

Rik Jansen is a 22-year old Bachelor student at the University of Twente. He used to live with his parents in Eibergen, but is now happy in his student apartment in Enschede, where he lives with 3 other male Bachelor students. He is currently studying Industrial Engineering & Management (IEM) and is most specifically interested in the purchasing part. He is quite certain he will do the Master of IEM after his graduation, but since the Master of Business Administration also provides a purchasing specialization, he keepsthis programme in mind as well. Furthermore, he also explores purchasing programmes at other Dutch universities.

Besides his study Rik likes to go out and attend live events. He also loves to cook for his roommates and play an Xbox game every now and then.

Preferred Channels



Brands

Persona 4 (Clusters 8 and 9)

Lieke Vermeer

Fashionista | Nature lover | Reading | Vegan | Digital Business

Age: 21
Occupation: Bachelor Student
Location: Amsterdam, The Netherlands
Archetype: Caregiver

Brands

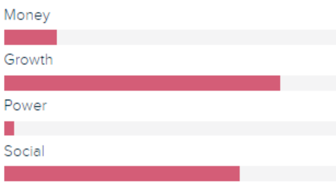
Browsing behaviour

- Only visits a few pages which seem to be most important, but she reads them very carefully
- Checked the admission requirements page to see what pre-Master is needed
- AIDA Stage: Interest

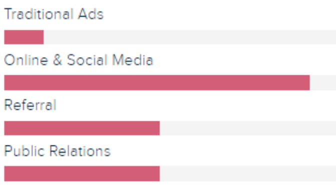
Bio

Lieke is a 20-year old fashonista living in Amsterdam. She currently studies at the Amsterdam Fashion Institute (AMFI) where she will receive her HBO-diploma in May. Besides fashion she also likes digital businesses and therefore, she is currently looking for a Master programme in this area. The University of Twente is one of the universities that offers a Digital Business programme. She could also choose to do such a programme at the University of Amsterdam, but she would like to explore the country a little bit more. She also likes nature, which she can find more in the east of The Netherlands compared to the west. She focuses on living ecologically by recycling clothing and using as little plastic as possible. In her spare time she likes to go thrift shopping or she reads a book, listens to some music or visits a vegan food tent.

Motivation



Preferred Channels



Persona 5 (Cluster 10)

Ananya Patel

Eager | Europe | Healthy lifestyle | Organized | Entrepreneurship

Age: 19
Occupation: Bachelor Student
Location: Bengaluru, India
Archetype: Lover

Brands

Browsing behaviour

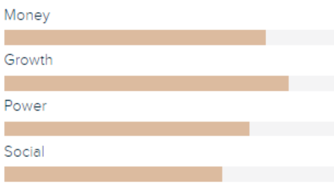
- Visits many pages for a long amount of time to get as much information as possible
- Knows what pages are important, so immediately leaves a page when it does not seem important. This way time is spent most efficiently.
- AIDA Stage: Desire

Bio

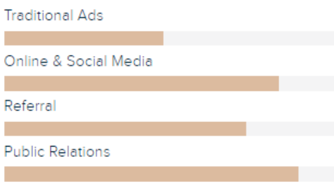
Ananya Patel is an eager female Indian student. When she wants something she really goes for it and nothing can stand in her way. At only 19 years old she is already almost finished with her 3-year Bachelor programme Business Management at the Banagalore University. Her goal is to be an entrepreneur, but not in India. She likes to go abroad and discover the world, preferably in Europe. After receiving her diploma at the end of the year she would like to study at the University of Twente. The Master of Business Administration seems most interesting to her, because of the specialization "Entrepreneurship, Innovation & Strategy".

In her spare time she likes to do fitness, eat and cook healthy or pamper herself in a nail or massage salon. She also likes to keep track of her finances and lives a very organized life.

Motivation



Preferred Channels



Persona 6 (Cluster 11)

Pedro Silva Santos

Age: 24
Occupation: Working
Location: Sao Paolo, Brazil
Archetype: Innocent

Brands

Art lover | Traditional | Human Resources

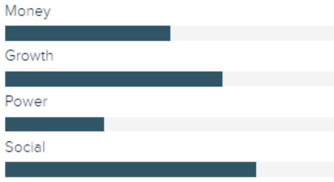
Browsing behaviour

- Visits only a few pages, but spends a lot of time on the website
- Only leaves when required information is gathered
- Visits the admission requirements page for quite a long time
- AIDA Stage: Interest

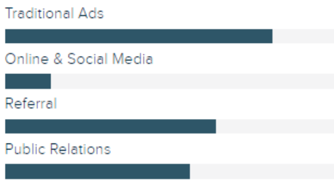
Bio

Pedro is a 24-year old male who currently lives and works in Sao Paulo, Brazil. He has already finished his Bachelor in Human Resources at the UNAR and decided to start working a full-time job after his graduation. Now that he has worked for a year he is interested in going back to college and expand his Human Resources knowledge a bit more. He has saved enough money to study abroad, so he is also considering that. During his search for a Human Resources programme abroad, he found the University of Twente and its Human Resource Management specialization within the Business Administration Master. This could be a very interesting one for him, but is not on top of his list, because of the technological/digital part. Pedro is a more traditional type of guy. He likes art very much and loves to visit musea and prefers to read a book instead of scrolling through his social media pages. Every now and then he visits a soccer game with his friends.

Motivation



Preferred Channels



Persona 7 (Cluster 13)

Defne Yilmaz

Age: 22
Occupation: Bachelor Student
Location: Istanbul, Turkey
Archetype: Everyman

Brands

Fashion | International Management | Movies | Consultancy

Browsing behaviour

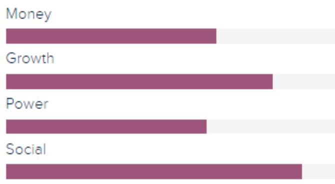
- Visits many pages, but only scans them for a short amount of time and then leaves again
- AIDA Stage: Attention

Bio

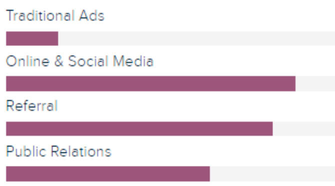
Defne is a 22-year old female from Turkey who is currently in the first semester of the third year of the Bachelor in Business Administration at the Istanbul University. In the second semester she will write her thesis to graduate. She would like to continue in september with a Master in Business Administration and prefers to do this abroad. When looking for a university in another country she came across the University of Twente. The Master in Business Administration provides a specialization in International Management & Consultancy, which she finds very interesting. However, she prefers to move to a bigger city, such as Amsterdam and therefore continues to look for other programmes.

In her spare time Defne loves to listen to music or watch a movie. She is not really into TV shows, but prefers to watch a romantic movie. Shopping with friends and looking for the latest fashion items is also something she likes to do. She always shows her new items to her 500,000 Instagram followers.

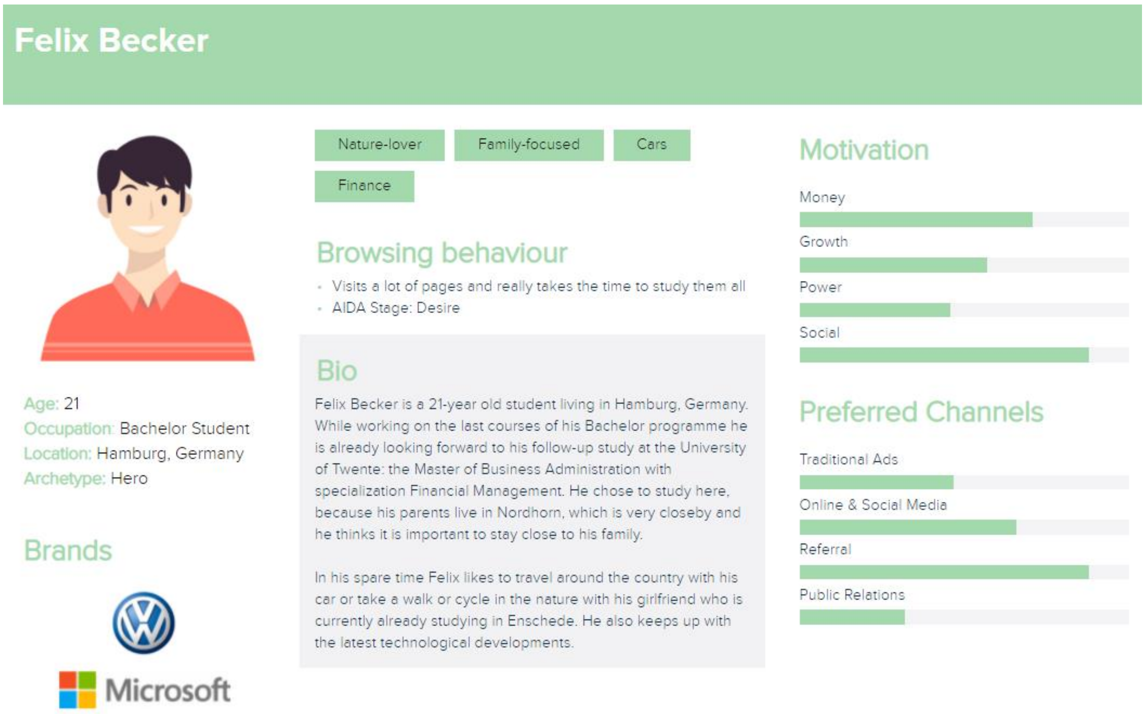
Motivation



Preferred Channels



Persona 8 (Clusters 12 and 14)



To analyze the personas and their goal conversions we have created a table with the personas and their corresponding goal conversions. The percentages between brackets are the individual conversion numbers as a percentage of the total amount of goal conversions for that goal, displayed in table 5. So, for example, Lukas Müller has a goal conversion of 242 at the second goal. The total amount of goal conversions for this goal is 9047. Therefore, 242 equals 3% of 9047. The percentages are rounded up to whole numbers where possible.

