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# Influencer Marketing

## The impact of the number of followers on influencer's likability for young Instagram users

Rita Magalhães Moreira Coelho

Católica Porto Business School 2019



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## The impact of the number of followers on influencer's likability for young Instagram users

Final Dissertation Work presented to Católica Porto Business School to obtain a Master's degree in Marketing

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Under the guidance of Prof. Dra. Joana César Machado

Católica Porto Business School, March 2019

"For our own good, we need to collectively learn to appreciate what we already have. At the end of it awaits a rare reward: serenity."

My brother, Gui

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### Acknowledgments

I would like to express my sincere gratitude to my advisor, Professor Joana César Machado, for the continuous support on my Masters' dissertation, for her motivation, patience and profound knowledge. Her guidance and demand were crucial to develop what is, in my perspective, a relevant work for companies and scientific community.

My sincere thankfulness also goes to Professor Carla Martins, for her paramount availability, encouragement and insightful observations. Her support was essential for the final part of the study, the results' discussion.

I also want to express my appreciation to my friend Ana Freitas, from Sonae MC, whose unconditional friendship, support, and statistical knowledge helped me to go even further with this study.

My biggest thank you goes to my mom and dad for all the love they bring to my education and for always encouraging me to follow my dreams.

To my brother, with whom I have a profound complicity and love, I want to thank for showing me the World is a big place and for inspiring me, each day, to have enough ambition and courage to explore it.

To Rafa, with whom I shared the utmost journey for the last eight years, I want to thank all the love, kindness and smiling future that I am already dreaming of.

My sincere gratitude to all, Rita Coelho This page was intentionally left with this sentence.

### Abstract

Understanding how customers respond to influencer marketing has become a priority for companies, since the impact of digital marketing in today's world is undeniable. The main goal of this research is to study how young Instagram users perceive the number of followers and followees of an influencer in terms of his/her overall likability and, if the influencer's ascribed opinion leadership works as a mediator of this relationship. In order to do so, we administered a questionnaire to young Instagram users between 18 and 34 years old, since 65% of Instagram users belong to this age group. Specifically, we created two fictitious influencers Instagram accounts, one female and one male, and manipulated the number of followers and followees. The responses of 672 people were analyzed with SPSS and AMOS, all of which Portuguese Instagram users (370 women and 301 men). The results show that the number of followers negatively affects influencer's likability, even though this relation does not exist when the influencer's ascribed opinion leadership is not controlled. In addition, we found that the number of people followed by the influencer is also an important variable to take into consideration: if it is low, the influencer's likability is negatively affected by the number of followers, but, if it is high, this negative effect does not occur. Evidence that women are more influenced by Instagram' influencers than men was also found. On the whole, this study sheds light into the characteristics that an Instagram influencer must have in order to increase his/her likability, as well as on how consumers demographic features and Instagram usage might affect their response to influencer marketing. An important contribution of this research is linked with the finding that microinfluencers (number of followers below 100K) seem to be more likable and, thus, more attractive for companies and marketing agencies.

**Keywords:** influencer marketing, number of followers, number of followees, young Instagram users, ascribed opinion leadership

### Resumo

Compreender de que forma é que os consumidores respondem ao influencer *marketing* tornou-se uma prioridade para as empresas, dado o inegável impacto que o marketing digital tem nos dias de hoje. Neste trabalho, o principal objetivo consiste em estudar como é que o número de seguidores e de contas seguidas por um influenciador no Instagram afeta a propensão dos jovens utilizadores para apreciarem os mesmos. Além disso, pretendeu-se compreender se a atribuição de poder de opinião a um influenciar medeia a relação previamente descrita. Neste sentido, recolheram-se dados através de um questionário, direcionado aos utilizadores jovens do Instagram com idades entre os 18 e 34 anos, uma vez que estes representam 65% dos utilizadores desta plataforma. Especificamente, criaram-se duas contas fictícias de influenciadores no Instagram, uma relativa a um influenciador masculino e outra a um feminino, tendo-se manipulado o número de seguidores e de contas seguidas pelos mesmos. As respostas de 672 pessoas, todas elas de nacionalidade portuguesa e utilizadoras do Instagram, foram analisadas através do SPSS e do AMOS (370 mulheres e 301 homens). Os resultados mostram que o número de seguidores afeta negativamente a propensão dos consumidores para gostarem dos influenciadores, apesar desta relação não se verificar quando o poder de opinião atribuído ao influenciador não é controlado. Adicionalmente, este estudo demonstrou que o número de pessoas seguidas pelos influenciadores é também uma variável importante a ter em conta: se este for baixo, a propensão dos consumidores para gostarem de um influenciador é negativamente afetada pelo número de seguidores do mesmo; pelo contrário, se for elevado, esta relação não existe. Importa ainda destacar que as mulheres são mais influenciadas por influenciadores do Instagram do que os homens. No global, foram retiradas conclusões úteis acerca das caraterísticas que um influenciador do Instagram deve ter, de forma a aumentar a propensão dos seus seguidores para o apreciarem. Ao mesmo tempo, estudou-se como é que as características demográficas dos consumidores e a sua utilização do Instagram influenciam a sua resposta ao *influencer marketing*. Uma concussão importante desta investigação prende-se com a constatação de que os micro influenciadores (com menos de 100m seguidores) tendem a ser mais apreciados e, assim, mais atrativos para empresas e agências de marketing.

**Palavras-chave:** *influencer marketing*, número de seguidores, número de contas a seguir, utilizadores jovens do Instagram, poder de opinião.

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## Chapter 1 Introduction

#### 1.1. Motivation

Social media Social media platforms (SMP) and Instagram, in particularly, have gained utmost relevance during the last years, becoming the focus of the majority of marketers and brands. The revolution in the way people communicate and interact with their peers brought different marketing strategies and ideas to engage with consumers. In fact, we live in an era where the ability to truly influence and establish emotional connections with consumers have the greatest value. Influencers became more and more relevant, as consumers started to be influenced not only by their family and friends, but also by people they follow and admire. Influencers have nowadays a paramount importance on marketing strategies, so that brands are increasing, year by year, their investment in this type of marketing and paying less attention to traditional advertising (Harvey, 2018).

As it is a relatively recent strategy, knowledge about influencer marketing continues to develop slowly. This, however, contrasts with companies' thirst for advice on how to use influencer marketing to communicate with consumers.

The fact that there is still a lack of information about the subject and several topics to be discovered was what motivated us the most to develop this work. Likewise, the relevance that our study might have for companies and agencies

that work with digital influencers was also one of the major motivations for us to pursue the study.

#### 1.2. Goal

The main purpose of this work is to study how consumers understand the number of followers and followees of an influencer in terms of his/her overall likability. Although some studies show that the number of followers positively influences influencer's likability (Veirman et al., 2017), other suggest that (in the particular case of Twitter) more followers does not necessarily mean more mentions or retweets (Cha et al., 2010), which are indicators of likability. Specifically, this work aims to identify if ascribed opinion leadership works as a mediating variable in the relation previously described. In other words, we aim to study if there is a positive effect of the number of followers on influencers likability because they are perceived as relevant opinion leaders. Even though some studies claim that ascribed opinion leadership does not work as a strong mediating variable in the relation previously described (Veirman et al., 2017), other studies state the opposite. In fact, Bene (2017) proofs that, for young people that rely on Facebook to have access to political information, negative opinions about democracy stem from the fact that, on this platform, information and opinions are mostly provided by their dissatisfied peers. This means that these discontented peers are perceived as opinion leaders to the point of influencing other's perspectives on politics.

The number of followees is a variable that might have several interpretations. According to some researches, consumers tend to follow only influencers who have a ratio followers/followees greater than 1, i.e., influencers who have more followers than following accounts (Garcia and Amatriain, 2010; Veirman et al., 2017). Indeed, an individual that follows several accounts might have more chances to learn about different topics, which might be valuable in terms of opinion leadership (Williams, 2006).

From a different perspective, following a lot of accounts could be noticed as an attempt to be followed back by those people (Siegler, 2009). However, there is also evidence that following only a few people and having a lot of followers may be perceived as artificial or "fake" (Cresci et al., 2015; Veirman et al., 2017).

This study aims to understand how young Instagram users in particular react to the variables previously exposed. The focus on this target group is particularly relevant, as young people represent a significant part of all Instagram users (65% of Instagram users worldwide have between 18 and 34 years old) and have distinctive characteristics, which affect their personality, consumer behavior and attitudes when compared to the former generations (Dimock, 2019; Statista, 2019a).

Finally, it should be remarked that special emphasis was placed on developing a work with managerial implications based on real-life events, so that the results could have a real significance for companies. Therefore, we created two fictitious Instagram influencers with real influencers photos, one female and one male. In order to avoid confusion related to the gender identification, the gender of the respondent matched the gender of the influencer. Both profiles were carefully created to be similar in terms of photos' background, bio description and interests. In the end, we developed four conditions (eight, if we consider the male and female' profiles) according to the manipulation of the variables under study: moderate followers/low followees, high followers/low followees, moderate followers/high followees and high followers/high followees.

#### 1.3. Outline

In this subchapter, we will briefly summarize the different chapters of this dissertation.

In the second chapter, the literature review will be presented. Firstly, we begin by explaining the definition of influencer marketing and how it has grown over the time. We will also describe its relevance, in terms of market size and value and the shift that many companies have been doing, from traditional advertising strategies to this new form of marketing. Secondly, we will present the definition of influencers and the main differences between micro and macro-influencers. Then, we will clarify the differences between influencers and main streams celebrities. Finally, we will discuss the major strategies used by companies to track relevant influencers and what kind of values it is possible to track and measure. Also, we will expose how the number of followers, followees and ascribed opinion leadership might affect influencer's likability in contexts slightly different from ours. To conclude, we will analyze our target audience, young Instagram users between 18 and 34 years old, in terms of generation dimension and importance and their distinctive characteristics.

In the third chapter, we will present our research model, explain the research gap and formulate hypotheses, supported by the literature review. This precedes the fourth chapter, during which we will present and discuss the main findings of this research.

Finally, in the fifth chapter, we will outline the conclusion of this study, highlighting its main implications, presenting its limitations and identifying directions for further research.

## Chapter 2 Literature Review

#### 2.1. Role of Influencer Marketing

#### 2.1.1. Definition

Influencer marketing is fundamentally virtual word-of-mouth communication that nowadays works as substitute to direct mass marketing (Li et al., 2011; Woods, 2016). Unlike other communication forms, that only focus on the inherent value of a customer, influencer marketing relies on a word-of-mouth strategy, exploring the network effect of a customer in order to measure its real value (Li et al., 2011).

That being sad, influencer marketing is full of ambiguity, regarding the type of influence that is being established and also the type of individual that is being considered as special and influential. In fact, ordinary people communicating with their friends, family or co-workers can be considered influencers as well as celebrities, journalists and government officials since they are highly visible public figures. Undoubtedly, these types of influencers can exert different types of influence through distinctive media channels. For instance, a public figure promoting a product in a magazine has a different influence from a trusted friend promoting the same product in person and this definitely has a difference influence from a well-known expert writing a review (Bakshy et al., 2011).

#### 2.1.2. The emergence

There is empirical evidence that information obtained by consumers through interpersonal sources (as family, friends and co-workers) has stronger positive effects on consumer decision-making process than traditional advertising techniques (Veirman et al., 2017). In fact, this type of promotion is likely to be more effective than traditional advertising campaigns, due to the higher authenticity and credibility which, consequently, leads to lower resistance to the message (Vries et al., 2012).

The assumption that consumers value other's opinions is not a recent statement. Although this is true, the growing popularity of social media platforms (SMP) made this effect cleaser, since it empowered consumers to share content, experiences and their life one-to-many (Boyd and Ellison, 2007; Knoll, 2016). Instagram, Facebook and other social media platforms (technologies that enable the spread of information and encourage people to connect with others who share similar interests) currently represent assertive tools to empower electronic word-of-mouth (eWOM). This is because consumers can easily and voluntarily express an opinion and disseminate a message, showing their brand preference and sharing brand-information with their peers (Boyd and Ellison, 2007; Jansen et al., 2009; Knoll, 2016; Lyons and Henderson, 2005). IT must be understood that eWOM is a person-to-person communication, either a positive or negative statement, diffused via the internet. In the light of this, it is more likely to remain over the time in social platforms, websites or blogs than traditional word-of mouth (WOM) that instantly disappears after in-person communication. Therefore, promoting brands through digital influencers can create more credible WOM, compared to traditional advertising, since these promotions are integrated in the daily interactions between influencers and every-day people through SMP, as Instagram or YouTube (Abidin, 2016). It is importance to refer that, besides direct influence, influencers can also indirectly influence their followers. This second effect, pursued mainly through their posts, happens because a large number of other people (their followers) might also share viral messages in their own social network, creating a cascade of influence (Gladwell, 2000; Thomas, 2004).

Although marketers tend to focus on negative WOM (the criticism and defects related to products which are spread through social media), the majority of the WOM communications are positive (a margin of 8 to 1). Additionally, positive WOM is perceived as more credible than the negative, reinforcing that brands should not let the fear of negative comments influence the motivation to engage with customers openly (Keller and Fay, 2016).

The decreasing relevance of traditional advertising strategies is linked to the fact that it seems to be very invasive and disruptive for consumers. Indeed, traditional advertising pushes them to face promotional campaigns when they are not available for that, with particular emphasis being placed on advertising between music sets on Spotify or commercials during movie breaks. As a consequence, consumers became more skeptical about those strategies, leading to the emergence of new methods that try to bypass them, as ad-blocking software's or the possibility to advance forward on TV to skip commercials. This clearly suggests that traditional advertising is losing strength and highlights the need for brands to use other types of marketing to reach their target consumers, such as influencer marketing, which overcomes the resistance and avoidance of traditional marketing and maximizes the effects of eWOM (Fransen et al., 2015; Kaikati and Kaikati, 2004; Veirman et al., 2017).

In summary, there is strong evidence that brands should effectively switch from traditional advertising strategies to focus on influencers to promote their products. Instead of reaching target markets through different forms of traditional advertising, brands are now being more selective in their strategies, encouraging influencers with considerable number of followers, that are admired

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and reliable by their network, to talk and recommend their products through social networks (Fransen et al., 2015; Kaikati and Kaikati, 2004). By using this strategy, brands can market their products indirectly and empower eWOM through social media (Fransen et al., 2015; Kaikati and Kaikati, 2004; Veirman et al., 2017). Statistics illustrate that content shared from consumer to consumer through WOM will drive more significant brand preference and purchase intention than content distributed by the brand itself. In other words, if a brand creates content on its social media page, it is less likely to go viral than if an influential consumer publishes that same content on his/her social page or posts it to an appropriate fans' community (Hall, 2010).

#### 2.1.3. The importance

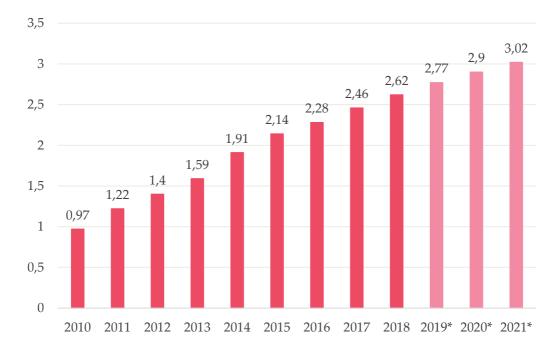
Influencer marketing, specifically the diffusion of WOM, generates a quickly and easily information spread throughout social networks. Therefore, proper influential marketing campaigns may increase sales volume and reduce promotion costs (Li et al., 2011). In fact, research indicates that influencer marketing can generate, annually, 11 times more return-on-investments (ROI) than other forms of traditional advertising (Kirkpatrick, 2016).

Also confirming the significance of influencer marketing, a joint study by Twitter and Annalect (an analytics company), found that 40 percent of the respondents have purchased a product online after seeing it used by an influencer on social media. Moreover, 20 percent of the respondents already shared something they saw from an influencer, which clarifies the importance and dimension that influencer marketing has nowadays (Swant, 2016).

Furthermore, a survey conducted by the Association of National Advertisers in April of 2018 (ANA, 2018) (involving 158 marketers with an average of 20 years of experience in the field) claims that 75% of the studied companies use influencer marketing and that 43% of them were planning to increase their spending in this type of marketing until April 2019. From the respondents that were not using influencer marketing at that time, 27% were planning to use it in the following 12 months. This visibly illustrates a progression of influencer marketing' relevance, reinforcing the need for companies to use this form of marketing.

According to Shaefer (2012), who presents a coherent perspective about the importance of influencer marketing, one of the reasons for Twitter's success is that it allows people to share their perspectives with the rest of the world. Nowadays, as we have access to instantaneous communication via SMP and communication often occurs through these platforms, companies cannot ignore them. As stated by Shaefer (2012, p.33), this "would be like ignoring the power of television, or the power of newspapers. This is now the way people communicate, the preferred means for many information gathering". Shaefer (2012) also emphasizes that social web is neither a business-to-business (B-B) channel nor a business-to-consumer (B-C), but rather a person-to-person channel (P-P), meaning that to succeed in this new communication platform, brands need to adopt a different mindset and strategy.

From the analysis of figure 1 (which depicts the number of social media users worldwide from 2010 to 2017 with projections until 2021), it is possible to conclude that in 2019 there will be 2.77 billion social media users around the world, following the 2.46 billion confirmed in 2017 (Statista, 2019b). This reinforces even more the increase of social network penetration around the globe. Adding to this, the number of internet users who are also social network users is expected to rise (in 2017, they hovered 71%). The increased usage of smartphones and mobile devices in general was responsible for creating new possibilities for mobile social networks with improved features. The majority of social networks were also available as mobile social apps and adjusted for mobile internet browsing in order to allow users to easily access virtual blogging sites via tablet or smartphones (Statista, 2019b).



**Figure 1**: Number of social media users worldwide from 2010 to 2021 (billions). Source: Statista, 2019b.

Also, considering the particular case of Instagram, a mobile social network that allows users to edit and share photos and videos amongst their network, we may observe a consistent and significant growth of monthly users from 2013 to 2018 (this is illustrated in figure 2) (Statista, 2019c). In June 2018, Instagram has reached 1 billion monthly active users, following the 800 million confirmed in September 2017. Besides, in 2015, Instagram has registered approximately 77.6 million active users only in the United States, a number that is estimated to exceed 111 million in 2019 (Statista, 2019c).

Instagram App is one of the most popular social networks around the globe, being even more trendy between teens and young Millennials (38% of the users are younger than 24 years old), which supports the relevance of the work developed. In fact, in the United States, Instagram beats Twitter and Facebook in terms of teens' preference (Statista, 2019a).



**Figure 2**: Number of monthly active Instagram users from January 2013 to June 2018 (millions). Source: Statista, 2019c.

After clarifying the growth and potential of Instagram, it is of paramount importance to illustrate the importance of social influencer market on Instagram. According to Statista (2019d), in 2017 the worldwide Instagram influencer market was valued in 1.07 billion dollars and projected to growth more than the double, to 2.38 billion dollars, in 2019. Moreover, the number of brand sponsored influencer posts on Instagram was 9,7 million in 2016 and it is projected to growth to 32.3 million posts in 2019, which reinforce not only the potential of the influencer marketing on Instagram but also its actual relevance (Satista, 2019).

#### 2.2. Working with influencers

#### 2.2.1. Definition

Influencers are individuals who excessively impact the spread of information or some other relevant behavior (Bakshy et al., 2011). To be precise, most marketeers define influencers as individuals on YouTube, Instagram, Snapchat or blogs that collect a significant volume of followers (moderate or large depending if it is a micro or macro-influencer) through the textual and visual description of their personal lives and lifestyles (Abidin, 2015; Cruz, 2018).

It is important to mention that influencers monetize their following by adding advertising to their blogs or social media posts (Abidin, 2015). Influencers are specialized in specific niches or topics and build their followings around that, so, depending on the brand's objectives, micro or macro-influencers can be used for different purposes by companies in order to suit different marketing purposes (Mediakix, 2016).

#### 2.2.2. Macro and Micro Influencers versus celebrities

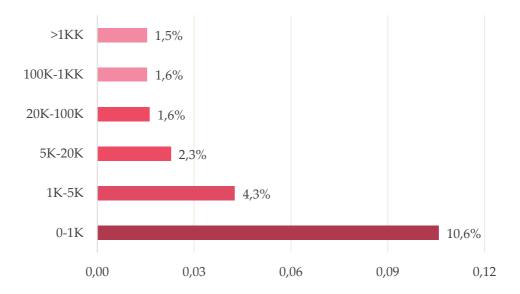
Although there are several opinions about the spectrum of the number of followers for micro and macro-influencer, we will consider micro-influencers as influencers with a relatively small volume of followers (between 5K and 100K) and macro influencers as influencers with a large volume of followers (100k or more) (Barker, 2017; Cruz, 2018; Komok, 2018).

As previously explained, depending on the brand's objectives, micro or macro-influencers can be best suited for different marketing strategies (Cruz, 2018; Mediakix, 2016). In fact, micro-influencers, due to their size, might beneficiate from some advantages. Firstly, micro-influencers stand-out in terms of their engagement rate (ER) (total likes and comments on paid posts, split by the number of posts, split by the number of followers). In essence, engagement rates of micro-influencers can be more than 60% higher than those of macro-influencers, since the first group has a smaller number but more loyal and engaged followers. Therefore, as the posts of micro-influencers are more likely to be considered as content published by friends and family, due to higher accessibility and authenticity, they can be more effective (Cruz, 2018; NewsWhip, 2018). As deeper engagement matters to brands, to bet on influencers with less

number of followers might be an efficient strategy to adopt (NewsWhip, 2018). Moreover, a survey of 2 million social media influencers conducted by Markerly (Markerly, 2016) (an influencer marketing platform), found that, considering unpaid posts, Instagram influencers with a volume of followers between 10K and 100K have a like rate (number of likes per post, divided by the number of followers) of 2.4 percent, compared to 1.7 percent for macro-influencers with more than 100K followers. Additionally, the comment rate (number of comments per post, divided by the number of followers) follows the same tendency (inversely proportional to the number of followers). The study was also applied to sponsored posts on Instagram, suggesting that the optimized point, in terms of maximum impact, is an influencer with a volume of followers between 10K to 100K (micro-influencers) (Chen, 2016).