Table 12 Goal conversions per persona before the pandemic

Goal / ***Persona***	***Download brochure***	***Visit 3+ pages***	***Check admission requirements***	***Do e-check***
Lukas Müller	4 *(2%)*	242 *(3%)*	125 *(2%)*	38 *(2%)*
Maria Soeharto	0 *(0%)*	167 *(2%)*	134 *(3%)*	58 *(2%)*
Rik Jansen	8 *(4%)*	601 *(7%)*	305 *(6%)*	25 *(1%)*
Lieke Vermeer	8 *(4%)*	246 *(3%)*	155 *(3%)*	13 *(0,5%)*
Ananya Patel	0 *(0%)*	58 *(1%)*	38 *(1%)*	21 *(1%)*
Pedro Silva Santos	4 *(2%)*	38 *(0,5%)*	17 *(0,5%)*	0 *(0%)*
Defne Yilmaz	0 *(0%)*	113 *(1%)*	79 *(1%)*	33 *(1%)*
Felix Becker	0 *(0%)*	33 *(0,5%)*	13 *(0,5%)*	0 *(0%)*

When analyzing table 12 we can remark several points. First, the goal “brochure download” has very few conversions. It seems that no one is actually interested in downloading a brochure or the fill-in form for the brochure is not clearly visible on the website. Second, when looking at the second and third goal, “visit 3+ pages” and “check admission requirements”, we can clearly see that Rik Jansen, a persona from Enschede, has the highest conversion rate. This means most often people from Enschede visit many pages and check the admission requirements. Lieke Vermeer, a persona from Amsterdam, is second on this list. Doing an e-check is not very interesting for these two personas, since this is only applicable for foreign students. Therefore, their conversions for this goal are low, while the conversion of doing an e-check for Maria Soeharto (Indonesia) is much higher.

If we check the personas on the AIDA stage they are in, which are based on the variables, we can see that most of them (6 out of 8) are in one of the first two stages, Attention or Interest. Only two of them are in the Desire stage. This is explainable, since we study the period between December 2019 and February 2020. This is the first semester of a programme’s year and most students start a Master in September. Therefore, in this period, not many students will already have decided which Master to do after their Bachelor and it is only an exploring phase. We should expect the stages to shift to Desire in the next period.

4.5.2 Behavioural profiles and user personas during the pandemic

For the period during the pandemic the following clusters will be merged:

- 1 and 3
- 5 and 6
- 7, 8, 9 and 10

This means we have to create 5 clusters.

Persona 1 (Clusters 1 and 3)

Lena Ten Hag

Age: 22
Occupation: Bachelor Student
Location: Enschede, The Netherlands
Archetype: Innocent

Brands

Nikon
NOVI Gran Caffè
ZAND

Shutterbug | Nature-lover | Food-lover | Insecure | Finance

Browsing behaviour

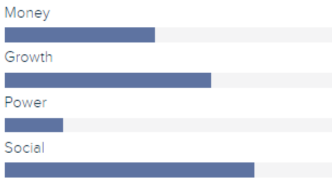
- Visits only a few important pages, but studies them very well and therefore spends a long time on the website.
- Also interested in the admission requirements of the programme
- AIDA stage: Interest

Bio

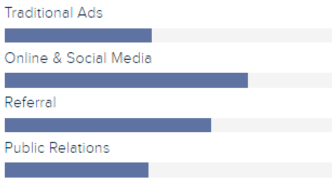
Lena ten Hag is a 22-year old female Bachelor student at the University of Twente. She is currently working on her thesis for the programme Industrial Engineering & Management (IEM) and plans to finish before summer. After summer she will continue a Master programme also at the University of Twente. She is still conflicted between the specialization Financial Engineering Management of IEM or the Financial Management specialization of Business Administration. She knows IEM is a tough programme in which she has to do programming a lot which is one of her weaknesses. This causes a lot of stress and insecurity, since she has to make a decision soon.

Besides studying Lena likes to go outside and take photographs of the nature. She also likes to go out with friends and eat lunch at restaurant or attend a live event.

Motivation



Preferred Channels



Persona 2 (Cluster 2)

Carlo Rossi

Age: 25
Occupation: Unemployed
Location: Milan, Italy
Archetype: Explorer

Brands

ITALIARAIL

Fastfood-lover | Traveling | Hopeful | Marketing

Browsing behaviour

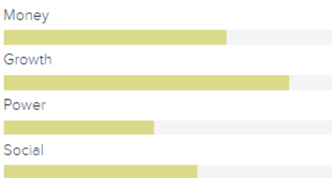
- Visits only a few pages, but spends quite a while on pages which are interesting and relevant
- Immediately leaves unneccessary pages with irrelevant information
- AIDA stage: Interest

Bio

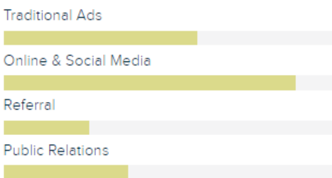
Carlo is a 25-year old male living in Milan, Italy. He followed his Bachelor programme International Marketing at a university in Paris, France, and decided to go back to his home town after graduation to look for a job. He graduated 3 years ago and succeeded in finding a proper start-up company to work at as Junior Marketeer. Unfortunately, due to the pandemic, the company did not last any longer, which made Carlo unemployed. Therefore, he decided to start a Master programme in September in The Netherlands. During his search he came across the University of Twente, which seems very interesting to him, because of the international approach and the specialization Strategic Marketing Management of the MSc Business Administration. It is still very uncertain whether it is possible to go there because of travel restrictions. However, he has high hopes it will be allright.

In his spare time Carlo likes to travel by train and visit fastfood restaurants all around the country, and preferably all around the world.

Motivation



Preferred Channels



Persona 3 (Cluster 4)

Hannah Schmidt

Age: 22
Occupation: Bachelor Student
Location: Berlin, Germany
Archetype: Creator

Brands

DIY | Cooking | Musical-lover | Finance

Browsing behaviour

- Visits many pages in a short amount of time and only scans important information rather than closely look at it
- AIDA stage: Interest

Bio

Hannah Schmidt is a 22-year old female Bachelor student. She currently follows the Bachelor programme Economics at the Freie Universität in Berlin where she lives in a student apartment with 5 roommates. For her Master she would like to move to a one-person student apartment at the University of Twente campus. She is very interested in the Master Business Administration with specialization Financial Management. However, she still hesitates to go, since lectures are currently only given online and she does not know when that will change. Staying in Germany in her familar environment and saving some time and money by not moving does not seem so bad under these pandemical circumstances.

Hannah is a real do-it-yourselfer. She likes to find out new recipes, creates her own furniture and sew most of her own clothing. She also loves to go to a theater to see a musical.

Motivation

Money

Growth

Power

Social

Preferred Channels

Traditional Ads

Online & Social Media

Referral

Public Relations

Persona 4 (Clusters 5 and 6)

Bart Jonker

Age: 21
Occupation: Bachelor Student
Location: Amsterdam, The Netherlands
Archetype: Sage

Brands

Gaming | TV shows | Motorcycles | Human Resource Management

Browsing behaviour

- Visits only a few pages and spends a very short time on the website.
- AIDA stage: Attention

Bio

Bart Jonker is a 21-year old Bachelor Student from Amsterdam. He currently still lives with his parents in Hoofddorp from where he travels to the university every day where he follows the Business Admistration programme. Now that he is 21 he decided to move out and therefore, he can choose more universities to study at. Since the rent for a small place in Enschede is not so high compared to the west of the country, he keeps the University of Twente in mind. However, also Rijksuniversiteit Groningen speaks to him. If he chooses the University of Twente, he will follow the Master in Business Administration with specialization Human Resource Management.

Besides studying Bart is really into online and offline gaming. He mostly plays adventurous games or solves puzzles. He also loves to binge watch television shows or take a ride on his motorcycle.

Motivation

Money

Growth

Power

Social

Preferred Channels

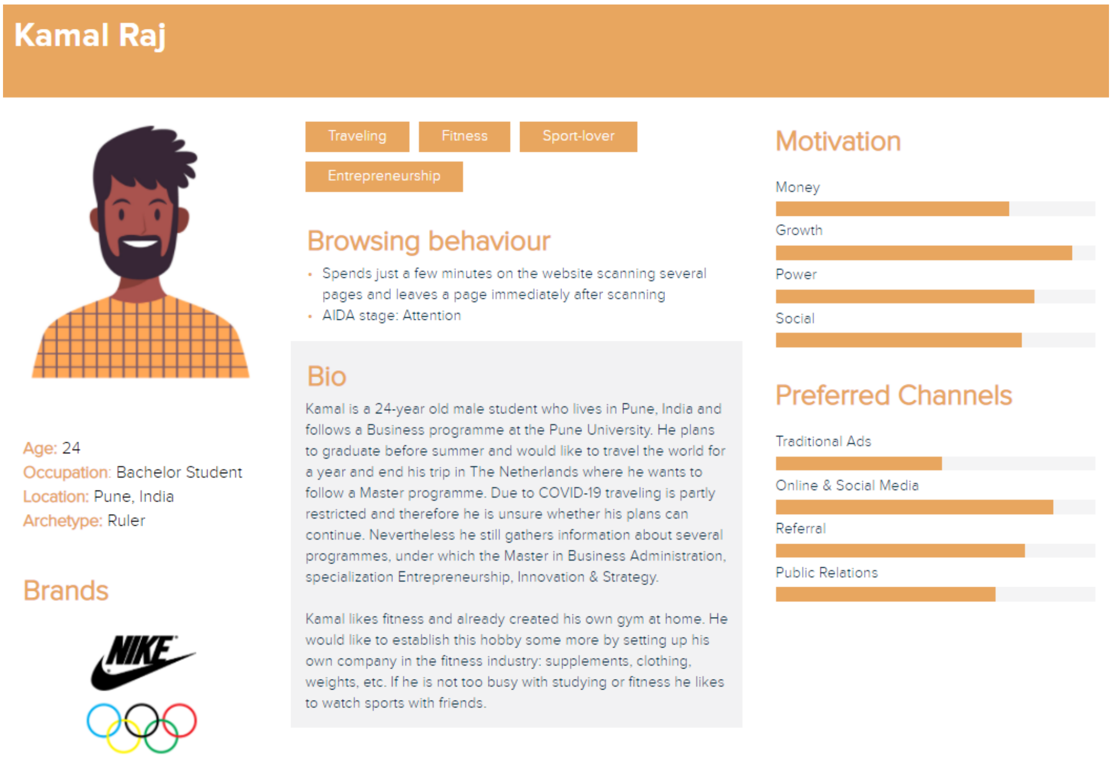
Traditional Ads

Online & Social Media

Referral

Public Relations

Persona 5 (Clusters 7 – 10)



Also for this period we have created a table with goal conversions and corresponding percentages.

Table 13 Goal conversions per persona during the pandemic

Goal / ***Persona***	***Download brochure***	***Visit 3+ pages***	***Check admission requirements***	***Do e-check***
Lena Ten Hag	5 *(3%)*	891 *(9%)*	508 *(9%)*	34 *(2%)*
Carlo Rossi	0 *(0%)*	43 *(1%)*	19 *(0,5%)*	5 *(0,5%)*
Hannah Schmidt	15 *(8%)*	62 *(1%)*	53 *(1%)*	19 *(1%)*
Bart Jonker	5 *(3%)*	225 *(2%)*	163 *(3%)*	10 *(0,5%)*
Kamal Raj	0 *(0%)*	48 *(0,5%)*	29 *(0,5%)*	0 *(0%)*

In table 13 we can see that all percentages are very low, except for the persona Lena Ten Hag, a Dutch student from Enschede. Also the conversions for Bart Jonker, a student from Amsterdam, are somewhat higher compared to the three foreign students. The conversions of the foreign students are very low, which could be explained by COVID-19. The virus was getting more and more severe each day, traveling was partially restricted and futures were not so certain anymore. This could be an influence for foreign students to decide not to study abroad.

Chapter 5. Conclusions and recommendations

This research was done for the sake of all universities in the Netherlands. A case study was done at the University of Twente; specifically the website for the Master of Business Administration was used. Data was gathered using Google Analytics and processed using Cluster Analysis in SPSS. From the research several conclusions can be drawn related to the impact of COVID-19. This section answers the research question "How did the pandemic of COVID-19 change and/or affect the different online behavioural profiles of students visiting the website of Business Administration?".

The first thing we analyzed were the global statistics of the website. We distinguished between two time periods: from December 1, 2019 until February 29, 2020 ("before the pandemic") and from March 1, 2020 until June 30, 2020 ("during the pandemic"). We noticed that the total amount of visitors dropped from 10.636 to 10.158. Even though this seems like a slight change, we must mention that the first period included 3 months while the second one included 4 months. Therefore, the average amount of visitors per month decreased from 3545 to 2540, which is a decrease of approximately 28%. We would have expected a positive change in total amount of visitors, because the first period is only an exploring phase and the second period is the phase in which potential students have to make a decision and eventually register for the programme. Therefore, the second period normally would have more visitors. Also, we checked the conversions for six goals. The monthly conversions for each goal decreased as well. We cannot fully conclude from these two analyses that COVID-19 had a negative influence on the behavioural profiles of the visitors. To conclude this, we must analyze more data and also, we must analyze more Dutch universities to draw a general conclusion.

After the general data analysis we performed the six steps of Cluster Analysis on the collected data. This resulted in a dendrogram from which we could create several clusters, before and during the pandemic. Each cluster contained a number of users with specific characteristics related to the four variables: bounce rate, pages per session, average session duration and affinity category. Based on these clusters and their characteristics we created personas: fictional human beings with certain demographic and geographic characteristics. We also included the AIDA (Attention, Interest, Desire, Action) stage of the cluster in the persona based on the three variables. Furthermore, the conversions for the four bigger goals (brochure download, visiting 3+ pages, checking the admission requirements page and doing the e-check) were analyzed per persona as well.

We can immediately notice that the clusters in the first period are more international than the clusters in the second period. In the first period we created personas for European, Asian and American users, whereas we created mostly European personas and only one Asian persona in the second time period. This can be a consequence of the pandemic, since the government advised not to travel abroad and some countries were a "danger zone". Foreign students, and mostly Asian, African and American students, could therefore choose not to study abroad to a country far away.

We can clearly see the impact of COVID-19 in the AIDA stages. We would expect the AIDA stages to shift from attention and interest (period before pandemic) to desire and action (period during pandemic). However, we can see that the personas are still in the first two phases in the second period. This could be explained by the fact that the pandemic created an uncertain future for the potential students. To accomplish this, the number of high pages per session and high average session duration must have been higher.

From Tables 14 and 15 (goal conversions before and during the pandemic, respectively) we can remark that the goal conversions in the period before the pandemic were spread out. The conversions for doing an e-check are higher with foreign students than with Dutch students, which makes sense, since e-checks are only applicable to foreign students. The two middle goals (visiting 3+ pages and checking the admission requirements) had higher conversions, mostly with Dutch students. In the second period the goal conversions were very low and especially the foreign students had very low goal conversions. This latter could again be a consequence of the pandemic, due to travel restrictions or uncertain futures. The brochure download goal had very low conversions in both time periods. The brochure download unit could be somewhat more visible. It is now all the way down on the main page. When putting it more upwards on the main page, it would be more visible and conversions for this goal could be higher.

Abovementioned conclusions indicate that the pandemic of COVID-19 did somehow impact the online behavioural profiles of the website visitors of Dutch universities in such a way that they did not view the website with much interest or desire as they should have. Especially foreign students did not have as much interest in the programme as expected a few months/weeks before the start of a new academic year. Goal conversions were low, meaning they did not view many pages, were less interested in admission requirements and did not do many e-checks. Also, the AIDA stages were stuck in the first two stages, attention and interest, while we would expect them to be in the last to stages, desire and interest. This is a consequence of the students not spending much time on the website, not visiting many pages per session and having high bounce rates. Even though this already indicates a change, we must further investigate Dutch universities to draw a general conclusion. Due to time limitations we were not able to analyze this case any further. Therefore, we recommend future researchers to analyze multiple Dutch universities, preferably international universities. Furthermore, it is useful to look for more variables. Some variables were hard to analyze which took a lot of time. When having more time, researchers could dive into these variables to make the research as detailed as possible. Analyzing heat maps could also be a positive addition to such research. By doing this, it is clear what buttons website visitors click the most and where the interests are. It is also interesting to study Dutch “HBO” schools (Higher Professional Education). These schools are also dealing with the pandemic and also attract international students. Therefore it could be interesting for them to know what the impact is of the pandemic on their student’s choices.

With the information of this research and in combination with research done previously, universities could optimize their websites and their marketing to make the programmes more attractive, so that potential students will eventually be persuaded to apply at a university.

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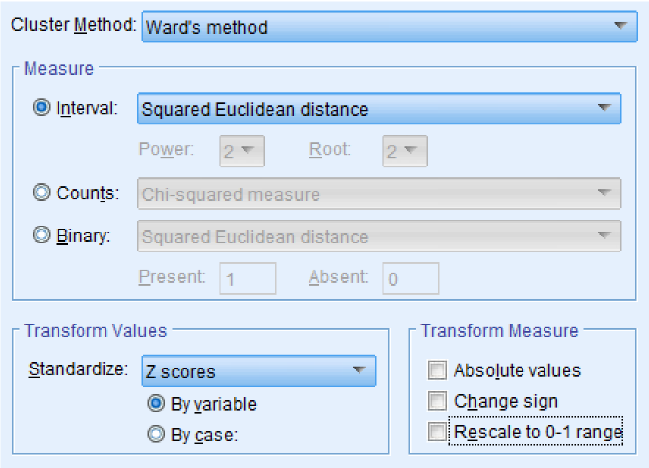
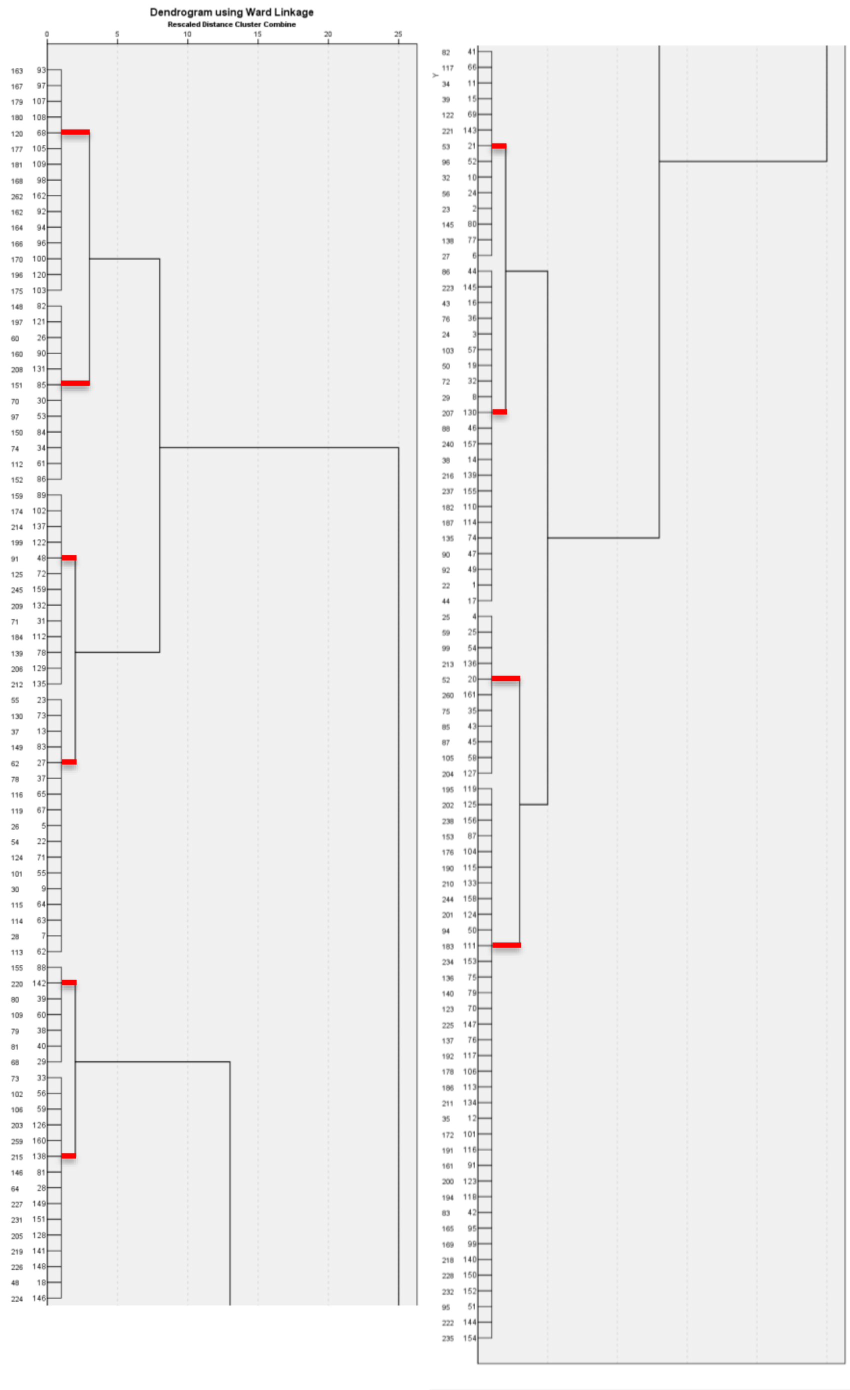
Appendix