Secondly, micro-influencers can create higher return-on-investments (ROIs), which means that engaging with macro-influencers, with higher reach, might become expensive. On average, marketeers expect to pay between 50K\$ to 100K\$ for one post from a macro-influence. As a result, by supporting micro-influencers, brands cannot only ensure they are targeting the right audience, but also that they are represented in several posts in order to create a high level of brand ubiquity in a specific niche (Mediakix, 2016).

As illustrated by figure 3, the more followers' influencers have, the less engagement they get. It is also noticeable that bloggers with 20K and those with more than 1 million followers do not have any significant difference in ER. Their average of ER is between 1.54% and 1.62% (HypeAuditor, 2018).



**Figure 3**: Engagement rate by number of followers of Instagram Influencers. Source: HypeAuditor, 2018.

According to some literature, the type of product that is being promoted plays an important role in the type of influencer chosen by marketeers. Exclusive products that should respond to consumer's need for uniqueness, can be perceived as less exclusive when promoted by influencers with a wide social network dimension. Instead, if the product is promoted by influencers with a moderate volume of followers, it is more likely to fulfill the consumer's needs for exclusivity. As a result, depending on the type of product, brands should address the best type of influencer to impact consumer's decision-making processes. According to Veirman et al. (2017), the number of followers negatively influences consumer's attitude towards the product when it is perceived as exclusive. In fact, a considerable number of followers is related to the fact that the product is attractive for a lot of people, reducing the feeling of uniqueness. Once again, it is crucial to emphasize as that the number of followers is not a guarantee for success.

Adding to the previous points, it is also necessary to highlight that, although celebrities might often be seen as influencers, there are clear differences between these two roles. Influencers, in opposition to celebrities, are content creators that are followed by a significant number of people (Abidin, 2016; Jensen and Gilly, 2003; Veirman et al., 2017). They share that content (insights about their personal life and experiences), through blogs, vlogs or SMP as Instagram or Facebook.

From a brand's perspective, the main goal on its relationship with influencers is to involve them (by offering products to try, inviting them to private events or even by paying them) and encourage them to recommend and promote the brand's offering within their social community. In contrast to general celebrities, influencers are perceived as accessible, believable, trustworthy and easy to connect, since they share in-deep personal and inaccessible information with their followers on an active basis (Abidin, 2016; Jensen and Gilly, 2003; Veirman et al., 2017). This constant sharing can generate para-social interaction, that is, an impression of a face-to-face relationship, in this case with an influencer, so that followers tend to be more influenced by their thoughts and attitudes (Knoll et al., 2015; Veirman et al., 2017). Thus, it is fundamental for marketers to distinguish influencers from mainstream celebrities, in order to leverage their influence on target consumers.

#### 2.3. Influencers' likability

#### 2.3.1. Tracking influencers

The first step of an influencer marketing strategy consists of identifying key influencers in the target market, a phase that can be assured using different methods (Araujo et al., 2017). For instance, some companies use scoring platforms to find and track relevant influencers and others rely on agencies that are experts in reaching influencers on behalf of their clients (Keller and Fay, 2016; Valos et al., 2016).

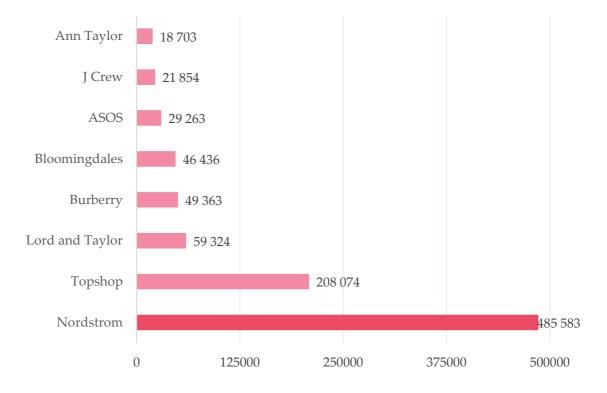
Firstly, when brands rely on those platforms (namely Klout, PeerIndex, Kred or NewsWhip), it is important to mention they use social media measures (as number of likes, followers or shares) and tend to focus on short-term strategies rather than on long-term goals. In fact, these scoring platforms tend to bypass the work required to generate long-term results and quantified value, making them valuable references to analyze product and brand amplification, but not to measure influencer marketing (Brown and Fiorella, 2013; Bughin et al., 2010).

Considering NewsWhip Analytics as an example, users can search for a specific target category as "teens" or "moms" and verify (within a three-month period) which are the Instagram leaders in that specific category, the types of products they tend to promote and what is the average number of comments and likes (an example is given in figure 4).

| # Instagram Handle      | Post Count | Average Likes + Comments | Total Likes + Comments |
|-------------------------|------------|--------------------------|------------------------|
| 1 mother_of_daughters   | 20         | 23,645                   | 472,900                |
| 2 thebucketlistfamily   | 5          | 54,375                   | 271,877                |
| 3 barbiestyle           | 2          | 74,574                   | 149,147                |
| 4 motherhoodinhollywood | 30         | 3,307                    | 99,214                 |
| 9 taza                  | 8          | 10,328                   | 82,624                 |
| 5 lynzyandco            | 23         | 3,427                    | 78,814                 |
| 6 cottonstem            | 9          | 5,817                    | 52,357                 |
| 7 somedayilllearn       | 21         | 2,298                    | 48,252                 |
| 10 whatmomslove         | 4          | 10,848                   | 43,390                 |
| 8 carliestylez          | 2          | 16,662                   | 33,324                 |

**Figure 4**: Parenting influencers on Instagram and theirs sponsored posts. Source: NewsWhip, 2018.

In NewsWhip platform, it is also possible to identify which type of influencer marketing the competitors are using. In other words, through this platform, it is possible to search for brand's competitors and know which had the most engaging campaigns<sup>1</sup> through influencer marketing in the last three months. As illustrated in figure 5, in a retail context, Nordstrom had the highest number of likes and comments on sponsored posts that contained the brand name (comparing to its competitors).



**Figure 5**: Total likes and comments on sponsored posts containing specific brand names. Source: NewsWhip, 2018.

Secondly, considering the agencies specialized in reaching influencers on the behalf of their clients, it is important to mention that each organization has its own strategy and approach which makes this topic even more relevant to analyze.

On the one hand, BzzAgent, one of the oldest agencies in the field, focuses on giving product samples to every influencer that agrees to try and recommend their products. This means that BzzAgent does not filter which kind of influencer should recommend the products (based on their personal characteristics, engagement rate with their followers or popularity). Instead, they welcome

<sup>&</sup>lt;sup>1</sup> In accordance to NewsWhip platform parameters.

everyone to try their client's products, as Coca-Cola, Danone or Procter and Gamble and, consequently recommend them. A study focusing on the consumers who try those products shows that they are six times more likely to be influencers or conversations catalysts than average, which means this is a great opportunity for brands to spread and promote their products (Keller and Fay, 2016).

On the other hand, there are agencies such as Experticy, an agency focused on building a community of influencers that are experts in specific areas, such as sports apparel or health and nutrition. In this case, even though some of the influencers might work in these industries, others are simply lovers and enthusiasts about them. With this in mind, it is important to highlight that these specialists tend to recommend products 22 times more often than an average person and that their recommendations are extremely reliable and actionable (Keller and Fay, 2016).

To sum up, depending on the communication objectives, brands can adopt different strategies to track relevant influencers, either by using scoring platforms or agencies. The most relevant aspect to take into consideration is which variables matter more to brands and which strategy they want to pursue. By adopting a less-risky strategy, brands can use scoring platforms or traditional agencies. However, if they are opened to irreverent strategies, to rely on agencies as BzzAgent or Experticy, might be a good approach.

### 2.3.2. Number of followers and followees

As mentioned before, influencer marketing consists of identifying influential social media users and convince them to promote a specific product or brand. Within this process, one of the major challenges is to identify a suitable influencer (likable for the brand's target audience) and opinion leader for a specific marketing purpose (Araujo et al., 2017). Nowadays, the number of followers is commonly used to identify influencers, since higher number of followers may

conduct to larger dissemination of the message and consequently, leverage the power of the WOM. For instance, apart from the social influence scoring platforms described in the previous subchapter, Zhang and Dong (2008) established a roadmap in order to identify online influencers. In this specific case, the first step also consists in finding out the users with higher volume of followers. In a nutshell, it is clear that the audience size is commonly used as a first step to consider in the search for influencers and opinion leaders (Veirman et al., 2017).

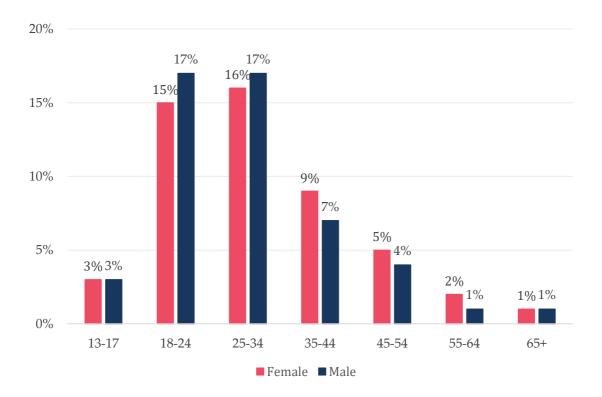
In fact, higher volume of followers can be helpful to spread ideas or messages in a fast manner (Bakshy et al., 2011). However, it remains unclear how consumers, specifically younger generations, process this information and use it to evaluate an influencer, specifically in terms of likability. A research from International Journal of Advertising (Veirman et al., 2017) shows that the number of followers positively influences attitudes towards the influencer. This is because they are perceived as more popular and these higher perceptions of popularity lead people to assign more opinion leadership to the influencer. Nevertheless, it remains uncertain how does the major segment of Instagram users, between 18 and 35 years old, react to those stimuli. Also, it is still unclear if the number of followers directly influence the ascribed opinion leadership of an influencer (Veirman et al., 2017).

Moreover, still related to the consumer perspective on influencers, Veirman et al. (2017) studied if the number of followees (the number of people the influencer follows) affects influencers' likability. In fact, nowadays there are rules about the ideal ratio (followers/followees) and even calculators that explain the result (e.g., Tff Ratio for Twitter's accounts). Altogether, the main objective of the study was to conclude if the ratio (followees/followees) affects influencers' likability from a consumer perspective. The results show there is a negative relationship between the number of followers and likability when the influencer follows a small number of people. However, it is still opened to discussion how young Instagram users, with very distinctive characteristics, react to this variable.

In general, an important consideration to retain is that brands should not automatically perceive influencers as likable or opinion leaders just because they have higher number of followers. Instead, they should also analyze the number of followees in order to understand how the influencer is perceived by their community.

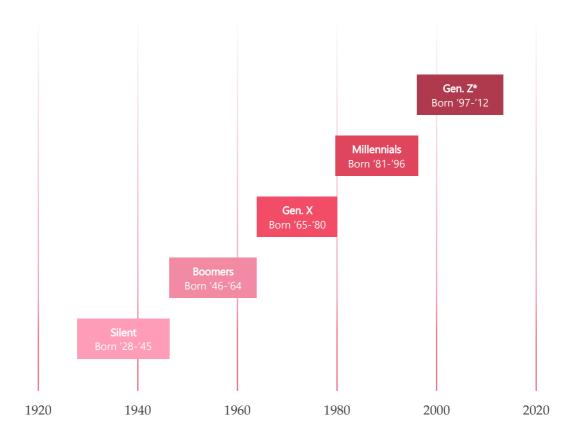
#### 2.3.3. Young Instagram users

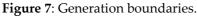
As previously explained, teenagers and young Millennials occupy a very significant part of the total Instagram users: 65% of Instagram users worldwide have between 18 and 34 years old (illustrated in figure 6) (Statista, 2019a). Also, distribution through gender is not so distinctive, showing that young Instagram users are almost equally represented by female and male users (34% and 31%, respectively) (Statista, 2019a).



**Figure 6**: Distribution of Instagram users worldwide as of January 2019, by age and gender. Source: Statista, 2019a.

Each generation holds singular characteristics that affect individual motivations, experiences and attitudes (Glass, 2007). As so, it is of paramount importance to characterize the generations of young Instagram users (Millennials and Generation Z), as they possess unique characteristics when compared to the previous generations and are also very different between themselves (Dimock, 2019; Myers and Sadaghiani, 2010). There are no exact generational cutoff points, however historical and political events that happened during childhood try to create boundaries between generations (identified in figure 7).





Source: Dimock, 2019.

Millennials were between 5 and 20 years old when the terrorist attack of 9/11 shook the world. The majority of them were old enough to understand the historical implication of that specific moment, while members of Generation Z

<sup>\*</sup> no chronological endpoint has been set for this group. For this analysis, Generation Z is defined as those ages 7 to 22 in 2019.

were very young and probably do not have memory of the event. Millennials also grew knowing about the wars in Iraq and Afghanistan, which contributed to the intense current political environment. Adding to this, most Millennials had between 12 and 27 during the elections of 2008 where the first black president was elected, a relevant political event in which youth votes have had a significant contribution. In general, Millennials are the most racially and ethnically diversified adult generation in the history, albeit some suggest that Generation Z can be even more diverse (Dimock, 2019).

Another significant factor that shapes generational cohorts is technology and the relevant changes in the way people communicate and interact. For instance, Baby Boomers grew up with the expansion of television, whereas generation X grew up with the computer revolution and Millennials with the internet dramatic explosion. By contrast, for Generation Z, all the innovations previously described took part of their life from the very beginning. If Millennials adopted social media, constant connectivity and entertainment throughout their adolescence, Generation Z were born with those innovations already assumed (Dimock, 2019). In fact, Millennials are the first generation to be digital natives as they grew up with an abundance of these technologies and with a plenty of other innovations being developed on a daily basis (Glass, 2007). They are commonly called by marketers, the "first adapters", the first to try, buy and share with the world their opinions about innovations, which might explain their relevance within social media community (Glass, 2007).

Despite the differences between Millennials and Generation Z, mainly because they were born in very distinctive time periods, they share many characteristics. As so, they combine deep knowledge about technology and a comfort-level with the global world. However, it is clear that Generation Z will show relevant differences in their consumer behavior when compared with Millennials, since the economic recession that accompanied these individuals' childhood, marked them strongly (Wood, 2013). Millennials reached the age of majority and joined the workforce in a moment of economic recession, which shaped their life choices, future earning and also arrival to adulthood (Dimock, 2019; Wood, 2013).

As a result, recent researches show the importance of tracking this last generation, since different studies predict there will be dramatic changes in the behaviors, attitudes and also lifestyle (either positive or negatives) for the ones who will reach the age of majority in this era (Dimock, 2019).

To sum up, it imperative to analyze Millennials and Generation Z' behavior in a context of social influence, as they are atypical when compared with previous generations, not to mention that they carry a significant weight in the total of Instagram users worldwide. This page was intentionally left with this sentence.

# Chapter 3 Method

## 3.1. Research Paradigm

As mentioned throughout the literature review, brands rely on short-term metrics to track the most valuable influencers and opinion leaders to promote their products. However, it is paramount to understand which variables affect influencers' likability from a consumers' perspective (Veirman et al., 2017). All in all, the final decision in the purchasing process relies on consumers.

Macro and micro-influencers can be suitable for different marketing strategies, depending on the brand objectives (Barker, 2017). From the one hand, it can be important to work with macro-influencers and take advantage of their ability to rapidly disseminate a message within a great number of followers (Gladwell, 2000; Thomas, 2004). From the other hand, it can be crucial to work with micro-influencers who established closer relationships with their followers, since they are known as credible and transparent individuals. Having this in mind, it is important to understand how consumers process influencers' data, in terms of number of followers and followees and in which extend this affects influencers' likability (Vries et al., 2012), as it is still uncertain how young Instagram users react and deal with those variables (Veirman et al., 2017). According to (Statista, 2019a), young Instagram users (from 18 years old to 34) are the age group with higher volume of users (as previously presented in figure 6). In fact, 65% of all

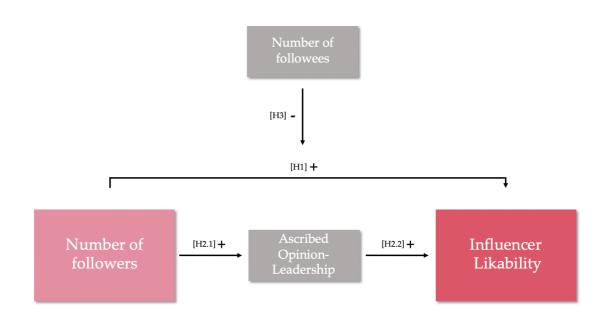
Instagram users are within this age group, which further reinforces the usefulness of the work developed. Also, the distribution through gender is not very distinctive, and, hence, it is important to analyze how both genders react to changes in those variables.

Therefore, this study aims to focus in two research gaps, starting by evaluating how consumers process changes in the number of followers and how this affects influencers' likability. Specifically, we will focus on ascribed opinion leadership as the main variable affecting this relationship. Following, we will study the impact that the ratio followers/followees has on influencers' likability, trying to understand if a higher number of followers negatively affects the positive relationship between number of followers and influencers' likability.

To conclude, it must be emphasized that this study will be relevant for the scientific community, as it will focus on the biggest and most influent age group within Instagram users (between 18 and 34 years old), which has never been the objective of academic studies before (Veirman et al., 2017).

## 3.2. Research Model and Hypothesis

Considering the research question of this study, "what is the impact of the number of followers and followees on influencers' likability for young Instagram users", and the main conclusions of the literature review previously presented, we propose the research model presented in figure 8.



**Figure 8**: Research Model. Source: Own Construction.

First of all, we will analyze if there is a positive relationship between the number of followers and influencers' likability for young Instagram users. In other words, we will analyze if a higher number of followers leads to a greater influencer likability. Following, the goal is to verify if ascribed opinion leadership works as a mediating variable in this relationship. In simplistic terms, this consists of understanding if this positive relationship occurs because influencers with higher number of followers are perceived as having higher opinion leadership. To conclude, we will focus on the last research gap and study if the number of followees (i.e., people followed by influencers) negatively affects influencers' likability in a scenario of a high number of followers. In this case, the number of followees will work as a moderating variable, meaning that the relationship between the number of followers and influencers' likability will be negatively affected if the number of accounts followed by the influencer is low.

Following this line of though, the number of followers will work as an independent variable, ascribed opinion leadership as a mediating variable, the

number of followees as a moderating variable and the influencers' overall likability as a dependent variable.

Regarding the hypotheses' formulation, whereas the previous studies focused on the influence and diffusion on Twitter (Cha et al., 2010; Weng et al., 2010) and on general Instagram population (Veirman et al., 2017), we will focus on a specific target of young Instagram users, because of its relevance within the Instagram community. According to the findings of these previous studies, the number of followers seems to positively influence influencer' likability (Veirman et al., 2017). However, studies have also shown that, on Twitter, the number of followers does not necessarily lead to an increase in the number of mentions or retweets (Cha et al., 2010), which could be an indicator of lack of likability. Considering all the previous findings, it is of utmost relevance to understand how young Instagram users are affected by the number of followers. Therefore, we propose the following hypothesis:

H1: For young Instagram users, the number of followers of an influencer has a positive effect on the overall likability of the influencer

According to previous studies, the positive relationship illustrated on [H1] seems to occur mostly because influencers are perceived as more popular, and also because these higher perceptions of popularity leads people to assign more opinion leadership to the influencer although this effect is weaker (Veirman et al., 2017). This study already proved a strong relationship between the number of followers and popularity, despite the fact that it suggests that ascribed opinion leadership is not a variable capable of mediating the relationship described.

From a different perspective, Bene (2017) found that Facebook is the main political information source for university students. In fact, for young people that rely on Facebook to have access to political information, the negative opinion about the way democracy works results from the fact that on this SMP information and opinions are mostly provided by their dissatisfied peers. This means that these discontented peers are perceived as opinion leaders to the point of influencing other's perspectives on politics. To sum up, it seems that SMP, in this case represented by Facebook, have a significant power to generate opinion leaders capable of influencing the opinions of others, specifically of young generations (Bene, 2017).

As explained in the literature review, there is a two-way influence path between consumers, since they are influenced by each others. This effect might be even stronger for consumers that act as role models, inspiring imitation among the ones that are paying attention to their consumption and purchasing behavior. Particularly, this happens when greater knowledge, experience and admiration is conferred to the ones that are being imitated, or in order words, when higher opinion leadership is assigned to a specific individual (Flynn et al., 1996).

In accordance with what was formerly described, it remains uncertain and controversial if ascribed opinion leadership works as mediator in the relation described on [H1] for our target audience, young Instagram users. In fact, this age group includes Millennials and Generation Z and has several distinctive characteristics when compared to older generations (Dimock, 2019). Thus, considering the findings of previous researches, we assume the following hypothesis:

H2: For young Instagram users, the positive effect of the number of followers on the likability of the influencer will be mediated by his/her ascribed opinion leadership.

As a consequence, for the aforementioned hypothesis to be proved, it is necessary to test the following direct effects:

H2.1: For young Instagram users, the number of followers of an influencer has a positive effect on his/her ascribed opinion leadership.

H2.1: For young Instagram users, the ascribed opinion leadership of an influencer has a positive effect on its overall likability.

Besides the number of followers, the number of followees and especially the combination of both (ratio followers/followees) may influence consumer's perception of the influencer, affecting his/her likability (Veirman et al., 2017). In some studies, it is assumed that popular individuals have a ratio bigger than one and that consumers tend to follow only influencers who have more followers than following accounts. However, it is still unclear how variations of this ratio (near or far from 1) are taken by the community of young Instagram users (Garcia and Amatriain, 2010; Veirman et al., 2017). From another perspective, an individual that follows several accounts has more chances to learn about different themes and consequently more ability to see beyond their own social environment, which might be valuable in terms of opinion leadership (Williams, 2006). However, following too much people is not favorable either, because it is unlikely that someone can keep track on all the account's updates. Similarly, following a lot of accounts could be noticed as an attempt to be followed back by those people (Siegler, 2009). To illustrate this phenomenon, it must be notices that, there are, on Instagram, hashtags as #followback, #follow4follow and others. In contrast, following only a few people and having a lot of followers may be perceived as artificial or "fake", which is not advantageous (Cresci et al., 2015; Veirman et al., 2017). Consequently, it is relevant to study if the number of accounts followed by the influencer negatively influences the relationship between the number of followers and influencer's overall likability [H1]. We are not aware about any research that has studied this moderating effect on our target audience, young Instagram users. Thus, we developed the following hypothesis:

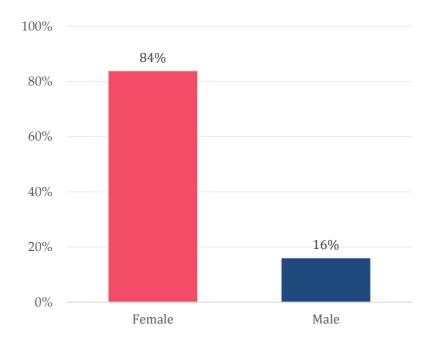
H3: For young Instagram users, if an influencer has a high number of followees, the effect of the number of followers on influencer likeability will be positive.

## 3.2. Methodology and Measures

In order to test the hypotheses previously exposed, we administrated a questionnaire to young Instagram users between 18 and 34 years old (illustrated in Appendix A). To maximize the answer rate and to guarantee response coverage, the questionnaire was promoted in different social contexts (companies, Instagram and Facebook pages).

To build the questionnaire, we created two fictitious influencers Instagram accounts with real influencers photos, one female (Emily Ballester) and one male (Logan Ballester), illustrated in Appendix B. Both profiles were carefully created to be similar in terms of photos background (one photo in a pool with a beach landscape, two photos of him/herself, one photo promoting a watch and one photo of his/her dog) and bio description (Emily/Logan Bellester 26 y/o | Lifestyle | Travel | Healthy life | Food | Photography). Also, both profiles are related with lifestyle in order to appeal to a wider audience. In order to avoid confusion related to the gender identification, the gender of the respondent will match with the gender of the influencer.

In order to do an appropriate and real manipulation of the variables to test (number of followers and number of followees), we decided to conduct a characterization of 100 real lifestyle influencers' Instagram accounts (shown in Appendix B). We analyzed, separately, 50 profiles of macro and micro influencers, since we believed the results will be distinct for these two types of influencers. As a result, we started to characterize the number of followers, followees and the ratio followees/followers for each Instagram account, taking into consideration a diversity in the influencers' communication language (i.e., we chose influencers that speak Portuguese, English or Spanish with their followers). Additionally, we also ensured a similar proportion of male and female influencers in that sample, when compared to the real-world statistics, that is 84% of female influencers and 16% of male influencers, as illustrated by figure 9 (Statista, 2018).



**Figure 9**: Distribution of influencers creating sponsored posts on Instagram worldwide in 2017, by gender. Source: Statista, 2018.

The main objective of the characterization previously explained was to apply *the Chebyshev's inequality* (Marshall and Olkin, 1960), which suggests that there is at least a 90% probability for the ratio followers/followees of our sample to be between the bounds given by:

$$\frac{F}{f} \in \left[\operatorname{AVG}\left(\frac{F}{f}\right) - 3 \cdot \operatorname{STD}\left(\frac{F}{f}\right), \operatorname{AVG}\left(\frac{F}{f}\right) + 3 \cdot \operatorname{STD}\left(\frac{F}{f}\right)\right],$$

where "F" is representing the number of followers, "f" the number of followees of the influencer sample, AVG the average and STD the standard deviation.

However, we found a large dispersal in the standard deviations, meaning that there is a limit of accounts following which does not continue to increase with the number of followers. As a result, we decided to use for the range of followers, 6.2K as the moderate value (it cannot be much lower because we are analyzing influencers) and 6.2M as the high value, based on the followers' range of micro (between 5K and 100K) and macro-influencer (more than 100K), previously described in the literature review, and which also suits our results. To settle the range of followees, we needed two extreme points (a low and high one), so we decided to consider a proxy of the minimum and maximum values found in the 100 accounts studied (42 and 2.4K following accounts).

Regarding the structure of the questionnaire, participants were initially asked questions linked with the requirements that will made them eligible to fill out the form. Firstly, we wanted to guarantee that they met the target audience (in terms of age and Instagram usage) and secondly, in terms of gender (in order to direct them to the female or male Instagram page).

After, participants were invited to read the following text that gives more information about the influencer, so that a personal connection could be easily established: "On Instagram, some users have a significant number of followers, commonly called Influencers. For big numbers, Instagram uses K as an abbreviation for thousand and M as an abbreviation for million. Please, look at the Instagram profile of Logan/Emily Ballester, an Instagram influencer who gives people, through Instagram, a preview of his/her life. He/She loves to travel (this year he/she will visit his/her 50th country) and to eat in a healthy and balanced way." Each respondent was arbitrarily allocated to one of the four conditions (moderate followers/low followees, high followers/low followees, moderate followers/high followees and high followers/high followees) and asked to view a screenshot of the influencer Instagram page (only differing in the volume of followers and people following).

In order to measure the variables under study and test the hypotheses previously presented, we divided our questionnaire in three parts. We started by making a manipulation check in order to guarantee that what we were considering, for instance, as a high number of followers was also considered as such by the respondents. In this part, we relied on the scale used by (Veirman et al., 2017), so respondents were asked, through a 7-point Likert-type scale (very small=1 or large=7) if they find the number of the influencer' followers very small=1 or very large=7. Consequently, they were asked to compare the number of influencer followers with the average number of followers of an influencer (also through a 7-point Likert-type scale where 1=less and 7=more). The same questions were asked in term of the number of followees.

In the second part, the purpose was to measure the recognized opinion leadership of the influencer. Therefore, we did a literature review to search for scales that served this purpose, and found, for instance, the scale adapted by Casaló et al. (2017). However, considering the stimuli presented to our respondents (a print screen of an Instagram account), we would not be able to measure some of the items considered in this scale (namely, if that Instagram account serves as a model for others or if it is one step ahead of others). As a result, we decided to use the scale adapted by (Veirman et al. (2017) based on a scale developed by (Flynn et al., 1996) about popular rock music and rock music recording which has already been tested in a questionnaire with a stimulus similar to ours. The original scale was developed by Rogers and Cartano (1962), firstly modified by King and Summers (1970), then by Childers (1986) and after by Flynn et al. (1996). These studies show that the scale is adaptable to a diversity of topics, has high internal consistency and test-re-test reliability, yields normally distributed scores and is free from acquiescence response bias (Flynn et al., 1996).

Consequently, in order to guarantee measurement consistency, we adopted a 7 Likert-type scale instead of a 5-type and asked if the respondents agree with the following questions (1= strongly disagree or 7=strongly agree):

- If I wanted a lifestyle advice, I would turn to Emily/Logan for advice;
- If I would follow Emily/Logan on Instagram, I would pick products based on what she/he posts;
- Emily/Logan's opinion on lifestyle could have an impact on me;
- Emily/Logan could influence my opinions about lifestyle.

Finally, in the third part of the questionnaire, influencers' likability was accessed. In order to do so, we used a scale developed by (Dimofte et al., 2003), that measures 4 items, through a 7-point Semantic Differential scale, to determine the likability of a spokesperson. Thus, the respondents were asked if they found Emily/Logan:

- Cold (=1) or warm (=7);
- Unlikable (=1) or likable (=7);
- Insincere (=1) or sincere (=7);
- Unfriendly (=1) or friendly (=7).

To conclude, respondents were asked about their socio-demographic characteristics. To be precise, they were asked how often they use Instagram (daily, weekly or monthly) and how many influencers do they think they follow on Instagram at the moment (none, between 1 to 5, between 5 to 20 or more than 20). In addition, they were asked about their place of residence and instruction level (basic education, high school, bachelor, master, doctoral or other). It is also important to notice that the questionnaire was conducted in Portuguese so that the language matched the nationality of the respondents.

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# Chapter 4 Results and Discussion

## 4.1. Validation

For the purpose of guaranteeing that our data is consistent and reliable we carried out a few validation checks which are presented with more detail in appendix C (as all the major analyses conducted in this work).

We started to check, in SPSS, if what we were considering as a high/low number of followers and a high/low number of followees was also interpreted in the same way by the respondents. As can be perceived through table 1<sup>2</sup>, the respondents who evaluated the influencer with a low number of followers attributed, on average, lower values to the number of followers (mean=4,08) than the ones who were exposed to the influencer with a high number of followers (mean=6,29). The same was observed for the number of followees, i.e., on average, the respondents who evaluated the influencer with a low number of followees (mean=1,69) than the ones exposed to the high number of followees' scenario (mean=4,12).

<sup>&</sup>lt;sup>2</sup> In this table, as well as in tables subsequently presented, "0" indicates "low/moderate" and "1" indicates "high".

| Scenario                            | Number of<br>followers/<br>followees | Mean | ho value |
|-------------------------------------|--------------------------------------|------|----------|
| Number of followers of Logan/Emily  | 0                                    | 4,08 | ,000     |
| Number of followers of Logan/ Entry | 1                                    | 6,29 | ,000     |
| Number of following of Logan /Emily | 0                                    | 1,69 | ,000     |
| Number of followees of Logan/Emily  | 1                                    | 4,12 | ,000     |

**Table 1:** Number of followers/followees' validity check (1).Source: SPSS, 2019.

Similarly, we analyzed if the respondents who evaluated the influencers with a low number of followers/followees believed that he/she had a lower number of followers/followees (on average) than the average influencers. The same check was made for the scenarios including a high number of followers/followees. Both validation checks were positive, as illustrated in table 2. Regarding the number of followers, respondents exposed to the scenario with a high number of followers agreed that, when compared to the average number of followers of an influencer, the number of followers of this influencer was higher (mean=5,49) than the one of the scenario with a low number of followers (mean=3,10). The same was observed for the number of followers, since the scenario with a low number of followees presented lower values (mean=2,41) than the one with a high number of followees (mean=4,47). Also, it is important to highlight that all of the aforementioned validity checks presented statistical significance.

| Scenario   | Number of<br>followers/<br>followees | Mean | ho value |
|--|--------------------------------------|------|----------|
| Number of followers of Logan/Emily comparing to the average of an influencer   | 0                                    | 3,10 | ,000     |
| Number of followers of Logan/Emily comparing to the average of an initialities | 1                                    | 5,49 | ,000     |
| Number of followees of Logan/Emily comparing to the average of an influencer   | 0                                    | 2,41 | ,000     |
| Number of followees of Logan/ Entity comparing to the average of an induciter  | 1                                    | 4,47 | ,000     |

**Table 2:** Number of followers/followees' validity check (2).Source: SPSS, 2019.

Finally, we measured, in SPSS, the scale reliability of the unidimensional variables, ascribed opinion leadership and likability. As shown in table 3, both male and female questionnaires show internal consistency, since Cronbach's Alphas (represented by  $\alpha$ ) are higher than 0,7.

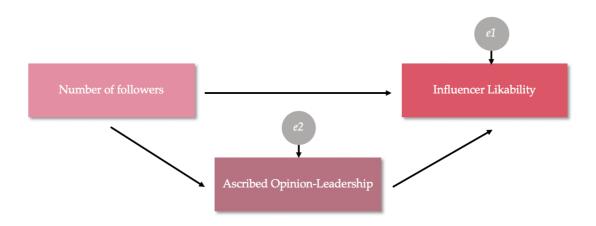
| Scale                                     | Cronbach's Alpha (α) | N of items |
|---|----------------------|------------|
| Ascribed Opinion Leadership – Scale Logan | 0,875                | 4          |
| Ascribed opinion Leadership Scale – Emily | 0,855                | 4          |
| Likability Scale – Logan                  | 0,791                | 4          |
| Likability Scale – Emily                  | 0,838                | 4          |

**Table 3:** Reliability analysis of scales.Source: Own Construction (generated by SPSS)

To conclude, we confirmed that the respondents agreed with what we have defined as a low/high value of number of followers and followees. Also, we ensured that the scales used to measure ascribed opinion leadership and influencers' likability were reliable and presented internal consistency. Therefore, findings seem to be in line with the theoretical background.

## 4.2. General overview

In other to test our model' hypotheses, we used SPSS and specifically, AMOS, a SPSS' add-in, because it allowed us to test the overall model at once, as illustrated by figure 11.



**Figure 10**: Model illustration at AMOS. Source: Own Construction (generated by AMOS)

We started to transform all the variables into observable ones to facilitate data analysis. After that, we created a summated scale, using the mean, for the two constructs (ascribed opinion leadership and likability) without making any differentiation in terms of gender. We are aware that, by using this approach, we may be slightly reducing the accuracy of the analysis, since all the scale' items are being given a similar weight. However, as we confirmed that the Cronbach alphas assume a consistent value and due to the fact that we have only a few items in each variable, we have decided to pursue with this simplification.

Starting with the first hypothesis, [H1], we tested if there is a positive impact of the number of followers on overall likability. According to our findings, we reject [H1], since we observed a negative relation (statistically significant, with  $\rho$  value  $\leq 0,05$ ), between the number of followers and influencer' likability. In other words, it is possible to conclude that, for young Instagram users, the higher the number of followers, the lower the overall likability of an influencer. This could be explained by the fact that influencers with a high number of followers are less likely to be considered as accessible and authentic (Cruz, 2018; NewsWhip, 2018). However, if we test the same hypothesis, but without controlling the ascribed opinion leadership' variable (i.e., considering its effect), we obtain very different results. In this case, we find that the number of followers does not have an impact on influencer's likability. In fact, although the regression weight is negative (suggesting a negative relation between the two variables), it does not present statistical significance (the *p value* is 0,153, as illustrated by table 4), which causes the relationship described to be null.

This led us to conclude that the negative relation between the number of followers and influencers' likability only happens when the ascribed opinion leadership is considered as a control variable. In other words, we can accomplish that, not only the number of followers has an effect on influencer' likability, but also the ascribed opinion leadership.

| Hypothesis                        | Standardized<br>Equation<br>weight (β) | ho value | T test |
|-----------------------------------|--|----------|--------|
| Number of followers -> Likability | -0,055                                 | 0,153    | -1,432 |

**Table 4:** Test of [H1] not controlling ascribed opinion leadership.Source: Own Construction (generated by SPSS)

Regarding the test of [H2.1], we could not confirm that there is a relationship between the number of followers and ascribed opinion leadership (the  $\rho$  value is 0,19, as illustrated by table 5). However, a strong relation ( $\beta \sim 0,4$ ), with statistical significance ( $\rho$  value = 0,00) is established between ascribed opinion leadership and influencer's likability, which lead us to accept [H2.2]. This shows that ascribed opinion leadership is a strong indicator of likability, meaning that the more opinion leadership is ascribed to an influencer, the more likable he/she is. Since we reject [H2.1] and accept [H2.2], we cannot conclude that ascribed opinion leadership works as a mediator variable. Indeed, this conclusion would only be possible if both relationships were positive and statistically significant. Hence, we would need to conduct another test to confirm the mediation relation.

All in all, we can conclude that, ascribed opinion leadership has definitely an impact on influencer's likability, since, as previously described, [H1] is only confirmed when this variable is controlled and we have confirmed [H2.2].

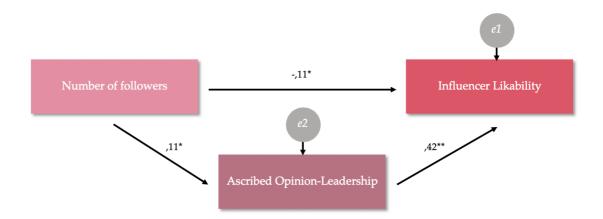
| Hypotheses  | Standardized<br>Equation<br>weight (β) | ho value | T test | S.E.  |
|---|--|----------|--------|-------|
| Number of followers -> Likability                     | -0,079                                 | 0,024    | -2,263 | 0,059 |
| Number of followers -> Ascribed<br>Opinion Leadership | 0,051                                  | 0,19     | 1,309  | 0,102 |
| Ascribed Opinion Leadership -><br>Likability          | 0,434                                  | ***      | 12,474 | 0,022 |

Table 5: Global model test

Source: Own Construction (generated by SPSS)

In order to test [H3], we proceeded to a multi-group analysis at AMOS (creating one group for the high number of followees and another for the low number of followees), so that we could verify how the model behaves for each of the groups. Within this context, we have concluded that, for the low number of followees' scenario, there is a negative relation between the number of followers and influencer's likability. Although this relation is not very strong ( $\beta = -0,107$ ), it is statistically significant ( $\rho$  value = 0,033). Also, within this group, it is possible to confirm that the relations conveyed in all other hypotheses (represented in figure 12) are also statistically significant. In other words, the number of followers positively influences the ascribed opinion leadership ( $\beta = -0,115$  and  $\rho$  value = 0,033) and the ascribed opinion leadership positively influences the influencer's likability ( $\beta = -0,419$  and  $\rho$  value = 0,00). This led us to conduct further tests in order to verify if ascribed opinion leadership works

as a mediator variable on the relationship between the number of followers and influencer's likability for the low number of followees' scenario.



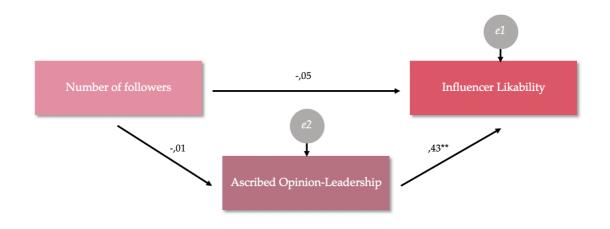
**Figure 11**: Model illustration at AMOS for low number of followees. Source: Own Construction (generated by AMOS)

As so, we pursued a bootstrap analysis at AMOS and verified that the mediation effectively exists in the aforesaid scenario. Specifically, we found that there is a statistically significant indirect effect ( $\rho$  value = 0,010) between the number of followers and influencer's likability caused by ascribed opinion leadership, as illustrated in table 6. In this case, when respondents ascribe opinion leadership to the influencer (i.e., when this variable works as a mediator), the relation between the number of followers and influencer's likability turns positive.

| Indirect effect   | Standardized<br>Indirect<br>Effect | ho value |
|---|------------------------------------|----------|
| Number of followers -> Likability (mediated by ascribed opinion leadership) | 0,048                              | 0,010    |

**Table 6:** Test of [H1] not controlling ascribed opinion leadership.Source: Own Construction (generated by AMOS)

For the other group, considering the scenario with a high number of accounts followed by influencers (which is covered in table 7), we cannot confirm a relation between the number of followers and influencer's likability, since it has no statistical significance ( $\rho$  value = 0,276). In this particular case, we can only confirm a relation between ascribed opinion leadership and influencer's likability (as portrayed in figure 13), which, as we previously highlighted, can be a strong metric to measure likability, as in all the tests we conducted, this relation was positive and significant. A valid explanation for the fact that, for the high number of followees' scenario, the number of followers does not have an impact on influencers' likability, stem from the fact that an influencer following several accounts can be perceived as fake or as an attempt to get more followers (Cresci et al., 2015; Veirman et al., 2017).



**Figure 12**: Model illustration at AMOS for high number of followees. Source: Own Construction (generated by AMOS)

|   | Low number of followees (N=335)        |       |        |       | High numb                              | er of follow | vees (N=3 | 37)   |
|---|--|-------|--------|-------|--|--------------|-----------|-------|
| Hypotheses  | Standardized<br>Equation<br>weight (β) |       |        | S.E.  | Standardized<br>Equation<br>weight (β) | ho value     | T test    | S.E.  |
| Number of followers -><br>Likability                  | -0,107                                 | 0,033 | -2,134 | 0,088 | -0,053                                 | 0,276        | -1,09     | 0,079 |
| Number of followers -><br>Ascribed Opinion Leadership | 0,115                                  | 0,035 | 2,111  | 0,142 | -0,013                                 | 0,805        | -0,247    | 0,145 |
| Ascribed Opinion Leadership -><br>Likability          | 0,419                                  | ***   | 8,392  | 0,034 | 0,433                                  | ***          | 8,832     | 0,03  |

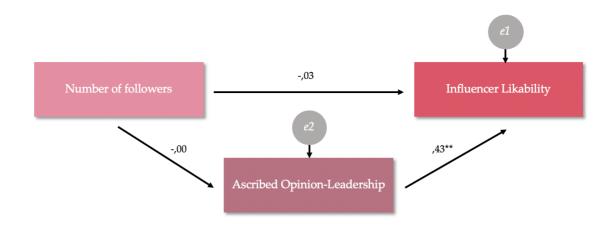
**Table 7:** Test of [H3]. Source: Own Construction (generated by AMOS)

### 4.3. Further Analysis

#### 4.3.1. Gender Impact

In order to understand if there is any variation throughout gender in terms of direction, strength and significance of the relations analyzed, we conducted a multi-group analysis at AMOS. As so, we analyzed how the global model behaves for female and male respondents. It is important to remember that, during the questionnaire' phase, gender identification was guaranteed, in order to avoid eventual errors associated to gender affinity.

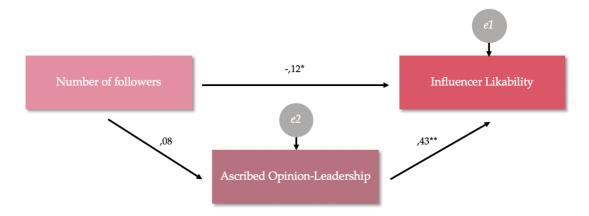
For the group of male respondents, we only identified a statistically significant relation between ascribed opinion leadership and influencer's likability, with a relevant strength ( $\beta = 0.43$ ), as depicted in figure 14.



**Figure 13**: Model illustration at AMOS for male respondents. Source: Own Construction (generated by AMOS)

However, for the female respondents, we obtained remarkably different results. In fact, we confirmed a negative relation between the number of followers and influencer's likability ( $\beta = -0.12$ ) with statistical significance ( $\rho$  value = 0.014). Also, for this group of respondents, we confirmed there is a positive relation between ascribed opinion leadership and influencers' likability

( $\rho$  value = 0,00) with a similar strength to the one observed for the male group ( $\beta = 0,434$ ) – this can be seen in figure 15.



**Figure 14**: Model illustration at AMOS for female respondents. Source: Own Construction (generated by AMOS)

Therefore, when analyzing the findings presented in table 8, we can conclude that female users are more influenced by this new form of marketing, since, unlike what happened for the male respondents, it is possible to establish strong and statistically significant relations between the variables considered in the model. We must remark though that these relations are sometimes negative (for instance, in the case of the impact of the number of followers on influencer's likability).