Appendix A: Cluster Analysis results

A.1 Cluster Analysis settings in SPSS



A.2 Dendrogram before the pandemic

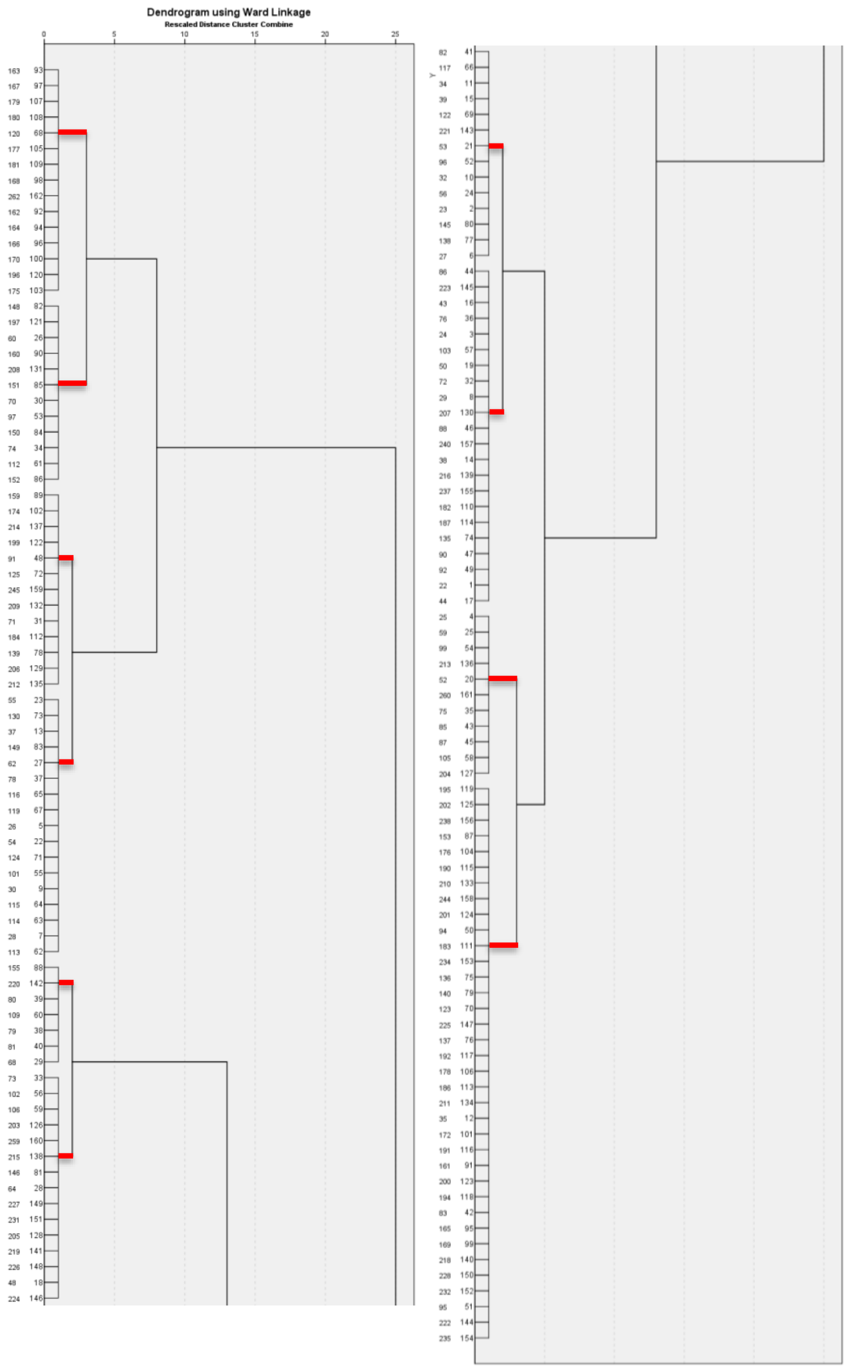


A.3 Clusters with user ID’s before the pandemic

Table A.3 Clusters with corresponding users before the pandemic

Cluster number	***User ID’s***
1	12, 13, 40, 43, 55, 79, 150, 151, 164, 167, 168, 171, 172, 174, 176, 230, 235, 243, 250, 316
2	1, 3, 6, 7, 16, 29, 31, 37, 41, 42, 50, 127, 159, 244, 247
3	57, 146, 147, 149, 155, 157, 158, 163, 165, 170, 173, 177, 178, 180, 246, 310
4	87, 91, 103, 107, 108, 148, 162, 166, 175, 184, 188, 190, 201, 203, 204, 205, 210, 218, 220, 226, 227, 228, 245
5	90, 99, 102, 104, 118, 122, 123, 131, 185, 187, 189, 194, 198, 202, 211, 214, 215, 216, 217, 238, 273, 280, 282, 287, 290, 292, 326
6	82, 85, 88, 89, 92, 96, 100, 105, 109, 111, 115, 124, 133, 233, 236, 325
7	25, 66, 68, 69, 70, 73, 76, 77, 95, 101, 114, 139, 169, 182, 193, 200, 207, 208, 209, 212, 213, 221, 222, 223, 224, 225, 229, 234, 239, 242, 248
8	64, 65, 67, 71, 119, 141, 195, 199, 265, 283, 285, 318, 319
9	17, 18, 20, 27, 98, 110, 125, 129, 130, 134, 137, 183, 186, 191, 192, 196, 197, 206, 231, 240
10	19, 22, 23, 97, 106, 112, 113, 117, 126, 128, 255, 259, 264, 279, 284, 286
11	2, 4, 9, 11, 14, 24, 135
12	32, 33, 34, 35, 36, 38, 39, 44, 45, 46, 47, 48, 49, 51, 53, 54, 58, 61, 62, 144, 152, 153, 154, 156, 161, 289, 313, 314
13	179, 303, 305, 306, 308, 309, 311, 312
14	8, 21, 30, 52, 56, 59, 60

A.4 Dendrogram during the pandemic



A.5 Clusters with user ID’s during the pandemic

Table A.5 Clusters with corresponding users during the pandemic

Cluster number	***User ID’s***
1	120, 162, 163, 164, 166, 167, 168, 170, 175, 177, 179, 180, 181, 196, 262
2	60, 70, 74, 97, 112, 148, 150, 151, 152, 160, 197, 208
3	71, 91, 125, 139, 159, 174, 184, 199, 206, 209, 212, 214, 245
4	26, 28, 30, 37, 54, 55, 62, 78, 101, 113, 114, 115, 116, 119, 124, 130, 149
5	68, 79, 80, 81, 109, 155, 220
6	48, 64, 73, 102, 106, 146, 203, 205, 215, 219, 224, 226, 227, 231, 259
7	23, 27, 32, 34, 39, 53, 56, 82, 86, 96, 117, 122, 138, 145, 221
8	22, 24, 29, 38, 43, 44, 50, 72, 76, 86, 88, 90, 92, 103, 135, 182, 187, 207, 216, 223, 237, 240
9	25, 52, 59, 75, 85, 87, 99, 105, 204, 213, 260
10	35, 83, 94, 95, 123, 136, 137, 140, 153, 161, 165, 169, 172, 176, 178, 183, 186, 190, 191, 192, 194, 195, 200, 201, 202, 210, 211, 218, 222, 225, 228, 232, 234, 235, 238, 244

Appendix B: Clusters with corresponding observations before the pandemic

Cluster 1

User no.	Country	Bounce rate	Pages/Session	Average Session Duration	Affinity Category
12	Brazil	7,41%	5,26	00:06:58	Media & Entertainment/Music Lovers/Pop Music Fans
13	Brazil	7,41%	5,65	00:04:32	Shoppers/Value Shoppers
40	Germany	4,17%	6,92	00:06:11	Lifestyles & Hobbies/Art & Theater Aficionados
43	Germany	4,35%	6,13	00:06:41	Media & Entertainment/Music Lovers
55	Germany	5,97%	6,30	00:06:22	Media & Entertainment/Light TV Viewers
79	Ghana	7,41%	5,26	00:07:55	Travel/Business Travelers
150	Indonesia	3,31%	7,25	00:05:18	Lifestyles & Hobbies/Art & Theater Aficionados
151	Indonesia	6,61%	7,39	00:05:53	Lifestyles & Hobbies/Green Living Enthusiasts
164	Indonesia	4,17%	7,05	00:05:44	Media & Entertainment/Book Lovers
167	Indonesia	0,00%	7,41	00:05:04	News & Politics/Avid News Readers
168	Indonesia	0,00%	7,47	00:05:08	News & Politics/Avid News Readers/Entertainment News Enthusiasts
171	Indonesia	0,00%	5,97	00:05:33	Media & Entertainment/Music Lovers/Pop Music Fans
172	Indonesia	6,35%	6,43	00:05:30	Media & Entertainment/Music Lovers/World Music Fans
174	Indonesia	6,90%	7,57	00:04:12	Media & Entertainment/Comics & Animation Fans
176	Indonesia	0,00%	5,76	00:04:54	Media & Entertainment/TV Lovers
230	The Netherlands	8,18%	5,49	00:05:48	Media & Entertainment/Gamers/Hardcore Gamers
235	The Netherlands	0,00%	5,88	00:05:05	Media & Entertainment/Comics & Animation Fans
243	The Netherlands	9,52%	5,87	00:05:21	Sports & Fitness/Sports Fans/Fight & Wrestling Fans
250	The Netherlands	5,63%	5,24	00:06:39	Shoppers/Shoppers by Store Type/Convenience Store Shoppers
316	United Arab Emirates	0,00%	6,63	00:04:36	Food & Dining/Cooking Enthusiasts/30 Minute Chefs

Cluster 2

User no.	Country	Bounce rate	Pages/Session	Average Session Duration	Affinity Category
1	Bangladesh	9,52%	7,36	00:10:10	Media & Entertainment/Movie Lovers
3	Brazil	4,35%	6,95	00:09:23	Media & Entertainment/Movie Lovers
6	Brazil	4,76%	7,70	00:09:50	Lifestyles & Hobbies/Green Living Enthusiasts
7	Brazil	0,00%	8,35	00:07:09	Travel/Business Travelers
16	China	10,13%	7,99	00:09:28	Lifestyles & Hobbies/Green Living Enthusiasts
29	China	0,00%	6,07	00:09:30	Travel/Travel Buffs
31	Germany	2,22%	7,47	00:07:46	Media & Entertainment/Movie Lovers
37	Germany	6,84%	8,46	00:08:11	Lifestyles & Hobbies/Nightlife Enthusiasts
41	Germany	8,33%	6,66	00:06:58	Beauty & Wellness/Frequently Visits Salons
42	Germany	8,33%	7,14	00:07:50	Food & Dining/Frequently Dines Out/Diners by Meal/Frequently Eats Dinner Out
50	Germany	10,13%	8,04	00:07:45	Shoppers/Shoppers by Store Type/Department Store Shoppers
127	India	13,00%	7,56	00:10:09	Media & Entertainment/Gamers
159	Indonesia	0,00%	8,51	00:06:46	Food & Dining/Cooking Enthusiasts/30 Minute Chefs
244	The Netherlands	8,33%	7,14	00:07:28	Media & Entertainment/Music Lovers/Electronic Dance Music Fans
247	The Netherlands	9,52%	6,96	00:08:01	Media & Entertainment/Movie Lovers/Sci-Fi & Fantasy Movie Fans