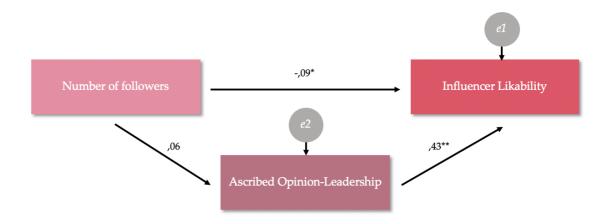
|   | Male                                   |       |        |       | Female                                 |          |        |       |
|---|--|-------|--------|-------|--|----------|--------|-------|
| Hypotheses  | Standardized<br>Equation<br>weight (β) |       |        | S.E.  | Standardized<br>Equation<br>weight (β) | ho value | T test | S.E.  |
| Number of followers -><br>Likability                  | -0,032                                 | 0,532 | -0,625 | 0,084 | -0,115                                 | 0,014    | -2,448 | 0,084 |
| Number of followers -><br>Ascribed Opinion Leadership | -0,003                                 | 0,956 | -0,055 | 0,151 | 0,081                                  | 0,120    | 1,553  | 0,136 |
| Ascribed Opinion Leadership -><br>Likability          | 0,431                                  | ***   | 8,287  | 0,032 | 0,434                                  | ***      | 9,254  | 0,032 |

**Table 8:** Multi-group analysis representation for male and female users.Source: Own Construction (generated by AMOS)

#### 4.3.2. Instagram' Affinity Impact

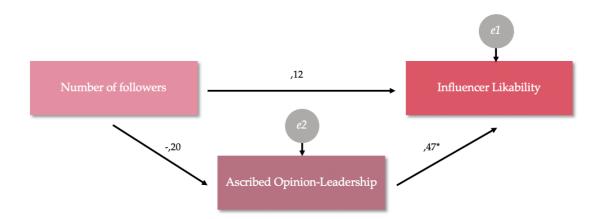
We found it would be relevant to understand if the described relations differ according to the Instagram usage and also according to the number of influencers followed on Instagram by the respondents.

Firstly, in which concerns the Instagram usage, as we only had 5 answers on the "monthly" alternative, we decided to group the weekly and monthly answers and create a new variable: Weekly/Monthly. As so, we compared, through a multi-group analysis at AMOS, how the model behaves for the respondents that use Instagram on a daily basis and for the ones that only use it on a weekly or monthly basis. For the first group of respondents (i.e., with a daily Instagram' usage) we could establish statistically significant relations between the number of followers and influencers' likability, and between ascribed opinion leadership and influencers' likability – this is evidenced in figure 16.



**Figure 15**: Model illustration at AMOS for daily Instagram' usage. Source: Own Construction (generated by AMOS)

On the contrary, for the group with a lower Instagram usage, we could only define a statistical, and positive, relation between ascribed opinion leadership and influencers' likability, as shown in figure 17.



**Figure 16**: Model illustration at AMOS for weekly/monthly Instagram' usage. Source: Own Construction (generated by AMOS)

Comparing both groups, we can clearly say that the vast majority of the participants (633 out of 672) use Instagram on a daily basis, which confirms what we have exposed in the literature review: this target audience is deeply engaged with this social platform and also has a significant weight on the overall Instagram users.

We can also conclude that, even though we have samples with very different dimensions, that the Instagram usage level can be related to the establishment of stronger relations between the variables tested. To put in another way, only for respondents that use the Instagram daily, we can confirm there is a negative relation between the number of followers and influencer's likability ( $\beta = -0,087$  and  $\rho$  value = 0,015) and a positive relation between the number of followers and ascribed opinion leadership ( $\beta = 0,433$  and  $\rho$  value = 0,00), which confirms that Instagram usage influences the respondent's opinion about the influencer (this can be observed in table 9).

|   | Daily Usage (N=633)                    |       |        |       | Weekly/N                               | fonthly Usa | age (N=39 | )     |
|---|--|-------|--------|-------|--|-------------|-----------|-------|
| Hypotheses  | Standardized<br>Equation<br>weight (β) |       |        | S.E.  | Standardized<br>Equation<br>weight (β) | ho value    | T test    | S.E.  |
| Number of followers -><br>Likability                  | -0,087                                 | 0,015 | -2,425 | 0,062 | 0,119                                  | 0,411       | 0,821     | 0,226 |
| Number of followers -><br>Ascribed Opinion Leadership | 0,056                                  | 0,162 | 1,397  | 0,105 | -0,203                                 | 0,195       | -1,296    | 0,432 |
| Ascribed Opinion Leadership -><br>Likability          | 0,433                                  | ***   | 12,070 | 0,023 | 0,471                                  | 0,001       | 3,244     | 0,082 |

**Table 9:** Multi-group analysis representation for daily and weekly/monthly Instagram' usage.Source: Own Construction (generated by AMOS)

Secondly, we checked if the number of influencers followed by the respondents affects the relations established in our model. Within this context, we found that the fact that the consumer follows more influencers positively affects the strength and statistical significance of the relations established. For instance, the relation between the number of followers and influencer's likability is only significant ( $\rho$  value = 0,001) for the respondents who follow more than 20 influencers on Instagram. This means that, if consumers have a deeper engagement with this form of marketing (i.e., follow several influencers on Instagram), this will strengthen the relation between the number of followers and influencer's likability. On the contrary, for respondents who follows few or none influencers' accounts, no relation is established between the two variables (this point is emphasized in table 10). It is also important to notice that, for all the scenarios, there is a positive and statistically significant relation between ascribed opinion leadership and influencers' likability, which reinforces what was previous mentioned about the relevance of ascribed opinion leadership as a key indicator to measure the overall likability of an influencer.

|   | Standardized<br>Equation<br>weight (β) | ho value    | T test     | S.E.  | Standardized<br>Equation<br>weight (β) | ho value  | T test    | S.E.  |
|---|--|-------------|------------|-------|--|-----------|-----------|-------|
| Hypotheses  | Follow                                 | 0 influence | ers (N=66) |       | Follow 1-5                             | influence | rs (N=245 | )     |
| Number of followers -><br>Likability                  | 0,149                                  | 0,180       | 1,342      | 0,181 | -0,020                                 | 0,729     | -0,346    | 0,082 |
| Number of followers -><br>Ascribed Opinion Leadership | -0,100                                 | 0,414       | -0,817     | 0,261 | 0,052                                  | 0,419     | 0,808     | 0,171 |
| Ascribed Opinion Leadership -><br>Likability          | 0,432                                  | ***         | 3,882      | 0,085 | 0,447                                  | ***       | 7,787     | 0,031 |
|   | Follow 5-                              | 20 influenc | ers (N=20  | 7)    | Follow +20 influencers (N=154)         |           |           |       |
| Number of followers -><br>Likability                  | -0,073                                 | 0,245       | -1,163     | 0,112 | -0,233                                 | 0,001     | -3,178    | 0,145 |
| Number of followers -><br>Ascribed Opinion Leadership | 0,027                                  | 0,695       | 0,392      | 0,176 | 0,093                                  | 0,245     | 1,162     | 0,209 |
| Ascribed Opinion Leadership -><br>Likability          | 0,441                                  | ***         | 7,055      | 0,044 | 0,386                                  | ***       | 5,264     | 0,056 |

 Table 10: Multi-group analysis representation by the range of influencers followed by respondents.

Source: Own Construction (generated by AMOS)

#### 4.3.3. Impact of Education Level

As previously mentioned, we asked a few demographic questions to our respondents in order to characterize our model accordingly. Specifically, we found it would be relevant to understand if the level of education influences the relation between the variables studied.

It is important to refer that, in order to have more accurate results, we have grouped some of the variables. For instance, as we only had one respondent with a PhD and another with primary school, we grouped the first one with the Master and created a new variable: Master/Doctoral. We decided to group the second case with the Highschool' answers so we created a new category, named Primary/Highschool. Also, we had 3 respondents that answered "other" as the type of education level, so we considered them as missing values (i.e., we did not consider them for this analysis in particular).

On the whole, the education level does not seem to affect respondent's perspective about influencers. In short, the main relation between the number of

followers and influencers' likability does not assume statistical significance in any scenario. By contrast, the positive relation between ascribed opinion leadership and influencers' likability has statistical significance in all the presented cases (as illustrated by table 11).

|   | Standardized<br>Equation<br>weight (β) | ho value   | T test    | S.E.  | Standardized<br>Equation<br>weight (β) | ho value    | T test | S.E.  |
|---|--|------------|-----------|-------|--|-------------|--------|-------|
| Hypotheses  | Primary                                | /Highscho  | ol (N=69) |       | Ba                                     | chelor (N=2 | 268)   |       |
| Number of followers -><br>Likability                  | -0,147                                 | 0,197      | -1,290    |       | -0,096                                 | 0,079       | -1,758 | 0,103 |
| Number of followers -><br>Ascribed Opinion Leadership | 0,163                                  | 0,170      | 1,371     |       | -0,010                                 | 0,874       | -0,159 | 0,170 |
| Ascribed Opinion Leadership -><br>Likability          | 0,364                                  | 0,001      | 3,199     |       | 0,441                                  | ***         | 8,067  | 0,037 |
|   | Maste                                  | r/Doctoral | (N=332)   |       |  |             |        |       |
| Number of followers -><br>Likability                  | -0,042                                 | 0,399      | -0,844    | 0,079 |  |             |        |       |
| Number of followers -><br>Ascribed Opinion Leadership | 0,059                                  | 0,283      | 1,074     | 0,141 |  |             |        |       |
| Ascribed Opinion Leadership -><br>Likability          | 0,437                                  | ***        | 8,811     | 0,031 |  |             |        |       |

**Table 11:** Multi-group analysis representation by the respondents' literary abilities. Source: Own Construction (generated by AMOS)

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# Chapter 5 Conclusion and Future Works

### 5.1. Main Conclusions

Influencer marketing has gained the utmost relevance during the last years, since several companies worldwide already use it and plan to increase their spending in this new form of marketing. Also, a significant part of the companies which have not yet adopted it, are planning to use it during 2019 (ANA, 2018). In particular, influencer marketing through Instagram, has attracted an increasing interest from the scientific community and companies (Djafarova and Rushworth, 2017; Hanan and Putit, 2017; Veirman et al., 2017).

With this work, we pretended to complement the studies already done and add relevant contributions, by focusing on a particularly relevant and influential target, the young Instagram users. Specifically, we wanted to fulfill the research gaps found and understand how young consumers perceive digital influencers in terms of their likability and which are the variables affecting their response to influencers.

Accordingly, our findings will have significant implications for brands that work with Instagram influencers, since we identified which characteristics should be taken into consideration, from a consumer perspective, when choosing an influencer, and which factors contribute to rendering the relationship between the consumer and the influencer more profitable for the brand. That being said, the main conclusions taken are compiled in the presented subchapter.

Firstly, contrarily to what Veirman et al. (2017) have found, we concluded that, for young Instagram users, the number of followers negatively affects influencer's likability. We believe these findings show how a specific country, Portugal, and a specific target, young Instagram users, might evaluate influencers differently. In fact, the study developed by Veirman et. al (2017) focused on different countries and on a more heterogeneous target in terms of age. Moreover, we might be facing a change in how consumers respond to this new form of marketing, showing that consumers might value more microinfluencers, who are capable of establishing stronger and more transparent connections with their followers. The fact that a high volume of followers is linked to an unreachable person, might be strengthening the negative relationship described.

However, it is important to highlight that we could not conclude that there is a strong negative relationship between the number of followers of an influencer and his/her likability, since  $\beta$  assumes a low value of -0.079. Thus, we can assume that, for a significant part of the respondents, the number of followers does not influence their opinion about the influencer, regarding his/her overall likability.

Also, we found that, when do not control the ascribed opinion leadership' variable, we cannot assume there is a relation between the number of followers and influencers' likability ( $\rho$  value = 0,153). As a result, we can definitely conclude that, besides the number of followers, ascribed opinion leadership is also a relevant variable affecting influencers' likability.

Secondly, this work provides evidence that ascribed opinion leadership does not work as a mediating variable in the relationship between the number of followers that an influencer has and his/her likability (with the exception of the low number of followees' scenario). Indeed, although we could confirm there is a positive relation between ascribed opinion leadership and influencers' likability, no relation was established between the number of followers and ascribed opinion leadership.

We also found that, the relation between the number of followers and influencers' likability is not established when the influencer follows a lot of accounts him/herself. As so, a condition for that relation to happen is that the influencer follows only a few accounts. Adding to this, in the particular case of influencers who follow only a few accounts, ascribed opinion leadership already works as mediator on the relationship between the number of followers and influencers' likability. Consequently, for influencers who follow a smaller number of accounts, when respondents ascribe them opinion leadership, the relation between the number of followers and influencer's likability turns positive.

Additional analyses were made in order to understand how respondent's characteristics (mostly demographics) affect their perspectives about influencers. Within this context, we concluded that women are more influenced by Instagram' influencers than men, since for women it is possible to establish strong and statistically significant relations between the variables considered in the model (namely, between the number of followers and likability and between ascribed opinion leadership and likability). By contrast, for men, a statistically significant relation was only established between ascribed opinion leadership and likability. As a result, although women and men are equally being represented on Instagram's community, women seem to be an easier target to reach through influencer marketing campaigns.

Also, in what concerns Instagram usage, it is possible to conclude that we can only confirm a negative relation between the number of followers and influencer's likability for respondents who use the Instagram daily. For those who use it less frequently, there does not seem to be any relationship. Hence, in respect to the engagement with this type of marketing, we confirmed that, only for the respondents who follow more than 20 influencer accounts, the number of followers negatively affects influencers' likability. For the ones who do not have a relevant engagement and interaction with influencers, this relationship does not seem to occur. Moreover, we found that the educational level does not affect respondents' perspective about the influencers.

On the whole, one of the most consistent findings was that ascribed opinion leadership has a direct and positive effect on influencer's likability, meaning that the more opinion leadership is ascribed to an influencer, more likable he/she will be. In fact, all the tests have confirmed this relationship in a consistent manner.

### 5.1. Future Works

In this research, we have studied how a particular target (the most relevant audience on Instagram) evaluates influencers in terms of their likability. This is particularly interesting for today's marketeers, as companies are currently channeling their marketing investments into influencer marketing.

Considering the tests performed and their outputs, we believe it would be also interesting to analyze how young generations of other countries understand influencers and evaluate their likability, since we believe response to influencer marketing might be strongly influenced by each country' culture and needs. It would also be relevant to create more complex Instagram profiles, so that the respondents could scroll down and look for more photos, comments, likes and descriptions. However, in that case, it would be difficult to isolate the effect of the number of followers and followees since more variables could influence the likability of an influencer. Regardless of that, if we could control all these variables and ensure that all the profiles are similar, this might be a pertinent complementary study, as respondents could better evaluate influencer likability (i.e., if he/she is warm, cold, sincere, insincere, etc.). Finally, it could be of interest to focus on the women' target since it is proved that, despite there is gender equality in terms of Instagram usage, women are much more influenced and involved with digital influencers. The focus on this specific target could allow to draw more accurate conclusions. This page was intentionally left with this sentence.

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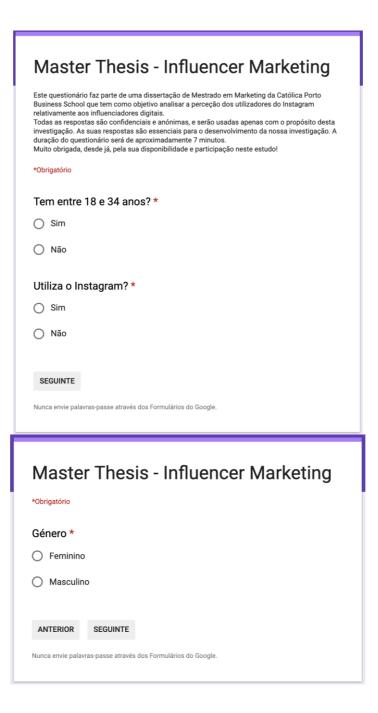
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# Appendix A Questionnaire

A.1. Example of version



#### Influencer Marketing

No Instagram, algumas pessoas chamadas Influenciadores têm um número de seguidores significativo. Para números grandes, o Instagram usa "m" como abreviatura para milhares e "M" como abreviatura para milhões. Por favor, preste atenção ao perfil de Instagram da Emily Ballester, uma influenciadora que partilha um resumo do seu estilo de vida pelo Instagram. Ela adora viajar (este ano vai visitar o seu 50º país) e alimentar-se de uma forma saudável e equilibrada.

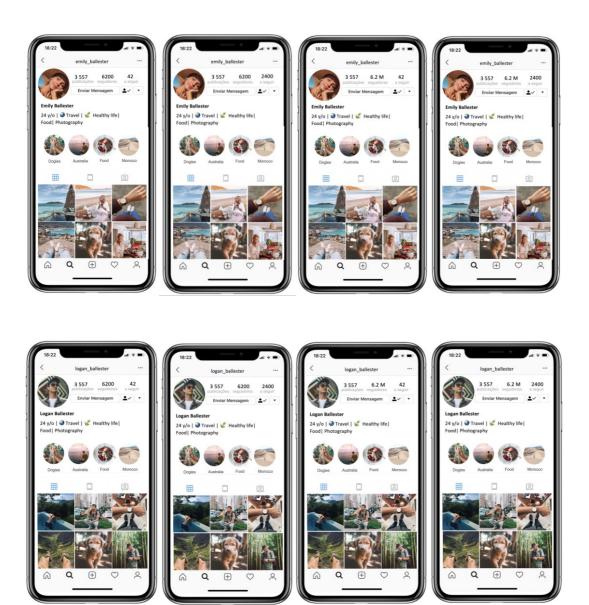


| Se eu quise<br>pediria à Ei |            | ım con     | selho      | sobre      | estilo     | de vio     | da ou      | viagens, eu            |
|-----------------------------|------------|------------|------------|------------|------------|------------|------------|------------------------|
|                             | 1          | 2          | 3          | 4          | 5          | 6          | 7          |                        |
| Não concord<br>de todo      |            | $\circ$    | $\bigcirc$ | $\bigcirc$ | $\bigcirc$ | $\bigcirc$ | $\bigcirc$ | Concordo<br>plenamente |
| Se eu segu<br>com base i    |            | -          |            |            | m, eu      | escolł     | neria p    | orodutos               |
|                             | 1          | 2          | 3          | 4          | 5          | 6          | 7          |                        |
| Não concord<br>de todo      |            | $\bigcirc$ | $\bigcirc$ | $\bigcirc$ | $\bigcirc$ | $\bigcirc$ | $\bigcirc$ | Concordo<br>plenamente |
| A opinião c<br>em mim *     | la Emi     | ily sob    | re esti    | ilo de '   | vida p     | oderia     | ter ur     | n impacto              |
|                             | 1          | 2          | 3          | 4          | 5          | 6          | 7          |                        |
| Não concord<br>de todo      |            | $\circ$    | $\bigcirc$ | $\bigcirc$ | $\bigcirc$ | $\bigcirc$ | $\bigcirc$ | Concordo<br>plenamente |
| A Emily po<br>de vida *     | deria i    | nfluen     | ciar a     | s minł     | nas op     | iniões     | acero      | a de estilo            |
|                             | 1          | 2          | 3          | 4          | 5          | 6          | 7          |                        |
| Não concord<br>de todo      |            | $\circ$    | $\bigcirc$ | $\bigcirc$ | $\bigcirc$ | $\bigcirc$ | $\bigcirc$ | Concordo<br>plenamente |
| Acha que a                  | Emily      | / é: *     |            |            |            |            |            |                        |
|                             | 1          | 2          | 3          | 4          | 5          | 6          | 7          |                        |
| Fria (                      | C          | $\bigcirc$ | $\bigcirc$ | $\bigcirc$ | $\bigcirc$ | $\bigcirc$ | $\bigcirc$ | Calorosa               |
| *                           |            |            |            |            |            |            |            |                        |
|                             | 1          | 2          | 3          | 4          | 5          | 6          | 7          |                        |
| Antipática                  | $\bigcirc$ | 0          | $\bigcirc$ | $\bigcirc$ | $\bigcirc$ | $\bigcirc$ | $\bigcirc$ | Simpática              |
| *                           |            |            |            |            |            |            |            |                        |
|                             | 1          | 2          | 3          | 4          | 5          | 6          | 7          |                        |
| Falsa                       | $\bigcirc$ | $\bigcirc$ | $\bigcirc$ | $\bigcirc$ | $\bigcirc$ | $\bigcirc$ | 0          | Sincera                |
| *                           |            |            |            |            |            |            |            |                        |
|                             | 1          | 2          | 3          | 4          | 5          | 6          | 7          |                        |
| Hostil                      | $\bigcirc$ | Amigável               |
|                             |            |            |            |            |            |            |            |                        |
| ANTERIOR                    | SEGU       | JINTE      |            |            |            |            |            |                        |

| Master Thesis - Influencer Marketing                                    |
|---|
| *Obrigatório  |
| Com que frequência utiliza o Instagram? *                               |
| O Diariamente   |
| O Semanalmente  |
| O Mensalmente   |
| Quantos influenciadores acha que segue neste momento no<br>Instagram? * |
| O Nenhum  |
| O Entre 1 e 5   |
| O Entre 5 e 20  |
| O Mais de 20  |
| Qual é a sua cidade de residência? *                                    |
| A sua resposta  |
|   |
| Qual é o seu grau de escolaridade? *                                    |
| C Ensino Secundário   |
| C Licenciatura  |
| Mestrado  |
| O Doutoramento  |
| Outro   |
|   |
| ANTERIOR SEGUINTE   |
| Nunca envie palavras-passe através dos Formulários do Google.           |
|   |
|   |
| Master Thesis - Influencer Marketing                                    |
| Obrigada pelo seu tempo!  |
| ANTERIOR SUBMETER   |
| Nunca envie palavras-passe através dos Formulários do Google.           |

# Appendix B Manipulation Stimuli

# B.1. Profiles



# B.2. Number of followers and followees' definition

|          | MA                          | ACRO-INFLUE | NCERS (>100 | K FOLLOWE               | RS)                       |        |
|----------|-----------------------------|-------------|-------------|-------------------------|---------------------------|--------|
| Rank     | Nome                        | Followers   | Followees   | Followees/<br>Followers | Communication<br>Language | Gender |
| 1        | Claudia Diniz               | 149 000     | 1 255       | 0,00842                 | English/Portuguese        | F      |
| 2        | Tess Homann                 | 164 000     | 1 316       | 0,00802                 | English                   | F      |
| 3        | Joana Freitas               | 115 000     | 906         | 0,00788                 | Portuguese                | F      |
| 4        | Coohuco                     | 126 000     | 975         | 0,00774                 | English/Spanish           | F      |
| 5        | Adriana Conti               | 139 000     | 988         | 0,00711                 | Portuguese                | F      |
| 6        | Anita da Costa              | 197 000     | 1 350       | 0,00685                 | English                   | F      |
| 7        | Alice Trewinnard            | 158 000     | 1 055       | 0,00668                 | Portuguese                | F      |
| 8        | Julieta Padrós              | 117 000     | 765         | 0,00654                 | English/Spanish           | F      |
| 9        | Joana Vaz                   | 147 000     | 949         | 0,00646                 | Portuguese                | F      |
| 10       | Hannah Perera               | 305 000     | 1 484       |                         | U U                       | F      |
|          | Alex Rivière                |             |             | 0,00487                 | English                   | F      |
| 11       |                             | 303 000     | 1 290       | 0,00426                 | English                   |        |
| 12       | Lucia Barcena               | 247 000     | 921         | 0,00373                 | English/Spanish           | F      |
| 13       | Barbara Corby               | 134 000     | 488         | 0,00364                 | Portuguese                | F      |
| 14       | Marcella Minelli            | 286 000     | 1 035       | 0,00362                 | Portuguese                | F      |
| 15       | Jelena Cikoja               | 290 000     | 997         | 0,00344                 | English                   | F      |
| 16       | Raquel Strada               | 350 000     | 1 175       | 0,00336                 | Portuguese                | F      |
| 17       | Matilda Djerft              | 446 000     | 993         | 0,00223                 | English                   | F      |
| 18       | Marcela Fetter              | 594 000     | 1 228       | 0,00207                 | Portuguese                | F      |
| 19       | Taty Betin                  | 332 000     | 686         | 0,00207                 | Portuguese                | F      |
| 20       | Mia Rose                    | 396 000     | 791         | 0,00200                 | English/Portuguese        | F      |
| 21       | Mafalda Sampaio             | 363 000     | 706         | 0,00194                 | Portuguese                | F      |
| 22       | Valeria Lipovetsky          | 346 000     | 578         | 0,00167                 | English                   | F      |
| 23       | Chelsea Jean                | 192 000     | 271         | 0,00141                 | English                   | F      |
| 24       | Belen Hostalet              | 782 000     | 1 025       | 0,00131                 | English                   | F      |
| 25       | Nina Urgell Cloquell        | 801 000     | 876         | 0,00109                 | English/Spanish           | F      |
| 26       | Teresa Andrés Gonzalvo      | 448 000     | 472         | 0,00105                 | Spanish                   | F      |
| 27       | Rocio Camacho               | 409 000     | 398         | 0,00097                 | Spanish                   | F      |
| 28       | Shantal Verdelho            | 974 000     | 807         | 0,00083                 | Portuguese                | F      |
| 30       | Coral Simanovich            | 677 000     | 538         | 0,00079                 | English/Greec             | F      |
| 31       | Paulo Del Vaile             | 382 000     | 296         | 0,00077                 | Portuguese                | М      |
| 32       | Vanessa Martins             | 506 000     | 386         | 0,00076                 | Portuguese                | F      |
| 33       | Marta Lozano                | 738 000     | 496         | 0,00067                 | English                   | F      |
| 34       | Maria Pombo                 | 983 000     | 496         | 0,00050                 | Spanish                   | F      |
| 35       | Mateus Verdelho             | 923 000     | 436         | 0,00047                 | Portuguese                | М      |
| 36       | Paola Antoni                | 2 600 000   | 1 226       | 0,00047                 | Portuguese                | F      |
| 37       | Alice Campello              | 1 900 000   | 875         | 0,00046                 | English/Spanish           | F      |
| 38       | Yasmin Brunet               | 2 100 000   | 966         | 0,00046                 | Portuguese                | F      |
| 39       | Valentina Ferragni          | 2 400 000   | 1 029       | 0,00043                 | English/Italian           | F      |
| 40       | Gabriela Pugliesi           | 3 900 000   | 1 075       | 0,00028                 | Portuguese                | F      |
| 41       | Matheus Mazzafera           | 2 400 000   | 585         | 0,00024                 | Portuguese                | M      |
| 42       | Aimee Song                  | 5 100 000   | 990         | 0,00019                 | English                   | F      |
| 43       | Stormi Bree                 | 1 000 000   | 186         | 0,00019                 | English                   | F      |
| 44       | Lauren Bullen               | 2 100 000   | 315         | 0,00015                 | English                   | F      |
| 45       | Jay Alvarrez                | 5 900 000   | 804         | 0,00013                 | English                   | M      |
| 46       | Camila Coelho               | 7 600 000   | 884         | 0,00014                 | English/Portuguese        | F      |
| 47       | Jack Morris                 | 2 800 000   | 290         | 0,00012                 | English                   | M      |
| 47       | Chiara Ferragni             | 16 000 000  | 290<br>905  | 0,00010                 | English/Italian           | F      |
| 40<br>49 | •                           |             | 903<br>308  |                         | e e                       | F      |
|          | Olivia Palermo<br>Zach King | 5 800 000   |             | 0,00005                 | English                   |        |
| 29<br>50 | Zach King                   | 20 700 000  | 49<br>44    | 0,00000                 | English                   | M      |
| 50       | Scott Disick                | 21 300 000  | 44          | 0,00000                 | English                   | Μ      |