Cluster 3

User no.	Country	Bounce rate	Pages/Session	Average Session Duration	Affinity Category
57	Germany	12,70%	10,81	00:08:50	Banking & Finance/Avid Investors
146	Indonesia	9,15%	9,82	00:07:32	Media & Entertainment/Movie Lovers
147	Indonesia	11,11%	11,68	00:08:31	Beauty & Wellness/Frequently Visits Salons
149	Indonesia	13,54%	9,09	00:06:58	Travel/Travel Buffs
155	Indonesia	9,09%	10,64	00:06:43	Food & Dining/Frequently Dines Out/Diners by Meal/Frequently Eats Dinner Out
157	Indonesia	13,00%	11,11	00:07:36	Shoppers/Value Shoppers
158	Indonesia	8,00%	8,40	00:05:53	Sports & Fitness/Health & Fitness Buffs
163	Indonesia	8,70%	10,67	00:07:12	Lifestyles & Hobbies/Shutterbugs
165	Indonesia	5,63%	8,70	00:06:44	Lifestyles & Hobbies/Nightlife Enthusiasts
170	Indonesia	22,41%	11,02	00:06:41	Food & Dining/Foodies
173	Indonesia	11,27%	10,59	00:06:33	Technology/Technophiles
177	Indonesia	6,35%	11,21	00:06:23	Shoppers/Luxury Shoppers
178	Italy	15,48%	12,48	00:07:19	Media & Entertainment/Music Lovers
180	Italy	10,67%	11,59	00:05:59	Lifestyles & Hobbies/Art & Theater Aficionados
246	The Netherlands	10,67%	9,47	00:06:46	Food & Dining/Frequently Dines Out/Diners by Meal/Frequently Eats Breakfast Out
310	Turkey	0,00%	10,76	00:05:40	Lifestyles & Hobbies/Frequently Attends Live Events

Cluster 4

User no.	Country	Bounce rate	Pages/Session	Average Session Duration	Affinity Category
87	Greece	14,81%	9,59	00:08:01	Food & Dining/Coffee Shop Regulars
91	Greece	16,00%	7,68	00:05:50	Lifestyles & Hobbies/Fashionistas
103	India	14,62%	7,99	00:08:53	Lifestyles & Hobbies/Fashionistas
107	India	19,86%	9,27	00:08:08	Food & Dining/Coffee Shop Regulars
108	India	16,67%	8,71	00:08:48	Lifestyles & Hobbies/Nightlife Enthusiasts
148	Indonesia	12,50%	8,27	00:05:49	Media & Entertainment/Music Lovers
162	Indonesia	10,67%	8,57	00:04:46	Lifestyles & Hobbies/Frequently Attends Live Events
166	Indonesia	18,31%	9,24	00:04:54	Media & Entertainment/Light TV Viewers
175	Indonesia	16,00%	8,86	00:06:24	Sports & Fitness/Sports Fans/Soccer Fans
184	The Netherlands	17,09%	7,77	00:07:50	Food & Dining/Cooking Enthusiasts/30 Minute Chefs
188	The Netherlands	15,41%	7,92	00:08:42	Travel/Business Travelers
190	The Netherlands	14,17%	8,15	00:08:14	Sports & Fitness/Health & Fitness Buffs
201	The Netherlands	17,53%	7,83	00:08:14	News & Politics/Avid News Readers
203	The Netherlands	14,21%	8,72	00:07:55	Lifestyles & Hobbies/Frequently Attends Live Events
204	The Netherlands	16,41%	8,03	00:06:45	Lifestyles & Hobbies/Outdoor Enthusiasts
205	The Netherlands	16,24%	7,98	00:06:50	Lifestyles & Hobbies/Nightlife Enthusiasts
210	The Netherlands	15,56%	8,27	00:07:20	Food & Dining/Coffee Shop Regulars
218	The Netherlands	15,45%	7,83	00:05:48	News & Politics/Avid News Readers/Avid Political News Readers
220	The Netherlands	18,58%	8,78	00:08:43	Media & Entertainment/Music Lovers/Pop Music Fans
226	The Netherlands	15,72%	7,52	00:08:00	Technology/Social Media Enthusiasts
227	The Netherlands	16,96%	7,91	00:07:22	Home & Garden/Home Decor Enthusiasts
228	The Netherlands	16,57%	8,97	00:08:01	Media & Entertainment/Music Lovers/Rap & Hip Hop Fans
245	The Netherlands	15,48%	7,76	00:07:57	Vehicles & Transportation/Auto Enthusiasts/Performance & Luxury Vehicle Enthusiasts

Cluster 5

User no.	Country	Bounce rate	Pages/Session	Average Session Duration	Affinity Category
90	Greece	24,07%	8,50	00:08:00	Travel/Travel Buffs
99	India	26,73%	9,32	00:09:46	Travel/Travel Buffs
102	India	25,66%	8,06	00:09:36	Food & Dining/Foodies
104	India	27,39%	7,03	00:07:42	Lifestyles & Hobbies/Shutterbugs
118	India	31,51%	10,10	00:09:16	Lifestyles & Hobbies/Outdoor Enthusiasts
122	India	27,88%	7,63	00:08:39	Food & Dining/Cooking Enthusiasts/Aspiring Chefs
123	India	28,22%	8,30	00:10:51	Food & Dining/Fast Food Cravers
131	India	23,86%	6,98	00:08:31	Shoppers/Bargain Hunters
185	The Netherlands	19,06%	7,80	00:09:00	Media & Entertainment/Movie Lovers
187	The Netherlands	20,27%	7,49	00:07:56	Lifestyles & Hobbies/Business Professionals
189	The Netherlands	23,54%	7,57	00:08:44	Media & Entertainment/Music Lovers
194	The Netherlands	19,17%	7,35	00:07:46	Food & Dining/Frequently Dines Out/Diners by Meal/Frequently Eats Dinner Out
198	The Netherlands	21,85%	7,13	00:09:24	Lifestyles & Hobbies/Shutterbugs
202	The Netherlands	20,36%	8,49	00:09:15	Beauty & Wellness/Beauty Mavens
211	The Netherlands	22,56%	8,82	00:09:45	Shoppers/Luxury Shoppers
214	The Netherlands	25,36%	7,06	00:08:34	Shoppers/Bargain Hunters
215	The Netherlands	24,71%	6,83	00:08:33	Lifestyles & Hobbies/Pet Lovers
216	The Netherlands	21,72%	7,43	00:09:03	Lifestyles & Hobbies/Family-Focused
217	The Netherlands	21,40%	7,72	00:08:01	Shoppers/Shoppers by Store Type/Department Store Shoppers
238	The Netherlands	24,04%	9,28	00:10:54	Media & Entertainment/Music Lovers/Rock Music Fans
273	Nigeria	32,95%	8,55	00:10:25	Lifestyles & Hobbies/Green Living Enthusiasts
280	Nigeria	25,37%	6,93	00:07:53	Food & Dining/Fast Food Cravers
282	Nigeria	20,63%	7,22	00:09:18	Banking & Finance/Avid Investors
287	Nigeria	30,95%	10,33	00:10:33	Technology/Social Media Enthusiasts
290	Pakistan	26,98%	8,10	00:09:07	Shoppers/Value Shoppers
292	Pakistan	24,07%	8,98	00:08:52	Media & Entertainment/Movie Lovers
326	Zimbabwe	26,00%	5,68	00:08:13	Lifestyles & Hobbies/Fashionistas

Cluster 6

User no.	Country	Bounce rate	Pages/Session	Average Session Duration	Affinity Category
82	Greece	31,34%	8,85	00:06:41	Lifestyles & Hobbies/Green Living Enthusiasts
85	Greece	29,31%	7,21	00:04:11	Beauty & Wellness/Beauty Mavens
88	Greece	29,31%	7,34	00:04:34	Food & Dining/Foodies
89	Greece	31,48%	9,06	00:06:07	Lifestyles & Hobbies/Art & Theater Aficionados
92	Greece	34,00%	7,36	00:05:02	Sports & Fitness/Health & Fitness Buffs
96	India	33,19%	5,05	00:05:48	Shoppers/Value Shoppers
100	India	30,32%	5,31	00:05:43	Media & Entertainment/Movie Lovers
105	India	34,18%	7,27	00:07:41	Travel/Business Travelers
109	India	35,00%	6,22	00:06:15	Technology/Technophiles
111	India	32,22%	5,64	00:06:46	Shoppers/Luxury Shoppers
115	India	29,68%	5,82	00:06:11	Media & Entertainment/Light TV Viewers
124	India	34,84%	5,68	00:06:10	Media & Entertainment/Movie Lovers/South Asian Film Fans
133	India	29,76%	5,17	00:07:40	Lifestyles & Hobbies/Business Professionals
233	The Netherlands	31,34%	5,80	00:07:08	Travel/Travel Buffs/Beachbound Travelers
236	The Netherlands	27,54%	6,09	00:04:35	Food & Dining/Cooking Enthusiasts
325	Zimbabwe	31,48%	5,33	00:07:37	Shoppers/Value Shoppers