| RankNomeFollowersFollowersFollowersCommunication<br>FollowersCommunication<br>LanguageGender1Elena Vidal939612700.13516SpanishF3Stephanie Baley2250028350.12600EnglishF4Helena Moure821710230.12456English/PortugueseF5Hello Rigby2550029620.11616EnglishF6Aubric Fick1510017200.11301EnglishM8Joana Paixao Brás2220021340.09613EnglishM8Joana Paixao Brás2220021340.09613EnglishM7Arrow_21193008590.08340PortugueseF9A Grace Abbott101008790.00521EnglishM10Christian Caro6 2054780.07703EnglishF11Christian Caro171008980.06223English/PortugueseF13Amanda Blakey16 0009250.04651EnglishM14Harta Carrasco171008980.04624EnglishM15Ines Degener Tomaz17 3008070.04651EnglishM16Allison (Allicarone)22 7001.2220.04332EnglishM17Laura Moutinho22 2001.0320.04649EnglishM18Allison (Allicarone)28 700   |            | MICRO-INFLUENCERS (>5K AND <100K FOLLOWERS) |           |           |            |                    |            |  |
|--|------------|---|-----------|-----------|------------|--------------------|------------|--|
| Followers         Language           1         Elena Vidal         9 396         1270         0.13516         Spanish         F           2         Filuoa Cortez Faria         20 800         2 678         0.12875         Portuguese         F           3         Stephanie Bailey         22 500         2 835         0.12850         English         F           4         Helen Noure         3 217         10 02         0.11391         English         F           6         Aubric Pick         15 100         1 720         0.11391         English         M           7         Arrow_21         19 300         2 027         0.10503         English         M           9         A Crace Abbott         10 100         878         0.08693         English         M           10         Francisca Sousa Vieira         10 300         897         0.08231         English         M           12         Isaura Quevedo         28 700         1 786         0.06223         English         M           12         Isaura Quevedo         28 700         1 252         0.04651         English         M           14         Marta Carrasco         17 100         897   | <b>D</b> 1 | N.  | T 11      | F 11      | Followees/ | Communication      | <b>C</b> 1 |  |
| 2         Filuo Cortez Faria         20 800         2 678         0,12875         Portuguese         F           3         Stephanic Bailey         22 500         2 835         0,12450         English         F           4         Helon Moure         8 217         10 23         0,12450         English         F           5         Helio Rigby         25 500         2 962         0,11616         English         F           6         Aubrie Pick         15 100         1720         0,11391         English         F           7         Arrow_21         19 300         2 027         0,0603         English         F           9         AGrace Abbott         10 100         878         0,0893         English         F           10         Fraicsa Sousa Vieira         10 300         859         0,0823         English         F           11         Christan Carro         6 2700         1786         0,0623         English         F           12         Isaura Quevedo         28 700         1279         0,04651         English         M           13         Marta Carrasco         17 100         878         0,0424         English         M  | Kank       | Nome  | Followers | Followees | Followers  | Language           | Gender     |  |
| 3         Stephanie Bailey         22 500         2 835         0.12600         English/Portuguese         F           4         Helen Moure         8 217         1 023         0.12450         English/Portuguese         F           5         Hello Rigby         25 500         2 962         0.11646         English/Portuguese         F           6         Aubrie Pick         15 100         1720         0.11391         English         M           7         Arrow 21         19 300         2 027         0.06633         English         F           9         Acrace Abbott         10 100         878         0.06233         English         M           12         Isaura Quevedo         2700         1766         0.06225         English         F           14         Marta Carrasco         17 100         898         0.05251         English         M           15         Ines Degener Tomaz         17 300         1279         0.04665         English         M           16         Allison (Allicarone)         22 800         1215         0.04324         English         M           17         Laura Moutinho         22 200         1032         0.04274         English  | 1          | Elena Vidal                                 | 9 396     | 1 270     | 0,13516    | Spanish            | F          |  |
| 4         Helena Moure         8 217         1 023         0.12450         English/Portuguese         F           5         Hello Rigby         25 500         2 962         0.11616         English         F           6         Aubrie Pick         15 100         1720         0.11391         English         M           7         Arrow 21         19 300         2027         0.10503         English         M           8         Joana Paixao Brás         22 200         2 134         0.09613         Portuguese         F           9         A Grace Abbott         10 100         878         0.08693         English         M           12         Isaura Quevedo         28 700         1786         0.06223         English/Portuguese         F           13         Amanda Blakley         16 000         925         0.03621         English         M           14         Marta Carrasco         17 100         894         0.02521         English         M           14         Marta Carrasco         17 000         807         0.04665         English         M           15         Ines Degener Tomaz         17 300         1279         0.04651         English         M <td>2</td> <td>Filuoa Cortez Faria</td> <td>20 800</td> <td>2 678</td> <td>0,12875</td> <td>Portuguese</td> <td>F</td>         | 2          | Filuoa Cortez Faria                         | 20 800    | 2 678     | 0,12875    | Portuguese         | F          |  |
| 5       Hello Rigby       25 500       2 962       0.11616       English       F         6       Aubrie Pick       15 100       1720       0.11391       English       F         7       Arrow_21       19 300       2 027       0.10503       English       F         9       A Grace Abbott       10 100       878       0.08693       English       F         10       Francisca Sousa Vieira       10 300       859       0.08340       Portuguese       F         11       Christian Caro       6 205       478       0.0703       English       F         13       Ananda Blakley       16 000       925       0.03781       English       F         14       Marta Carrasco       17 100       898       0.05251       English       M         15       Ines Degmert Tomaz       27 300       1279       0.04651       English       M         16       Allison Graham       27 500       1 229       0.04324       English       M         17       Laura Moutinho       22 2001       1032       0.0424       Portuguese       F         18       Allison Graham       27 500       1231       0.04024       Portuguese </td <td>3</td> <td>Stephanie Bailey</td> <td>22 500</td> <td>2 835</td> <td>0,12600</td> <td>English</td> <td>F</td>   | 3          | Stephanie Bailey                            | 22 500    | 2 835     | 0,12600    | English            | F          |  |
| 6         Aubrie Pick         15 100         1720         0,11391         English         F           7         Arrow,21         19 300         2 027         0,00503         English         M           8         Joana Paixao Brás         2 2200         2 134         0,09613         Portuguese         F           9         A Grace Abbott         10 100         878         0,08693         English         F           10         Francisca Sousa Vieira         10 300         859         0,08540         Portuguese         F           11         Christian Caro         6 205         478         0,07703         English         F           13         Amanda Blakley         16 000         925         0,05781         English         F           14         Marta Carrasco         17 100         898         0,05251         English         M           17         Laura Moutinho         22 200         1 032         0,04662         English         M           17         Laura Moutinho         22 200         1 215         0,04339         English         M           20         Maison (Alicarone)         28 700         1 215         0,04342         English         M   | 4          | Helena Moure                                | 8 217     | 1 023     | 0,12450    | English/Portuguese | F          |  |
| 7         Arrow_21         19 300         2 027         0,10503         English         M           8         Joana Paixao Brás         22 200         2134         0.09613         Portuguese         F           9         A Grace Abbott         10 100         878         0.08693         English         M           10         Francisca Sousa Vieira         10 300         859         0.08340         Portuguese         F           11         Christian Caro         6 205         478         0.07703         English/Portuguese         F           13         Amanda Blakley         16 000         925         0.05781         English/Portuguese         F           14         Marta Carrasco         17 100         898         0.05251         English         M           17         Laura Moutinho         22 200         1 032         0.04662         English         M           17         Laura Moutinho         22 000         1 215         0.04339         English         M           10         Om Baza         28 000         1 215         0.04622         Spanish         F           18         Allison (Allicarone)         28 000         1 215         0.04639         English  | 5          | Hello Rigby                                 | 25 500    | 2 962     | 0,11616    | English            | F          |  |
| 8         Joan Paixao Brás         22 200         2 134         0.09613         Portuguese         F           9         A Grace Abbott         10 100         878         0.08893         English         F           10         Francisca Sousa Vieira         10 300         859         0.08340         Portuguese         F           11         Christian Caro         6 205         478         0.07703         English/Portuguese         F           13         Amanda Blakley         16 000         925         0.05781         English/Portuguese         F           14         Marta Carrasco         17 100         898         0.05251         English         M           15         Ines Degener Tomaz         17 300         807         0.04665         English         M           17         Laura Moutinho         22 200         1 022         0.04362         English         M           19         Dom Baza         28 000         1 215         0.04324         English         M           20         Mikey Wu         20 100         859         0.04224         Portuguese         F           23         Sofia Hamela         27 400         987         0.03602         Spanish   | 6          | Aubrie Pick                                 | 15 100    | 1 720     | 0,11391    | English            | F          |  |
| A Grace Abbott         10 100         878         0,08693         English         F           10         Francisca Sousa Vieira         10 300         859         0,08340         Portuguese         F           11         Christian Caro         6 205         478         0,07703         English         M           12         Isuar Quevedo         28 700         1766         0,66223         English         F           13         Amanda Blakley         16 000         925         0,05781         English         F           14         Marta Carrasco         17 100         898         0,05251         English         M           17         Laura Moutinho         22 200         1 032         0,04649         Portuguese         F           18         Allison (Allicarone)         28 700         1 252         0,0452         English         M           21         Carina Caldeira         42 200         1 698         0,04024         Portuguese         F           22         Sophia Ippoliti         20 800         811         0,03500         German         M           23         Sofia Hamela         27 400         987         0,03602         Spanish         F  | 7          | Arrow_21                                    | 19 300    | 2 027     | 0,10503    | English            | М          |  |
| 10         Francisca Sousa Vieira         10 300         859         0.08340         Portuguese         F           11         Christian Caro         6 205         478         0.07703         English         M           12         Isaura Quevedo         28 700         1786         0.06223         English/Portuguese         F           13         Amanda Blakley         16 00         925         0.05781         English         F           14         Marta Carrasco         17 100         898         0.05251         English         M           15         Ines Degener Tomaz         17 300         807         0.04665         English         M           16         Allison Graham         27 500         1 229         0.04362         English         M           17         Laura Moutinho         22 200         1 032         0.04324         English         M           20         Mikey Wu         20 100         859         0.04324         English         F           21         Carina Caldeira         42 200         1698         0.04024         Portuguese         F           22         Sofia Hamela         27 400         987         0.03025         Spanish   | 8          | Joana Paixao Brás                           | 22 200    | 2 134     | 0,09613    | Portuguese         | F          |  |
| 11Christian Caro $6\ 205$ $478$ $0.07703$ EnglishM12Isaura Quevedo $28\ 700$ $1\ 786$ $0.06223$ English/PortugueseF13Amanda Blakley $16\ 000$ $925$ $0.05781$ EnglishF14Marta Carrasco $17\ 100$ $898$ $0.05251$ EnglishF15Ines Degener Tomaz $17\ 300$ $807$ $0.04665$ English/PortugueseF16Allison Graham $27\ 500$ $1\ 279$ $0.04651$ EnglishM17Laura Moutinho $22\ 200$ $1\ 032$ $0.0449$ PortugueseF18Allison (Allicarone) $28\ 700$ $1\ 252$ $0.04330$ EnglishM20Mikey Wu $20\ 100$ $859$ $0.04274$ EnglishM21Carina Caldeira $4\ 2200$ $1\ 688$ $0.04024$ PortugueseF23Sofia Hamela $27\ 400$ $9877$ $0.03602$ SpanishF24Daniel (dnnmodd) $24\ 300$ $814$ $0.03503$ GermanM25Helena Coelho $7\ 2600$ $24\ 130$ $0.03244$ EnglishF26María Romeu Escorial $39\ 300$ $1\ 228$ $0.03125$ SpanishF27Mariana Martinho $5\ 700$ $1\ 223$ $0.02640$ PortugueseF24Ines Costa $41\ 900$ $1\ 102$ $0.02630$ PortugueseF25Ines Costa $41\ 900$ $1\ 102$ </td <td>9</td> <td>A Grace Abbott</td> <td>10 100</td> <td>878</td> <td>0,08693</td> <td>English</td> <td>F</td>   | 9          | A Grace Abbott                              | 10 100    | 878       | 0,08693    | English            | F          |  |
| 12         Isaura Quevedo         28 700         1 786         0,06223         English/Portuguese         F           13         Amarda Blakley         16 000         925         0,05781         English         F           14         Marta Carrasco         17 100         898         0,05251         English         F           15         Ines Degener Tomaz         17 300         807         0,04655         English         M           17         Laura Moutinho         22 200         1 032         0,04649         Portuguese         F           18         Allison (Allicarone)         28 700         1 252         0,04324         English         M           00         Mikey Wu         20 100         859         0,04274         English         M           21         Carina Caldeira         42 200         1 698         0,0302         Sparish         F           23         Sofia Harnela         27 400         987         0,03602         Sparish         F           24         Daniel (dnmmod)         24 300         814         0,03324         English         F           25         María Romeu Escorial         39 300         1 228         0,02159         Portuguese  | 10         | Francisca Sousa Vieira                      | 10 300    | 859       | 0,08340    | Portuguese         | F          |  |
| 13       Amanda Blakley       16 000       925       0.05781       English       F         14       Marta Carrasco       17 100       898       0.05251       English       F         15       Ines Degener Tomaz       17 300       807       0.04665       English       M         16       Allison Graham       27 500       1 279       0.04661       English       M         7       Laura Moutinho       22 200       1 032       0.04649       Portuguese       F         18       Allison (Allicarone)       28 700       1 252       0.04322       English       M         20       Mikey Wu       20 100       859       0.04024       Portuguese       F         21       Carina Caldeira       42 200       1 698       0.04024       Portuguese       F         22       Sofnia Hamela       27 400       987       0.03602       Spanish       F         23       Sofnia Hamela       27 400       987       0.0302       Spanish       F         24       Daniel (dnmmod)       24 300       814       0.03324       English       F         25       Helena Coelho       72 600       2 413       0.0240       Por   | 11         | Christian Caro                              | 6 205     | 478       | 0,07703    | English            | М          |  |
| 14Marta Carrasco17 1008980.05251EnglishF15Ines Degener Tomaz17 3008070.04665English/PortugueseF16Allison Graham27 5001 2790.04651EnglishM17Laura Moutinho22 2001 0320.04649PortugueseF18Allison (Allicarone)28 7001 2520.04362EnglishF19Dom Baza28 0001 2150.04339EnglishM20Mikey Wu20 1008590.04274EnglishF21Sofia Ippoliti20 8008110.03899EnglishF22Sopia Ippoliti20 8008140.0350CermanM25Helena Coelho72 6002 4130.03244EnglishF26María Romeu Escorial39 3001 2280.02125SpanishF27Mariana Martinho57 7001 5230.02640PortugueseF28Ines Costa41 9001 1020.02630PortugueseF30Teresa Vu73 1001 6350.02237EnglishF31Cristiana Rocha27 2006030.02217English/PortugueseF33Abril Raluy90 60017810.01966English/SpanishF34Michelle Crossan59 2001 1630.01965EnglishF35Margarida Martinho56 7001 0920.01  | 12         | Isaura Quevedo                              | 28 700    | 1 786     | 0,06223    | -                  | F          |  |
| 15Ines Degener Tomaz17 300807 $0.04665$ English/PortugueseF16Allison Graham27 5001 279 $0.04651$ EnglishM17Laura Mottinho22 2001 032 $0.04649$ PortugueseF18Allison (Allicarone)28 7001 252 $0.04362$ EnglishM00Mikey Wu20 100859 $0.04274$ EnglishM21Carina Caldeira42 2001 698 $0.04024$ PortugueseF22Sophia Ippoliti20 800811 $0.03899$ EnglishF23Sofia Hamela27 400987 $0.0602$ SpanishF24Daniel (dnnmodd)24 300814 $0.03324$ EnglishF25Hena Coelho72 6002 413 $0.03324$ EnglishF26María Romeu Escorial39 3001 228 $0.03125$ SpanishF27Mariana Martinho57 7001 523 $0.02640$ PortugueseF28Ines Costa41 9001 102 $0.02630$ PortugueseF30Teresa Vu73 1001 635 $0.02217$ English/PortugueseF31Cristiana Rocha27 200603 $0.02217$ English/PortugueseF33Abril Raluy90 6001 781 $0.01966$ English/SpanishF34Michelle Crossan59 2001 163 $0.01262$ PortugueseF35M   | 13         | Amanda Blakley                              | 16 000    | 925       | 0,05781    |                    | F          |  |
| 16       Allison Graham       27 500       1 279       0.04651       English       M         17       Laura Moutinho       22 200       1 032       0.04649       Portuguese       F         18       Allison (Allicarone)       28 700       1 252       0.04362       English       M         20       Mikey Wu       20 100       859       0.04274       English       M         21       Garina Caldeira       42 200       1 698       0.04024       Portuguese       F         22       Sophia Ippoliti       20 800       811       0.03899       English       F         23       Sofia Hamela       27 400       987       0.03602       Spanish       F         24       Daniel (dnnmodd)       24 300       814       0.03320       German       M         25       Helena Coelho       72 600       2 413       0.03125       Spanish       F         26       Maria Romeu Escorial       39 300       1 228       0.02599       Portuguese       F         28       Ines Costa       41 900       1 102       0.02630       Portuguese       F         30       Teresa Vu       73 100       1635       0.02217 <t< td=""><td>14</td><td>Marta Carrasco</td><td>17 100</td><td>898</td><td>0,05251</td><td>English</td><td>F</td></t<>   | 14         | Marta Carrasco                              | 17 100    | 898       | 0,05251    | English            | F          |  |
| 17       Laura Moutinho       22 200       1 032       0,04649       Portuguese       F         18       Allison (Allicarone)       28 700       1 252       0,04362       English       F         19       Dom Baza       28 000       1 215       0,04339       English       M         20       Mikey Wu       20 100       859       0,04274       English       F         22       Sophia Ippoliti       20 800       811       0,03899       English       F         23       Sofia Hamela       27 400       987       0,03602       Spanish       F         24       Daniel (dnnmodd)       24 300       814       0,03350       German       M         25       Helena Coelho       72 600       2 413       0,03125       Spanish       F         26       María Romeu Escorial       39 300       1 228       0,02599       Portuguese       F         27       Mariana Martinho       57 700       1 523       0,02237       English       F         30       Teresa Vu       73 100       1 635       0,02237       English/Portuguese       F         31       Cristiana Rocha       27 200       603       0,02237  | 15         | Ines Degener Tomaz                          | 17 300    | 807       | 0,04665    | English/Portuguese | F          |  |
| 18         Allison (Allicarone)         28 700         1 252         0.04362         English         F           19         Dom Baza         28 000         1 215         0.04339         English         M           20         Mikey Wu         20 100         859         0.04274         English         M           21         Carina Caldeira         42 200         1 698         0.04024         Portuguese         F           22         Sofia Hamela         27 400         987         0.03602         Spanish         F           23         Sofia Hamela         27 400         987         0.03324         English         F           24         Daniel (drnmodd)         24 300         811         0.03324         English         F           25         Helena Coelho         72 600         2 413         0.03125         Spanish         F           26         María Romeu Escorial         39 300         1 228         0.02404         Portuguese         F           27         Maria Romau Escorial         39 300         1 228         0.02599         Portuguese         F           28         Ines Costa         41 900         1 102         0.02089         English/Portuguese   | 16         | Allison Graham                              | 27 500    | 1 279     | 0,04651    | English            | М          |  |
| 19         Dom Baza         28 000         1 215         0,04339         English         M           20         Mikey Wu         20 100         859         0,04274         English         M           21         Carina Caldeira         42 200         1 698         0,04024         Portuguese         F           22         Sophia Ippoliti         20 800         811         0,03899         English         F           23         Sofia Hamela         27 400         987         0,03602         Spanish         F           24         Daniel (dnnmodd)         24 300         814         0,03320         German         M           25         Helena Coelho         7 2600         2 413         0,03125         Spanish         F           26         María Romeu Escorial         39 300         1 228         0,02599         Portuguese         F           27         Mariana Martinho         57 700         1 523         0,02237         English         F           30         Teresa Vu         73 100         1 635         0,02237         English/Portuguese         F           31         Christiana Rocha         27 200         603         0,01766         English/Fortuguese  | 17         | Laura Moutinho                              | 22 200    | 1 032     | 0,04649    | Portuguese         | F          |  |
| 20         Mikey Wu         20 100         859         0.04274         English         M           21         Carina Caldeira         42 200         1 698         0,04024         Portuguese         F           22         Sophia Ippoliti         20 800         811         0,03899         English         F           23         Sofia Hamela         27 400         987         0,03602         Spanish         F           24         Daniel (dnnmodd)         24 300         814         0,03320         German         M           25         Helena Coelho         72 600         2 413         0,03125         Spanish         F           26         María Romeu Escorial         39 300         1 228         0,02640         Portuguese         F           27         Mariana Martinho         57 700         1 523         0,02630         Portuguese         F           28         Ines Costa         41 900         1 102         0,02630         Portuguese         F           30         Teresa Vu         73 100         1 635         0,02217         English/Portuguese         F           31         Cristiana Rocha         27 200         603         0,01765         English/Portuguese <td>18</td> <td>Allison (Allicarone)</td> <td>28 700</td> <td>1 252</td> <td>0,04362</td> <td>English</td> <td>F</td> | 18         | Allison (Allicarone)                        | 28 700    | 1 252     | 0,04362    | English            | F          |  |
| 21       Carina Caldeira       42 200       1 698       0,04024       Portuguese       F         22       Sophia Ippoliti       20 800       811       0,03899       English       F         23       Sofia Hamela       27 400       987       0,03602       Spanish       F         24       Daniel (dmmodd)       24 300       814       0,03320       German       M         25       Helena Coelho       72 600       2 413       0,03125       Spanish       F         26       María Romeu Escorial       39 300       1 228       0,03125       Spanish       F         27       Mariana Martinho       57 700       1 523       0,02640       Portuguese       F         29       Drizinha       38 200       933       0,02379       English       F         30       Teresa Vu       73 100       1 635       0,02217       English/Portuguese       F         31       Cristiana Rocha       27 200       603       0,01767       Portuguese       F         33       Abril Raluy       90 600       1 781       0,0166       English/Portuguese       F         34       Michelle Crossan       59 200       1 163       0,017  | 19         | Dom Baza                                    | 28 000    | 1 215     | 0,04339    | English            | М          |  |
| 21       Carina Caldeira       42 200       1 698       0,04024       Portuguese       F         22       Sophia Ippoliti       20 800       811       0,03899       English       F         23       Sofia Hamela       27 400       987       0,03602       Spanish       F         24       Daniel (dmmodd)       24 300       814       0,03320       German       M         25       Helena Coelho       72 600       2 413       0,03125       Spanish       F         26       María Romeu Escorial       39 300       1 228       0,03125       Spanish       F         27       Mariana Martinho       57 700       1 523       0,02640       Portuguese       F         29       Drizinha       38 200       933       0,02379       English       F         30       Teresa Vu       73 100       1 635       0,02217       English/Portuguese       F         31       Cristiana Rocha       27 200       603       0,01767       Portuguese       F         33       Abril Raluy       90 600       1 781       0,0166       English/Portuguese       F         34       Michelle Crossan       59 200       1 163       0,017  | 20         | Mikey Wu                                    | 20 100    | 859       | 0,04274    | English            | М          |  |
| 23         Sofia Hamela         27 400         987         0.03602         Spanish         F           24         Daniel (dnnmodd)         24 300         814         0.03320         German         M           25         Helena Coelho         72 600         2 413         0.03324         English         F           26         María Romeu Escorial         39 300         1 228         0.03125         Spanish         F           27         Mariana Martinho         57 700         1 523         0.02640         Portuguese         F           28         Ines Costa         41 900         1 102         0.02630         Portuguese         F           29         Drizitinha         38 200         993         0.02279         Portuguese         F           30         Teresa Vu         73 100         1 635         0.02217         English/Portuguese         F           31         Cristiana Rocha         27 200         603         0.01966         English/Portuguese         F           33         Abril Raluy         90 600         1781         0.01967         Portuguese         F           34         Michelle Crossan         52 500         904         0.01767         Portuguese <td>21</td> <td>Carina Caldeira</td> <td>42 200</td> <td>1 698</td> <td>0,04024</td> <td>-</td> <td>F</td>           | 21         | Carina Caldeira                             | 42 200    | 1 698     | 0,04024    | -                  | F          |  |
| 23         Sofia Hamela         27 400         987         0.03602         Spanish         F           24         Daniel (dnnmodd)         24 300         814         0.03350         German         M           25         Helena Coelho         72 600         2 413         0.03324         English         F           26         María Romeu Escorial         39 300         1 228         0.03125         Spanish         F           27         Mariana Martinho         57 700         1 523         0.02640         Portuguese         F           28         Ines Costa         41 900         1 102         0.02630         Portuguese         F           29         Driziinha         38 200         993         0.02217         English/Portuguese         F           30         Teresa Vu         73 100         1 635         0.02237         English/Portuguese         F           31         Cristiana Rocha         27 200         603         0.01965         English/Portuguese         F           33         Abril Raluy         96 600         1 781         0.01965         English/Spanish         F           34         Michelle Crossan         59 200         1 163         0.01767 <t< td=""><td>22</td><td>Sophia Ippoliti</td><td>20 800</td><td>811</td><td>0,03899</td><td>English</td><td>F</td></t<>  | 22         | Sophia Ippoliti                             | 20 800    | 811       | 0,03899    | English            | F          |  |
| 25       Helena Coelho       72 600       2 413       0.03324       English       F         26       María Romeu Escorial       39 300       1 228       0.03125       Spanish       F         27       Mariana Martinho       57 700       1 523       0.02640       Portuguese       F         28       Ines Costa       41 900       1 102       0.02630       Portuguese       F         29       Driziinha       38 200       993       0.02237       English       F         30       Teresa Vu       73 100       1 635       0.02217       English/Portuguese       F         31       Cristiana Rocha       27 200       603       0.02217       English/Portuguese       F         32       Madalena Bonvalot       53 700       1 122       0.02089       English/Portuguese       F         33       Abril Raluy       90 600       1 781       0.01966       English       F         34       Michelle Crossan       59 200       1 163       0.01965       English       F         35       Margarida Martinho       56 700       1 092       0.01926       Portuguese       F         36       Ines Patrocinio       83 400       1 4   | 23         | Sofia Hamela                                | 27 400    | 987       | 0,03602    | -                  | F          |  |
| 26         María Romeu Escorial         39 300         1 228         0,03125         Spanish         F           27         Mariana Martinho         57 700         1 523         0,02640         Portuguese         F           28         Ines Costa         41 900         1 102         0,02630         Portuguese         F           29         Driziinha         38 200         993         0,02599         Portuguese         F           30         Teresa Vu         73 100         1 635         0,02237         English         F           31         Cristiana Rocha         27 200         603         0,02217         English/Portuguese         F           32         Madalena Bonvalot         53 700         1 122         0,02089         English/Portuguese         F           33         Abril Raluy         90 600         1 781         0,01765         English/Spanish         F           34         Michelle Crossan         59 200         1 163         0,01722         Portuguese         F           35         Margarida Martinho         56 700         1 092         0,01722         Portuguese         F           36         Ines Patrocinio         83 400         1474         0,01689   | 24         | Daniel (dnnmodd)                            | 24 300    | 814       | 0,03350    | German             | М          |  |
| 27       Mariana Martinho       57 700       1 523       0,02640       Portuguese       F         28       Ines Costa       41 900       1 102       0,02630       Portuguese       F         29       Driziinha       38 200       993       0,02599       Portuguese       F         30       Teresa Vu       73 100       1 635       0,02237       English/Portuguese       F         31       Cristiana Rocha       27 200       603       0,02217       English/Portuguese       F         32       Madalena Bonvalot       53 700       1 122       0,02089       English/Portuguese       F         33       Abril Raluy       90 600       1 781       0,01965       English       F         34       Michelle Crossan       59 200       1 163       0,01955       English       F         35       Margarida Martinho       56 700       1 092       0,01767       Portuguese       F         36       Ines Patrocinio       83 400       1 474       0,01675       English       F         37       Catarina Beato       52 500       904       0,01722       Portuguese       F         38       Chrissa Benson       72 100       1 21   | 25         | Helena Coelho                               | 72 600    | 2 413     | 0,03324    | English            | F          |  |
| 28         Ines Costa         41 900         1 102         0,02630         Portuguese         F           29         Driziinha         38 200         993         0,02599         Portuguese         F           30         Teresa Vu         73 100         1 635         0,02237         English         F           31         Cristiana Rocha         27 200         603         0,02217         English/Portuguese         F           32         Madalena Bonvalot         53 700         1 122         0,02089         English/Portuguese         F           33         Abril Raluy         90 600         1 781         0,01966         English/Spanish         F           34         Michelle Crossan         59 200         1 163         0,01965         English         F           35         Margarida Martinho         56 700         1 092         0,01926         Portuguese         F           36         Ines Patrocinio         83 400         1 474         0,01767         Portuguese         F           37         Catarina Beato         52 500         904         0,01722         Portuguese         F           38         Chrissa Benson         72 100         1 218         0,01688  | 26         | María Romeu Escorial                        | 39 300    | 1 228     | 0,03125    | Spanish            | F          |  |
| 28Ines Costa41 9001 1020,02630PortugueseF29Driziinha38 2009930,02599PortugueseF30Teresa Vu73 1001 6350,02237EnglishF31Cristiana Rocha27 2006030,02217English/PortugueseF32Madalena Bonvalot53 7001 1220,02089English/PortugueseF33Abril Raluy90 6001 7810,01966English/SpanishF34Michelle Crossan59 2001 1630,01965EnglishF35Margarida Martinho56 7001 0920,01926PortugueseF36Ines Patrocinio83 4001 4740,01767PortugueseF37Catarina Beato52 5009040,0122PortugueseF38Chrissa Benson72 1001 2180,01688PortugueseF39Bruna Corby48 1008120,0168PortugueseF40Mafalda Patricio53 0008880,01675EnglishF41Pitty Bernard82 0001 0190,01431EnglishF43Yolanda Tati39 0005510,01431PortugueseF44Adriana Gastelum96 1001 0190,01020PortugueseF45Oneika Raymond75 2007800,0137EnglishF45Oneika Raymond75 200780 <td< td=""><td>27</td><td>Mariana Martinho</td><td>57 700</td><td>1 523</td><td>0,02640</td><td>Portuguese</td><td>F</td></td<>  | 27         | Mariana Martinho                            | 57 700    | 1 523     | 0,02640    | Portuguese         | F          |  |
| 29Driziinha38 2009930,02599PortugueseF30Teresa Vu73 1001 6350,02237EnglishF31Cristiana Rocha27 2006030,02217English/PortugueseF32Madalena Bonvalot53 7001 1220,02089English/PortugueseF33Abril Raluy90 6001 7810,01966English/SpanishF34Michelle Crossan59 2001 1630,01926PortugueseF35Margarida Martinho56 7001 0920,01926PortugueseF36Ines Patrocinio83 4001 4740,01767PortugueseF37Catarina Beato52 5009040,01722PortugueseF38Chrissa Benson72 1001 2180,01688EnglishF39Bruna Corby48 1008120,01688PortugueseF40Mafalda Patricio53 0008880,01675EnglishF41Pitty Bernard82 0001 2010,01465SpanishF42Daniella Gomez37 1005310,01431EnglishF43Yolanda Tati39 0005510,01037EnglishF44Adriana Gastelum96 1001 0190,01060English/SpanishF45Oneika Raymond75 2007800,01037EnglishF46Carlota Santos30 500311 <td>28</td> <td>Ines Costa</td> <td>41 900</td> <td>1 102</td> <td>0,02630</td> <td>0</td> <td>F</td>  | 28         | Ines Costa                                  | 41 900    | 1 102     | 0,02630    | 0                  | F          |  |
| 30Teresa Vu73 1001 6350,02237EnglishF31Cristiana Rocha27 2006030,02217English/PortugueseF32Madalena Bonvalot53 7001 1220,02089English/PortugueseF33Abril Raluy90 6001 7810,01966English/SpanishF34Michelle Crossan59 2001 1630,01965English/SpanishF35Margarida Martinho56 7001 0920,01926PortugueseF36Ines Patrocinio83 4001 4740,01767PortugueseF38Chrissa Benson72 1001 2180,01689EnglishF39Bruna Corby48 1008120,01688PortugueseF40Mafalda Patricio53 0008880,01675EnglishF41Pitty Bernard82 0001 2010,01465SpanishF42Daniella Gomez37 1005310,01431EnglishF43Yolanda Tati39 0005510,01040English/SpanishF44Adriana Gastelum96 1001 0190,01020PortugueseF45Oneika Raymond75 2007800,01037EnglishF46Carlota Santos30 5003110,01020PortugueseF47Andre Macedo39 4003160,00802PortugueseF48Jani Gabriel42 600 <t< td=""><td>29</td><td>Driziinha</td><td>38 200</td><td>993</td><td></td><td>e</td><td>F</td></t<>   | 29         | Driziinha                                   | 38 200    | 993       |            | e                  | F          |  |
| 31       Cristiana Rocha       27 200       603       0,02217       English/Portuguese       F         32       Madalena Bonvalot       53 700       1 122       0,02089       English/Portuguese       F         33       Abril Raluy       90 600       1 781       0,01966       English/Spanish       F         34       Michelle Crossan       59 200       1 163       0,01965       English       F         35       Margarida Martinho       56 700       1 092       0,01926       Portuguese       F         36       Ines Patrocinio       83 400       1 474       0,01767       Portuguese       F         37       Catarina Beato       52 500       904       0,01722       Portuguese       F         38       Chrissa Benson       72 100       1 218       0,01688       Portuguese       F         40       Mafalda Patricio       53 000       888       0,01675       English       F         41       Pitty Bernard       82 000       1 201       0,01465       Spanish       F         42       Daniella Gomez       37 100       531       0,01431       English       F         43       Yolanda Tati       39 000       5   | 30         | Teresa Vu                                   | 73 100    | 1 635     | 0,02237    | U U                | F          |  |
| 32Madalena Bonvalot53 7001 1220,02089English/PortugueseF33Abril Raluy90 6001 7810,01966English/SpanishF34Michelle Crossan59 2001 1630,01965EnglishF35Margarida Martinho56 7001 0920,01926PortugueseF36Ines Patrocinio83 4001 4740,01767PortugueseF37Catarina Beato52 5009040,01722PortugueseF38Chrissa Benson72 1001 2180,01689EnglishF39Bruna Corby48 1008120,01675EnglishF40Mafalda Patricio53 0008880,01675EnglishF41Pitty Bernard82 0001 2010,01431EnglishF42Daniella Gomez37 1005310,01431PortugueseF43Yolanda Tati39 0005510,01070English/SpanishF44Adriana Gastelum96 1001 0190,01060English/SpanishF45Oneika Raymond75 2007800,01037EnglishF46Carlota Santos30 5003110,01020PortugueseF47Andre Macedo39 4003160,00802PortugueseF48Jani Gabriel42 6002940,00690PortugueseF49Jacquie Alexander90 0005  | 31         | Cristiana Rocha                             | 27 200    | 603       |            | U                  | F          |  |
| 33Abril Raluy90 6001 7810,01966English/SpanishF34Michelle Crossan59 2001 1630,01965EnglishF35Margarida Martinho56 7001 0920,01926PortugueseF36Ines Patrocinio83 4001 4740,01767PortugueseF37Catarina Beato52 5009040,01722PortugueseF38Chrissa Benson72 1001 2180,01689EnglishF39Bruna Corby48 1008120,01688PortugueseF40Mafalda Patricio53 0008880,01675EnglishF41Pitty Bernard82 0001 2010,01465SpanishF42Daniella Gomez37 1005310,01431EnglishF43Yolanda Tati39 0005510,01600English/SpanishF44Adriana Gastelum96 1001 0190,01060English/SpanishF45Oneika Raymond75 2007800,01037EnglishF46Carlota Santos30 5003110,01020PortugueseF47Andre Macedo39 4003160,00802PortugueseF48Jani Gabriel42 6002940,00690PortugueseF49Jacquie Alexander90 0005360,00596EnglishF   | 32         | Madalena Bonvalot                           | 53 700    | 1 122     |            |                    | F          |  |
| 34       Michelle Crossan       59 200       1 163       0,01965       English       F         35       Margarida Martinho       56 700       1 092       0,01926       Portuguese       F         36       Ines Patrocinio       83 400       1 474       0,01767       Portuguese       F         37       Catarina Beato       52 500       904       0,01722       Portuguese       F         38       Chrissa Benson       72 100       1 218       0,01689       English       F         39       Bruna Corby       48 100       812       0,01688       Portuguese       F         40       Mafalda Patricio       53 000       888       0,01675       English       F         41       Pitty Bernard       82 000       1 201       0,01465       Spanish       F         42       Daniella Gomez       37 100       531       0,01431       English       F         43       Yolanda Tati       39 000       551       0,01413       Portuguese       F         44       Adriana Gastelum       96 100       1019       0,01060       English/Spanish       F         45       Oneika Raymond       75 200       780       0,0103  | 33         | Abril Raluy                                 | 90 600    | 1 781     |            |                    | F          |  |
| 35       Margarida Martinho       56 700       1 092       0,01926       Portuguese       F         36       Ines Patrocinio       83 400       1 474       0,01767       Portuguese       F         37       Catarina Beato       52 500       904       0,01722       Portuguese       F         38       Chrissa Benson       72 100       1 218       0,01689       English       F         39       Bruna Corby       48 100       812       0,01688       Portuguese       F         40       Mafalda Patricio       53 000       888       0,01675       English       F         41       Pitty Bernard       82 000       1 201       0,01465       Spanish       F         42       Daniella Gomez       37 100       531       0,01431       English       F         43       Yolanda Tati       39 000       551       0,01413       Portuguese       F         44       Adriana Gastelum       96 100       1019       0,01060       English       F         45       Oneika Raymond       75 200       780       0,01037       English       F         45       Oneika Raymond       30 500       311       0,01020   | 34         | •   |           | 1 163     | 0,01965    | • ·                | F          |  |
| A         Ines         Patrocinio         83 400         1 474         0,01767         Portuguese         F           37         Catarina Beato         52 500         904         0,01722         Portuguese         F           38         Chrissa Benson         72 100         1218         0,01689         English         F           39         Bruna Corby         48 100         812         0,01688         Portuguese         F           40         Mafalda Patricio         53 000         888         0,01675         English         F           41         Pitty Bernard         82 000         1 201         0,01465         Spanish         F           42         Daniella Gomez         37 100         531         0,01431         English         F           43         Yolanda Tati         39 000         551         0,01413         Portuguese         F           44         Adriana Gastelum         96 100         1019         0,01060         English         F           45         Oneika Raymond         75 200         780         0,01037         English         F           46         Carlota Santos         30 500         311         0,01020         Portuguese  |            |   |           |           |            | -                  |            |  |
| 37       Catarina Beato       52 500       904       0,01722       Portuguese       F         38       Chrissa Benson       72 100       1 218       0,01689       English       F         39       Bruna Corby       48 100       812       0,01688       Portuguese       F         40       Mafalda Patricio       53 000       888       0,01675       English       F         41       Pitty Bernard       82 000       1 201       0,01465       Spanish       F         42       Daniella Gomez       37 100       531       0,01431       English       F         43       Yolanda Tati       39 000       551       0,01431       Portuguese       F         44       Adriana Gastelum       96 100       1019       0,01060       English       F         45       Oneika Raymond       75 200       780       0,01037       English       F         46       Carlota Santos       30 500       311       0,01020       Portuguese       F         47       Andre Macedo       39 400       316       0,00802       Portuguese       F         48       Jani Gabriel       42 600       294       0,00690       Portugue   | 36         | 0   | 83 400    |           | 0,01767    | 0                  | F          |  |
| 38       Chrissa Benson       72 100       1 218       0,01689       English       F         39       Bruna Corby       48 100       812       0,01688       Portuguese       F         40       Mafalda Patricio       53 000       888       0,01675       English       F         41       Pitty Bernard       82 000       1 201       0,01465       Spanish       F         42       Daniella Gomez       37 100       531       0,01431       English       F         43       Yolanda Tati       39 000       551       0,01433       Portuguese       F         44       Adriana Gastelum       96 100       1019       0,01060       English       F         45       Oneika Raymond       75 200       780       0,01037       English       F         46       Carlota Santos       30 500       311       0,01020       Portuguese       F         47       Andre Macedo       39 400       316       0,00802       Portuguese       F         48       Jani Gabriel       42 600       294       0,00690       Portuguese       F         49       Jacquie Alexander       90 000       536       0,00596       Engli   |            | Catarina Beato                              | 52 500    |           |            | Ũ                  | F          |  |
| 39       Bruna Corby       48 100       812       0,01688       Portuguese       F         40       Mafalda Patricio       53 000       888       0,01675       English       F         41       Pitty Bernard       82 000       1 201       0,01465       Spanish       F         42       Daniella Gomez       37 100       531       0,01431       English       F         43       Yolanda Tati       39 000       551       0,01433       Portuguese       F         44       Adriana Gastelum       96 100       1 019       0,01060       English       F         45       Oneika Raymond       75 200       780       0,0137       English       F         46       Carlota Santos       30 500       311       0,01020       Portuguese       F         47       Andre Macedo       39 400       316       0,00802       Portuguese       M         48       Jani Gabriel       42 600       294       0,00690       Portuguese       F         49       Jacquie Alexander       90 000       536       0,00596       English       F  | 38         | Chrissa Benson                              |           | 1 218     |            | U U                | F          |  |
| 41       Pitty Bernard       82 000       1 201       0,01465       Spanish       F         42       Daniella Gomez       37 100       531       0,01431       English       F         43       Yolanda Tati       39 000       551       0,01433       Portuguese       F         44       Adriana Gastelum       96 100       1 019       0,01060       English/Spanish       F         45       Oneika Raymond       75 200       780       0,01037       English       F         46       Carlota Santos       30 500       311       0,01020       Portuguese       F         47       Andre Macedo       39 400       316       0,00802       Portuguese       M         48       Jani Gabriel       42 600       294       0,00690       Portuguese       F         49       Jacquie Alexander       90 000       536       0,00596       English       F   | 39         | Bruna Corby                                 | 48 100    | 812       | 0,01688    | -                  | F          |  |
| 41Pitty Bernard82 0001 2010,01465SpanishF42Daniella Gomez37 1005310,01431EnglishF43Yolanda Tati39 0005510,01413PortugueseF44Adriana Gastelum96 1001 0190,01060English/SpanishF45Oneika Raymond75 2007800,01037EnglishF46Carlota Santos30 5003110,01020PortugueseF47Andre Macedo39 4003160,00802PortugueseM48Jani Gabriel42 6002940,00690PortugueseF49Jacquie Alexander90 0005360,00596EnglishF   | 40         |   | 53 000    | 888       | 0,01675    | U U                | F          |  |
| 42       Daniella Gomez       37 100       531       0,01431       English       F         43       Yolanda Tati       39 000       551       0,01413       Portuguese       F         44       Adriana Gastelum       96 100       1019       0,01060       English/Spanish       F         45       Oneika Raymond       75 200       780       0,01037       English       F         46       Carlota Santos       30 500       311       0,01020       Portuguese       F         47       Andre Macedo       39 400       316       0,00802       Portuguese       M         48       Jani Gabriel       42 600       294       0,00690       Portuguese       F         49       Jacquie Alexander       90 000       536       0,00596       English       F  | 41         | Pitty Bernard                               | 82 000    | 1 201     | 0,01465    | -                  | F          |  |
| 43Yolanda Tati39 0005510,01413PortugueseF44Adriana Gastelum96 10010190,01060English/SpanishF45Oneika Raymond75 2007800,01037EnglishF46Carlota Santos30 5003110,01020PortugueseF47Andre Macedo39 4003160,00802PortugueseM48Jani Gabriel42 6002940,00690PortugueseF49Jacquie Alexander90 0005360,00596EnglishF   |            |   |           |           |            |                    | F          |  |
| 44Adriana Gastelum96 1001 0190,01060English/SpanishF45Oneika Raymond75 2007800,01037EnglishF46Carlota Santos30 5003110,01020PortugueseF47Andre Macedo39 4003160,00802PortugueseM48Jani Gabriel42 6002940,00690PortugueseF49Jacquie Alexander90 0005360,00596EnglishF   |            |   |           |           |            | -                  |            |  |
| 45Oneika Raymond75 2007800,01037EnglishF46Carlota Santos30 5003110,01020PortugueseF47Andre Macedo39 4003160,00802PortugueseM48Jani Gabriel42 6002940,00690PortugueseF49Jacquie Alexander90 0005360,00596EnglishF   |            |   |           |           |            | U U                |            |  |
| 46Carlota Santos30 5003110,01020PortugueseF47Andre Macedo39 4003160,00802PortugueseM48Jani Gabriel42 6002940,00690PortugueseF49Jacquie Alexander90 0005360,00596EnglishF   |            |   |           |           |            | 0 1                | F          |  |
| 47       Andre Macedo       39 400       316       0,00802       Portuguese       M         48       Jani Gabriel       42 600       294       0,00690       Portuguese       F         49       Jacquie Alexander       90 000       536       0,00596       English       F  |            |   |           |           |            | e e                |            |  |
| 48         Jani Gabriel         42 600         294         0,00690         Portuguese         F           49         Jacquie Alexander         90 000         536         0,00596         English         F  |            |   |           |           |            | e e                |            |  |
| 49 Jacquie Alexander 90 000 536 0,00596 English F  |            |   |           |           |            | Ũ                  |            |  |
|  |            |   |           |           |            | Ũ                  |            |  |
|  | 50         | -   | 51 700    | 243       | 0,00470    | -                  | F          |  |

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# Appendix C Outputs from SPSS and AMOS

# C.1. Validity Checks

Estatísticas de confiabilidade

| Alfa de Cronbach | N de itens |
|------------------|------------|
| 0,875            | 4          |

#### Estatísticas de item-total

| Se eu quisesse um<br>conselho sobre estilo<br>de vida ou viagens, eu<br>pediria ao Logan           | Média de escala<br>se o item for<br>excluído<br>7,99 | Variância de<br>escala se o item<br>for excluído<br>16,306 | Correlação de<br>item total<br>corrigida<br>0,621 | Cronbach se<br>o item for<br>excluído<br>0,887 |
|--|--|--|---|--|
| Se eu seguisse o<br>Logan no Instagram,<br>eu escolheria<br>produtos com base no<br>que ele postou | 8,16   | 16,783   | 0,734   | 0,839  |
| A opinião do Logan<br>sobre estilo de vida<br>poderia ter um<br>impacto em mim                     | 8,03   | 15,454   | 0,795   | 0,814  |
| O Logan poderia<br>influenciar as minhas<br>opiniões acerca de<br>estilo de vida                   | 8,05   | 15,795   | 0,791   | 0,816  |

a. Exclusão de lista com base em todas as variáveis do procedimento.

#### Estatísticas de confiabilidade

| Alfa de Cronbach | N de itens |
|------------------|------------|
| 0,855            | 4          |

#### Estatísticas de item-total Variância de Média de escala Correlação de Cronbach se se o item for escala se o item item total o item for excluído for excluído corrigida excluído 16,749 9,28 0,550 0,881 Se eu quisesse um conselho sobre estilo de vida ou viagens, eu pediria à Emily 9,21 16,252 0,820 0,686 Se eu seguisse à Emily no Instagram, eu escolheria produtos com base no que ela postou 9,24 15,282 0,802 0,771 A opinião da Emily sobre estilo de vida poderia ter um impacto em mim 9,35 15,920 0,776 0,784 A Emily poderia influenciar as minhas opiniões acerca de estilo de vida

#### Estatísticas de confiabilidade

| Alfa de Cronbach | N de itens |   |
|------------------|------------|---|
| 0,791            |            | 4 |

#### Estatísticas de item-total

|                        | Média de escala | Variância de     | Correlação de | Cronbach se |
|------------------------|-----------------|------------------|---------------|-------------|
|                        | se o item for   | escala se o item | item total    | o item for  |
|                        | excluído        | for excluído     | corrigida     | excluído    |
| Acha que o Logan é     | 12,68           | 6,091            | 0,641         | 0,719       |
| (frio/caloroso)        |                 |                  |               |             |
| Acha que o Logan é     | 12,55           | 5,896            | 0,699         | 0,689       |
| (antipático/simpático) |                 |                  |               |             |
| Acha que o Logan é     | 13,22           | 6,927            | 0,434         | 0,821       |
| (falso/sincero)        |                 |                  |               |             |
| Acha que o Logan é     | 12,48           | 6,164            | 0,645         | 0,718       |
| (hostil/amigavel)      |                 |                  |               |             |

#### Estatísticas de confiabilidade

| Alfa de Cronbach | N de itens |   |
|------------------|------------|---|
| 0,838            |            | 4 |

#### Estatísticas de item-total

|                        | Média de escala | Variância de     | Correlação de | Cronbach se |
|------------------------|-----------------|------------------|---------------|-------------|
|                        | se o item for   | escala se o item | item total    | o item for  |
|                        | excluído        | for excluído     | corrigida     | excluído    |
| Acha que a Emily é     | 12,83           | 7,309            | 0,672         | 0,794       |
| (fria/calorosa)        |                 |                  |               |             |
| Acha que a Emily é     | 12,84           | 6,866            | 0,781         | 0,744       |
| (antipática/simpática) |                 |                  |               |             |
| Acha que a Emily é     | 13,47           | 8,228            | 0,532         | 0,852       |
| (falsa/sincera)        |                 |                  |               |             |
| Acha que a Emily é     | 12,93           | 7,242            | 0,704         | 0,780       |
| (hostil/amigavel)      |                 |                  |               |             |

# C.2. General Overview

## C.2.1. General Model

#### Regression Weights: (Group number 1 - Default model)

|                        |       |                             | Estimate | S.E.  | C.R.   | Р     |
|------------------------|-------|-----------------------------|----------|-------|--------|-------|
| Ascribed_Opinion_Leade | ers < | №seguidores                 | 0,134    | 0,102 | 1,309  | 0,19  |
| Influencer_Likability  | <     | Nºseguidores                | -0,134   | 0,059 | -2,263 | 0,024 |
| Influencer_Likability  | <     | Ascribed_Opinion_Leadership | 0,279    | 0,022 | 12,474 | ***   |

#### Standardized Regression Weights: (Group number 1 - Default model)

|                        |       |                             | Estimate |
|------------------------|-------|-----------------------------|----------|
| Ascribed_Opinion_Leade | ers < | N⁰seguidores                | 0,051    |
| Influencer_Likability  | <     | №seguidores                 | -0,079   |
| Influencer_Likability  | <     | Ascribed_Opinion_Leadership | 0,434    |

#### Means: (Group number 1 - Default model)

|              | Estimate | S.E.  | C.R.   | Р   |
|--------------|----------|-------|--------|-----|
| Nºseguidores | 0,537    | 0,019 | 27,852 | *** |

#### Intercepts: (Group number 1 - Default model)

|                             | Estimate | S.E.  | C.R.   | Р   |
|-----------------------------|----------|-------|--------|-----|
| Ascribed_Opinion_Leadership | 2,836    | 0,075 | 37,919 | *** |
| Influencer_Likability       | 3,556    | 0,077 | 46,231 | *** |

#### Variances: (Group number 1 - Default model)

|             | Estimat<br>e | S.E.  | C.R.   | Р   |
|-------------|--------------|-------|--------|-----|
| №seguidores | 0,249        | 0,014 | 18,303 | *** |
| e1          | 1,739        | 0,095 | 18,317 | *** |
| e2          | 0,585        | 0,032 | 18,316 | *** |

# C.2.2. [H1] without controlling ascribed opinion leadership

|          | Variáveis Inseridas/Removidas <sup>a</sup> |                        |         |  |  |  |  |  |
|----------|--|------------------------|---------|--|--|--|--|--|
| Modelo   | Variáveis inseridas                        | Variáveis<br>removidas | Método  |  |  |  |  |  |
| 1        | Nseguidores <sup>b</sup>                   |                        | Inserir |  |  |  |  |  |
| a. Variá | ivel Dependente: Influ                     | encer Likability       | 7       |  |  |  |  |  |

b. Todas as variáveis solicitadas inseridas.

|            |                   |            | Resumo do 1 | modelo                  |         |         |         |     |                 |
|------------|-------------------|------------|-------------|-------------------------|---------|---------|---------|-----|-----------------|
|            |                   |            | Erro        | Estatísticas de mudança |         |         |         |     |                 |
| Model      | R                 | R quadrado | R quadrado  | padrão da               | Mudança | Mudança | 1.04    | 1/2 | Sig.<br>Mudanca |
| 0          | 1                 | ajustado   | estimativa  | de R F                  | df1     | df2     | Mudança |     |                 |
|            |                   |            |             | quadrado                |         |         |         | F   |                 |
| 1          | ,055 <sup>a</sup> | 0,003      | 0,002       | 0,85026                 | 0,003   | 2,051   | 1       | 670 | 0,153           |
| a Proditor | oci (Constanta) N | aguidaraa  |             |                         |         |         |         |     |                 |

a. Preditores: (Constante), Nseguidores

#### ANOVA<sup>a</sup>

| Mod | elo       | Soma dos<br>Quadrados | df  | Quadrado<br>Médio | Z     | Sig.              |
|-----|-----------|-----------------------|-----|-------------------|-------|-------------------|
|     | Regressão | 1,482                 | 1   | 1,482             | 2,051 | ,153 <sup>b</sup> |
| 1   | Resíduo   | 484,377               | 670 | 0,723             |       |                   |
|     | Total     | 485,859               | 671 |                   |       |                   |
|     |           |                       |     |                   |       |                   |

a. Variável Dependente: Influencer\_Likability

b. Preditores: (Constante), Nseguidores

|                          | Co                               | eficientes <sup>a</sup> |             |        |       |
|--------------------------|----------------------------------|-------------------------|-------------|--------|-------|
|                          | Coeficientes não<br>padronizados |                         | Coeficiente |        |       |
| Modelo                   |                                  |                         | s           | t      | Sig.  |
|                          | В                                | Erro Erro               | Beta        |        |       |
| 1 (Constante)            | 4,347                            | 0,048                   |             | 90,304 | 0,000 |
| <sup>1</sup> Nseguidores | -0,094                           | 0,066                   | -0,055      | -1,432 | 0,153 |

a. Variável Dependente: Influencer\_Likability

### C.2.3. Low number of followees

#### **Regression Weights: (baixo - Default model)**

|                             |   |                             | Estimate | S.E.  | C.R.   | Р     |
|-----------------------------|---|-----------------------------|----------|-------|--------|-------|
| Ascribed_Opinion_Leadership | < | №seguidores                 | 0,3      | 0,142 | 2,111  | 0,035 |
| Influencer_Likability       | < | №seguidores                 | -0,188   | 0,088 | -2,134 | 0,033 |
| Influencer_Likability       | < | Ascribed_Opinion_Leadership | 0,282    | 0,034 | 8,392  | ***   |

#### Standardized Regression Weights: (baixo - Default model)

|                             |   |                             | Estimate |
|-----------------------------|---|-----------------------------|----------|
| Ascribed_Opinion_Leadership | < | №seguidores                 | 0,115    |
| Influencer_Likability       | < | №seguidores                 | -0,107   |
| Influencer_Likability       | < | Ascribed_Opinion_Leadership | 0,419    |

#### Means: (baixo - Default model)

|              | Estimate | S.E.  | C.R.   | Р   |
|--------------|----------|-------|--------|-----|
| N⁰seguidores | 0,533    | 0,027 | 19,498 | *** |

#### Intercepts: (baixo - Default model)

|                             | Estimate | S.E.  | C.R.   | Р   |
|-----------------------------|----------|-------|--------|-----|
| Ascribed_Opinion_Leadership | 2,601    | 0,104 | 25,107 | *** |
| Influencer_Likability       | 3,472    | 0,108 | 32,085 | *** |

#### Variances: (baixo - Default model)

|              | Estimate | S.E.  | C.R.   | Р   |
|--------------|----------|-------|--------|-----|
| N⁰seguidores | 0,249    | 0,019 | 12,904 | *** |
| e1           | 1,671    | 0,129 | 12,922 | *** |
| e2           | 0,632    | 0,049 | 12,922 | *** |

#### Matrices (baixo - Default model)

#### Total Effects (baixo - Default model)

|                             | Nº<br>seguidores | Ascribed Opinion Leadership |
|-----------------------------|------------------|-----------------------------|
| Ascribed_Opinion_Leadership | 0,3              | 0                           |
| Influencer_Likability       | -0,103           | 0,282                       |

#### Standardized Total Effects (baixo - Default model)

|                             | Nº<br>seguidores | Ascribed Opinion Leadership |
|-----------------------------|------------------|-----------------------------|
| Ascribed_Opinion_Leadership | 0,115            | 0                           |
| Influencer_Likability       | -0,059           | 0,419                       |

#### **Direct Effects (baixo - Default model)**

|                             | Nº<br>seguidores | Ascribed Opinion Leadership |
|-----------------------------|------------------|-----------------------------|
| Ascribed_Opinion_Leadership | 0,3              | 0                           |
| Influencer_Likability       | -0,188           | 0,282                       |

#### Standardized Direct Effects (baixo - Default model)

|                             | Nº<br>seguidores | Ascribed Opinion Leadership |
|-----------------------------|------------------|-----------------------------|
| Ascribed_Opinion_Leadership | 0,115            | 0                           |
| Influencer_Likability       | -0,107           | 0,419                       |

#### Indirect Effects (baixo - Default model)

|                             | Nº<br>seguidores | Ascribed Opinion Leadership |
|-----------------------------|------------------|-----------------------------|
| Ascribed_Opinion_Leadership | 0                | 0                           |
| Influencer_Likability       | 0,085            | 0                           |

#### Standardized Indirect Effects (baixo - Default model)

|                             | Nº<br>seguidores | Ascribed Opinion Leadership |
|-----------------------------|------------------|-----------------------------|
| Ascribed_Opinion_Leadership | 0                | 0                           |
| Influencer_Likability       | 0,048            | 0                           |

## C.2.4. Mediation of ascribed opinion leadership in the low number

### of followees' scenario

#### Standardized Indirect Effects (Low - Default model)

#### Standardized Indirect Effects - Lower Bounds (PC) (Low - Default model)

|                             | Nº<br>seguidores | Ascribed<br>Opinion<br>Leadership |
|-----------------------------|------------------|-----------------------------------|
| Ascribed_Opinion_Leadership | 0                | 0                                 |
| Influencer_Likability       | 0,017            | 0                                 |

#### Standardized Indirect Effects - Upper Bounds (PC) (Low - Default model)

|                             | Nº<br>seguidores | Ascribed<br>Opinion<br>Leadership |
|-----------------------------|------------------|-----------------------------------|
| Ascribed_Opinion_Leadership | 0                | 0                                 |
| Influencer_Likability       | 0,093            | 0                                 |

#### Standardized Indirect Effects - Two Tailed Significance (PC) (Low - Default model)

|                             | Nº<br>seguidores | Ascribed<br>Opinion<br>Leadership |
|-----------------------------|------------------|-----------------------------------|
| Ascribed_Opinion_Leadership |                  |                                   |
| Influencer_Likability       | 0,01             |                                   |

# C.2.5. High number of followees

#### Regression Weights: (alto - Default model)

|                             |   |                             | Estimate | S.E.  | C.R.   | Р     |
|-----------------------------|---|-----------------------------|----------|-------|--------|-------|
| Ascribed_Opinion_Leadership | < | №seguidores                 | -0,036   | 0,145 | -0,247 | 0,805 |
| Influencer_Likability       | < | Nºseguidores                | -0,086   | 0,079 | -1,09  | 0,276 |
| Influencer_Likability       | < | Ascribed_Opinion_Leadership | 0,262    | 0,03  | 8,832  | ***   |

#### Standardized Regression Weights: (alto - Default model)

|                             |   |                             | Estimate |
|-----------------------------|---|-----------------------------|----------|
| Ascribed_Opinion_Leadership | < | Nºseguidores                | -0,013   |
| Influencer_Likability       | < | Nºseguidores                | -0,053   |
| Influencer_Likability       | < | Ascribed_Opinion_Leadership | 0,433    |

#### Means: (alto - Default model)

|              | Estimate | S.E.  | C.R.   | Р   |
|--------------|----------|-------|--------|-----|
| N⁰seguidores | 0,54     | 0,027 | 19,863 | *** |

#### Intercepts: (alto - Default model)

|                             | Estimate | S.E.  | C.R.   | Р   |
|-----------------------------|----------|-------|--------|-----|
| Ascribed_Opinion_Leadership | 3,074    | 0,106 | 28,898 | *** |
| Influencer_Likability       | 3,688    | 0,108 | 34,213 | *** |

#### Variances: (alto - Default model)

|             | Estimate | S.E.  | C.R.   | Р   |
|-------------|----------|-------|--------|-----|
| №seguidores | 0,248    | 0,019 | 12,961 | *** |
| e1          | 1,749    | 0,135 | 12,961 | *** |
| e2          | 0,515    | 0,04  | 12,961 | *** |