Cluster 7

User no.	Country	Bounce rate	Pages/Session	Average Session Duration	Affinity Category
25	China	14,81%	6,65	00:10:08	Food & Dining/Foodies
66	Ghana	19,32%	6,45	00:09:23	Beauty & Wellness/Beauty Mavens
68	Ghana	21,52%	5,61	00:07:14	Lifestyles & Hobbies/Family-Focused
69	Ghana	19,32%	5,27	00:07:42	Lifestyles & Hobbies/Fashionistas
70	Ghana	16,46%	6,29	00:08:58	Media & Entertainment/Movie Lovers
73	Ghana	17,33%	5,68	00:09:06	Food & Dining/Coffee Shop Regulars
76	Ghana	18,31%	5,59	00:08:18	Travel/Travel Buffs
77	Ghana	19,40%	5,18	00:08:04	Media & Entertainment/Music Lovers
95	Greece	19,05%	5,38	00:08:21	Travel/Business Travelers
101	India	21,74%	6,47	00:06:55	Media & Entertainment/Music Lovers
114	India	13,60%	5,98	00:08:12	Food & Dining/Frequently Dines Out/Diners by Meal/Frequently Eats Dinner Out
139	India	22,41%	6,84	00:07:25	Food & Dining/Frequently Dines Out/Diners by Meal/Frequently Eats Breakfast Out
169	Indonesia	20,63%	7,70	00:05:38	Sports & Fitness/Sports Fans
182	The Netherlands	17,71%	7,28	00:07:07	Shoppers/Value Shoppers
193	The Netherlands	18,46%	6,11	00:05:28	Technology/Technophiles
200	The Netherlands	15,88%	6,99	00:07:06	Banking & Finance/Avid Investors
207	The Netherlands	18,01%	6,02	00:04:41	Sports & Fitness/Sports Fans
208	The Netherlands	21,26%	5,16	00:04:24	Technology/Mobile Enthusiasts
209	The Netherlands	16,39%	6,83	00:06:38	Media & Entertainment/Light TV Viewers
212	The Netherlands	18,45%	5,76	00:07:22	Media & Entertainment/Gamers
213	The Netherlands	17,12%	6,15	00:05:56	Vehicles & Transportation/Auto Enthusiasts
221	The Netherlands	19,01%	5,09	00:05:26	Food & Dining/Frequently Dines Out/Diners by Meal/Frequently Eats Lunch Out
222	The Netherlands	15,21%	6,28	00:06:28	Home & Garden/Do-It-Yourselfers
223	The Netherlands	19,35%	6,47	00:05:20	Food & Dining/Cooking Enthusiasts/Aspiring Chefs
224	The Netherlands	23,33%	6,29	00:07:25	Food & Dining/Fast Food Cravers
225	The Netherlands	24,00%	7,28	00:05:45	News & Politics/Avid News Readers/Avid Local News Readers
229	The Netherlands	23,90%	6,49	00:05:47	News & Politics/Avid News Readers/Entertainment News Enthusiasts
234	The Netherlands	22,60%	5,75	00:05:22	News & Politics/Avid News Readers/Avid Business News Readers
239	The Netherlands	17,71%	5,96	00:06:23	Travel/Travel Buffs/Luxury Travelers
242	The Netherlands	18,48%	5,45	00:04:05	Media & Entertainment/Movie Lovers/Action & Adventure Movie Fans
248	The Netherlands	20,63%	6,03	00:06:26	Media & Entertainment/TV Lovers/TV Drama Fans

Cluster 8

User no.	Country	Bounce rate	Pages/Session	Average Session Duration	Affinity Category
64	Ghana	14,13%	6,82	00:12:24	Beauty & Wellness/Frequently Visits Salons
65	Ghana	18,48%	7,86	00:12:41	Sports & Fitness/Health & Fitness Buffs
67	Ghana	21,52%	6,03	00:10:54	Food & Dining/Cooking Enthusiasts/30 Minute Chefs
71	Ghana	22,67%	7,47	00:13:40	Shoppers/Value Shoppers
119	India	17,61%	8,88	00:11:33	Shoppers/Shopaholics
141	India	12,70%	7,10	00:12:33	Shoppers/Shoppers by Store Type/Convenience Store Shoppers
195	The Netherlands	18,97%	8,03	00:11:14	Shoppers/Shopaholics
199	The Netherlands	20,40%	8,43	00:11:36	Media & Entertainment/Book Lovers
265	Nigeria	22,94%	8,73	00:13:51	Lifestyles & Hobbies/Art & Theater Aficionados
283	Nigeria	24,07%	7,43	00:10:50	Media & Entertainment/Book Lovers
285	Nigeria	28,26%	9,43	00:13:28	News & Politics/Avid News Readers/Avid Political News Readers
318	United States	24,07%	9,20	00:14:48	Lifestyles & Hobbies/Green Living Enthusiasts
319	United States	26,00%	8,02	00:14:26	Lifestyles & Hobbies/Art & Theater Aficionados

Cluster 9

User no.	Country	Bounce rate	Pages/Session	Average Session Duration	Affinity Category
17	China	10,67%	10,25	00:09:45	Lifestyles & Hobbies/Art & Theater Aficionados
18	China	11,27%	9,65	00:09:27	Media & Entertainment/Music Lovers
20	China	11,94%	8,67	00:11:27	Lifestyles & Hobbies/Fashionistas
27	China	14,81%	9,52	00:09:35	Shoppers/Shoppers by Store Type/Department Store Shoppers
98	India	17,51%	10,41	00:10:03	Lifestyles & Hobbies/Art & Theater Aficionados
110	India	17,61%	10,00	00:09:49	Beauty & Wellness/Beauty Mavens
125	India	17,71%	8,48	00:10:05	Home & Garden/Home Decor Enthusiasts
129	India	16,35%	9,08	00:09:41	Technology/Social Media Enthusiasts
130	India	13,00%	8,94	00:10:15	Lifestyles & Hobbies/Family-Focused
134	India	18,48%	9,80	00:11:11	Lifestyles & Hobbies/Pet Lovers
137	India	10,67%	9,64	00:10:59	Media & Entertainment/TV Lovers
183	The Netherlands	15,73%	8,31	00:10:10	Travel/Travel Buffs
186	The Netherlands	18,38%	9,03	00:09:52	Beauty & Wellness/Frequently Visits Salons
191	The Netherlands	11,13%	9,14	00:09:41	Lifestyles & Hobbies/Green Living Enthusiasts
192	The Netherlands	17,80%	8,96	00:09:47	Lifestyles & Hobbies/Fashionistas
196	The Netherlands	19,91%	9,48	00:10:00	Food & Dining/Foodies
197	The Netherlands	18,79%	9,48	00:10:15	Lifestyles & Hobbies/Art & Theater Aficionados
206	The Netherlands	18,64%	8,12	00:10:12	Media & Entertainment/TV Lovers
231	The Netherlands	14,00%	8,91	00:10:38	Media & Entertainment/TV Lovers/Game, Reality & Talk Show Fans
240	The Netherlands	11,50%	10,75	00:10:07	Media & Entertainment/Music Lovers/World Music Fans

Cluster 10

User no.	Country	Bounce rate	Pages/Session	Average Session Duration	Affinity Category
19	China	12,70%	10,60	00:11:40	Food & Dining/Coffee Shop Regulars
22	China	12,70%	9,87	00:12:51	Beauty & Wellness/Beauty Mavens
23	China	13,79%	10,36	00:11:57	Media & Entertainment/Movie Lovers
97	India	15,10%	11,09	00:12:13	Beauty & Wellness/Frequently Visits Salons
106	India	15,72%	10,96	00:12:25	Food & Dining/Cooking Enthusiasts/30 Minute Chefs
112	India	17,12%	11,62	00:12:57	Lifestyles & Hobbies/Green Living Enthusiasts
113	India	12,69%	11,87	00:11:31	Shoppers/Shoppers by Store Type/Department Store Shoppers
117	India	16,80%	10,73	00:10:59	Lifestyles & Hobbies/Frequently Attends Live Events
126	India	16,80%	12,10	00:13:32	Media & Entertainment/Book Lovers
128	India	20,19%	11,05	00:11:28	Sports & Fitness/Health & Fitness Buffs
255	Nigeria	16,11%	8,96	00:13:42	Media & Entertainment/Movie Lovers
259	Nigeria	15,22%	10,17	00:14:31	Technology/Technophiles
264	Nigeria	11,50%	10,58	00:13:31	Food & Dining/Frequently Dines Out/Diners by Meal/Frequently Eats Dinner Out
279	Nigeria	17,33%	9,75	00:12:42	Travel/Travel Buffs
284	Nigeria	14,81%	12,83	00:13:37	Media & Entertainment/Light TV Viewers
286	Nigeria	17,39%	11,89	00:10:41	Technology/Mobile Enthusiasts

Cluster 11

User no.	Country	Bounce rate	Pages/Session	Average Session Duration	Affinity Category
2	Brazil	3,67%	9,89	00:12:45	Lifestyles & Hobbies/Art & Theater Aficionados
4	Brazil	5,06%	9,09	00:14:01	Media & Entertainment/Music Lovers
9	Brazil	0,00%	8,14	00:13:38	Beauty & Wellness/Beauty Mavens
11	Brazil	5,06%	8,99	00:14:13	Media & Entertainment/Book Lovers
14	Brazil	0,00%	7,96	00:12:46	Lifestyles & Hobbies/Fashionistas
24	China	0,00%	7,00	00:14:31	Beauty & Wellness/Frequently Visits Salons
135	India	5,33%	9,19	00:12:33	Sports & Fitness/Sports Fans

Cluster 12

User no.	Country	Bounce rate	Pages/Session	Average Session Duration	Affinity Category
32	Germany	5,97%	8,82	00:09:59	Shoppers/Value Shoppers
33	Germany	5,97%	8,85	00:09:27	Food & Dining/Coffee Shop Regulars
34	Germany	3,10%	8,84	00:08:34	Lifestyles & Hobbies/Green Living Enthusiasts
35	Germany	3,42%	11,60	00:10:30	Food & Dining/Foodies
36	Germany	6,84%	9,53	00:09:14	Lifestyles & Hobbies/Fashionistas
38	Germany	3,85%	9,80	00:08:10	Travel/Travel Buffs
39	Germany	7,69%	10,52	00:09:07	Travel/Business Travelers
44	Germany	4,35%	11,45	00:09:46	Shoppers/Luxury Shoppers
45	Germany	4,55%	10,25	00:08:29	Sports & Fitness/Health & Fitness Buffs
46	Germany	4,35%	9,53	00:09:50	Technology/Technophiles
47	Germany	4,55%	9,44	00:08:37	Beauty & Wellness/Beauty Mavens
48	Germany	5,06%	8,57	00:08:57	Lifestyles & Hobbies/Frequently Attends Live Events
49	Germany	0,00%	11,22	00:09:52	Lifestyles & Hobbies/Outdoor Enthusiasts
51	Germany	5,06%	9,73	00:08:43	Lifestyles & Hobbies/Family-Focused
53	Germany	5,63%	10,06	00:09:00	Food & Dining/Frequently Dines Out/Diners by Meal/Frequently Eats Lunch Out
54	Germany	0,00%	10,18	00:08:41	Lifestyles & Hobbies/Business Professionals
58	Germany	7,41%	9,20	00:09:20	Sports & Fitness/Sports Fans/Soccer Fans
61	Germany	0,00%	12,17	00:11:49	Media & Entertainment/TV Lovers
62	Germany	0,00%	8,74	00:10:15	Vehicles & Transportation/Auto Enthusiasts
144	India	6,35%	10,35	00:10:47	Media & Entertainment/Music Lovers/World Music Fans
152	Indonesia	4,00%	10,02	00:08:30	Beauty & Wellness/Beauty Mavens
153	Indonesia	4,35%	10,99	00:08:37	Shoppers/Shoppers by Store Type/Department Store Shoppers
154	Indonesia	3,85%	11,97	00:08:22	Travel/Business Travelers
156	Indonesia	4,35%	10,99	00:09:12	Lifestyles & Hobbies/Fashionistas
161	Indonesia	5,33%	11,75	00:08:31	Food & Dining/Coffee Shop Regulars
289	Nigeria	0,00%	10,98	00:10:52	Lifestyles & Hobbies/Shutterbugs
313	Turkey	0,00%	11,24	00:08:52	Technology/Technophiles
314	Turkey	0,00%	12,07	00:11:24	Travel/Business Travelers