#### Matrices (alto - Default model)

#### Total Effects (alto - Default model)

|                             | Nº<br>seguidores | Ascribed Opinion Leadership |
|-----------------------------|------------------|-----------------------------|
| Ascribed_Opinion_Leadership | -0,036           | 0                           |
| Influencer_Likability       | -0,095           | 0,262                       |

#### Standardized Total Effects (alto - Default model)

|                             | Nº<br>seguidores | Ascribed_Opinion_Leadership |
|-----------------------------|------------------|-----------------------------|
| Ascribed_Opinion_Leadership | -0,013           | 0                           |
| Influencer_Likability       | -0,059           | 0,433                       |

#### Direct Effects (alto - Default model)

|                             | Nº<br>seguidores | Ascribed_Opinion_Leadership |
|-----------------------------|------------------|-----------------------------|
| Ascribed_Opinion_Leadership | -0,036           | 0                           |
| Influencer_Likability       | -0,086           | 0,262                       |

#### Standardized Direct Effects (alto - Default model)

|                             | Nº<br>seguidores | Ascribed_Opinion_Leadership |
|-----------------------------|------------------|-----------------------------|
| Ascribed_Opinion_Leadership | -0,013           | 0                           |
| Influencer_Likability       | -0,053           | 0,433                       |

#### Indirect Effects (alto - Default model)

|                             | Nº<br>seguidores | Ascribed_Opinion_Leadership |
|-----------------------------|------------------|-----------------------------|
| Ascribed_Opinion_Leadership | 0                | 0                           |
| Influencer_Likability       | -0,009           | 0                           |

#### Standardized Indirect Effects (alto - Default model)

|                             | Nº<br>seguidores | Ascribed_Opinion_Leadership |
|-----------------------------|------------------|-----------------------------|
| Ascribed_Opinion_Leadership | 0                | 0                           |
| Influencer_Likability       | -0,006           | 0                           |

# C.3. Further analysis

### C.3.1. Gender impact – men

#### Regression Weights: (Male - Default model)

|              |                             | Estimate | S.E.  | C.R.   | Р     |
|--------------|-----------------------------|----------|-------|--------|-------|
| Ascribed_ <  | №seguidores                 | -0,008   | 0,151 | -0,055 | 0,956 |
| Influence: < | №seguidores                 | -0,052   | 0,084 | -0,625 | 0,532 |
| Influence: < | Ascribed_Opinion_Leadership | 0,265    | 0,032 | 8,287  | ***   |

#### Standardized Regression Weights: (Male - Default model)

|              |                             | Estimate |
|--------------|-----------------------------|----------|
| Ascribed_ <  | N⁰seguidores                | -0,003   |
| Influence: < | №seguidores                 | -0,032   |
| Influence: < | Ascribed_Opinion_Leadership | 0,431    |

#### Means: (Male - Default model)

|              | Estimate | S.E.  | C.R.   | Р   |
|--------------|----------|-------|--------|-----|
| Nºseguidores | 0,507    | 0,029 | 17,584 | *** |

#### Intercepts: (Male - Default model)

|                             | Estimate | S.E.  | C.R.   | Р   |
|-----------------------------|----------|-------|--------|-----|
| Ascribed_Opinion_Leadership | 2,69     | 0,107 | 25,07  | *** |
| Influencer_Likability       | 3,558    | 0,105 | 33,965 | *** |

#### Variances: (Male - Default model)

|             | Estimate | S.E.  | C.R.  | Р   |
|-------------|----------|-------|-------|-----|
| №seguidores | 0,25     | 0,02  | 12,27 | *** |
| E2          | 1,71     | 0,139 | 12,27 | *** |
| E1          | 0,528    | 0,043 | 12,27 | *** |

### C.3.2. Gender impact – women

#### **Regression Weights: (Female - Default model)**

|              |                             | Estimate | S.E.  | C.R.   | Р     |
|--------------|-----------------------------|----------|-------|--------|-------|
| Ascribed_ <  | N⁰seguidores                | 0,212    | 0,136 | 1,553  | 0,12  |
| Influence: < | N⁰seguidores                | -0,205   | 0,084 | -2,448 | 0,014 |
| Influence: < | Ascribed_Opinion_Leadership | 0,294    | 0,032 | 9,254  | ***   |

#### Standardized Regression Weights: (Female - Default model)

|              |                             | Estimate |
|--------------|-----------------------------|----------|
| Ascribed_ <  | N⁰seguidores                | 0,081    |
| Influence: < | №seguidores                 | -0,115   |
| Influence: < | Ascribed_Opinion_Leadership | 0,434    |

#### Means: (Female - Default model)

|             | Estimate | S.E.  | C.R.   | Р   |
|-------------|----------|-------|--------|-----|
| №seguidores | 0,561    | 0,026 | 21,686 | *** |

#### Intercepts: (Female - Default model)

|                             | Estimate | S.E.  | C.R.   | Р   |
|-----------------------------|----------|-------|--------|-----|
| Ascribed_Opinion_Leadership | 2,971    | 0,102 | 29,099 | *** |
| Influencer_Likability       | 3,545    | 0,113 | 31,326 | *** |

#### Variances: (Female - Default model)

|             | Estimate | S.E.  | C.R.   | Р   |
|-------------|----------|-------|--------|-----|
| №seguidores | 0,246    | 0,018 | 13,563 | *** |
| E2          | 1,685    | 0,124 | 13,581 | *** |
| E1          | 0,628    | 0,046 | 13,581 | *** |

## C.3.3. Instagram usage

#### **Regression Weights: (Diariamente - Unconstrained)**

|              |                             | Estimate | S.E.  | C.R.   | Р     |
|--------------|-----------------------------|----------|-------|--------|-------|
| Ascribed_ <  | №seguidores                 | 0,146    | 0,105 | 1,397  | 0,162 |
| Influence: < | №seguidores                 | -0,15    | 0,062 | -2,425 | 0,015 |
| Influence: < | Ascribed_Opinion_Leadership | 0,283    | 0,023 | 12,07  | ***   |

#### Standardized Regression Weights: (Diariamente - Unconstrained)

|              |                             | Estimate |
|--------------|-----------------------------|----------|
| Ascribed_ <  | Nºseguidores                | 0,056    |
| Influence: < | Nºseguidores                | -0,087   |
| Influence: < | Ascribed_Opinion_Leadership | 0,433    |

#### Means: (Diariamente - Unconstrained)

|              | Estimate | S.E. | C.R.   | Р   |
|--------------|----------|------|--------|-----|
| N⁰seguidores | 0,547    | 0,02 | 27,584 | *** |

#### Intercepts: (Diariamente - Unconstrained)

|                             | Estimate | S.E.  | C.R.   | Р   |
|-----------------------------|----------|-------|--------|-----|
| Ascribed_Opinion_Leadership | 2,868    | 0,077 | 37,081 | *** |
| Influencer_Likability       | 3,552    | 0,081 | 43,782 | *** |

#### Variances: (Diariamente - Unconstrained)

|              | Estimate | S.E.  | C.R.   | Р   |
|--------------|----------|-------|--------|-----|
| N⁰seguidores | 0,248    | 0,014 | 17,764 | *** |
| E2           | 1,711    | 0,096 | 17,764 | *** |
| E1           | 0,593    | 0,033 | 17,764 | *** |

#### Variances: (Semanalmente/Mensalmente - Unconstrained)

|             | Estimate | S.E.  | C.R.  | Р   |
|-------------|----------|-------|-------|-----|
| №seguidores | 0,23     | 0,052 | 4,409 | *** |
| E2          | 1,666    | 0,378 | 4,409 | *** |
| E1          | 0,437    | 0,099 | 4,409 | *** |

#### Regression Weights: (Semanalmente/Mensalmente - Unconstrained)

|              |                             | Estimate | S.E.  | C.R.   | Р     |
|--------------|-----------------------------|----------|-------|--------|-------|
| Ascribed_ <  | №seguidores                 | -0,559   | 0,432 | -1,296 | 0,195 |
| Influence: < | №seguidores                 | 0,185    | 0,226 | 0,821  | 0,411 |
| Influence: < | Ascribed_Opinion_Leadership | 0,266    | 0,082 | 3,244  | 0,001 |

#### Standardized Regression Weights: (Semanalmente/Mensalmente - Unconstrained)

|              |                             | Estimate |
|--------------|-----------------------------|----------|
| Ascribed_ <  | №seguidores                 | -0,203   |
| Influence: < | N⁰seguidores                | 0,119    |
| Influence: < | Ascribed_Opinion_Leadership | 0,471    |

#### Means: (Semanalmente/Mensalmente - Unconstrained)

|              | Estimate | S.E.  | C.R.  | Р   |
|--------------|----------|-------|-------|-----|
| N⁰seguidores | 0,359    | 0,077 | 4,666 | *** |

#### Intercepts: (Semanalmente/Mensalmente - Unconstrained)

|                             | Estimate | S.E.  | C.R.           | Р   |
|-----------------------------|----------|-------|----------------|-----|
| Ascribed_Opinion_Leadership | 2,47     | 0,259 | 9 <i>,</i> 553 | *** |
| Influencer_Likability       | 3,502    | 0,242 | 14,466         | *** |

# C.3.4. Influencers' affinity

"0" means the respondent follows 0 influencers Regression Weights: (0 - Default model)

|                             |   |                             | Estimate | S.E.  | C.R.   | P Label     |
|-----------------------------|---|-----------------------------|----------|-------|--------|-------------|
| Ascribed_Opinion_Leadership | < | Nºseguidores                | -0,214   | 0,261 | -0,817 | 0,414 par_2 |
| Influencer_Likability       | < | N⁰seguidores                | 0,242    | 0,181 | 1,342  | 0,18 par_1  |
| Influencer_Likability       | < | Ascribed_Opinion_Leadership | 0,329    | 0,085 | 3,882  | *** par_3   |

#### Standardized Regression Weights: (0 - Default model)

|                             |   |                             | Estimate |
|-----------------------------|---|-----------------------------|----------|
| Ascribed_Opinion_Leadership | < | №seguidores                 | -0,1     |
| Influencer_Likability       | < | Nºseguidores                | 0,149    |
| Influencer_Likability       | < | Ascribed_Opinion_Leadership | 0,432    |

#### Means: (0 - Default model)

|              | Estimate | S.E.  | C.R.  | P Label   |
|--------------|----------|-------|-------|-----------|
| Nºseguidores | 0,47     | 0,062 | 7,623 | *** par_4 |

#### Intercepts: (0 - Default model)

|                             | Estimate | S.E.  | C.R.   | P Label   |
|-----------------------------|----------|-------|--------|-----------|
| Ascribed_Opinion_Leadership | 2,157    | 0,179 | 12,039 | *** par_6 |
| Influencer_Likability       | 3,247    | 0,221 | 14,723 | *** par_5 |

#### Variances: (0 - Default model)

|              | Estimate | S.E.  | C.R.  | P Label    |
|--------------|----------|-------|-------|------------|
| N⁰seguidores | 0,249    | 0,043 | 5,727 | *** par_25 |
| E2           | 1,117    | 0,195 | 5,727 | *** par_26 |
| E1           | 0,527    | 0,092 | 5,727 | *** par_27 |

#### "1" means the respondent follows between 1-5 influencers Regression Weights: (1 - Default model)

|                             |   |                             | Estimate | S.E.  | C.R.   | P Label     |
|-----------------------------|---|-----------------------------|----------|-------|--------|-------------|
| Ascribed_Opinion_Leadership | < | N⁰seguidores                | 0,138    | 0,171 | 0,808  | 0,419 par_8 |
| Influencer_Likability       | < | №seguidores                 | -0,028   | 0,082 | -0,346 | 0,729 par_7 |
| Influencer_Likability       | < | Ascribed_Opinion_Leadership | 0,24     | 0,031 | 7,787  | *** par_9   |

#### Standardized Regression Weights: (1 - Default model)

|                             |   |                             | Estimate |
|-----------------------------|---|-----------------------------|----------|
| Ascribed_Opinion_Leadership | < | №seguidores                 | 0,052    |
| Influencer_Likability       | < | №seguidores                 | -0,02    |
| Influencer_Likability       | < | Ascribed_Opinion_Leadership | 0,447    |

#### Means: (1 - Default model)

|              | Estimate | S.E.  | C.R.   | P Label    |
|--------------|----------|-------|--------|------------|
| N⁰seguidores | 0,531    | 0,032 | 16,592 | *** par_10 |

#### Intercepts: (1 - Default model)

|                             | Estimate | S.E.  | C.R.   | P Label    |
|-----------------------------|----------|-------|--------|------------|
| Ascribed_Opinion_Leadership | 2,654    | 0,124 | 21,333 | *** par_12 |
| Influencer_Likability       | 3,607    | 0,101 | 35,628 | *** par_11 |

#### Variances: (1 - Default model)

|             | Estimate | S.E.  | C.R.   | P Label    |
|-------------|----------|-------|--------|------------|
| №seguidores | 0,249    | 0,023 | 11,035 | *** par_28 |
| E2          | 1,77     | 0,16  | 11,035 | *** par_29 |
| E1          | 0,408    | 0,037 | 11,035 | *** par_30 |

#### "2" means the respondent follows between 5-20 influencers Regression Weights: (2 - Default model)

|                             |   |                             | Estimate | S.E.  | C.R.   | P Label      |
|-----------------------------|---|-----------------------------|----------|-------|--------|--------------|
| Ascribed_Opinion_Leadership | < | Nºseguidores                | 0,069    | 0,176 | 0,392  | 0,695 par_14 |
| Influencer_Likability       | < | Nºseguidores                | -0,13    | 0,112 | -1,163 | 0,245 par_13 |
| Influencer_Likability       | < | Ascribed_Opinion_Leadership | 0,311    | 0,044 | 7,055  | *** par_15   |

#### Standardized Regression Weights: (2 - Default model)

|                             |   |                             | Estimate |
|-----------------------------|---|-----------------------------|----------|
| Ascribed_Opinion_Leadership | < | №seguidores                 | 0,027    |
| Influencer_Likability       | < | Nºseguidores                | -0,073   |
| Influencer_Likability       | < | Ascribed_Opinion_Leadership | 0,441    |

#### Means: (2 - Default model)

|              | Estimate | S.E.  | C.R.   | P Label    |
|--------------|----------|-------|--------|------------|
| N⁰seguidores | 0,507    | 0,035 | 14,554 | *** par_16 |

#### Intercepts: (2 - Default model)

|                             | Estimate | S.E.  | C.R.   | P Label    |
|-----------------------------|----------|-------|--------|------------|
| Ascribed_Opinion_Leadership | 3,164    | 0,126 | 25,174 | *** par_18 |
| Influencer_Likability       | 3,476    | 0,161 | 21,634 | *** par_17 |

#### Variances: (2 - Default model)

|             | Estimate | S.E.  | C.R.   | P Label    |
|-------------|----------|-------|--------|------------|
| №seguidores | 0,25     | 0,025 | 10,143 | *** par_31 |
| E2          | 1,602    | 0,158 | 10,143 | *** par_32 |
| E1          | 0,642    | 0,063 | 10,143 | *** par_33 |

# "3" means the respondent follows more than 20 influencers

Regression Weights: (3 - Default model)

|                             |   |                             | Estimate | S.E.  | C.R.   | P Label      |
|-----------------------------|---|-----------------------------|----------|-------|--------|--------------|
| Ascribed_Opinion_Leadership | < | №seguidores                 | 0,242    | 0,209 | 1,162  | 0,245 par_20 |
| Influencer_Likability       | < | Nºseguidores                | -0,462   | 0,145 | -3,178 | 0,001 par_19 |
| Influencer_Likability       | < | Ascribed_Opinion_Leadership | 0,295    | 0,056 | 5,264  | *** par_21   |

#### Standardized Regression Weights: (3 - Default model)

|                             |   |                             | Estimate |
|-----------------------------|---|-----------------------------|----------|
| Ascribed_Opinion_Leadership | < | №seguidores                 | 0,093    |
| Influencer_Likability       | < | №seguidores                 | -0,233   |
| Influencer_Likability       | < | Ascribed_Opinion_Leadership | 0,386    |

#### Means: (3 - Default model)

|              | Estimate | S.E.  | C.R.   | P Label    |
|--------------|----------|-------|--------|------------|
| Nºseguidores | 0,61     | 0,039 | 15,486 | *** par_22 |

#### Intercepts: (3 - Default model)

|                             | Estimate | S.E.  | C.R.   | P Label    |
|-----------------------------|----------|-------|--------|------------|
| Ascribed_Opinion_Leadership | 3,021    | 0,163 | 18,526 | *** par_24 |
| Influencer_Likability       | 3,688    | 0,204 | 18,118 | *** par_23 |

#### Variances: (3 - Default model)

|              | Estimate | S.E.  | C.R.  | P Label    |
|--------------|----------|-------|-------|------------|
| N⁰seguidores | 0,238    | 0,027 | 8,749 | *** par_34 |
| E2           | 1,586    | 0,181 | 8,749 | *** par_35 |
| E1           | 0,762    | 0,087 | 8,749 | *** par_36 |

## C.3.5. Education level

#### "0" means the following education level: Primary/Highschool Regression Weights: (0 - Default model)

|              |                             | Estimate | S.E.  | C.R.  | Р     |
|--------------|-----------------------------|----------|-------|-------|-------|
| Ascribed_ <  | Nºseguidores                | 0,436    | 0,318 | 1,371 | 0,17  |
| Influence: < | Nºseguidores                | -0,223   | 0,173 | -1,29 | 0,197 |
| Influence: < | Ascribed_Opinion_Leadership | 0,207    | 0,065 | 3,199 | 0,001 |

#### Standardized Regression Weights: (0 - Default model)

|              |                             | Estimate |
|--------------|-----------------------------|----------|
| Ascribed_ <  | №seguidores                 | 0,163    |
| Influence: < | N⁰seguidores                | -0,147   |
| Influence: < | Ascribed_Opinion_Leadership | 0,364    |

#### Means: (0 - Default model)

|              | Estimate | S.E.  | C.R.  | Р   |
|--------------|----------|-------|-------|-----|
| N⁰seguidores | 0,406    | 0,059 | 6,849 | *** |

#### Intercepts: (0 - Default model)

|                             | Estimate | S.E.  | C.R.   | Р   |
|-----------------------------|----------|-------|--------|-----|
| Ascribed_Opinion_Leadership | 2,823    | 0,202 | 13,943 | *** |
| Influencer_Likability       | 3,861    | 0,212 | 18,171 | *** |

#### Variances: (0 - Default model)

|              | Estimate | S.E.  | C.R. | Р   |
|--------------|----------|-------|------|-----|
| Nºseguidores | 0,241    | 0,041 | 5,86 | *** |
| E2           | 1,673    | 0,286 | 5,86 | *** |
| E1           | 0,481    | 0,082 | 5,86 | *** |

#### "1" means the following education level: Bachelor Regression Weights: (1 - Default model)

|              |                             | Estimate | S.E.  | C.R.   | Р     |
|--------------|-----------------------------|----------|-------|--------|-------|
| Ascribed_ <  | Nºseguidores                | -0,027   | 0,17  | -0,159 | 0,874 |
| Influence: < | Nºseguidores                | -0,182   | 0,103 | -1,758 | 0,079 |
| Influence: < | Ascribed_Opinion_Leadership | 0,3      | 0,037 | 8,067  | ***   |

#### Standardized Regression Weights: (1 - Default model)

|              |                             | Estimate |
|--------------|-----------------------------|----------|
| Ascribed_ <  | Nºseguidores                | -0,01    |
| Influence: < | Nºseguidores                | -0,096   |
| Influence: < | Ascribed_Opinion_Leadership | 0,441    |

#### Means: (1 - Default model)

|              | Estimate | S.E. | C.R.   | Р   |
|--------------|----------|------|--------|-----|
| N⁰seguidores | 0,616    | 0,03 | 20,674 | *** |

#### Intercepts: (1 - Default model)

|                             | Estimate | S.E.  | C.R.   | Р   |
|-----------------------------|----------|-------|--------|-----|
| Ascribed_Opinion_Leadership | 3,068    | 0,133 | 22,986 | *** |
| Influencer_Likability       | 3,528    | 0,14  | 25,187 | *** |

#### Variances: (1 - Default model)

|              | Estimate | S.E.  | C.R.  | Р   |
|--------------|----------|-------|-------|-----|
| Nºseguidores | 0,237    | 0,02  | 11,55 | *** |
| E2           | 1,827    | 0,158 | 11,55 | *** |
| E1           | 0,675    | 0,058 | 11,55 | *** |

#### "1" means the following education level: Master/Doctoral Regression Weights: (2 - Default model)

|              |                             | Estimate | S.E.  | C.R.   | Р     |
|--------------|-----------------------------|----------|-------|--------|-------|
| Ascribed_ <  | №seguidores                 | 0,152    | 0,141 | 1,074  | 0,283 |
| Influence: < | №seguidores                 | -0,067   | 0,079 | -0,844 | 0,399 |
| Influence: < | Ascribed_Opinion_Leadership | 0,27     | 0,031 | 8,811  | ***   |

#### Standardized Regression Weights: (2 - Default model)

|              |                             | Estimate |
|--------------|-----------------------------|----------|
| Ascribed_ <  | №seguidores                 | 0,059    |
| Influence: < | №seguidores                 | -0,042   |
| Influence: < | Ascribed_Opinion_Leadership | 0,437    |

#### Means: (2 - Default model)

|              | Estimate | S.E.  | C.R.  | Р   |
|--------------|----------|-------|-------|-----|
| N⁰seguidores | 0,503    | 0,028 | 18,29 | *** |

#### Intercepts: (2 - Default model)

|                             | Estimate | S.E. | C.R.   | Р   |
|-----------------------------|----------|------|--------|-----|
| Ascribed_Opinion_Leadership | 2,702    | 0,1  | 26,946 | *** |
| Influencer_Likability       | 3,533    | 0,1  | 35,37  | *** |

#### Variances: (2 - Default model)

|              | Estimate | S.E.  | C.R.   | Р   |
|--------------|----------|-------|--------|-----|
| N⁰seguidores | 0,25     | 0,019 | 12,855 | *** |
| E2           | 1,651    | 0,128 | 12,855 | *** |
| E1           | 0,513    | 0,04  | 12,855 | *** |