Cluster 13

User no.	Country	Bounce rate	Pages/Session	Average Session Duration	Affinity Category
179	Italy	9,09%	13,58	00:09:43	Lifestyles & Hobbies/Outdoor Enthusiasts
303	Turkey	0,00%	13,30	00:09:49	Media & Entertainment/Movie Lovers
305	Turkey	0,00%	14,54	00:10:18	Lifestyles & Hobbies/Green Living Enthusiasts
306	Turkey	0,00%	13,43	00:08:26	Media & Entertainment/Book Lovers
308	Turkey	0,00%	13,19	00:06:49	Shoppers/Value Shoppers
309	Turkey	0,00%	14,83	00:07:15	Lifestyles & Hobbies/Fashionistas
311	Turkey	0,00%	15,20	00:07:46	Media & Entertainment/Light TV Viewers
312	Turkey	0,00%	14,83	00:07:53	Media & Entertainment/Music Lovers

Cluster 14

User no.	Country	Bounce rate	Pages/Session	Average Session Duration	Affinity Category
8	Brazil	0,00%	10,44	00:14:31	Travel/Travel Buffs
21	China	0,00%	10,88	00:13:22	Lifestyles & Hobbies/Frequently Attends Live Events
30	France	0,00%	15,02	00:12:23	Shoppers/Value Shoppers
52	Germany	5,63%	13,89	00:12:49	Sports & Fitness/Sports Fans
56	Germany	6,35%	12,27	00:14:02	Food & Dining/Cooking Enthusiasts/30 Minute Chefs
59	Germany	0,00%	13,36	00:14:29	Media & Entertainment/Book Lovers
60	Germany	0,00%	13,43	00:14:58	Media & Entertainment/Gamers
281	Nigeria	6,35%	11,94	00:13:39	Lifestyles & Hobbies/Frequently Attends Live Events
304	Turkey	0,00%	14,57	00:11:58	Lifestyles & Hobbies/Art & Theater Aficionados
307	Turkey	0,00%	16,78	00:14:40	Travel/Travel Buffs

Appendix C: Clusters with corresponding observations during the pandemic

Cluster 1

User no.	Country	Bounce rate	Pages/Session	Average Session Duration	Affinity Category
120	Indonesia	4,76%	7,62	0:10:32.00	Shoppers/Shoppers by Store Type/Department Store Shoppers
162	The Netherlands	9,71%	7,66	0:11:07.00	Beauty & Wellness/Frequently Visits Salons
163	The Netherlands	7,44%	8,05	0:11:31.00	Media & Entertainment/Music Lovers
164	The Netherlands	9,34%	7,66	0:11:00.00	Shoppers/Value Shoppers
166	The Netherlands	8,69%	7,86	0:11:20.00	Lifestyles & Hobbies/Business Professionals
167	The Netherlands	7,58%	8,09	0:11:28.00	Travel/Travel Buffs
168	The Netherlands	10,32%	7,88	0:11:31.00	Lifestyles & Hobbies/Shutterbugs
170	The Netherlands	8,58%	7,79	0:11:12.00	Travel/Business Travelers
175	The Netherlands	8,08%	7,44	0:11:33.00	Banking & Finance/Avid Investors
177	The Netherlands	9,15%	7,85	0:10:14.00	Lifestyles & Hobbies/Outdoor Enthusiasts
179	The Netherlands	6,61%	8,36	0:11:03.00	Lifestyles & Hobbies/Frequently Attends Live Events
180	The Netherlands	6,96%	8,40	0:11:23.00	Shoppers/Luxury Shoppers
181	The Netherlands	10,15%	7,49	0:10:33.00	Sports & Fitness/Sports Fans
196	The Netherlands	8,53%	7,91	0:11:07.00	Shoppers/Shoppers by Store Type/Department Store Shoppers
262	Turkey	10,42%	7,69	0:11:49.00	Media & Entertainment/Music Lovers

Cluster 2

User no.	Country	Bounce rate	Pages/Session	Average Session Duration	Affinity Category
60	Germany	12,99%	8,14	0:11:21.00	Media & Entertainment/TV Lovers
70	Greece	10,42%	10,08	0:10:31.00	Shoppers/Value Shoppers
74	India	15,93%	9,00	0:09:27.00	Media & Entertainment/Music Lovers
97	India	11,63%	10,74	0:10:55.00	Food & Dining/Fast Food Cravers
112	India	14,93%	8,94	0:08:42.00	Technology/Social Media Enthusiasts
148	Italy	14,08%	8,37	0:11:03.00	Media & Entertainment/Music Lovers
150	Italy	15,10%	10,00	0:10:56.00	Food & Dining/Foodies
151	Italy	15,69%	7,48	0:10:08.00	Media & Entertainment/Movie Lovers
152	Italy	18,10%	10,86	0:09:28.00	Shoppers/Luxury Shoppers
160	Italy	11,66%	8,37	0:10:54.00	Travel/Travel Buffs
197	The Netherlands	13,71%	8,43	0:10:57.00	Food & Dining/Fast Food Cravers
208	The Netherlands	12,24%	7,96	0:10:02.00	Home & Garden/Home Decor Enthusiasts

Cluster 3

User no.	Country	Bounce rate	Pages/Session	Average Session Duration	Affinity Category
71	India	7,14%	10,70	0:10:25.00	Media & Entertainment/Movie Lovers
91	India	5,49%	9,36	0:10:09.00	Media & Entertainment/Movie Lovers/South Asian Film Fans
125	Indonesia	5,81%	9,30	0:09:49.00	Food & Dining/Coffee Shop Regulars
139	Indonesia	6,17%	10,11	0:11:09.00	Shoppers/Luxury Shoppers
159	Italy	9,46%	9,03	0:10:58.00	Travel/Business Travelers
174	The Netherlands	8,08%	8,78	0:10:40.00	Lifestyles & Hobbies/Fashionistas
184	The Netherlands	6,44%	10,65	0:10:45.00	Media & Entertainment/Book Lovers
199	The Netherlands	9,93%	8,73	0:09:58.00	Food & Dining/Frequently Dines Out/Diners by Meal/Frequently Eats Lunch Out
206	The Netherlands	6,36%	9,97	0:11:02.00	News & Politics/Avid News Readers/Avid Political News Readers
209	The Netherlands	3,86%	8,95	0:10:12.00	News & Politics/Avid News Readers/Entertainment News Enthusiasts
212	The Netherlands	4,74%	9,87	0:10:51.00	News & Politics/Avid News Readers/Avid Business News Readers
214	The Netherlands	8,14%	9,49	0:10:15.00	Food & Dining/Cooking Enthusiasts/Aspiring Chefs
245	Nigeria	6,17%	9,69	0:09:40.00	Shoppers/Value Shoppers

Cluster 4

User no.	Country	Bounce rate	Pages/Session	Average Session Duration	Affinity Category
26	Germany	4,65%	10,40	0:09:27.00	Lifestyles & Hobbies/Art & Theater Aficionados
28	Germany	2,17%	10,93	0:08:26.00	Travel/Business Travelers
30	Germany	3,94%	9,80	0:09:11.00	Technology/Technophiles
37	Germany	2,91%	11,94	0:10:40.00	Lifestyles & Hobbies/Nightlife Enthusiasts
54	Germany	5,49%	11,05	0:09:48.00	Food & Dining/Cooking Enthusiasts/30 Minute Chefs
55	Germany	4,76%	11,50	0:10:46.00	Shoppers/Shopaholics
62	Germany	8,77%	11,68	0:06:59.00	Home & Garden/Do-It-Yourselfers
78	India	10,45%	11,22	0:09:10.00	Lifestyles & Hobbies/Green Living Enthusiasts
101	India	5,49%	11,10	0:08:51.00	News & Politics/Avid News Readers
113	Indonesia	3,60%	10,37	0:08:32.00	Media & Entertainment/Movie Lovers
114	Indonesia	3,47%	9,94	0:08:50.00	Travel/Travel Buffs
115	Indonesia	3,38%	9,68	0:09:04.00	Beauty & Wellness/Frequently Visits Salons
116	Indonesia	3,88%	10,17	0:10:08.00	Technology/Mobile Enthusiasts
119	Indonesia	4,17%	10,42	0:09:57.00	Food & Dining/Frequently Dines Out/Diners by Meal/Frequently Eats Dinner Out
124	Indonesia	4,95%	10,81	0:10:00.00	Lifestyles & Hobbies/Art & Theater Aficionados
130	Indonesia	5,49%	11,68	0:11:04.00	Media & Entertainment/Book Lovers
149	Italy	9,15%	11,71	0:11:45.00	Sports & Fitness/Health & Fitness Buffs

Cluster 5

User no.	Country	Bounce rate	Pages/Session	Average Session Duration	Affinity Category
68	Greece	16,13%	7,81	0:08:56.00	Media & Entertainment/Music Lovers
79	India	17,27%	7,61	0:08:07.00	Technology/Mobile Enthusiasts
80	India	18,95%	7,92	0:07:53.00	Lifestyles & Hobbies/Shutterbugs
81	India	17,27%	7,55	0:08:03.00	Shoppers/Luxury Shoppers
109	India	19,44%	7,71	0:07:56.00	Media & Entertainment/Music Lovers/World Music Fans
155	Italy	19,20%	5,94	0:08:15.00	Lifestyles & Hobbies/Nightlife Enthusiasts
220	The Netherlands	19,79%	6,69	0:08:47.00	Vehicles & Transportation/Auto Enthusiasts/Performance & Luxury Vehicle Enthusiasts

Cluster 6

User no.	Country	Bounce rate	Pages/Session	Average Session Duration	Affinity Category
48	Germany	15,83%	6,83	0:06:12.00	Home & Garden/Home Decor Enthusiasts
64	Ghana	17,54%	5,79	0:07:02.00	Lifestyles & Hobbies/Family-Focused
73	India	17,79%	6,44	0:05:48.00	Shoppers/Value Shoppers
102	India	18,18%	6,78	0:05:13.00	Food & Dining/Cooking Enthusiasts/Aspiring Chefs
106	India	16,13%	6,26	0:05:15.00	Food & Dining/Frequently Dines Out/Diners by Meal/Frequently Eats Lunch Out
146	Indonesia	17,54%	6,72	0:07:15.00	Shoppers/Bargain Hunters
203	The Netherlands	15,26%	6,29	0:07:45.00	Lifestyles & Hobbies/Thrill Seekers
205	The Netherlands	13,74%	7,26	0:07:17.00	Media & Entertainment/Gamers/Hardcore Gamers
215	The Netherlands	15,19%	6,61	0:07:18.00	Media & Entertainment/Gamers/Casual & Social Gamers
219	The Netherlands	12,73%	7,71	0:06:53.00	Media & Entertainment/Gamers/Adventure & Strategy Game Fans
224	The Netherlands	15,38%	7,89	0:06:29.00	Media & Entertainment/Gamers/Roleplaying Game Fans
226	The Netherlands	12,35%	6,68	0:07:10.00	Media & Entertainment/Gamers/Action Game Fans
227	The Netherlands	16,28%	5,67	0:06:56.00	Media & Entertainment/TV Lovers/TV Drama Fans
231	The Netherlands	13,89%	5,65	0:07:18.00	Sports & Fitness/Sports Fans/Motor Sports Enthusiasts
259	Nigeria	16,13%	6,03	0:07:33.00	Shoppers/Bargain Hunters

Cluster 7

User no.	Country	Bounce rate	Pages/Session	Average Session Duration	Affinity Category
23	Germany	7,59%	9,08	0:07:33.00	Shoppers/Value Shoppers
27	Germany	7,14%	8,38	0:07:19.00	Media & Entertainment/Music Lovers
32	Germany	5,10%	9,51	0:07:28.00	Lifestyles & Hobbies/Frequently Attends Live Events
34	Germany	2,60%	8,43	0:07:36.00	Shoppers/Shoppers by Store Type/Department Store Shoppers
39	Germany	3,38%	7,80	0:07:14.00	Media & Entertainment/Light TV Viewers
53	Germany	5,21%	8,18	0:06:59.00	Vehicles & Transportation/Auto Enthusiasts
56	Germany	4,95%	9,67	0:06:38.00	Banking & Finance/Avid Investors
82	India	4,00%	7,66	0:08:11.00	Travel/Travel Buffs
86	India	9,09%	9,10	0:07:04.00	Food & Dining/Cooking Enthusiasts/30 Minute Chefs
96	India	4,17%	8,66	0:07:10.00	Beauty & Wellness/Beauty Mavens
117	Indonesia	4,00%	7,86	0:07:46.00	Sports & Fitness/Health & Fitness Buffs
122	Indonesia	4,55%	8,62	0:08:14.00	Media & Entertainment/Music Lovers
138	Indonesia	6,94%	9,25	0:07:00.00	Media & Entertainment/Light TV Viewers
145	Indonesia	6,49%	8,83	0:07:38.00	Media & Entertainment/Music Lovers/Pop Music Fans
221	The Netherlands	4,95%	8,40	0:07:51.00	Media & Entertainment/Gamers/Shooter Game Fans

Cluster 8

User no.	Country	Bounce rate	Pages/Session	Average Session Duration	Affinity Category
22	Germany	7,36%	9,44	0:08:34.00	Media & Entertainment/Movie Lovers
24	Germany	9,27%	8,91	0:07:29.00	Lifestyles & Hobbies/Green Living Enthusiasts
29	Germany	9,22%	8,07	0:07:00.00	Lifestyles & Hobbies/Fashionistas
38	Germany	11,05%	9,24	0:08:35.00	Media & Entertainment/Book Lovers
43	Germany	10,07%	8,51	0:07:41.00	Beauty & Wellness/Beauty Mavens
44	Germany	7,19%	9,40	0:09:06.00	Lifestyles & Hobbies/Family-Focused
50	Germany	12,17%	8,24	0:07:36.00	Lifestyles & Hobbies/Shutterbugs
72	India	11,66%	7,85	0:07:48.00	Food & Dining/Foodies
76	India	10,07%	8,58	0:07:48.00	Food & Dining/Coffee Shop Regulars
86	India	9,09%	9,10	0:07:04.00	Food & Dining/Cooking Enthusiasts/30 Minute Chefs
88	India	11,20%	8,70	0:09:03.00	Lifestyles & Hobbies/Nightlife Enthusiasts
90	India	7,75%	8,91	0:08:08.00	Lifestyles & Hobbies/Frequently Attends Live Events
92	India	8,70%	8,96	0:08:18.00	Shoppers/Shoppers by Store Type/Department Store Shoppers
103	India	9,52%	8,75	0:07:47.00	Home & Garden/Home Decor Enthusiasts
135	Indonesia	6,17%	8,16	0:09:37.00	Lifestyles & Hobbies/Fashionistas
182	The Netherlands	7,10%	8,76	0:09:27.00	Shoppers/Shopaholics
187	The Netherlands	7,71%	8,63	0:08:54.00	Media & Entertainment/TV Lovers
207	The Netherlands	11,31%	8,38	0:06:41.00	Food & Dining/Cooking Enthusiasts
216	The Netherlands	6,36%	8,47	0:08:55.00	News & Politics/Avid News Readers/Avid Local News Readers
223	The Netherlands	8,70%	8,78	0:06:53.00	Travel/Travel Buffs/Beachbound Travelers
237	The Netherlands	6,49%	8,27	0:08:51.00	Media & Entertainment/TV Lovers/TV Comedy Fans
240	Nigeria	9,90%	8,63	0:08:56.00	Media & Entertainment/Movie Lovers

Cluster 9

User no.	Country	Bounce rate	Pages/Session	Average Session Duration	Affinity Category
25	Germany	6,09%	8,12	0:06:02.00	Food & Dining/Coffee Shop Regulars
52	Germany	9,09%	7,01	0:05:46.00	Technology/Mobile Enthusiasts
59	Germany	6,94%	8,25	0:05:39.00	Lifestyles & Hobbies/Thrill Seekers
75	India	11,31%	6,67	0:05:32.00	Lifestyles & Hobbies/Fashionistas
85	India	13,19%	7,18	0:05:36.00	Sports & Fitness/Health & Fitness Buffs
87	India	4,95%	6,40	0:05:44.00	Food & Dining/Frequently Dines Out/Diners by Meal/Frequently Eats Dinner Out
99	India	6,17%	7,63	0:06:02.00	Lifestyles & Hobbies/Business Professionals
105	India	6,49%	6,96	0:05:33.00	Banking & Finance/Avid Investors
204	The Netherlands	7,34%	5,25	0:05:54.00	Media & Entertainment/Music Lovers/Rap & Hip Hop Fans
213	The Netherlands	8,33%	7,98	0:05:23.00	Media & Entertainment/Comics & Animation Fans
260	Turkey	8,77%	7,14	0:05:56.00	Sports & Fitness/Health & Fitness Buffs

Cluster 10

User no.	Country	Bounce rate	Pages/Session	Average Session Duration	Affinity Category
35	Germany	9,15%	7,35	0:07:27.00	Food & Dining/Foodies
83	India	8,00%	7,09	0:08:03.00	Beauty & Wellness/Frequently Visits Salons
94	India	10,42%	8,08	0:08:37.00	Shoppers/Shopaholics
95	India	9,52%	6,25	0:07:20.00	Travel/Business Travelers
123	Indonesia	4,95%	7,21	0:08:59.00	Sports & Fitness/Sports Fans
136	Indonesia	6,49%	6,40	0:08:54.00	Beauty & Wellness/Beauty Mavens
137	Indonesia	6,94%	7,51	0:07:09.00	Media & Entertainment/Comics & Animation Fans
140	Indonesia	7,46%	6,64	0:09:12.00	Sports & Fitness/Sports Fans/Soccer Fans
153	Italy	12,17%	7,45	0:09:12.00	Food & Dining/Coffee Shop Regulars
161	The Netherlands	8,85%	7,06	0:07:33.00	Media & Entertainment/Movie Lovers
165	The Netherlands	7,74%	7,28	0:08:12.00	Technology/Technophiles
169	The Netherlands	6,66%	7,70	0:08:02.00	Food & Dining/Cooking Enthusiasts/30 Minute Chefs
172	The Netherlands	8,71%	7,44	0:07:41.00	Food & Dining/Frequently Dines Out/Diners by Meal/Frequently Eats Dinner Out
176	The Netherlands	11,96%	7,09	0:08:55.00	Lifestyles & Hobbies/Green Living Enthusiasts
178	The Netherlands	8,02%	7,25	0:06:55.00	Lifestyles & Hobbies/Nightlife Enthusiasts
183	The Netherlands	7,79%	7,20	0:09:14.00	Vehicles & Transportation/Auto Enthusiasts
186	The Netherlands	8,25%	6,96	0:06:55.00	Media & Entertainment/Light TV Viewers
190	The Netherlands	10,94%	7,51	0:08:57.00	Media & Entertainment/Gamers
191	The Netherlands	9,67%	7,37	0:07:49.00	Home & Garden/Do-It-Yourselfers
192	The Netherlands	7,30%	7,55	0:07:15.00	Technology/Mobile Enthusiasts
194	The Netherlands	8,41%	6,81	0:07:23.00	Food & Dining/Coffee Shop Regulars
195	The Netherlands	10,44%	6,57	0:08:24.00	Lifestyles & Hobbies/Pet Lovers
200	The Netherlands	9,27%	7,06	0:07:36.00	Media & Entertainment/Music Lovers/Pop Music Fans
201	The Netherlands	11,65%	7,75	0:08:17.00	Technology/Social Media Enthusiasts
202	The Netherlands	9,32%	6,65	0:08:14.00	Sports & Fitness/Sports Fans/Soccer Fans
210	The Netherlands	11,16%	7,51	0:08:28.00	Media & Entertainment/TV Lovers/Game, Reality & Talk Show Fans
211	The Netherlands	6,51%	6,64	0:07:26.00	Media & Entertainment/Music Lovers/Electronic Dance Music Fans
218	The Netherlands	8,33%	7,90	0:08:04.00	Travel/Travel Buffs/Luxury Travelers
222	The Netherlands	9,09%	6,27	0:07:18.00	Media & Entertainment/Music Lovers/Rock Music Fans
225	The Netherlands	5,21%	6,89	0:09:51.00	Media & Entertainment/Music Lovers/World Music Fans
228	The Netherlands	5,49%	5,53	0:08:27.00	Shoppers/Shoppers by Store Type/Convenience Store Shoppers
232	The Netherlands	7,46%	5,51	0:08:07.00	Media & Entertainment/Gamers/Sports Game Fans
234	The Netherlands	6,94%	7,71	0:09:00.00	Media & Entertainment/Music Lovers/Indie & Alternative Rock Fans
235	The Netherlands	10,42%	5,19	0:06:55.00	Media & Entertainment/Movie Lovers/Comedy Movie Fans
238	Nigeria	10,85%	6,91	0:08:40.00	Food & Dining/Foodies
244	Nigeria	10,99%	7,74	0:08:32.00	Lifestyles & Hobbies/Nightlife Enthusiasts